WILLINGNESS-TO-PAY FOR POMEGRANATES: IMPACT OF PRODUCT AND HEALTH FEATURES USING NONHYPOTHETICAL PROCEDURES

A Thesis

by

CALLIE PAULINE MCADAMS

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

August 2011

Major Subject: Agricultural Economics

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Chair of Committee,	Marco A. Palma
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Major Subject: Agricultural Economics

ABSTRACT

Willingness-to-Pay for Pomegranates: Impact of Product and Health Features Using Nonhypothetical Procedures. (August 2011)

Callie Pauline McAdams, B.S., North Carolina State University

Chair of Advisory Committee: Dr. Marco A. Palma

The use of functional foods by individuals to address health issues is now gaining attention. Pomegranate fruits and other pomegranate products contain phytochemicals, including antioxidants with potential human health benefits. The production of pomegranates in the United States is concentrated in California; yet pomegranates can be grown in other regions. The purpose of this study was two-fold: 1) to address the market potential and consumer preferences for pomegranate fruits and other pomegranate products in Texas and 2) to address issues of experimental auction design and estimation in regards to novel products and health benefits of food products. A nonhypothetical experimental procedure was developed that combined preference rankings with a uniform nth-price auction to elicit preferences and willingness-to-pay (WTP) for pomegranate fruit products.

A representative sample of subjects (n=203) from the Bryan-College Station area of Texas submitted baseline rankings and bids on six pomegranate products and a control fruit product. Of the participants, 75.4% had never purchased a pomegranate fruit. Three additional information treatments were imposed: tasting information, health

and nutrition information, and anti-cancer information. Subjects had the greatest WTP for the control product and the processed pomegranate products; the whole pomegranate fruits had the lowest WTP. The preference rankings for the baseline round indicated the same order of preferences as the bids.

Random-effects tobit models and mixed linear models on the full bids and individual changes in bids were used to make estimates of WTP. Unengaged bidders and bid censoring were addressed. Previous purchases of pomegranates and household size were the most robust demographic/behavioral predictors of WTP. Tasting information had a greater effect on WTP than health and nutrition information or anti-cancer information. Providing a reference price also increased WTP. Preference rankings were estimated using a rank-ordered logit and a mixed rank-ordered logit model. There was an interaction effect of each information treatment with the product characteristics, indicating that studies of effects of information treatments on preferences are not generalizable across products. There was divergence in the results for the preference rankings from the results of the experimental auction; preference rankings and bids gave conflicting results for the same products.

DEDICATION

I would like to dedicate this work to my amazing family: parents, sister, aunts, uncles, and grandparents. You have inspired my love of agriculture as well as my dedication and work ethic. You have each played an important part in this process, and I could not have done it without you. For that, I will never be able to sufficiently express my gratitude. I would also like to dedicate this thesis to the memory of my late grandfather, Howard H. McAdams Sr., who was one of the strongest, most humble men I have ever known.

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To my friends and classmates throughout the master's program who have offered a smile, an opinion, encouragement, or even a diversion, I say a special thank you for making the experience I have had in College Station one that I will not soon forget. I would also like to thank my friends and family in North Carolina who tolerated the time I have spent away from them and for all of their support.

I owe a particular debt of gratitude to the participants of the practice auctions and the actual study as well as all those who assisted with the auctions: Dr. Marco Palma, Brad Roberson, Alba Collart-Dinarte, Antonio Ruiz DeKing, and Carolina Rivas. I am

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NOMENCLATURE

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BDM	Becker, DeGroot, and Marschak
CRRAM	Constant Relative Risk Aversion Model
EPA	Environmental Protection Agency
FDA	Food and Drug Administration
fMRI	Functional Magnetic Resonance Imaging
GM	Genetically Modified
ha	Hectare
HT	Hydrolyzable Tannin
kg	Kilogram
kPa	Kilopascal
IIA	Independence of Irrelevant Alternatives
lbs	Pounds
MAP	Modified Atmosphere Packaging
MNL	Multinomial Logit
MSL	Maximum Simulated Log-Likelihood
OB	Ordered Bid
OLS	Ordinary Least Squares
RNNE	Risk Neutral Nash Equilibrium

RPL	Random Parameters Logit (or Mixed Logit)
RTE	Ready-to-Eat
US	United States
USDA	United States Department of Agriculture
WTA	Willingness-to-Accept
WTP	Willingness-to-Pay

CHAPTER I

INTRODUCTION

Marketing opportunities for new products rely on innovation and creativity, but they also rely on the adequacy of information that is available to decision-makers. One marketing opportunity that has seen growth in recent years is the development of foods that address health issues; in particular, this includes foods that are plant-derived (Espín, García-Conesa, and Tomás-Barberán 2007). The cost of traditional health care is on the rise with total national health expenditures in the United States (US) in 2009 estimated at $2.5 trillion, a staggering 17.3 percent of gross domestic product (GDP) (Truffer et al. 2010). The government has many incentives to reduce health care costs as well with $1.1 trillion in public funds going towards health expenditures in 2008, and it is projected that by 2012 half of total spending on healthcare will be from public rather than private sources (Truffer et al. 2010). Orszag and Ellis (2007) went so far as to suggest that the financial health of the United States will be determined by the growth rate of per capita health care costs and to indicate that serious policy discussions of how to slow increases in spending will be necessary to limit healthcare spending as a percent of GDP. This is coupled with a rising life expectancy in the US; life expectancy at birth has increased by almost 10 years in the last half century to 78.4 years in 2008 (World Bank 2010). The combination of rising health care costs and longer life expectancies

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This thesis follows the style of the *American Journal of Agricultural Economics*.

affords an opportunity for businesses to market products with which consumers can take a proactive and preventative approach to managing their own health. Epidemiological studies have demonstrated for years the relationship between diet and disease risk, and most scientists accept that consuming plant-derived products can have some beneficial effect on health, particularly on age-related diseases. Diet is only one area that affects an individual's health; however, each individual has a greater degree of control over his or her own nutrition than over many of the other factors that may affect health, including genetics or environmental hazards. This awareness of health, and the role that nutrition can play in it, has spawned the development of so-called "functional foods" (American Dietetic Association 2004).

The term functional foods can include any food that is consumed as a part of the regular diet and has health benefits other than direct nutrition from energy, vitamins, and minerals. In reference to plant-derived functional foods, the compounds in plant material that are not yet identified as essential nutrients are called phytochemicals. Phytochemicals may have positive effects on health when consumed despite the fact that they do not provide direct nutrition (Seeram et al. 2006a). Consumption of fruits and vegetables, including phytochemicals, can potentially reduce the risk of a number of chronic illnesses, including many diseases believed to be oxidation-related (Kelawala and Ananthanarayan 2004). This includes certain cancers, inflammatory diseases, cardiovascular diseases, and neurodegenerative diseases (Seeram et al. 2006a). Several important plant phytochemicals are known to have antioxidant activity (Larson 1988). Antioxidants in the body protect against oxidative stress that can damage cells. Thus,

the potential implication is that some of the many antioxidants in plants may be able to defend against the development of these diseases.

Pomegranates are among the many plants that have been researched for potential health benefits. The pomegranate fruit, along with several other components of the plant, contain high levels of several active antioxidant species called polyphenols (e.g., Kelawala and Ananthanarayan 2004; Adams et al. 2010). These polyphenols, including tannins, lignins, and flavonoids, are named due to their characteristic of having multiple hydroxyl groups on phenolic rings. Some claim that polyphenols are the most powerful antioxidant species in the body (Williamson and Holst 2008). This makes the pomegranate, with its high antioxidant levels, of particular interest for future *in vivo* research on the health benefits of polyphenols.

This spark of interest in functional foods and antioxidants comes at the same time as the growth of the pomegranate industry in several parts of the world in recent years. The pomegranate is widely cultivated in regions with the high summer temperatures required for fruit maturation; these include the Mediterranean basin, Southern Asia, and several areas in North and South America (Martínez et al. 2006). Despite a lack of direct and accurate information regarding the size of the pomegranate industry, estimates are that pomegranate fruit production worldwide has grown by a tremendous amount in the past decade and has reached about 3.3 billion pounds per annum (Holland and Bar-Ya'akov 2008). USDA stopped reporting average prices and shipping amounts for pomegranate production in 1989. However, based on the 2007 US Census of Agriculture, 518 California farms reported a total plantings area of 24,458 acres, and the

remaining states with production (Arizona, Florida, Georgia, Hawaii, Louisiana, Mississippi, Nevada, New Mexico, North Carolina, Texas, Utah, and Washington) had a production in 2007 of a total of 59 acres across 82 farms. This gives a total U.S. production in 2007 of 24, 517 acres of pomegranates planted, with that acreage approximately evenly divided among bearing (12,103) and nonbearing (12,415) acres. In the case of Texas, USDA reports indicate there were 12 acres planted on 18 farms in 2007. The total number of acres planted for the United States is a sharp increase in 2007 from the reports in the 2002 US Census of Agriculture, when there were 9,535 acres planted across 369 farms (National Agricultural Statistics Service 2007). Based on historical US Census of Agricultures for the state of California, acreage fluctuated from reported levels of 524 to 1,093 acres between 1920 and 1950, with between approximately 24,000 and 110,000 trees of bearing age during that time frame (USBC 1950). In 1992, there were over 3,000 acres and almost 430,000 trees planted in the state of California (NASS 1992). Several producers in the pomegranate industry in California, where the majority of the crop in the United States is grown, have mentioned the large amount of growth in acreage and total pounds harvested that they have seen in recent years (e.g., Bryant 2003; “Pomegranate Acreage” 2009; Castellon 2010; Kinoshita 2010).

Although pomegranate has historically survived in the southern half of the United States (Hodgson 1917), within the US the crop has not been cultivated extensively outside of California (Pomegranate Council 2007). For example, a 2005 report of pomegranate acreage in Texas indicates a total reported planting of only 5 acres

for the state (Smith and Ancisco 2005), and while there is always a chance of unreported acreage, this report suggests with considerable certainty that the acreage grown in Texas was small. With recent growth in the demand for pomegranate fruit, juice, and other pomegranate products, there has been interest in other states (e.g., Florida- DuBois and Williamson 2008) and nations (e.g., Australia- Lye 2008) in the possibility of producing pomegranates. However, accurate estimates of the market potential for pomegranates are needed before these efforts can be undertaken. Experimental economics offers a novel way to analyze not only consumer interest in pomegranates, but also to look at the effect that the provision of information has on those consumers.

Experimental economics is useful for elicitation of willingness-to-pay estimates from consumers and has been used for such estimates of a number of horticultural products. The methodology of experimental economics is designed to be incentive compatible; that is, the methods are designed to induce consumers to reveal their true preferences to researchers. Particularly in the case of pomegranates, which are not a familiar product to US consumers in comparison to many other fruits, experimental economics provides a useful way to gather information on market potential for a novel product.

Further, experimental economics (including laboratory and field experiments) affords an opportunity for control of conditions that is not available using traditional observational or stated preference methodologies. This is one of the primary differences between observational and experimental data. However, there can easily be unobserved variables that are confounding results in an experimental versus an observational

approach; these unobserved or uncontrolled variables may be equally difficult to sort out in either approach (Roth 1995).

However, if experimental methods are to be used for the data collection, there are a number of considerations that must be accounted for by the researcher. These include issues of internal and external validity, as well as a careful decision-making process for which type of experimental technique should be used. There has been much discussion of the benefits and drawbacks of many of these within the experimental economics literature. The current state of research on the topic suggests that the experiment that should be selected depends on the specific purpose of the experiment and the decisions that are to be made using the information that is gathered.

The question of whether to use willingness-to-pay (WTP) or willingness-to-accept (WTA) estimates is somewhat contentious, and the preference for one or the other often depends on the specific item that is being valued. Not only has this been as a practical concern, but also as a question of economic theory to explain the deviations (or lack thereof) between WTP and WTA in empirical results. Learning behaviors, an endowment effect, differences in the hypothetical vs. nonhypothetical nature of the auction, reference relevance, and differences in experimental auctions procedures have all been proposed as possible explanations.

There are also a range of specific auction protocols that can be utilized in experimental methodology. These include open outcry or sealed bid types; examples of methods are traditional English or first-price sealed bids auctions that are commonly used in real marketplaces, or techniques that are only used in the experimental

environment such as the random *n*th-price auction. Regardless of which technique is used, the experiment must create a direct connection between maximizing the benefits of participation and the truthfulness of the responses made by participants.

In the case of a novel product not yet available on the market, it is nearly impossible to determine whether the results obtained from experimental procedures are reliable since there is no benchmark market or sales data for comparison. This makes the justification for utilization of one auction mechanism over another even more subjective. Another consideration is whether multiple rounds of bidding are necessary or a single round is sufficient to do accurate value elicitation; further debate could center around whether subjects should be given a product and asked to bid for an upgraded product ("endowed approach") or be asked to bid the full-price for each product ("full bidding approach"). The list of possible factors influencing outcomes extends to include whether subjects should bid for a single unit or multiple units of a good. Therefore, until there is greater theoretical understanding of which auction mechanism is preferred, the analogy of experimental auctions as tools may be helpful. One would not use a hammer to sew on a button, nor would one use a needle to loosen a bolt. The appropriate tool for the job means choosing the auction that is tailored to suit the analysis that will be conducted, and ultimately, the economic decision that will be made as a result of information gathered in the experiment.

Regardless of which experimental auction technique is used, there remain fundamental experimental principles that should not be violated. Among these principles are internal and external validity. For an experiment to be internally valid, the

procedure used should guarantee that conclusions can be made within the experiment and that observed differences are a result of true differences or differences in treatment, not differences compounded with other effects or influences (Loewenstein 1999). Internally valid experiments test the experimenter's hypothesis and are generally consistent with the predictions of economic theory. Also, any assumptions must be applied uniformly throughout the experiment. In keeping with the traditional scientific methodology, results that are internally valid can be replicated by other researchers or in other locations under similar conditions.

External validity, unlike internal validity, does not describe the consistency of results within an experiment; rather, external validity refers to the consistency of experimental results with the real world. Any factors that are different in an experimental setting than they are in the situation that is being analyzed could potentially influence results from the experiment and invalidate the extrapolation of those results to a broader context. Economic theory is a necessity in explaining results of any analytical economic technique, from econometric modeling to experiments in a laboratory (Levitt and List 2009). This can lead to questions of what the role of experiments should be. Should they test economic theory, or should they provide information that will be applied to the real world? If experimental results are applied to the real world, should they be applied literally or in a qualitative sense? These questions have led to debate over the external validity of almost every type of experimental auction. Differences in experimental techniques discussed earlier have often been analyzed in terms of which technique led to results that had greater external validity.

Despite the lack of clarity among experimental auction techniques and the generalizability of such methods, many value elicitation studies have been undertaken for food and plant-based products. The procedures used by these studies include choice-based conjoint analysis (e.g., Darby et al. 2006), best-worst surveys (e.g., Lusk and Parker 2009), and a range of auctions (e.g., Maynard and Franklin 2003; Yue, Alfnes, and Jensen 2009). Many of these involve situations that are artificial but nonhypothetical, meaning that although they would not be normally encountered in the outside world by consumers, the experimental situation has real monetary consequences for the participant. Some of the products analyzed range from beef (Lusk and Parker 2009) to potted plants (Hall et al. 2010) to the value of food safety (Fox et al. 1995). Of particular interest are studies with some attribute that adds value to the underlying good. Examples include whether consumers are willing to pay a premium for produce that is grown locally or for food with health benefits.

This final case, foods with potential health benefits, is of particular relevance to this study and brings us back to the previous discussion of functional foods. Although value elicitation analysis is not necessarily generalizable from one product to another, there have been some lessons and points of interest from earlier studies. The necessity of scientific evidence to validate health claims, the amount of information that is provided, how fresh a product is, how novel a product is, and the prior knowledge and demographics of the consumer are all considerations in value elicitation procedures for functional foods. Functional foods are relatively new to the marketplace, and much information is needed by those wishing to enter the market and by potential consumers

of functional foods. This includes scientific research on what effect, if any, consumption of functional food products may have in human subjects and what the long term effects of functional food consumption may be; much of the initial evidence in support of the disease prevention and treatment effects of functional foods is on the basis of *in vitro* or animal studies. The size of the functional food market was estimated at $27 billion in the United States alone in 2007, attracting a range of companies that have introduced new functional food products (Granato et al. 2010). Research suggests that consumers may consider the underlying attributes of the food when making a purchase decision, but the decision on whether to purchase also depends on the underlying attributes of the consumer. Differentiated marketing by the many companies involved in the functional food market may be achieved if more information can be gained about demand for functional food products and the characteristics of functional food consumers.

Specific to experimental design for this type of product, lifestyle and food culture factors must be considered. For example, the use of a primarily college-aged subject population could bias results when analyzing WTP for additional health benefits; college students may not be as concerned with health issues as older age groups. Other demographic factors, as well as food habits, may influence results. This is in addition to the considerations mentioned previously that may affect the outcome of experiments. Therefore, the auction must be structured in order to make the most accurate estimates of willingness-to-pay and to also allow for the most valid conclusions to be drawn.

There are several goals of this analysis ranging from gathering applied marketing information to an analysis of auction procedures and econometric methods. More

specifically, information gathered on consumers and their purchasing behaviors was used to make inferences about the characteristics of products and information that affect individual preferences. Information gathered on experimental economics procedures can be analyzed to add to the discussion of which procedures are most useful for which types of applications, and the modeling and estimation of these preference elicitation results was further investigated. As an additional task, information on the specifics of cultivating and marketing pomegranates is necessary for producers in order to take advantage of any premium in WTP for pomegranates that may be found.

The overarching goals of this analysis can be further divided into the aim of measuring specific WTP and determining preference rankings for a novel fruit product using incentive compatible, nonhypothetical methods. Changes in preference rankings and experimental auction due to additional information on a novel good will be studied further. The implementation of a procedure for obtaining both rankings data and bids from a set of participants in order to make paired comparisons of responses will also be discussed.

This paper proceeds as follows. First is a literature review of the specifics of value elicitation and experimental methods, along with a discussion of the most highly contested points in the literature. Particular attention is given to previous research that analyzed WTP for functional foods, as well as the scientific basis behind the use of functional foods. A description of the pomegranate and its chemical composition follows, as well as a description of cultivation practices for pomegranate and the current state of the industry. Next is a description of the experimental procedures used in this

study. The results and a discussion of those results follow. The conclusion describes the implications of this study's findings, as well as possible implications for expansion of the pomegranate industry.

CHAPTER II

LITERATURE REVIEW

Experimental Economics and Value Elicitation

Experimental methods have been adopted in the field of agricultural economics as a means of eliciting willingness-to-pay (WTP) in an incentive-compatible manner. The willingness-to-pay refers to the maximum amount that a consumer will pay for a given quantity of a good. This research has helped to develop an understanding of consumer preferences and the influence of non-price factors in purchase decision-making (Unnevehr et al. 2010 and references therein). An increase in consumer affluence suggests a need for greater understanding of factors affecting consumer choice, and there is the general need within the field to understand whether, and if so how, the results of experiments can be applied to actual marketplace decision-making. The methodology and results described here attempt to assist in this endeavor.

Types of Data

There are a number of methods that have been utilized in the past to both measure willingness-to-pay and consumer attitudes towards different food attributes. These include transactions data, survey data, and auction experiments (Werternbroch and Skiera 2002). All of these methods seek to determine the value that the consumer brings to the experiment for the good, sometimes termed the “homegrown value” (e.g., Cummings, Harrison,and Rutström 1995; Lusk, Feldkamp, and Schroeder 2004), making

it even more of a challenge to determine which method is the most accurate way to elicit values when compared to "induced value" mechanisms. Induced values refer to the values that experimenters induce in subjects during laboratory investigations (Smith 1976); these mechanisms have been used historically for testing economic theories of auction equivalence and to test models of causes of deviations from the predictions of economic theory in the real world (Rutström 1998).

Transactions Data

Transactions data, including revealed preferences from scanner data, are high in external validity because they are based on actual purchases made by consumers in their day-to-day lives. However, the information provided from such data indicates that the consumers' WTP is at least as high as the transaction price and does not inform the researcher on the actual level of WTP (Wertenbroch and Skiera 2002). Transactions data is sometimes used in conjunction with other data as a measure of external validity; hypothetical choices and nonhypothetical choices and rankings were compared to retail shopping behavior by Chang, Lusk, and Norwood (2009), who conclude that nonhypothetical procedures, and the nonhypothetical ranking procedure in particular, have higher external validity (in terms of prediction of sales) than hypothetical choice experiments.

Survey Data

Survey data can be used to elicit willingness-to-pay in the form of conjoint

analysis, which presents consumers with various bundles of goods and examines rankings of those bundles or the amount of money that would make participants indifferent among the bundles. However, there is little incentive in this approach for consumers to reveal their true WTP, as all decisions are hypothetical in nature (Green and Srinivasan 1978). At best, this could be termed incentive-neutral as there is no incentive to be either truthful or dishonest about willingness-to-pay (Wertenbroch and Skiera 2002). Fox et al. (1995) conclude that experimental auctions can be used to complement or serve as an alternative to the more common nonmarket valuation methods of stated preference and contingent valuation.

Experimental Data

Experimental methods that have been used in the past include choice experiments, willingness-to-use measurements, and willingness-to-accept and willingness-to-pay auctions. The details of each of these are discussed in the subsection on experimental design.

Two key advantages exist for experimental methodology, both within economics and across the sciences: replicability and control (Davis and Holt 1993). The replicability of an experiment is the capacity to reproduce the experimental results, either by the original researchers or by others. In contrast to experimental results, observational data lacks replicability. Secondly, control gives researchers the ability to manipulate conditions and test alternative theories based on observations of behavior in the experimental setting. Control is generally lacking in observational approaches as a

number of assumptions are made to carry out any sort of analysis. Smith (1976) suggests that there are also two key uses for experimentation in economics: one, that laboratory results can be used to test economic theory, and two, that experimental results can be useful in the understanding and interpretation of data collected in the field.

Reservations about experimentation as a means of understanding economic phenomena include questions of external validity. This is discussed in greater detail later. However, as a brief introduction, Davis and Holt (1993) offer examples of cases where extrapolation of laboratory results to the marketplace could be inaccurate and misleading. First, there is the question of whether subjects included in the experiment possess the same knowledge and behave in the same way as actual participants in the marketplace. Second, experiments generally greatly simplify markets and other complicated economic institutions for the purpose of the experiment, and this leads to questions of whether the failure of a theory in an experiment justifies its rejection in a broader context. However, Plott (1982, 1989, 1991) suggests that the rejection of a theory in the simplified experimental context can serve as justification for its rejection in the more complicated world.

Categorizing Experimental Data

In general, experiments can be divided into three categories proposed by Roth (1995) as 1) ‘speaking to theorists,’ 2) ‘searching for facts,’ and 3) ‘whispering in the ears of princes.’ These divisions are based on the intended goals of the experiment; more specifically, whether the experiments are intended to validate (or disprove)

economic theory, explain real-world data not sufficiently explained by economic models, or provide guidance for policy-making, respectively. However, these categories are not mutually exclusive, as some experiments may seek to accomplish one or more of these three broad goals. Experimental auctions dealing with value elicitation can be divided by several criteria; these include divisions on the basis of the nature of goods offered in the auction (private value vs. common value), the number of units auctioned (single-unit vs. multiple unit), and the auction procedure used (e.g., English, first price sealed bid, BDM mechanism).

Types of Goods

Separation based on the nature of the goods leads to two broad categories: those experiments that deal with independent private value goods and those that deal with common value goods (Kagel and Levin 1986). Independent private value goods are those goods for which an individual has his own value for the good that may be different from the values of other individuals and is assumed to be independent of those other values. Examples in this category would be the sale of sculptures or memorabilia. Common value goods are those which should have the same value to all individuals, but in this case, the information that each individual has regarding the underlying value varies. One frequent example of a good in this category is the auctioning of oil rights (e.g., Thaler 1980; Milgrom 1989). However, many goods may fall somewhere between these distinctions with elements of both common value and private value goods (Goeree

and Offerman 2003). Corrigan and Rousu (2010) suggest that almost all private value goods have at least some common value component.

Where Experiment Occurs

Experiments can also be categorized on the basis of where they take place: in the field or in the laboratory. Laboratory experiments occur in a more structured and limited environment, whereas field experiments occur in the natural environment where economic decision-making occurs. There are benefits and limitations to both; there is also value in the description of the two as a spectrum, with intermediate values in between. Harrison and List (2004) argue that there are characteristics of each present in the other and that results from the field and results from the lab can offer important intuition into further research in the opposite setting. Additionally, they suggest that results should not be taken cumulatively from the two, but rather integrated into a single, more thorough understanding of the question at hand. Differences between the field and experimental environment do not necessarily influence results, but each one may impose factors that could have a measurable outcome in terms of behavior. For example, the lack of real monetary incentives does not by necessity bias results, but it is an artificiality that has the potential to do so. Also, some studies have indicated that fees paid for participation in laboratory experiments may influence estimations of WTP (Rutström 1998). Marette, Roosen, and Blanchemanche (2008) found that decreases in demand predicted by a lab experiment were less than those observed in a field experiment for similar products. A criticism of the control that is frequently described as

an advantage of laboratory experimentation is that such control is somewhat illusory and could create other compounding effects that are difficult to measure if the controlled conditions are in fact artificial (Harrison and List 2004).

Uses for Value Elicitation Procedures

The relevance of all of these types of data collection lies in the way that they can be applied to real world problems and decision-making. A number of applications have been discussed in the literature. These include judgments on new products as well as on the effects of public policy. In general, procedures that are used for such purposes are based on eliciting the "homegrown value" of the subjects rather than the induced value; induced values are applied in many experiments to test the mechanisms that are being used or some aspect of theory (e.g.; Cherry et al. 2004, Andersen et al. 2006). An example in the literature of the application of these procedures to real problems is the study by Lusk and Marette (2010) that analyzed the welfare effects of food labels and bans on particular qualities. In doing so, they looked at the net effects of changes in government policy and if those changes would have a positive or negative impact on society based on changes in the cost of production, limits on consumer choice, or increased availability of information to consumers. Other authors have suggested the use of auction design theory from experimental economics as useful in designing real world auctions, such as the sale by governments and their agencies of spectrum licenses, (including 3G mobile phone licenses) to telecommunications companies (Klemperer 2002, 2004). Additionally, some studies have analyzed the effect that the presence of

genetically modified and non-genetically modified foods has on consumer surplus (Moon, Balasubramanian, and Rimal 2007). However, there have been more recent suggestions of limitations of WTP estimates as a sole basis for computing consumer welfare effects; consumer demand estimations were shown to be dependent on the price elasticity of demand for a good where information is inadequate about a characteristic and further, that consumer demand based on laboratory results was not reflective of time-series demand for the good (Marette, Lusk, and Roosen 2010). Based on the range of opinions on the application of WTP to the public arena, the robustness of welfare estimates should be thoroughly examined before they are used as the basis for public policy decisions.

In terms of marketing decisions, several applications have been developed by both agricultural economists and others to aid in decision-making. For example, Umberger and Feuz (2004) suggest that experimental auctions may be useful in determining quality factors that influence whether consumers will choose to buy the product and if so, what premium they will be willing to pay. Guala and Mittone (2005) suggest that for experiments in economics with the goal of informing policy, modifications should be made to the experiment according to differences in the specific situations where results will be applied. Hoffman et al. (1993) described the use of a sealed bid experimental auction of beef as a test market for new products; they suggest that this may be a cost effective way to determine the demand for a product prior to spending large sums of money on product development only to find that consumers are unwilling to purchase the new product. Other studies have found evidence of market

segmentation, which might be valuable information to marketers developing a marketing strategy for a product, in this case bison meat (Hobbs, Sanderson, and Haghiri 2006). Briedert, Hahsler, and Reutterer (2006) provide a review of the literature focusing on the marketing uses of various WTP elicitation methods. These include uses for private companies determining pricing structure for products, management of brands, and competitive strategy.

Other studies have analyzed the use of geographical-based produce marketing and whether consumers are willing to pay a premium for produce labeled as such (e.g.; Hu, Woods, and Bastin 2009; Giraud, Bond, and Bond 2005). Still other researchers have used experimental economics for elicitation of values for environmental goods (e.g., Cummings and Taylor 1999; Hanley, Wright, and Alvarez-Farizo 2006; Shogren, Parkhurst, and Hudson 2010).

Specific to estimates of WTP, Lusk and Hudson (2004) suggest that there is a high degree of applicability of experimental auction procedures to agribusiness decision-making. The WTP estimates based on individual-level data can be used to construct an inverse demand curve for the sample marketplace. This can be used as a basis for development of a demand curve for the larger market. However, these authors also present several notes of caution when using auctions or other WTP elicitation techniques. These include the degree of substitutability of the products (i.e. cross-price effects). If such an effect is suspected, the econometric model to be used must relax the independence of irrelevant alternatives (IIA) assumption. Further, there may be a need to address issues of consumer heterogeneity. Variance in consumer characteristics from

the sample to the targeted market may influence the ability of experimental results to accurately predict market potential. Finally, agribusiness should not rely solely on the results of experimental economics procedures to determine potential profitability. In addition to a number of assumptions that are made in modeling and potential biases that may be introduced to the results by sample selection, experimental procedures, and others, the agribusiness firm faces the possibility of reduction in sales of a current product with the introduction of a new product or potential price-lowering by competitors in the marketplace.

Since economically important decisions are sometimes made based on the results of experimental economics, the auctions must be conducted carefully and methodically in order to obtain results that are relevant. The factors mentioned later regarding experimental design and the discussions of internal and external validity are necessary if experimental results are to be used as a basis for decision-making. The understanding of these must be based on consideration of the wide range, and sometimes conflicting, results of many previous experiments within the experimental economics field.

Experimental Design

The range of experimental methods that can be utilized in value elicitation is quite broad, with an equally broad number of considerations to be made when designing experiments. Binmore (1999) suggests that as long as certain requirements are met in the experimental design then the results of the experiment can be useful. The criteria used are as follows: 1) the problem faced by subjects is not only “simple” but seems

simple to the subjects, 2) the incentives provided are sufficient, and 3) adequate time is allowed for adjustment following trial-and-error.

Conjoint Analysis and Choice Experiments

There are a number of conjoint analytical techniques and choice experiments that have been conducted in order to analyze consumer WTP. In conjoint analysis, the characteristics of the product are varied systematically, and the differences in preference for each product are measured. These differences ("part-worths") are used to construct WTP estimates for the whole product. However, one major theoretical problem with conjoint analysis is that it frequently uses price as one of the attributes for which the part-worth is estimated. This is in violation of neoclassical economic theory and the premise that price does not in and of itself have a utility; rather, the price is the exchange rate between different utility scales. Specifically, the price reflects the value of the composite product, the budget constraint, and the utility that must be given up from not consuming relevant substitutes (Briedert, Hahsler, and Reutterer 2006). When analyzing the range of choice experiments, there is a range from dichotomous choice to open-ended choice to the ranking of members of a discrete choice set. The latter of these is of greatest relevance to the discussion that follows.

Conjoint choice analysis is a combination of the conjoint analysis and choice techniques and has served as a means of eliciting consumer valuations for decades (e.g., Bohm 1972; Bishop and Heberlein 1979). However, a meta-analysis by List and Gallet (2001) of much of the collected data indicates that the elicited values using this

technique are not consistent with actual decision-making if consumers do not face real economic decisions. That is, the results of the hypothetical choice experiments are not always statistically equivalent to results from nonhypothetical choice experiments. Cummings, Harrison, and Rutström (1995) also tested whether hypothetical dichotomous choice surveys were equivalent to real dichotomous choice surveys and found that there were statistically significant differences in the two that were robust to differences in private goods, location, and subject populations. Alfnes et al. (2006) generated incentive compatibility in an auction of salmon filets by requiring participants to purchase the salmon filet they had indicated as preferred in a randomly drawn round of a dichotomous choice experiment. However, as Lusk, Fields, and Prevatt (2008) indicate, there is an informational inefficiency of choice experiments as compared with ranking experiments. Therefore, these authors suggest the use of an incentive compatible profile ranking mechanism that they developed as a means of gathering more information while still maintaining a nonhypothetical preference elicitation setting. Chang, Lusk, and Norwood (2009) compared the nonhypothetical ranking procedure with other experimental procedures in addition to an analysis of differences in econometric models to analyze results. The incentive compatible ranking procedures described by the Chang, Lusk, and Norwood (2009) and Lusk, Fields, and Prevatt (2008) papers call for subjects in the experiment to rank their preferences for a bundle of goods. One round was randomly selected as binding, and then the experimenters assigned probabilities to each good based on the ranking order to determine the likelihood that each good from the binding round would be purchased. Only one good was purchased

after a random draw from the goods for that round. Results suggested that the nonhypothetical ranking procedure was the best predictor of buying behavior, but that both nonhypothetical procedures outperformed the hypothetical choice procedure.

For choice experiments, experimental design can have a significant impact on the results; Sándor and Franses (2009) find that presenting subjects with choice alternatives that are similar in utility leads to choices that are inconsistent, thereby biasing estimates of consumer preferences. They further suggest designing the experiment with the use of an algorithm to maximize statistical efficiency while varying the choice complexity variables (i.e. the number of options faced by subjects) within the experiment. However, Lusk and Norwood (2005) indicate that a large sample size can compensate for poor experimental design in choice-based conjoint analysis. Other research comparing choice-based experiments and experimental auctions found that subjects' WTP values elicited from choice experiments were greater than those from experimental auction, with the implication of this being that people may purchase steaks in a retail setting (where they face a choice task) for more than they would bid for them at auction (Lusk and Schroeder 2006).

Value Elicitation

Several techniques of estimating value for a private value product are utilized in the literature. Willingness-to-pay (WTP) is the maximum monetary amount that an individual would give up to have a good, willingness-to-accept (WTA) is the minimum monetary amount that an individual would have to be given in order to give up a product

(also known as compensation demanded), and willingness-to-use is a scale value used as a measure of the level of desire to use a product. A more simple, but perhaps less informative definition is that WTP is the price a buyer would pay for a good and WTA is the price a seller would take for a good (Lusk and Shogren 2007).

Although WTP and WTA are utilized most frequently in private value elicitation for a good, willingness-to-use a good is sometimes a preferred approach to willingness-to-pay in the case where a good is not well-established or new to the marketplace (Urala and Lähteenmäki 2007), although the ability to extrapolate information from this measure is not as strong since it lacks a monetary basis.

Experimental design is of similar importance in experimental auctions, where the accuracy of value estimates can be affected by the use of various auction procedures, the use of within-subject or between-subject comparisons, and whether WTP or WTA is estimated (List and Gallett 2001).

Differences in Willingness-to-Pay and Willingness-to-Accept

The differences in elicited values for willingness-to-pay and willingness-to-accept can be large, with WTA generally exceeding WTP by a factor of two to five times (Dubourg, Jones-Lee, and Loomes 1994). Various studies have found WTP estimates to either diverge (e. g., Knetsch and Sinden 1984) or converge (e.g., Coursey, Hovis, and Schulze 1987) with WTA estimates. Meta-analysis by List and Gallett (2001) suggests that, *ceteris paribus*, the WTP estimates are closer to subjects' true valuations than WTA estimates. Coursey, Hovis, and Schulze (1987) also theorized that the convergence in

their study was explained by learning behavior that occurs over the course of several trials; this was also explicitly described by Coursey (1987) as useful for inducing subjects to engage in demand-revealing behavior. Later results from experiments where the opportunity for learning behavior was provided contradicted a hypothesis of learning behavior as an explanation for a disparity between WTP and WTA (Kahneman, Knetsch, and Thaler 1990). Kahneman, Knetsch, and Thaler (1990) found WTA estimates to decrease over subsequent rounds of the experiment and suggested an "endowment effect," or the increased value of a good once it is a part of an individual's endowment, as a manifestation of loss aversion (Thaler 1980), is responsible for the discrepancy between WTP and WTA. Kahneman, Knetsch, and Thaler (1991) also consider the possibility of an endowment effect in combination with a preference to maintain the status quo in a loss aversion effect. Tversky and Kahneman (1991) introduced a theory of "reference dependent preferences" based on the premise of loss aversion, deformation of the indifference curve about the reference point, and a greater weight placed on losses and disadvantages than on gains and advantages. Reference dependent preferences are also discussed by Tversky and Kahneman (1992).

Other theories or variations on the theory of reference dependent preferences followed. For example, a similar theory was proposed by Munro and Sugden (2003) that did not require as many deviations from traditional expected utility theory and that also allowed for endogenous reference points. Köszegi and Rabin (2006; 2007) follow with a model of reference dependent preferences and loss aversion and predict that disparities in WTP and WTA seen in the laboratory are the result of an endowment effect and that

their disappearance in the real market is a result of an expectation to trade; they also apply this model to preferences over varying levels of monetary risk. These results were in contrast to those of by Plott and Zeiler (2005), who were able to manipulate the presence of a WTP/WTA gap by controlling several aspects of the auction mechanism. This supported the suggestion of Shogren and Hayes (1997) that the lack of convergence of WTP and WTA estimates in Vickrey second price versus BDM auctions may not be due to an endowment effect but to fundamental differences in the auction types. Still, Bateman et al. (1997) analyze eight different methods of value elicitation and cannot disprove a WTP/WTA disparity in their analysis and indicate that the results favor an interpretation as loss aversion under the theory of reference dependence.

In another meta-analysis of WTP and WTA estimates, Horowitz and McConnell (2002) find that goods that are less similar to ordinary private goods have a pattern of more divergent WTP and WTA estimates. Furthermore, they suggest that the influence of hypothetical versus nonhypothetical elicitation procedures, student subjects versus a broader subject base, and the opportunity for learning do not affect the disparity between WTP and WTA. Knetsch (2007) contends that WTP should be used to measure gains and WTA should be used to measure losses, indicating further support for the "reference relevance" in eliciting valuation. For example, Moon, Balasubramanian, and Rimal (2007) find mean WTA a discount for genetically modified food to be greater than mean WTP a premium for non-genetically modified food; therefore, the reference frame of having GM or non-GM food was important to subject responses.

Even the difference between WTP and WTA has been disputed; other

experiments showed neither a disparity between WTP and WTA when a within-subject design was used nor a change in WTP and WTA over repeated trials (Harless 1989). Still others have suggested that the convergence of WTP and WTA estimates depends heavily on the degree of substitutability of the goods (Hanemann 1991; Shogren et al. 1994). Singh (1991) found that there was less variation in median WTP values when "bounded" commodities with a maximum value (such as a percentage of annual income) were used in the experiment; this could have implications for public policy based on the use of these techniques. Environmental and ecological applications of choice experiments to elicit WTP and WTA are commonly used as a basis for estimating the economic impacts of environmental policy (Hanley, Wright, and Alvarez-Farizo 2006; White et al. 2005). Lusk and Shogren (2007) suggest that differences in WTP and WTA may be partially a result of available information on the good up for auction, the ease of reversing the auction transaction, the difficulty of delaying the decision, and the availability of substitutes under conditions of imperfect information. Under conditions of no uncertainty, they find that the disparity between WTP and WTA may depend on price, income, and the elasticity of substitution between the auction good and any relevant substitute or complement goods. This idea was previously introduced by Zhao and Kling (2004), who found that the theoretical equivalence of WTP and WTA did not hold under conditions of irreversibility, uncertainty, and learning over time. They suggest that if such a divergence arises, the estimated WTP premiums may not be useful for welfare analysis. Zhao and Kling (2004) further hold that under any of the three previously mentioned conditions, the bid subjects place will include the expected value

of the good, along with option values for purchasing the good at present and another option value for delaying the purchase decision.

Plott and Zeiler (2005) conducted an experimental auction using a modified BDM mechanism and were able to eliminate the WTP/ WTA disparity by controlling for incentive compatibility of the elicitation device, training of subjects with the auction mechanism, paid practice with the auction mechanism, and maintained anonymity during the experiment. These authors conclude that while it is certainly possible to observe a WTP/WTA disparity using experimental auctions, the results of their experiment indicate a lack of support for the endowment effect theory as the cause of this disparity as they were able to turn the disparity on and off by modifying experimental procedures. Further, they suggest that experimental procedures must by necessity affect WTP/WTA gaps.

Incentive Compatibility of Auction Mechanisms

In designing the experiment, the auction mechanism to be used is a critical decision. Individuals must have an incentive to truthfully reveal their valuations; when the dominant strategy is to bid in order to do so, an auction mechanism is said to be "incentive-compatible" (Lusk, Feldkamp, and Schroeder 2004). This term was previously introduced into the literature and developed further by Hurwicz (1960; 1972). Vickrey (1961) suggested the term incentive-compatible be used when a given bid determines *only* that the buyer has the right to buy the good up for auction; it does not determine the price that the buyer pays. For example, in a Vickrey second price auction,

a participant can never win, and the participant can lose, by not bidding exactly his true WTP (Hoffman et al. 1993). Since the experimenter cannot force subjects to give truthful responses, the experiment must be designed so that there is no incentive to be dishonest in order to estimate true valuations (Myerson 1979). However, if an individual does not believe that he is likely to win, then the incentive to bid truthfully is greatly reduced; thus, the ability of the researcher to estimate the entire demand curve may be limited because of inaccurate responses by low-value subjects in the experiment (Shogren et al. 2001). Lusk, Alexander, and Rousu (2004) also point out that although an incentive compatible mechanism should encourage bidders to submit their homegrown values truthfully, it does not guarantee that they will do so. Rather, incentive compatibility simply increases the cost of deviating from the dominant strategy of submitting truthful bids.

Experimental procedures should also take saliency into account (Davis and Holt 1993). Subjects must perceive a relationship between the decisions they make and the rewards offered by the experimenter; they must further conclude that those rewards are substantial enough to be a motivation to provide true information. An extensive literature describes the hypothetical bias that exists when subjects express values in a hypothetical context lacking these motivations versus values provided in a real context with real economic incentives, although the size of that bias varies considerably across experiments (For extensive reviews, please see Harrison and Rutström 2008; Murphy et al. 2005). In particular, subjects answering hypothetical questions may perceive their answers to have an impact on their future utility and thus bias results; one suggested

solution to this is ‘instrument calibration’ to measure and then account for this effect (Cummings et al. 1997). Calibration for WTP estimates was proposed most prominently by the National Oceanic and Atmospheric Administration (NOAA 1994, 1996) as the use of a bias function to correct hypothetical estimates of WTP to actual WTP values. The NOAA proposed dividing by a factor of 2 to correct for systematic bias unless WTP estimates could be calibrated using market information. Unfortunately, this estimated calibration factor has not been further validated to be an exact value. However, Blackburn, Harrison, and Rutström (1994) suggest that there is indeed merit to this approach and that there was some predictability for the hypothetical bias observed in private value, dichotomous choice experiments. Still, the range of estimated values for such a calibration factors can, at the very minimum, be characterized as broad with values ranging from 0.3 to 28.2, but most values falling between 1.0 and 10.0 for the ration of hypothetical/actual statements of value (see List and Gallett 2001). Hofler and List (2004) describe one calibration procedure using a stochastic frontier approach that could be used to correct for bias in previously collected estimates of willingness-to-pay. Nevertheless, List and Shogren (1998) found treatment effects in comparisons of hypothetical versus real auctions of baseball cards; Lusk and Shogren (2007) suggest that the results of the baseball card study present evidence for the need for a separate auction for each good that is to be calibrated. This would be a major problem for hypothetical value elicitation and subsequent calibration for public or other goods that cannot be delivered in a real auction due to time or financial constraints. This also

presents challenges to any intention to generalize results of experimental auctions for one private good to other private goods.

At least two other methods are used in dichotomous choice field experiments to control for hypothetical bias: “cheap talk” and certainty adjustment. Cheap talk, as described by Cummings and Taylor (1999), refers to an explicit discussion by researchers of hypothetical bias, and a certainty adjustment refers to asking subjects how certain they are about their response and removing uncertain responses from the analysis. Blumenschein et al. (2008) suggest that the certainty approach is effective at removing hypothetical bias from WTP estimates but that cheap talk is not. There is a lack of consensus on this topic, with others finding effective reduction of hypothetical bias using a cheap talk script (e. g., Lusk 2003; List 2001).

Hayes et al. (1996) used nonhypothetical experimental auctions to replicate the decisions made by consumers in a retail setting. They contend that realism is achieved with this procedure by using real products, real money, multiple trials, and market discipline by not taking the highest bid as the price. An experimental auction is nonhypothetical when subjects are given money to participate in the auction, and the preferences that those subjects state have a monetary consequence (Jaeger and Harker 2005).

Auction Mechanisms

Several types of auction are commonly mentioned in the literature; these include the English auction, Dutch auction, first price sealed bid auction, second price sealed bid

auction, random *n*th-price auction, and the BDM mechanism for auctions (Lusk, Feldkamp, and Schroeder 2004). Descriptions of these mechanisms, along with considerations for using the mechanisms, follow.

Types of Auctions

The English auction starts at a relatively low price, and participants stay in the auction by either indicating that they want to stay in as price ascends or by offering successively higher bids. The auction ends when only one participant is willing to pay the current price; that participant pays the last price offered (Vickrey 1961; Coppinger, Smith, and Titus 1980). In a first-price sealed bid auction, all participants submit sealed bids; the winner is the participant who submits the highest bid, and he then pays the amount he bid (the highest bid). The Vickrey second price auction is a sealed bid analogy to the English auction but in this case, competitors concurrently submit sealed bids. In a second price auction, the winning bidder is the one who submitted the highest bid; however, he pays an amount equal to the second-highest bid (Vickrey 1961).

A Dutch auction is a descending bid scheme that operates in the reverse manner of the English auction. The auctioneer starts at a relatively high price, and the price descends until one of the participants indicates he is willing to pay that price; however, it is not as well-established that this method gives a price that is at or very close to Pareto-optimality (Vickrey 1961; Coppinger, Smith, and Titus 1980). If bidders are nonhomogeneous, then the item being auctioned may go to a bidder with the lower

value. This is also true if there are differences in the expectations of the actions of other bidders.

In contrast, in the BDM elicitation procedure introduced by Becker, DeGroot and Marschak (1964), the price is randomly drawn from a predetermined uniform distribution, and all the individuals who submitted sealed bids higher than the random price selected must purchase a unit of the good at the random price. Shogren et al. (2001) describe a random *n*th-price auction that they contend can be used to predict consumers' true preferences for products. In a random *n*th-price auction, one bid (the *n*th-bid) is selected from all of the sealed bids submitted by the participants, and all participants who bid above that price must buy one unit at the *n*th-price. Thus, the random *n*th-price auction is a combination of the features of the second price auction and the BDM method. Ausubel (2004) introduces an alternative auction type for bidders with demands for multiple units as an ascending-bid Vickrey auction which should promote efficiency in a multiple-unit setting. Also, many consumers now face real-world encounters with online auctions (e.g., eBay® and Amazon®) that allow them to bid in an auction or end the auction by purchasing the item at a buy price that is preset by the seller (e.g., Shunda 2009).

Auction Mechanism Issues

An analysis of general issues with experimental auctions leads to several points of interest. One of these is the "winner's curse" discussed by Capen, Clapp, and Campbell (1971) in reference to the winning bidder for oil rights; a theoretical analysis

of the winner's curse was conducted earlier by Wilson (1969). More specifically, in a first-price common value auction, the winner is generally the participant who over-estimated the value of the product, and hence he experiences the "winner's curse" (Roth 1995). Others conclude that the winner's curse decreases with experience and changes in the bidding environment and that the availability of public information may increase or decrease the role of the winner's curse (Kagel and Levin 1986; Kagel, Harstad, and Levin 1987). Crawford and Iriberri (2007) describe similarities in the winner's curse in common value auctions and overbidding in independent private value auctions, explaining both with a non-equilibrium model of bidding responses based on strategic thinking. Recent work in private value auctions has focused on regret as a means of explaining overbidding in first-price auctions, both for the winners and losers of the auction (e.g., Nuegebauer and Selten 2006; Filiz-Ozbay and Ozbay 2007), with contradictory results across experiments. Further, results varied with different number of bidders in the auctions (Nuegebauer and Selten 2006).

Which Type of Auction Is Preferred?

The preference among types of auctions is conflicting in the literature, both in regards to which type of auction is preferred and in regards to the theoretical basis for divergences from expected results. Other questions of experimental design that have been addressed in detail include the use of a single round versus multiple rounds of bidding and the use of an endowment versus full bidding approach.

Divergence from Expectations

Several models have been provided that give expectations for the outcomes of experimental auctions; Nash equilibrium models include the risk-neutral Nash equilibrium (RNNE) that was predicted in first-price auctions by Vickrey (1961) on the assumption of identical probabilities and strategies, as well as the constant relative risk aversion model (CRRAM) described by Cox, Smith and Walker (1982; 1983; 1988) that allowed for generalization of Vickrey's hypothesis to account for heterogeneity among bidders. The results of Cox, Smith, and Walker (1988) also indicate support for a risk aversion hypothesis to explain divergence from RNNE. Kahneman, Knetsch and Thaler (1990) suggest that the divergence is explained by errors in the decision-making of inexperienced auction participants as a manifestation of the habits of standard bargaining behavior: buyers are often rewarded for understating their true value, and sellers are frequently rewarded for overstating their true value (Knez, Smith, and Williams 1985). Davis and Holt (1993) conclude that the positive deviations from RNNE conditions in first-bid auctions are consistent with risk aversion. However, Kagel and Levin (1993) found a tendency for subjects to make errors (as consistent deviations from the dominant strategy) by overbidding in second price auctions as well. They further report that some subjects increased bids in response to an increase in the number of bidders, but conclude that Nash equilibrium bidding theory is able to describe the main strategies behind the observed behaviors of participants.

Riley and Samuelson (1981) reject a hypothesis of uniform risk aversion as an explanation for deviations from the dominant strategy of bidding. Furthermore, Harrison

(1989; 1992) presented and defended an alternative hypothesis of "payoff dominance" as an explanation of deviations from dominant strategy, suggesting that the region of the payoff curve where participants bid is flat, and therefore little incentive exists to make a bid in accordance with the dominant strategy. If this hypothesis is true, then bids in such auctions cannot be interpreted as true measures of maximum WTP. Kagel and Roth (1992) suggest that risk aversion could be one factor contributing to overbidding, but that it is not necessarily the most important factor. More recent results from Neugebauer and Selten (2006) offer evidence that providing information on the winning bid (information feedback) to subjects may enhance the likelihood of overbidding. Other problems with information feedback, such as bid affiliation over rounds, are discussed in more detail later.

In a quite different approach to this much debated topic of overbidding and the winner's curse, a synergism of economics and neuroscience by Delgado et al. (2008) utilized functional magnetic resonance imaging (fMRI) to construct a hypothesis suggesting overbidding in auctions as a result of a fear of losing in a social setting. The results from the single-price auctions analyzed should be distinguished from a pure risk aversion model; subjects showed differences in bid levels even when the level of risk was equivalent. Rather, the subjects showed a "social loss aversion" that was consistent with existing scientific knowledge of the brain's reward circuitry. (The application of neuroscience to economic decision-making and understanding of economic behavior is discussed further in Camerer 2007).

Vickrey's (1961) description of incentive compatible strategy for sealed bid auctions was extended by Coppinger, Smith, and Titus (1980) to include that bidding a full (true) value is a dominant strategy because "it maximizes the probability of winning the award while the gain obtained depends only on the bid of an independent bidder." Comparisons of dominant strategies among auction types indicate English auctions and second price auctions are isomorphic in the sense that the weakly dominant strategy in both is to bid the value of the good regardless of risk preferences and rival bids (Coppinger, Smith, and Titus 1980; Cox, Roberson and Smith 1982), but that this is not the dominant strategy for Dutch and first price auctions (Cox, Roberson, and Smith 1982). An additional comparison of auction types found that of first price sealed bid, second price sealed bid, and Dutch auctions, second price auctions were the most efficient, followed by first price auctions, and then Dutch auctions; efficiency is characterized as a situation where there are no unrealized gains from exchange, which is consistent with a Pareto-optimal allocation (Cox, Roberson, and Smith 1982). Davis and Holt (1993) point out that the incentives to bid based on value are similar for a first price and second price auction, and that price and efficiency predictions are the same for both of these types of auctions. Since the bidder with the highest value is predicted to bid the highest amount, it is predicted that the outcome for English and second price auctions is therefore efficient.

The auction mechanism can have a significant effect on the willingness-to-pay estimates of the experiment. This is true for the random *n*th-price auction and later bidding rounds of second price auctions (Lusk, Feldkamp, and Schroeder 2004).

Furthermore, “the second-price auction works better on-margin, and the random *n*th-price auction works better off-margin” in an analysis of those two types (Shogren et al. 2001). Those bidders in a second price auction who are disengaged because they possess a WTP much lower than the second price are, conversely, engaged and have a chance of buying the good in a random *n*th-price auction.

Conflicting results have been obtained from evaluations of the BDM mechanism and the Vickrey second price auction. Some research indicates the second price auction is a more effective WTP elicitation device than the BDM mechanism, possibly due to differences in the shape of the payoff function (Noussair, Robin, and Ruffieux 2004). Others (Lusk, Alexander, and Rousu 2004) suggest that of these two types of auctions, the BDM mechanism may be preferable for elicitation of WTP for low-value (off-margin) subjects provided that the price distribution that is chosen is close to the true value for the individual; however, the second price auction was still preferred for high-value (on-margin) subjects. The BDM procedure can be a means to elicit WTP in a point-of-purchase setting and overcomes the problems of incentive-compatibility of reverse (Dutch) auctions, but is not useful for new products not already on the market (Wertenbroch and Skiera 2002). This has implications for the choice of mechanisms in this study, where some of the products are available on the market, but only in a limited geographical region. Rutström (1998) compared Vickrey, English, and BDM mechanism auctions to look for differences in the behavior of participants. In an analysis of auctions to elicit homegrown values of bidders, she found that when compared to Vickrey auctions, English auctions produced lower bids, had less residual

variance, were more affected by the number of bidders, and were influenced by learning over multiple rounds. Further, auctions using the BDM mechanism produced values that had a statistically significant difference from either the English or the Vickrey auction.

The comparisons of auction mechanism also extend to differences between first-price and second-price auctions. Kagel and Levin (1993) saw differences in the values elicited in first-, second-, and third-price auctions. Lusk et al. (2001a) did not see differences in bid levels for first- and second-price auctions, but indicate that a larger sample size could have produced results with significant differences. They did, however, find differences in the probability that participants would pay to exchange their product for the new product (using an endowed auction approach); marginal bidders may have been more willing to bid their true WTP values in the second-price auction. In a theoretical analysis, Milgrom (1989) points out that when demand is inelastic, the average price is the same in first-price and second-price auctions. Still, he suggests that when demand is elastic, the incentives of a bidder as a price-taker in a second-price auction are different than the incentives of a bidder as a price-setter in a first-price auction and result in a lower average price in first price auctions than in second price auctions. In a study by Kagel, Harstad, and Levin (1987), Nash equilibrium theory is able to organize the outcomes of first-price (and English) auctions, but does not do a good job of organizing the results of second-price auctions. Additionally, these authors suggest that the increased revenues in second-price (and English) auctions over first-price auctions predicted by Nash equilibrium are not seen empirically due to the potential for risk-averse bidding. The effect of the level of compensation provided for

participation in an experimental auction can vary among auction types. Rutström (1998) found that there was an effect on bids as a result of differences in the participation payment given to subjects and suggested that this was an income effect, sample selection effect, or some combination of the two in a Vickrey second price auction. No obvious income or sample selection effects were seen in English auctions.

Even in a comparison of two Vickrey-type auctions (second price and ninth price), the manipulation of exchange price significantly impacted the values stated by the subjects (Knetsch, Tang, and Thaler 2001). That is, in contradiction to many other results, the context of the valuation influenced the outcome of the Vickrey auctions. These authors found that endowment effects remained over repeated trials in a second price/ninth price study, suggesting that the Vickrey auction may not be robust to these effects and thus not revealing of true consumer values. Shogren and Hayes (1997) suggest that the lack of convergence of WTP and WTA estimates in Vickrey second price versus BDM auctions may not be due to an endowment effect but to fundamental differences in the auction types; the BDM market does not allow for market learning and pricing is exogenous, whereas a second price auction enforces market discipline with an endogenous market price to provide feedback to subjects.

A model of reference-dependence (Tversky and Kahneman 1991) for WTP values elicited by auctions predicts that such values will vary depending on the frame of reference of the participants; for example, the number of goods available in the auction, aversion to loss if subjects are given one good and the opportunity to bid for an upgrade,

or the repetition of the auction over several rounds are all suggested to influence the estimated valuations.

In a summary of comparisons of several auction types, Lusk and Shogren (2007) reject second-price auctions as continually producing overbidding. They further state that in terms of efficiency, English auction are best. They are followed by second price auctions. Auctions utilizing the BDM mechanism are demand revealing, but do so to a lesser extent than the two previously mentioned. The random nth-price auction is also demand revealing, but perhaps not best for high-value buyers. The auction mechanisms discussed and their characteristics are summarized in Table 1.

Table 1. Auction Mechanisms Summary

Auction Type	Examples	Price	Open Outcry or Sealed Bid	Number of Winners
English Auction	Vickrey (1961); Coppinger, Smith and Titus (1980)	Just higher than the 2nd price bid	Outcry	1
2nd-Price (Vickrey) Auction	Vickrey (1961); Coppinger, Smith and Titus (1980)	2nd price bid	Sealed Bid	1
Dutch Auction	Coppinger, Smith, and Titus (1980); Wertenbroch and Skiera (2002)	1st price bid	Outcry	1
1st-Price Sealed Bid Auction	Harrison (1989), (1992); Lusk et al. (2001a)	1st price bid	Sealed Bid	1
Random nth-price Auction	Shogren et al. (2001); Lusk, Feldkamp, and Schroeder (2004)	nth-price bid (random)	Sealed Bid	n-1
BDM	Becker, DeGroot, and Marschak (1964); Rutström (1998)	Drawn from predetermined uniform distribution	Sealed Bid	Number over selected price
Uniform nth-price auction	Kagel and Levin (1993); Hoffman et al. (1993)	nth-price bid (stated)	Sealed Bid	n-1

Single Round vs. Multiple Round Bidding

Auctions can be conducted in a single round of bidding or over several rounds. The necessity for additional rounds has been confirmed by some and challenged by others. Alfnes and Rickertsen (2003) suggest that using a modified Vickrey second price auction for several goods simultaneously, one trial was sufficient to find the level of the WTP a premium for one good over another. Corrigan and Rousu (2006b) suggest that the practice of conducting multiple rounds of the Vickrey second price auction be done away with completely, citing a tendency for "bid affiliation" of bids in subsequent rounds, particularly with high posted prices. Harrison (2006) further recommends that the use of single-round auction mechanisms would elicit more accurate WTP estimates. He says that this is for two primary reasons. The first reason suggested is that if experimental auctions are truly designed to elicit participants' subjective values for the good being auctioned, then subjects may perceive that others have more knowledge of the attributes of the good and update their subjective values based on that information. The second reason Harrison (2006) suggests is that knowledge of bidding behavior of other participants may suggest a market value for the good that is below some participants' value for the good, thus causing them to deviate from a strategy of bidding their true value for the good. This would be a violation of the incentive compatibility of the auction. Bernard (2005) tests a second-price auction for the presence of bid affiliation over multiple rounds across three goods that differed in their novelty to subjects. He found that differences that appeared to be based on perceptions of quality as expressed in the first round of the auction disappeared over repeated rounds of the

auction and suggested that bid affiliation was a likely cause of the subsequent loss of information about the initial values held by subjects. Corrigan and Rousu (2010) conclude that for goods with both private and common value, bid affiliation is less of a concern than the potential for the auction to "overheat" (for bids to exceed the private value, observed in this case in an induced value experiment).

However, others have questioned the validity of "single-shot" auction mechanisms in Vickrey single unit auctions that do not allow for a learning process; the necessity of the learning process is suggested based on the fact that the dominant strategy in Vickrey auctions is not immediately obvious to some participants (Coppinger, Smith, and Titus 1980; Cox, Roberson, and Smith 1982). Kahneman and Tversky (1979) further suggest that an "isolation effect" causes people to discard the components of all prospects that are uniform, causing differences in preferences when the same choices are presented in different forms. In another type of sequencing effect, Huffman et al. (2003) found that the order that different products were presented in an auction setting also had a significant effect on results.

Shogren (2006) suggests that the use of a single round auction mechanism does not cure the problem of bid affiliation implicitly, since other signals could be relied on to generate affiliation in bids. Further, he suggests that the use of an auction with the purpose of inducing a market-like experiment could be violated by using a single round mechanism or even a multiple round mechanism with no price feedback; there is no market learning in either of these cases. In a study of consumer valuations for several retail beef options, Lusk and Shogren (2007) found that changes in bid levels were

consistent across the different qualities of beef over repeated rounds, thus raising the question of whether the subjective views of quality of each participant influenced bids or if the bids changed due to participant learning of the auction mechanism. Drichoutis et al. (2009) note the differences between single shot and multiple round auctions, and suggest an econometric procedure to test for the presence of bid affiliation. However, this test requires at least four repeated rounds to be applied, and Drichoutis et al. (2009) make the specific point that although their procedure has the ability to test for the presence of bid affiliation, the authors refrain from taking a position on whether bid affiliation is necessarily a problem that should be corrected for in an experimental auction setting.

Bateman et al. (2008) analyze choice-based contingent valuation procedures; however, their findings are pertinent to the discussion of single or multiple rounds in other valuation procedures. They recommend against single-shot value elicitation and contend that the learning process associated with unfamiliar goods and unfamiliar institutions require the need for the opportunity for subjects to practice in order to obtain more stable results.

There are also differences among the auction mechanism for multiple unit auctions and auctions for products with possible negative values. Marked demand reduction effects were seen in multiple unit uniform price auctions as compared to the dynamic Vickrey/ Ausubel auction (Kagel and Levin 2001). In an induced value experiment, aggregate bidding in a Vickrey second price auction was precise but biased (high value bidders and low value bidders overstated benefits and understated costs,

respectively), while aggregate bidding in a random *n*th-price experiment was demand revealing (unbiased) but lacking in precision (large variances) (Parkhurst, Shogren and Dickinson 2004). Still, Menkhaus et al. (1992) point out that multiple unit Vickrey auctions (e.g. third price auctions selling two units or fifth price auctions selling four units) abide by the same theoretical incentive-compatibility as second price auctions.

Endowment Approach vs. Full Bidding Approach

Once an auction type has been selected, the type of bidding utilized can still have an effect. Caution must be used at this point; auction bidding, which is a competition for a limited quantity of goods, does not necessarily equate to the decision-making process in point-of-purchase situations where consumers are price-takers for a practically unlimited quantity of goods (Hoffman et al. 1993). In an endowment approach, subjects receive a product and bid the amount that he or she would pay to exchange the "endowed" product for another product; the amount bid is the WTP premium. In a full-bidding approach, the participants in the auction bid the full price for each of the different products and differences in bids can be used to calculate WTP premiums (Alfnes 2009). It is important to distinguish the endowed approach described here from the endowment effect that has been described as the cause for disparity among WTP and WTA (Kahneman, Knetsch, and Thaler 1990).

There is disparity on whether an endowed approach is the necessary bidding set-up (Lusk and Shogren 2007) or whether a full-bidding method is preferable (Alfnes 2009). Hoffman et al. (1993) suggested that experimental auctions are most valuable for

determining *differences* in WTP among products rather than for determining full values. This is echoed by Hayes et al. (1996), who endow auction participants with a good and seek the premium (or discount) that subjects have for another improved product. They allow that the full bidding approach may be useful when the motivation for the research is general information on the base good. A direct comparison of random *n*th-price, second-price, BDM, and English auctions found differences in the significance of the effect from the use of the endowed approach versus the full-bidding approach; a lower value for the auctioned item was obtained using the endowed approach with the random *n*th-price auction, but higher valuations of the auctioned good were obtained in the second price auction (Lusk, Feldkamp, and Schroeder 2004). In general, the results of Lusk, Feldkamp, and Schroeder (2004) were mixed. They found that in multiple round auctions the endowment effect became more pronounced in later rounds. In terms of differences in auction mechanisms, there was statistically significant evidence of loss aversion in the random nth-price auction but not in the BDM or English auction mechanisms. Lusk and Shogren (2007) contend that the endowment approach has the benefits of controlling for the problem of field substitutes and outside option values, allowing for imposition of a consumption requirement, and making a more useful experimental outcome of estimating differences in WTP rather than actual values. In a field experiment on WTP for steak tenderness, Lusk et al. (2001b) suggest that by asking consumers which good they prefer and then endowing them with the opposite good, some of the potential problems of the endowment approach will be avoided. However, the incentive compatibility of the choice decision used here seems to be lacking in some

cases, as consumers would not have even a weakly dominant strategy to answer this question in such a way that their true preferences are revealed. For example, if consumers prefer good A over good B, they may receive good A without additional payment by stating that they prefer good B.

On the other hand, Alfnes (2009) contends that since the effect of outside options is similar for goods with the same outside substitutes, the Vickrey auction used with the full-bidding approach should still provide good WTP estimates for product characteristics. In an endowed auction, interpreting the bid for the new good as the value placed on the trait of interest is in defiance of the reference dependence of preferences, and the results may therefore be biased (Corrigan and Rousu 2006a). Corrigan and Rousu (2006a) further suggest that it is impossible to predict the net direction of the bias in the case of the endowed approach, as there is an upward bias from reciprocal obligation and a downward bias from loss aversion, with the magnitudes of these biases not predicted by theory. The approach they used compared bids for one and two goods with bids to upgrade from one endowed unit of a good to another unit of the same good; thus eliminating the possibility of a so-called "endowment effect," since subjects never had to give up an endowed good. As an alternative means of WTP elicitation, using a comparison of the difference in bids for two goods from the same subject in a full-bidding approach facilitates the canceling out of the values of outside options (including the same good and substitutes); the between-subjects comparisons of bid differences should then provide an estimate of the distribution of willingness-to-pay a price premium for one of the two goods over the other (Alfnes 2009). Despite Lusk

and Shogren's (2007) criticisms of the full-bidding approach, they indicate that experimental auctions that utilize the full-bidding procedure may be appropriate if and when few outside options exist, the endowment effect is a pervasive phenomenon, actual consumption of the product is not an important part of the value, there is little opportunity to learn about the value of the good in the future, and subjects will want to "return the favor" of the endowment by altering their bids.

In the distinction between private value goods and common value goods, many private value goods have a value in the outside marketplace that would be similar for all individuals, breaking the private value condition; the usefulness of a common value good to an individual may be enhanced by some private value (Laffont 1997). Further, in markets for goods with both private value and common value traits, greater inefficiency is expected in those that have higher levels of uncertainty about the common value (Goeree and Offerman 2002; 2003).

Auction Mechanism Considerations

Unfortunately, there is a lack of formal theory to explain why, even among incentive-compatible auction mechanisms, there is discrepancy among estimates of willingness-to-pay. Thus, choice of auction mechanism may be based on the sort of consumer the WTP analysis is targeting, with more emphasis given to the entire marketplace and those consumers with low- to moderate-value with the BDM procedure or the random *n*th-price auction and emphasizing higher-value consumers with the Vickrey second price auction (Lusk, Alexander, and Rousu 2004; Shogren et al. 2001).

If these auctions are extended to private industry as a means of market analysis prior to launching new products as suggested by several authors (i.e. Levitt and List 2009, Hayes et al. 1996, Jaeger and Harker 2005), the absence of a clearly defined theoretical understanding of the differences in auction results requires a careful consideration of which auction type is most appropriate. Concessions are also made among the full-bidding and endowed approaches when designing an auction, and exceptions are made to suggest the endowed approach if 1) a consumption requirement is applied or if 2) the two goods being compared are a novel good not available outside the experiment and a conventional good that is available outside the experiment in order to prevent an overestimate of the WTP premium value for the novel good (Corrigan and Rousu 2006a). Lusk and Shogren (2007) indicate that, based on the study of Lusk, Feldkamp, and Schroder (2004), rejection of equivalence among bid mechanisms does not exclude a conclusion that bids across mechanisms are highly correlated. The lack of unanimity in the research on value elicitation is an indication not only that a great deal of experimentation in this field has been carried out, but also that considerably more experimental work is needed (Plott 1991).

Internal Validity

Internal validity refers to the ability to draw conclusions about causation from the results of an experiment (Loewenstein 1999). An alternative definition is provided by Samuelson (2005), who suggests that internal validity is the strength of the link between the imposed experimental environment and the observed behavior of subjects. For an

experiment to be internally valid it must, therefore, be constructed in such a way as to accurately test the hypothesis of the experimenter. The experiment might also be an internally valid test of economic theory if it reproduces the assumptions of that theory in order to generate results that are relevant to the predictions the theory makes (Croson 2005). Flaws in procedures that are not consistent with assumptions of the hypothesis can lead to results that are biased. The testing of each causal hypothesis must be conducted in isolation in order to sort out effects and either confirm or disprove the hypotheses one by one (Guala and Mittone 2005). Economic theory is a strong tool for testing the internal validity of experimental results (Samuelson 2005). Davis and Holt (1993) list general methodology for controlling undesired effects within the experiment to accurately and reproducibly test the hypotheses of the experiment. These strategies are fairly consistent across the literature, and statistical tests can help determine the strength of results in terms of internal validity. If results are not internally valid, then either the researcher will fail to correctly identify the relationship between the situation and the outcomes or he will be unable to do so because the results will be too noisy to allow conclusions to be drawn (Samuelson 2005). Factors of internal validity that might be of concern in experimental design include types of treatments to be applied, elicitation method, randomization, subject pool and number of subjects, psychological influences, learning behavior, and incentives.

Replication of results is perhaps the simplest way to test the internal validity of an experiment (Samuelson 2005). For example, to further test a theory of bargaining, Binmore, Shaked, and Sutton (1985) replicated previously reported results in their own

experiment, stating that "under similar conditions, we obtained similar results." This replication as a control treatment in an experiment is useful in making comparisons across time and space.

External Validity

External validity, on the other hand, refers to the generalization of experimental results to the broader context of the world. There is generally some contradiction between high levels of internal validity and high levels of external validity (Schram 2005). The discussion of the validity of experimental procedures within economics has generally focused on the internal validity of experimental auctions, although discussions of external validity are on the rise (Grebitus et al. 2010).

The ability to extrapolate the results from experimental auctions in a contained, laboratory setting to the outside world has been questioned by those within and outside the field of experimental economics (Umberger and Feuz 2004; Levitt and List 2007). However, the external validity of experimental procedures and their application to the field of economics is also extensive, with Plott (1982) arguing that experimental methods have an important role in testing the validity of theories. This position was also taken by Smith (1976), who extended it to include interpretation of field data as well.

As economists frequently take on normative roles in addressing policy, there are certain strategies to improve external validity of experiments in such situations. If the problems and exact circumstances that experimental results will be generalized to are known, then those problems of external validity can be addressed as modifications in the

experimental design (Guala and Mittone 2005).

Levitt and List (2007) mention five factors that, in addition to monetary considerations, influence the behavior of subjects in the laboratory. These are: the presence of moral and ethical considerations, the nature and extent of scrutiny by others, the context in which the decision is embedded (including artificial time and location constraints), self-selection of the individuals making the decisions, and the stakes of the game; all of these could influence the external validity of an experimental market. The factors mentioned are generally different in a laboratory setting than in a naturally occurring environment.

However, the generalizability of experimental results is key to their external validity and is a question of which components of the experimental environment are valid to use in making predictions of real-world results (Campbell and Stanley 1966). Plott (1982) holds that the key to success in experimental design is asking questions that can be sufficiently answered in an experimental context where a study of the simple case can be generalized to the complex. Levitt and List (2007) also point out that the generalizability of results based on observational data is not infallible and that caution should be used when extending those results to real-world markets as well. Sound economic theory is needed in both cases for data to hold value. These authors later (2009) suggest that framed field experiments, including these types of auctions, lie on the spectrum between laboratory experiments and econometric modeling based on observational data. Further, they indicate that auctions avoid some of the problems of randomization bias and attention bias on the laboratory end and identification

assumptions on the observational end. Roth (1995) questions the extrapolation of some of the problems that can be commonly identified in experimental auctions to the field as irrelevant in some cases. He suggests that for example, participants in an experimental auction may be inexperienced and show evidence of the winner's curse, whereas in the field participants in the same sort of auction may have experience and the phenomena may not be seen. This particular distinction was disputed by Dyer, Kagel, and Levin (1989) who found similarities in experimental results for bids of both naïve and experienced subjects. Lange and Ratan (2010) base their criticism of the external validity of first price and second price auctions on a theory of loss aversion; they find that reference dependent preferences may affect the elicited valuations from a laboratory setting versus a field setting on the basis of differences in the dimensions of the consumption space (specifically, monetary value and actual item value).

Just and Wu (2009) hold that experimental economics can be useful in testing the validity of a theory, particularly in the case that Binmore's (1999) criteria are met; however they suggest that the greater usefulness of experimental economics as a means of testing economic theory over making specific quantitative predictions can be a result of the lack of practicality in implementing many proposed experiments. This view is narrower than that taken by Guala and Mittone (2005), who advocate for the application of experimental results to the real-world but suggest that the necessity for every experiment to be externally valid in every situation is unrealistic. They suggest that a more preferable approach is to categorize the results of some experiments as "phenomena" and take the range of these, including various anomalies, biases, and

paradoxes, into consideration when making applications to particular cases. Harrison, Lau, and Rutström (2010) emphasize that economic theory, experimental results, and econometric techniques should be integrated for a more thorough understanding of economics, rather than analyzing each of these as mutually exclusive. Thus, experiments in the laboratory or in the field can be interpreted by taking the considerations and findings of the other areas into account.

Relative WTP values obtained through experimental auction procedures appear valid, but actual WTP values may be prejudiced by characteristics of the experimental design. Specifically, panel size and the initial endowment were found to affect auction prices by Umberger and Feuz (2004); the results of their auction were that market price for a beef steak increased as the number of participants in the auction increased. Coursey and Smith (1984) found that in a Vickrey fifth-price auction the subjects underbid their maximum WTP, but that these underbids were consistent insomuch as the underbids among subjects and for different objects were indicative of meaningful differences in value. Ariely, Loewenstein, and Prelec (2003) conducted a series of six experiments and found that in many cases, preferences measured by experimental economics show what they term "coherent arbitrariness." That is, the preferences may be heavily influenced by the context of the experiment; however, relative valuations (e.g., value for more versus less of an auction good) respond in the way predicted by economic theory. Lusk and Shogren (2007) discuss several empirical results that show that preferences are likely not entirely arbitrary based on analysis of contingent valuations of public policy where people are less likely to vote to implement more costly

policies as well as analysis of the effects of positive and negative information when compared to a bid with no information.

Bateman et al. (2008) tested three hypotheses on the nature of preferences; these included the *a priori* theory of well-formed and readily-divined preferences, the discovered preference hypothesis introduced by Plott and Zeiler (2005), and the coherent arbitrariness hypothesis of Ariely, Loewenstein, and Prelec (2003). Using a contingent valuation method, Bateman et al.'s (2008) results suggest that there are likely at least two types of learning that occur over multiple rounds of an auction: value learning (learning of individual preferences) and institutional learning (learning of the valuation mechanism). They also suggest support for the discovered preference hypothesis of preferences in which stable preferences are gained through practice and repetition with both the good and the market institution. These are important considerations in eliciting the homegrown value for good.

Carlsson (2010) discusses the application of theories of behavioral economics to value elicitation procedures. He raises four areas that are all relevant to the external validity of such studies; these include revealed versus normative preferences, learning and construction of preferences, context dependence, and hypothetical bias. In particular, the context dependence of preferences is pointed out, but a number of methods (such as the use of the random-utility model and design of experiments with different contexts as different treatments) that have been used to analyze such context-dependence in value elicitation are suggested.

The use of experimental auctions or other experimental techniques to elicit

homegrown values are subject to certain issues that are not relevant for induced value auctions. However, they are highly relevant to any results that will be extrapolated to the real world. Many of these issues have been documented over the years; for example, Milgrom and Weber (1982) suggested that bids may be affiliated at the beginning of an auction or may become affiliated over the course of the auction. Others have made pointed criticisms of the external validity of some mechanisms; the three main issues discussed by Harrison, Harstad, and Rutström (2004) are "field-price censoring," affiliation of beliefs about field prices, and affiliation of beliefs about the quality of the auctioned good. Experimenters must account for field-price censoring, or the curtailing of bids at the price level for an outside substitute of the good they are auctioning in analyzing results, as rational consumers would not bid more in an experimental auction for a good than the price they could purchase it for outside the experimental market plus some transaction cost, assuming they know the price of the outside good. Secondly, institutions that reveal information to the consumer about the value of the good may cause the estimated WTP to be biased over multiple rounds. Consumers could believe that the bids expressed by other participants reflect knowledge of the pricing of perfect and imperfect substitutes, as well as complements, in the outside marketplace. This affiliation could be prevented by using simultaneous or one time value elicitation, but if the experimenter believes that learning is a necessary part of obtaining valid results, then the posting of bids is generally a component of that learning process. The third methodological issue discussed by Harrison, Harstad, and Rutström (2004) is that an affiliation of the perceived quality of goods up for auction may occur over multiple

rounds. If participants are unsure of the quality of the good up for auction, they may assume that other participants have more knowledge of the quality of the good then they do and adjust the bids they place accordingly.

Alfnes (2009) contends that if product attributes are to be valued using experimental methods, the levels of the bids in a Vickrey second price auction are not generally useful because they are curtailed at the market price for that good and reduced by the value of the surplus that could be obtained by purchasing substitutes. He suggests that products that would normally be purchased in the market place will generate bids that are at the market price. However, for goods that would not typically be purchased in the marketplace, participants will still seek to generate the same surplus they would have had by purchasing substitutes in the marketplace; therefore, the bid they submit should be less than the market price. Cherry et al. (2004) also found bid shaving (reduced bids when homegrown value exceeds the value of the outside good) in real and hypothetical induced-value auctions where information on outside substitute goods was provided. Possible options to control for the effect of providing prices for substitutes are to account for bids that are truncated (Harrison, Harstad, and Rutström (2004) or by asking subjects what their perceptions of available substitutes and prices are for the good being auctioned (Corrigan 2005).

Shunda (2009) found that the price set by sellers to end an online auction early affected the valuations that consumers had for goods. He suggests that bidding behavior more closely mirrors a reference-dependent theory than the reference-free expected utility theory. In the case of economic development, Deaton (2009) argues that scientific

progress is unlikely based on uncertain experimental results and that the usefulness of experimentation in that field may be limited. Nunes and Boatwright (2004) discuss the effects of incidental prices on WTP, defining "incidental prices" as the prices for unrelated goods whose prices are irrelevant to the good for which WTP is being elicited. The anchoring effect often discussed in psychology literature was observed using incidental in three studies by Nunes and Boatwright (2004); this indicates yet another example of the context-dependence of WTP estimates. These authors further suggest that the effects that they observe could be strategically manipulated by marketers to target the numerical values that consumers are exposed to near the time of purchase and influence consumer WTP. Nevertheless, this effect remains relevant to experimental economics in that subjects are likely to be influenced by any prices they are exposed to during the span of an experimental session, but also in that subjects may exhibit effects of incidental prices they were exposed to prior to the experimental session. Ariely, Loewenstein, and Prelec (2003) also discussed the anchoring effect in their presentation of a coherent arbitrariness hypothesis for the formation of preferences.

In a series of studies to analyze the unique complexity of price, the difficulty of evaluating an infinite number of other uses for money, and the evidence that consumer preferences are influenced by price, Lee, Bertini, and Ariely (2008) report evidence that the decline in preference consistency is not an information effect. They further suggest that preferences appeared to be more stable when price was not included as a factor in the decision-making; however, they counter this with the fact that from a consumer standpoint, subjects seem to be more satisfied and better able to make decisions when

price information is included. An important methodological consideration they find is that there is a reduction in variability of preferences when an explicit suggestion is made by experimenters to participants suggesting that they consider the opportunity cost of using money to make other purchases. As a final note, there may be factors that confound any type of data, be it experimental or observational; care must be taken to make accurate conclusions based on the available information (Roth 1995).

Incentive compatibility is also applicable to methods of value elicitation other than auctions, although it was traditionally lacking in hypothetical choice experiments (see Murphy et al. 2005). Proposals have been made and utilized to develop incentive compatibility in conjoint analysis of choice-based experiments (e.g. Alfnes et al. 2006) and ranking experiments (Lusk, Fields, and Prevatt 2008). Analysis by others also indicated that the preferences of an individual were not context dependent in a study to determine whether rational decision-making by individuals was transferred from market to non-market settings (Cherry, Crocker, and Shogren 2003).

It should be noted that comparisons of dichotomous choice surveys, open-ended surveys, and auction procedures as methods of value elicitation indicate that dichotomous choice questions overstate values (for both public and private goods), and that open-ended questions also overstate the values obtained in auction results but do not do so as severely as dichotomous choice questions (Balistreri et al. 2001). One possible solution to this issue is to combine the use of surveys and auctions for a single analysis of WTP and the factors that affect it in order to correct for the problems of each approach (Yue, Alfnes, and Jensen 2009).

In determining whether survey methods that are hypothetical or nonhypothetical are preferable, Chang, Lusk, and Norwood (2009) found nonhypothetical methods (nonhypothetical choices and nonhypothetical rankings) to outperform hypothetical choices as a means of predicting retail choices. They contend that real-world decisions, if they are to be based on either of these two types of survey results, should be more accurate when based on the incentive-compatible (nonhypothetical) option. However, previous results suggested that although total WTP was sensitive to the hypothetical or nonhypothetical nature of a choice experiment, there was no significant difference in the estimates of marginal willingness-to-pay by either method (Lusk and Schroeder 2004). A comparison of stated preferences from a conjoint ranking procedure and revealed preference from scanner data for consumers of dry-cured ham in Spain used a nested logit model and found that stated preferences could be useful for predicting general market trends and choices, but not for predicting market shares (Resano-Ezcaray, Sanjuán-López, and Albisu-Aguado 2010). However, Grebitus et al. (2010) found that hypothetical nonmarket results were consistent with actual market behavior for purchases of country-of-origin labeled meat products.

Some researchers (e.g., Shin et al. 1992; Yue, Alfnes, and Jensen 2009) include a consumption requirement as a component of the experimental design; that is, participants must eat the food item they bid on to ensure that true preferences are revealed. Lusk and Shogren (2007) suggest that this is an important component of value elicitation if a large part of the value of the good is derived from the consumption value.

Random lottery procedures are sometimes utilized in order to create an incentive-compatible auction mechanism. In such an auction, several trials of the auction are completed and one of the trials is randomly drawn to be binding for the subjects (e.g., Becker, DeGroot and Marschak 1964; Shin et al. 1992; Lund et al. 2006). This is intended to control for the potential income effect as a result of a difference in the endowment of the subjects in subsequent trials of the auction; bias could occur when subjects experience changes in their endowment or in expectations of rewards from the beginning to the end of the experimental procedure (Grether and Plott 1979). Holt (1986) criticized the use of the random lottery procedure and presented results supporting the conclusion that it is only appropriate to use the random lottery procedure when the axioms (the independence axiom, in particular) of the von-Neumann Morgenstern expected utility theory are not violated. If one of these axioms is violated, the random lottery procedure may not ensure unbiased estimations of value. This procedure has also been criticized for lack of saliency, since the expected payoff for each task is small (Harrison 1992; 1989). Kagel and Roth (1992) agree that the payoff space may influence subjects to deviate from the dominant bidding strategy, while Merlo and Schotter (1992) hold that the payoff will only dominate the results of the auction depending on when and how much subjects learn during the auction. Hey and Lee (2005) carry out a direct test of the effectiveness of the random lottery procedure and find no differences in expressed preferences if the questions are answered individually versus in a series, confirming the “separation hypothesis” (that rounds of an auction are addressed separately instead of as a whole by subjects) of Starmer and Sugden (1991).

Corrigan and Rousu (2006a) also found results to be consistent across multiple rounds of auctions when participants were explicitly told the dominant bidding strategy.

Placing an auction bid can be thought of as a type of lottery for the subjects. More specifically, subjects participating in an experimental auction face a series of uncertain outcomes. They do not know who will win the auction (and win the good if the auction is nonhypothetical); the best estimate of the outcome would generally be each individual's own subjective probability (Lusk and Shogren 2007). This leads to the question of whether Bayesian updating occurs for participants when they are provided with additional information.

Subjects may submit bids that reflect what they perceive as the socially preferred option, rather than truthfully representing what their own buying decisions would be in the marketplace (Levitt and List 2007). There has been some work to suggest that the use of inferred valuation to address the problem of social desirability bias may reduce this problem of external validity and produce more accurate predictions of market purchasing behavior (Fisher 1993). This may be accomplished through the use of indirect questioning (Lusk and Norwood 2010); for example, asking "How much would the *average consumer* pay for environmentally friendly goods?" instead of "How much would *you* pay for environmentally friendly goods?" Lusk and Norwood (2009) utilize this strategy for both goods with a normative dimension and goods with a novel dimension; they find that utilization of an inferred valuation method based on indirect questioning may eliminate some of the gaps between laboratory and field behavior if the source of the gap are the social concerns of the good. However, for a novel good with

minimal social concerns, Lusk and Norwood (2009) do not find significant differences between estimates based on direct and indirect questioning for elicitation of WTP.

The prior information and beliefs held by consumers may also affect the results of experimental auctions. Subjects who are provided with "reference prices," defined as the price of the good in the outside world at retail markets, were shown by Drichoutis, Lazaridis, and Nayga (2008) to raise estimates of WTP based on bids in Vickrey second price auctions. While this finding may not hold absolutely, it does raise questions on whether prior information on market prices or providing such information during an experiment will affect value elicitation procedures. Grunert (2005) mentions the role of reference prices in consumers' decisions on how much they are willing to pay, particularly in the case of novel goods. In contrast, experimental results from Gil and Soler (2006) found that the decision of Spanish consumers on whether to pay a premium for organic olive oil was independent of whether they were provided with reference prices.

In keeping with the discussion of reference prices, there are also possible effects of other context aspects of an experiment. Choice heuristics and framing effects may influence the levels of WTP that are elicited (Bateman et al. 2008). The "focusing illusion" discussed in the psychology literature is also likely a contributor to possible problems with the external validity of WTP estimates (Schkade and Kahneman 1998). Lancaster's (1966) theory of demand proposes that the utility derived from a good is not derived from the good as a whole, but from the multiple attributes of the good. However, valuations of goods based on the division of values for different quality based

on this theory of demand may be susceptible to an artificial focus that is perceived by participants in experimental valuations procedures, causing them to inflate their perception of the value of the good (Bateman et al. 2008).

Previous Measures of Willingness-to-Pay for Food and Horticultural Products

Previous studies have analyzed WTP using a variety of experimental techniques. In one, a survey of best-worst questions was used to analyze differences in WTP for different types of beef (Lusk and Parker 2009). Alternatively, real choice (RC) experiments can be used in which numerous price scenarios are introduced for two products at the time, and subjects must indicate which product they would purchase (Alfnes et al. 2006). One of these scenarios is then randomly chosen to be binding to induce incentive compatibility in estimates of WTP. These types of experiments closely match the situations consumers face in a retail store, where they must select between similar products with different prices.

Bougherara and Combris (2009) used experimental auctions to determine WTP for an eco-labeled product and to determine the motivations that WTP was based on. Subjects demonstrated an increased willingness-to-pay for both the eco-labeled and the control products based on the availability of more information, making the level of information provided an important consideration in the design of this analysis of willingness-to-pay. The diversity in demographic characteristics of purchasers of flowering potted plants was also reflected in heterogeneity of WTP for biodegradable packaging of those products (Hall et al. 2010).

There is evidence from conjoint analysis procedures that consumers in Kentucky are willing to pay more for blueberry products made from blueberries produced in Kentucky (Hu, Woods, and Bastin 2009). These authors express caution in generalizing this result to other products and other states, but it does indicate promise for garnering a price premium for goods produced and marketed locally. Darby et al. (2006) find that there is also a willingness by Ohio consumers to pay a premium for Ohio-grown strawberries, based on the results of a choice experiment and conjoint analysis. However, a guarantee of freshness derived a higher WTP premium than the Ohio-grown claim, which they suggest indicates that at least the majority of the WTP premium was as a result of this attribute. Other dichotomous choice contingent valuation procedures have shown WTP premiums for goods produced within state in the New England region; further, that those premiums vary with the base price of the good (Giraud, Bond, and Bond 2005). Other WTP questions found a lower willingness-to-pay for males and lower income respondents for locally produced foods (Adams and Adams 2008).

Experiments have also been conducted on whether consumers are willing to pay more for health benefits by analyzing WTP for dairy products with high levels of conjugated linoleic acid, which has been proposed as a cancer-fighting agent (Maynard and Franklin 2003). Conclusions were that validation of claims from the medical community is necessary for statements made regarding the health benefits of food.

Another study by Umberger, Boxall, and Lacy (2009) utilized experimental auctions to determine the effects of credence and health information on consumers' WTP. More specifically, they sought to determine the product attributes and consumer

characteristics that influenced the purchase decisions of United States consumers for Australian grass-fed beef. They found that providing health information had a significant effect on consumer WTP when modeled with a two-stage Cragg model. Variations in WTP were analyzed for consumers who were provided with production and health information as well as an opportunity to taste the product offerings.

Several other studies also analyzed experimental auctions with the provision of health information and the implications of such on the development of public policy. Marette, Roosen, and Blanchemanche (2008) found that in both laboratory and field experiments, subjects showed a decrease in consumption of some types of fish when provided with information on possible health benefits from omega-3 fatty acids and possible health risks from methyl-mercury. They suggest, based on differences in response to different types of fish, that lab estimates of WTP would be more useful for products with a large market share; they also indicate that bias may be introduced in the laboratory because consumer choice is artificially restricted. In a study relating to the potential gains and losses from genetically modified foods, Rousu et al. (2007) analyzed the effects of providing consumers with positive, negative, and third-party information. The results of their random *n*th-price auction indicate that in a market with a controversial product and voluntary labeling requirements, providing verifiable third-party information has the most impact and thus social value when activist groups (or others) are also distributing negative information in the marketplace. They suggest that in the case of GM food, verifiable third-party information may have a social value of up

to $2.6 billion annually, and that the use of experimental techniques similar to theirs may allow policymakers to balance costs and benefits for information.

Colson, Huffman, and Rousu (2010) conducted an experimental analysis of consumers' WTP for various components of GM foods (broccoli, tomatoes, and potatoes). Of particular methodological note is that the information received by consumers within these random nth-price auctions was randomized within each auction session, and that consumers were presented with both biased and factual information. They used estimates from the auctions to develop welfare estimates and compare these to the results of welfare estimates based on a single parameter for preference for GM products.

Poole, Martínez, and Giménez (2007) evaluated consumer demand for citrus fruit using a Vickrey second price experimental auction and found that bidding behavior closely reflected tasting scores of mandarin oranges; they suggest that this serves to validate the use of auction procedures for evaluating food preferences. Consumer valuations were elicited after visual appraisal, peeling the fruit, and tasting the fruit. These authors also contend that industry and policymakers should not focus solely on providing nutrition information when encouraging individuals to purchase and consume healthful foods and that they should also focus on promoting foods that provide the most consumption value from a pleasurable eating experience.

Nalley, Hudson, and Parkhurst (2006) used an experimental auction to test the effects of health information and location of origin on WTP for sweet potatoes. Results from that experiment indicate that both types of information studied affected the level of

bids. However, the information on the location of origin not only affected the level of the bids, but the marginal differences in bids as well. They further suggest that attempts to value separate attributes of food products may not be successful since the food is purchased as a whole, rather than as a sum of individual attributes. One interesting question raised by these authors is if there is an ordering effect when providing subjects with an opportunity to taste a product and providing them with other information.

The use of nutrition labels on processed food products was analyzed using a bounded dichotomous choice model by Loureiero, Gracia, and Nayga (2006). Although this methodology may have more limitations than experimental auctions for value elicitation (as discussed previously), the qualitative findings of the study are still of relevance. These authors found that consumers were willing to pay more for products with a nutrition label; further, they found that consumers suffering from diet-related health problems were more willing to pay a premium for products with a nutrition label than those not suffering from diet-related health problems.

Bernard and Bernard (2009) used a variation on the Vickrey second price auction to analyze consumer WTP for various attributes of milk. They found that the valuations for several credence attributes, including organic and no antibiotics used types, were not additive; this suggested a diminishing marginal utility for additional attributes. However, they also found differences in the demographic characteristics of consumers who preferred each type of milk. They conjectured that this may allow marketers to segment the market and target some of these consumers with other milk products that are less expensive to produce.

Hayes et al. (1995) used an experimental auction to analyze WTP and WTA responses to additional food safety information for a meat sandwich. These authors found that marginal WTP to upgrade from a typical sandwich to a sandwich with a guaranteed level of safety decreased as the level of risk decreased. They suggest that subjects place a high value on their prior conceptions of illness even when new information on the odds of illness is provided. They also observed a tendency for some bids to cluster around the posted price of the previous round, a tendency called bid affiliation in the literature (e.g., Corrigan and Rousu 2006b).

Willingness-to-pay for apples elicited using a second price experimental auction procedure was influenced by both sensory (taste-testing) and emotional (opinion on information regarding length of time since harvest) aspects of freshness (Lund et al. 2006). Multiple-round second price auctions had previously been carried out on apples in relation to insecticide application, with WTP being income elastic (Roosen et al. 1998). Product attributes and packaging were more important than brand in WTP for fresh-cut melon (Mayen, Marshall, and Lusk 2007). Willingness-to-pay for food safety (specifically regarding *Salmonella*) was analyzed by Fox et al. (1995), with emphasis placed on the use of real food, real incentives, and multiple rounds as components of the auction market.

Consumers' level of health concern, *ceteris paribus*, did not generally affect their WTP a premium for organic foods, and many consumers lacked a prior knowledge of the National Organic Program (Batte et al. 2007). The lack of effect from recognition of the organic seal raises questions on the usefulness of a national standard label for functional

foods, although Batte et al. (2007) concluded that the National Organic Program had shown a positive effect on the market for multi-ingredient organic foods.

Gao and Schroeder (2009) used choice experiments to evaluate the effects of the availability of additional information on WTP. They found evidence that the omission of attribute information could influence WTP, that cue attribute information affected WTP more than independent attribute information when provided solely but the effect diminished when more attribute information was provided, and finally, that the relative ranking of the importance of attributes did not vary significantly when additional attribute information was presented regardless of changes in WTP. Gao and Schroeder (2009) further suggest that marketers utilizing such information to release new products should emphasize the attribute that has been shown to be most important relative to its cost.

In an application of WTP valuations to analysis of changes in welfare, Lusk and Marette (2010) found that estimates of effects on welfare varied across the use of hypothetical stated preference data and nonhypothetical experimental auction data; however, the direction of the welfare change was consistent. One solution to this problem would be to provide a range for the estimate of effects on welfare based not simply within a single valuation method, but across valuation methods to give a more robust estimate. This is particularly important if estimates will be used to analyze the effect of policy changes.

Most foods are what are known as “experience goods.” That is, they are products for which the value of consumption cannot be fully determined prior to

purchase (Nelson 1970). Consumption of new experience goods can provide value from consumption as well as value from information regarding potential surplus that can be gained in the future. In experimental results from Vickrey auctions for new experience goods, optimal bids were higher than the expected consumption value and the difference between the two (the information value) was affected by the purchasing frequency, the expected future prices, and the degree of uncertainty about the consumption value (Alfnes 2007). Alfnes (2007) also noted that the information value concept applies to other incentive compatible methods for elicitation of WTP for novel goods. The degree of uncertainty about consumption value may be reduced if consumers are allowed to sample the new experience good prior to bidding.

Studies of WTP for various food products are valuable for several reasons as discussed by Yue, Alfnes, and Jensen (2009). These include the ability to compare WTP values for similar products, whereas a consumer would generally not purchase multiple products in the same category (i.e. different types of apples). Further, these authors stated an additional benefit of auctions: the ability to compare WTP for established goods directly with WTP for goods that are not yet available in the marketplace. Choice experiments were useful for making estimates of WTP for quality differences in a study on beef products (Lusk and Schroeder 2004).

The willingness of consumers to pay for new varieties and types of fruit is of particular relevance to this pomegranate study. The novelty of an unfamiliar product, such as mango, may influence subjects to bid relatively high price premiums as a result of “preference learning,” defined as the desire to learn where a new good fits into an

individual's preference set (Shogren, List, and Hayes 2000). A premium was paid for goods that had never been tried before, but this was reduced after trying the good. This is consistent with a description of the product as having experience attributes. Gil and Soler (2006) also found that the novelty of a product could bias WTP premiums upward, and suggest that in the case of novel goods, any reference price that is provided may also influence WTP premiums. Similarly, consumers in New Zealand were willing to pay a premium to exchange an older variety of kiwifruit for a new, brightly-colored variety (Jaeger and Harker 2005). This was an introduction of the use of experimental methods for application to horticultural innovation. Moreover, if new horticultural varieties are very different from those on the market, experimental methods could have applications for new product development.

Urala and Lähteenmäki (2007) found the best predictor of willingness-to-use functional foods was based on consumers' perceived benefits from using the functional foods. In the same study, consumers were unwilling to sacrifice taste for additional health benefits from the food. Participants were asked to evaluate numerous statements regarding these so-called "functional foods" as a part of a telephone survey. The researchers elected to evaluate willingness-to-use a product, rather than willingness-to-pay, in order to establish a more reasonable comparison between established and new-to-the-market products.

Many functional food claims are made on the basis of compounds naturally occurring in food products, but many other claims are on the basis of the addition of bioactive ingredients to an existing product. The use of a new coating rich in

antioxidants (flavonoids and stilbenes) on apples was analyzed using a contingent valuation technique found a positive attitude towards functional foods in general and that WTP values varied with location (Markosyan, Wahl, and McCluskey 2007); these antioxidant compounds have the potential be used on other whole fruit products. The WTP of consumers in a region of Spain for a red wine product enriched with resveratrol (a phenolic antioxidant in the stilbenes group) was analyzed using choice experiments; researchers found a 55% premium for enrichment of the wine product over the non-enriched product (Barreiro-Hurlé, Colombo, and Cantos-Villar 2008). However, there are limitations to the generalizability of such exact premium values to other products or other regions.

Functional Foods

There has been movement within some parts of the scientific community to analyze whole foods rather than summing the individual nutrients of a food to thus better understand the heath-nutrition interface (Jacobs and Tapsell 2007). This has been coupled with the explosion of interest in so-called "functional foods," which include whole or enhanced foods that provide health benefits beyond the provision of essential nutrients (i.e. calories, fiber, vitamins, etc.) when consumed on a regular basis (Hasler 2002). Demand for functional foods appears to be driven, at least in part, by 1) a rising average age, 2) increasing healthcare costs, 3) greater availability of information allowing for greater individual control of health status, 4) progressing scientific evidence

that diet can alter disease prevalence, and 5) changes in food regulation (ADA 2004). Similar drivers of demand are also suggested by Siro et al. (2008).

The range of functional food products is large, with over 1,700 functional food products having been introduced in Japan alone within the span from 1988 to 1998 (Menrad 2003). The products cited as having potential to be marketed as functional foods include everything from fruits and vegetables (Kaur and Kapoor 2001) to olive oil (Stark and Madar 2002) to enriched custard pudding dessert (Sun et al. 2007).

The creation of marketing strategies for functional foods is complicated by the additional credence attributes associated with the majority of food products in the developed world beyond the experience attributes common in the less-developed world (Barrena and Sánchez 2010). Credence attributes cannot be checked directly by the consumer (Darby and Karni 1973), and therefore decision-making depends on information the consumer possesses and that are provided in the market (Azzurra and Paola 2009).

The three largest markets for functional foods are the United States, Japan, and Europe (Bech-Larsen and Scholderer 2007). These markets have varying degrees of regulation for the use of the "functional food" terminology. In the United States there is no regulatory definition for the term functional food, so product labelers must only abide by existing regulations regarding health claims on food (Hasler 2002). In September 2003, the United States Food and Drug Administration (FDA) began accepting "qualified health claims" based on scientific evidence; this rule was proposed with the purpose of providing additional health information with a scientific basis to consumers

(FDA 2006). However, not all groups in the United States are in support of such a labeling scheme (e.g., ADA 2004; Lupton 2009). At least 15 such claims have been approved by the FDA to date, covering a range of health-related issues from cancer to cardiovascular disease to cognitive function (FDA 2009). Still, some suggest that the use of health claims in this way is in fact confusing to consumers rather than a useful means of providing them with health information (Hasler 2008).

In Europe, however, there are much more strict qualifications for the term as laid out by the European Council (EC), and sufficient scientific evidence of a product's health benefits must be provided to the European Food Safety Agency prior to making a claim of a beneficial effect (EC 2006). Further, these regulations enforce a uniform set of standards for functional foods across all the European Union member nations, possibly helping to improve the acceptability and credibility of health claims to consumers there (Asp and Bryngelsson 2008). Japan has a series of regulations to categorize food with health claims as either foods for specified health use (FOSHU) or foods with nutrient function claims (FNFC) based on a relatively long (since the 1980's) history of functional food use (Ohama, Ikeda, and Moriyama 2006). Several other nations have either passed or are discussing the implementation of health claims regulations to address some of the issues associated with making health claims about functional foods (e.g., Tapsell 2008; Yang 2008).

Scientific Basis for Functional Foods

The chemical compounds in plants that have been shown to have positive health

implications but are not included in the traditional essential nutrients are broadly known as "phytochemicals." These compounds have been shown to appear in a range of foods, from garlic to tomatoes to citrus, and to have a range of health-improving properties including the ability to reduce the risk of certain cancers (Rafter 2002). Polyphenols, a class of phytochemicals characterized as having multiple hydroxyl groups on phenolic rings, have been frequently referred to as having antioxidant properties based on results *in vitro*; however, their action is much more complicated *in vivo* (Williamson and Holst 2008). These compounds have not been shown to be necessary for growth and development, but have been shown to have positive effects for disease reduction, causing them to be termed "lifespan essential" by Holst and Williamson (2008). The antioxidant effects of phenolic compounds function most frequently by free radical scavenging and metal chelation activities (Shahidi 2009).

The activity of polyphenols is believed to be in conjunction with other phytochemicals present in foods (Shahidi 2009). Further, the other compounds that are bioingested at the same time as flavonoids, one of the most common classes of polyphenols, and the complexity of the food matrix may affect bioavailability (Williamson 2009). Bioavailability and bioefficacy vary widely across types of polyphenols as well, as measured by changes in plasma concentration (Manach et al. 2005). Still, polyphenols have been linked to anticarginogenic activity (Duthie 2007) and prevention of cardiovascular disease (Wilcox, Curb, and Rodriguez 2008); however, both these papers indicate a need for further evidence before claims can be made regarding the certainty of these effects in human populations.

In terms of safety, it is believed that non-nutrient antioxidants are not a cause of health problems as they appear in the average daily diet; however, comprehensive studies of concentrations and effects are needed, as well as more evidence that polyphenols are absorbed by human subjects and distributed to the tissue in order to have an antioxidant effect (Diplock et al. 1998). There is also some evidence that whole-food sources, including the skin and hulls (i.e. total phenolic content in wheat and barley- Shahidi 2009) have a greater level of bioactive compounds, but this is not always the case as some processed foods have higher concentrations of phytochemicals (i.e. lycopene in tomatoes- Rao and Ali 2007).

Another important note is the lack of *in vivo* research on the efficacy of phytochemicals. A great deal of additional research is needed before sound scientific claims can be made regarding recommended dietary levels of these compounds, and polyphenols in particular, in order to prevent harmful effects (Williamson and Holst 2008). Westrate, van Poppel, and Verschuren (2002) list eight areas of research within both science and economics that have potential to yield valuable information regarding potential functional food products; the scientific questions include determination of which molecules could have potential health benefits, if those compounds are digested and absorbed, and if the product is effective on a human level with effects that can be measured quantitatively. Although considerable research has been done in the functional foods area since that time, these are still relevant questions to be answered. The American Dietetic Association suggests that well-developed clinical trials are needed to further establish the benefits and clinical efficacy of functional foods (ADA

2004).

Functional Food Market

Functional foods, as defined previously, are a market segment that has received increased interest from both consumers desiring to protect their health and by those involved in the food industry as a potential growth sector (Rafter 2002). For an extensive review of the current state of the functional food market segment, please see Siró et al. (2008). The global market for functional food generated $33 billion in 2000 and $73.5 billion in 2005 with an anticipated growth rate of 10% per annum; in the United States alone the market size was $27 billion in 2007 (Granato et al. 2010).

Both food manufacturers and pharmaceuticals companies have become interested in the functional foods market. Pharmaceutical companies are attracted to this market due to much shorter development times than pharmaceutical products. Development costs are also much lower for functional food products (Siró et al. 2008). However, pharmaceutical companies have been met with limited success in this market (Bech-Larsen and Scholderer 2007), possibly due to inadequate ability to develop and market a consumer-accepted food product. Also, this market segment varies by location, with more stringent labeling requirements in place in Europe (EC 2006) than in the United States (Siró et al. 2008). One of the largest segments of the functional food market is for probiotics, or living bacteria that generally promote digestion and digestive health, and there have been some products marketed using fruits and fruit juices (Granato et al. 2010). This represents a potential market for pomegranates as a functional food with

multiple functional attributes.

Based on a means-end approach to analysis of consumer cognitive structure for functional foods, Barrena and Sánchez (2010) concluded that in the case of a *Bifidus spp*. dairy product, households with children would be most affected by marketing emphasizing the overall health benefits and quality of the product, but households without children would be more concerned with ease of consumption and time savings. In the case of an enhanced tomato juice product, the level of demand for the functional food was actually reduced when the product in question had multiple functional attributes as opposed to a single functional attribute (Teratanavat and Hooker 2006). A consumer survey in Canada found that approximately one-fourth of respondents expressed a decreased value for a tomato product with functional properties, although the mean change was a 67% increase in value for a functional conventional tomato product (West et al. 2002).

Survey data indicates that as the market size and awareness for functional foods has grown, the unconditional acceptance of such foods has decreased; consumers now place a greater emphasis on the taste of food and surprisingly, are more reluctant to believe that functional foods can be included as a part of a tasteful and healthy diet (Verbeke 2006). However, over the same survey interval from 2001-2004, Verbeke found not only an increase in perceived importance of functional foods but also a decrease in the assumed tradeoff between healthfulness of food and taste (2005; 2006). Foods with a strong health benefit claim may be an exception to the lack of willingness to compromise on taste (Urala and Lähteenmäki 2007). Careful consideration should be

given to the taste of a functional food relative to close substitutes if experimental results are extrapolated to the marketplace and used to develop marketing strategies.

The underlying nutrient properties of the food are a determinant of consumer attitude towards the functional food product (Bech-Larsen and Grunert 2003). Consumers are more willing to accept functional foods that are plant-based rather than animal-based (Larue et al. 2004; West et al. 2002) but these general assumptions have been contradicted by some specific products (i.e. lamb versus strawberries-Traill et al. 2008). Functional foods seem to be evaluated by consumers as foods first and as functional foods second (Bech-Larsen and Scholderer 2007). Some results indicate that consumers who trust innovations made in agriculture and also have a concern for the relationship between health and food are more likely to use a functional food product (specifically, antioxidant-enriched wine) (Barreiro-Hurlé, Colombo, and Cantos-Villar 2008). Other studies of willingness to try functional foods have found innovativeness of the consumer to have some predictive ability of reported willingness to use new foods (Huotilainen, Pirttilä-Backman, and Tuorila 2006). O'Connor and White (2010) found risk dread to be a significant negative predictor of consumers who were non-users' willingness to try functional foods.

Siró et al. (2008) suggest that information on the health effects of specific products should be transmitted in a simple way through credible media in order to increase the knowledge base of consumers, who cannot independently check the credence attributes of functional foods. West et al. (2002) further suggest that information on the health attributes of products should come from government officials

or health experts, citing a lack of trust for claims made by food manufacturers.

Introduction of genetically modified (GM) functional foods appears to be less than promising, with household consumers generally avoiding purchasing GM products (West et al. 2002). However, other studies found that consumers' attitudes on GM products may be affected by the type of information provided (e.g. Lusk et al. 2004; Hallman et al. 2003) and that consumers were not specifically concerned with how the functional attributes in the food had been added (Larue et al. 2004).

Considerations for Developing Auction Procedures

Lifestyle and food culture factors have been shown to impact the fruit and vegetable consumption of college students (Schroeter, House, and Lorence 2007), and therefore these are important consideration for an experimental auction used to determine whether an increase in WTP would be seen for additional health benefits in food. A number of other factors may also influence the decisions that consumers make regarding food purchases. Hallman et al. (2003) found consumers' attitudes towards biotech foods to be influenced by their inclination to avoid risk, which was in addition to their immediate economic interests. Based on survey data for consumers in China, purchasing decisions for biotech foods are influenced by age (both young and old vs. middle), income, and residence in a large city (Chen, Zhong, and Zhou 2009). Although the health benefits of food are not equivalent to the issues of biotech food and labeling, many of the positive health benefits of functional foods may be the opposite end of a continuum from some consumers' concerns with biotech food, resulting in the

need to account for these factors in an experimental auction. Further, providing information on the benefits of a product can influence the willingness-to-accept (WTA) value of consumers, depending on the location, type of information provided, and the previously-held beliefs of the subjects (Lusk et al. 2004). On the other hand, the provision of positive and/or negative information can affect WTP, with negative information generally dominating positive information regardless of the source (Fox, Hayes, and Shogren 2002).

The randomization of treatments is a necessary component of experiments where multiple goods are auctioned in sequence in order to prevent bias in estimates of WTP (Huffman et al. 2003). Randomization can also have other positive effects to prevent bias (Shogren, List, and Hayes 2000).

There is also the consideration of the ability of subjects to learn how the auction mechanism works. Auctions that are too complex in their design may be difficult to implement and result in valuations that take longer to converge to equilibrium (Lusk and Shogren 2007). Milkman et al. (2008) examined a mechanism they refer to as a "clamped second price auction mechanism" and compare it to a standard second price auction. While they find that certain types of learners performed better with the alternative mechanism, they found values to converge to equilibrium faster in the standard mechanism. Therefore, mechanisms that seem theoretically to be more likely to converge quickly do not always follow such a pattern, and experimenters have numerous factors to account for in their auction design, not the least of which is clearly communicating how the auction works.

Differences in WTP were found for information on the genetically modified status and allowing tasting in the kiwifruit study mentioned previously, and there was some tendency for differences based on an individual's desire to try new foods (Jaeger and Harker 2005). In addition, the characteristics of the product being auctioned are not the only factors that should be considered. Depending on what the goals of the experiment are, the number of winning bids preferred by the experimenters, a desire to maintain the interest of subjects, a minimum sample size needed, and the number and types of treatments applied can all shape the auction mechanism and bidding approach that are selected (Hoffman et al. 1993). For example, experimental auctions may be selected over posted-price markets if obtaining values for price data is the goal of the experiment (Menkhaus et al. 1992).

Difficulty arises in generalizing the data obtained for one particular product to other types of functional foods. As demonstrated by de Jong et al. (2003), the determinants of consumption of functional foods depend on each individual product, in addition to gender, age, education, and vegetable intake. Barrena and Sánchez (2010) also warn of the limited generalization potential of results for one particular functional food to the whole category, especially when the results are based on a limited geographic area or small sample size. One theory suggested by Teratanavat and Hooker (2006) to explain this limited ability to generalize consumer preferences and WTP for functional foods is that as scientific evidence in favor of the health benefit of certain foods develops and the offering of products in the marketplace grows, more consumers are attracted to these products as a means of enhancement of health; those consumers vary in knowledge

level, product familiarity, motivation, and health conditions. They find that even for a single functional food product there can be significant heterogeneity among subjects in WTP. However, oversimplification of characteristics of functional foods and consumers of such is treacherous territory and may lead to inaccurate conclusions.

Econometric Modeling of Preference Elicitation Procedures

A number of econometric models have been utilized in analysis of experimental auction results. These include linear models, tobit models, and the Cragg double-hurdle model (1971) to name a few. Such models may be used to estimate demographic and behavioral characteristics that influence willingness-to-pay, as well as product characteristics that can be predictors of WTP. Depending on the nature of the data, practitioners may need to account for bid censoring when selecting an econometric model (Lusk and Shogren 2007). Aggregating bids for multiple products or made by the same bidder on multiple occasions may result in a need for further modifications of the model (Greene 2003). The selection of a particular econometric modeling procedure for the auction results may be directed by the actual data obtained from the study.

In models for discrete choice data, multinomial logit or probit models would fail to account for the ordered nature of the data (Greene 2003). Greene (2003) further suggests the use of an ordered logit or probit model to account for the ordered nature of the data, which in this case would be applicable to any rankings. However, Greene (2003) reminds the users of such a model that the coefficients in ordered models should be interpreted with caution.

Beggs, Cardell, and Hausman (1981) first introduced the rank-ordered logit model for use in analyzing ranking data in an assessment of the potential demand for electric cars; the derivation of the model is on the basis of the random-utility model. Chapman and Staelin (1982) further develop the "explosion" of ranking data by decomposing rankings into a series of unranked and statistically independent choice decisions for a multinomial logit (MNL). Such a procedure provides additional information when compared to a single choice decision. Hausman and Ruud (1987) developed two alternative estimators for the rank-ordered logit model. First, the rank-ordered logit can be generalized to allow for heteroskedasticity at different levels of the rankings; more specifically, it allows for more preciseness in the top-ranked choices than in the bottom-ranked choices. Second, Hausman and Ruud (1987) also introduce a consistent estimator that alleviates problems of misspecification of the distribution for the rank-ordered logit. Train (2003) describes the use of a model to relax the independence of irrelevant alternatives (IIA) assumption that is required by multinomial models; this is accomplished by using a mixed logit model, also commonly called the random parameters logit (RPL) model. For further clarification of the necessity of relaxing this assumption, it is necessary to further investigate the implications of IIA. The independence of irrelevant alternatives assumption, as stated by McFadden (1974; 109) says, "The relative odds of one alternative being chosen over a second should be independent of the presence or absence of unchosen third alternatives." Train (2003) describes further details of the IIA assumptions and gives examples of situations where the assumption would and would not hold.

Srinivasan, Bhat, and Holguin-Veras (2006) describe the use of a panel rank-ordered mixed logit model that is approximated using a quasi-Monte Carlo procedure; parameter estimation was conducted using a maximum simulated log-likelihood (MSL) estimation procedure.

A more specialized version of the rank-ordered logit is the latent class rank-ordered logit (LCROL). This is a specific version of the rank-ordered logit introduced by Van Dijk, Fok, and Paap (2007) intended to use all observed rankings while also taking into account a lack of complete reflection of true preferences in the rankings. The use of the latent class type of model allows a researcher to control for heterogeneity of ranking-abilities; such a procedure increases the efficiency of the model. In discussion of the LCROL, it is pointed out that relaxation of the IIA assumption would require the use of rank-ordered probit or mixed logit models (Van Dijk, Fok, and Paap 2007).

Other versions of logit models have frequently been used to compensate for certain characteristics and assumptions of the multinomial logit model. The first of these is the random parameters logit (RPL) model, also called the “mixed” logit model. The RPL model allows for variation in preferences for product attributes within a sample population (preference heterogeneity). Also, the RPL model relaxes the IIA assumption mentioned previously (Abidoye et al. 2011).

In designing an experimental auction methodology for valuation of WTP, Davis and Holt (1993) recommend consideration of possible outcomes that would either confirm or dispute the hypotheses of interest. They recommend that the decision of which structural test to use should be structured based on 3 factors: the data type (binary,

discrete, or continuous), the structure of the hypothesis (regarding a single parameter, multiple parameters, or the entire distribution), and whether the sample contains matched or independent observations. Davis and Holt further suggest that although both parametric and nonparametric tests may be used, it may be useful to focus on nonparametric tests which are less restrictive in their underlying assumptions on the nature of the distributions tested. Experimental data may frequently have distributions other than normal (Gaussian), and nonparametric methods may be more useful for analysis, and finally, nonparametric methods can be particularly useful in estimation for categorical data. Specific tests that are suggested depend on the nature of the data and of the sample design, but include binomial tests, χ^2 tests, Kolmogorov-Smirnov tests, and Wilcoxon tests.

There is an extensive literature relevant to value elicitation for novel functional food products. Much research has been conducted previously, but there are many questions left to be answered regarding experimental design and interpretation of results.

CHAPTER III

POMEGRANATES AND THE POMEGRANATE INDUSTRY

The Pomegranate

Pomegranate (*Punica granatum* L.) is a fruit-bearing large shrub to small tree that has been prized for many years for its sweet fruit; the common name 'pomegranate' in English derives from "Pomum granatum" (the plant's name in the Middle Ages) and literally means "seeded apple" (Hodgson 1917). In general, areas with hot, dry summers and cool winters will produce the largest yields (Dubois and Williamson 2008). Some fruiting may begin in rare cases as early as the first year, but full production generally starts between three and five years (Glozer and Ferguson 2008). The life of an orchard is estimated to be 25 years (Day et al. 2005).

The native range of the pomegranate is from Iran to northern India, and it was cultivated throughout the Mediterranean region in very early times (Morton 1987); some estimates are that Iran is the native range and that the pomegranate was spread later (Islamic Republic of Iran 2009). Its history dates back to references in ancient Greek and Roman literature, the Old Testament (Hodgson 1917), and the Qur'an (Mohseni 2009). The current distribution of the pomegranate is worldwide, but mainly in the tropics and sub-tropics; arid to semi-arid conditions are the preferred production environment (Stover and Mercure 2007). Some varieties of pomegranate can withstand temperatures down to 12°F, but lower temperatures cause severe damage to the plant (Morton 1987).

Pomegranate has historically been categorized in the family Punicaceae, but more recent genetic analysis provides evidence that it should be classified in the family Lythraceae (e.g., Huang and Shi 2002; Currò et al. 2010). The plant is typically deciduous in subtropical to temperate climates, but may be evergreen in tropical climates (Glozer and Ferguson 2008). The plants may have more or less thorns and grow to a mature height of 12-20 feet (Stover and Mercure 2007), although mature heights of up to 30 feet occur in rare instances (Morton 1987). Leaves are oblong-lanceolate, and stems are short (Hodgson 1917). The plants sucker abundantly from the base and roots and grow in a shrub form unless trained (Morton 1987).

Pomegranate fruits may be yellow to deep red in color and are generally less than five inches in diameter (Glozer and Ferguson 2008). Each fruit is generally round and has a prominent calyx or "crown" that is maintained through maturity, giving the pomegranate fruit its distinctive shape. Botanically, the pomegranate fruit is characterized as a berry (Kader 2006). The pomegranate fruit consists of a tough outer husk surrounding a cavity filled with angular sacs called arils that develop from the seed coat. The edible parts of the fruit are the arils; they are the juicy, pulpy surroundings of each seed. Arils may range in color from crimson to deep red in the 'Wonderful' cultivar commonly grown in California to whitish pink in the 'Mollar' cultivar grown in Spain (Kader 2006). The peel of the fruit is smooth and leathery, and just inside the outer peel is the spongy layer where the arils attach; the rind of the fruit is typically called the husk (Morton 1987). The peel and the spongy membrane are collectively known as the pericarp (Lansky and Newman 2007). The arils are bright red in color in

the most widely planted cultivars, but can range from dark red to nearly colorless (Stover and Mercure 2007). Arils can be eaten fresh, pressed into juice, made into syrup, or preserved in a number of other ways. The membranous divisions (septal membranes) of the fruit that divide the cavity into sections are bitter and not recommended for fresh consumption (Stover and Mercure 2007).

The pharmaceutical properties of the tree have also been of value, with historical references to the medicinal properties of the pomegranate (Lansky and Newman 2007 and sources therein). Additionally, secondary products of the pomegranate tree, including but not limited to the bark and peel, are sources of tannins and dyes (Mirdeghan and Rahemi 2007).

Based on data in the United States Department of Agriculture (USDA) National Nutrient Database for Standard Reference, one 4 inch diameter pomegranate (weight of 282 g, California Wonderful variety) has 234 Calories, 4.7 g of protein, and 3.3.g fat (USDA 2009a). It also contains 28.8 mg of Vitamin C, or 48% of the recommended daily value (FDA 2008). The nutrition information of pomegranate fruit (Wonderful variety) is detailed in Table 2.

Table 2. Pomegranate Nutrition Information

Nutrient	Units	Value per 100 grams	1 Pomegranate Fruit, 4 inch diameter	One-half cup arils
Weight		100 g	282 g	87 g
Water	g	77.93	219.76	67.8
Energy	kcal	83	234	72
Protein	g	1.67	4.71	1.45
Total lipid (fat)	g	1.17	3.3	1.02
Carbohydrate	g	18.7	52.73	16.27
Fiber, Total dietary	g	4	11.3	3.5
Sugars, total	g	13.67	38.55	11.89
Calcium, Ca	mg	10	28	9
Iron, Fe	mg	0.3	0.85	0.26
Magnesium, Mg	mg	12	34	10
Phosphorous, P	mg	36	102	31
Potassium, K	mg	236	666	205
Sodium, Na	mg	3	8	3
Zinc, Zn	mg	0.35	0.99	0.3
Copper, Cu	mg	0.158	0.446	0.137
Manganese, Mn	mg	0.119	0.336	0.104
Selenium, Se	mcg	0.5	1.4	0.4
Vitamin C, total ascorbic acid	mg	10.2	28.8	8.9
Thiamin	mg	0.067	0.189	0.058
Riboflavin	mg	0.053	0.149	0.046
Niacin	mg	0.293	0.826	0.255
Pantothenic acid	mg	0.377	1.063	0.328
Vitamin B-6	mg	0.075	0.211	0.065
Folate, total	mcg	38	107	33
Folic acid	mcg	0	0	0
Folate, food	mcg	38	107	33
Folate, DFE	mcg_DFE	38	107	33
Choline, total	mg	7.6	21.4	6.6
Vitamin B-12	mcg	0	0	0
Vitamin D	IU	0	0	0
Vitamin D (D2 + D3)	mcg	0	0	0
Vitamin A	IU	0	0	0
Vitamin A, RAE	mcg_RAE	0	0	0
Vitamin E	mg	0.6	1.69	0.52
Vitamin K	mcg	16.4	46.2	14.3
Lipids, Total Saturated Fatty Acic	g	0.12	0.338	0.104
Lipids, Total Trans Fatty Acids	g	0.009	0.025	0.008
Cholesterol	mg	0	0	0

Note: The nutritional information above is for whole pomegranate fruit with 44% refuse (husk and membrane) for a California Wonderful variety pomegrante fruit.
Source: United States Department of Agriculture, 2009a.

Chemical Composition

In addition to carbohydrates, fats, and proteins, pomegranate also contains many phytochemicals; these include several classes of phenols and organic acids that may have flavor and health implications (Mirdeghan and Rahemi 2007). Polyphenols present include flavonoids (e.g., flavonols, flavanals, and anthocyanins), hydrolyzable tannins (e.g., ellagitannins and gallotannins), and condensed (nonhydrolyzable) tannins (e.g., proanthocyanidins) (Seeram et al. 2006a). Specific compounds present in pomegranate fruit include gallic acid, catechin, chlorogenic acid, protecatechuic acid, caffeic acid, ferulic acid, *o*-coumaric acid, *p*-coumaric acid, phloridzin, and quercetin (Poyrazoğlu, Gökmen, and Artık 2002).

There is significant variability in the chemical composition of pomegranates by cultivar (Poyrazoğlu, Gökmen, and Artık 2002), as well as by growing site (e.g.; Melgarejo, Salazar, and Artés 2000; Al-Maiman and Ahmad 2002; Poyrazoğlu, Gökmen, and Artık 2002). Composition of the fruit may also be affected by maturity and cultural practices, resulting in potential changes in the phenolic and mineral contents (Mirdeghan and Rahemi 2007).

The chemical components of pomegranates that have been of the most interest are the antioxidants contained both in the fruit and the rest of the plant. These properties and the implications of such are discussed in more detail later.

Pomegranates and Antioxidants

Several major human health problems have been shown to be related to free

radicals and reactive oxygen species, as discussed by Kehrer (1993). He continued by describing some of the important terminology pertinent to such a discussion: Any molecule that contains unpaired electrons is considered a radical, and radicals are a normal byproduct of several metabolic pathways. However, when these radicals exist in a free form they can interact with tissue and cause dysfunction. The interaction with tissue that alters the prooxidant-antioxidant balance towards prooxidants and potentially leads to damage is termed "oxidative stress." "Reactive oxygen species" include chemicals with oxygen-containing functional groups that are not necessarily radicals nor necessarily react with tissue through radical reactions; these reactive oxygen species are not always good oxidizing agents so that terminology would be incorrect in some cases. The list of diseases that have been implicated as having a free radical mechanism of action is extensive and includes diseases of the lungs, brain, heart and cardiovascular system, kidney, liver, gastrointestinal tract, blood, eye, skin, and muscle, in addition to general inflammation and aging. Despite these links, it has been difficult to establish some free radical interactions with tissue as a cause (versus a consequence) of disease. Nonetheless, many studies have indicated a link between the two, suggesting further interest in the connection between free radicals, reactive oxygen species, antioxidants, and disease.

Antioxidants are generally described as molecules that inhibit oxidation reactions. In more specific terms, antioxidants must meet two conditions described by Rosenblat and Aviram (2006). One, they have the ability to neutralize (by delaying, retarding, or preventing) autooxidation or free-radical-mediated oxidation when they are

present at a low concentration relative to that of the substrate to be oxidized. Two, the resulting molecule that is formed must be stable in order to disrupt the oxidation chain reaction. Vitamin C and Vitamin E are two commonly known antioxidants in fruits and vegetables that play an important role in human health; however, the main antioxidant effects of fruits and vegetables may be from other chemicals (including polyphenols) also found in the fruits and vegetables (Wang, Cao, and Prior 1996). Cao et al. (1998) rejected a hypothesis that increased plasma antioxidant capacity as a result of consumption of a diet rich in fruits and vegetables could be explained by increases in α-tocopherol (form of Vitamin E) and carotenoid (related to Vitamin A) in the plasma. Tsao and Deng (2004) suggest that this and other evidence have led to the focus on research on the roles of antioxidant phytochemicals. However, these authors also indicate the difficulty in separating and detecting the large number (thousands) of such compounds in order to elucidate specific effects.

Pomegranates have a high level of antioxidants (e. g., Kelawala and Ananthanarayan 2004; Lansky and Newman 2007). Important polyphenols that have been noted in pomegranate include two main types: hydrolyzable tannins and flavonoids (McCutcheon, Udani, and Brown 2008). Hydrolyzable tannins present include ellagitannins, gallotannins, and gallagoyl esters (Gil et al. 2000). Flavonoids found in pomegranate include members of the classes of flavan-3-ols, anthocyanidins, flavanol glycosides, flavonols, and anthocyanins (Lansky and Newman 2007), with the first three of these being the most common (McCutcheon, Udani, and Brown 2008). Anthocyanins are the most important group of water-soluble plant pigments and give red, blue, and

purple colors to flowers and fruits (Rosenblat and Aviram 2006). Specific flavonoids present include catechin, quercetin, and phloridzin (Poyrazoğlu, Gökmen, and Artık 2002). Hydrolyzable tannins (HT) are found predominantly in the husk of the fruit. In pomegranate juice made from pressing the whole pomegranate fruit, hydrolyzable tannins account for 92 percent of pomegranate juice's antioxidant activity, with the HT punicalagin accounting for about half the antioxidant capacity of pomegranate juice made from the whole fruit (Seeram et al. 2006a).

The total polyphenol concentration of pomegranate juice is higher than that of several other fruit juices, including apple, cranberry, grape, grapefruit, orange, peach, pear, and pineapple juices (Rosenblat and Aviram 2006). Figure 1 diagrams the relationship between the different categories of phytochemicals.

The suggested health benefits of these antioxidants range from reductions of atherosclerosis indicators and blood pressure in humans (Aviram et al. 2004) to improvements in prostate cancer indicators (specifically, prostate specific antigen doubling time) in prostate cancer patients (Pantuck et al. 2006), in addition to the many health effects on diabetes, cancer, and other diseases as shown in animal studies (e.g., Huang et al. 2005; Shiner, Fuhrman, and Aviram 2007). Inflammation and cancer are the most common discussions of application of pomegranate to treat disease (Lansky and Newman 2007). This is in addition to the recent explosion in literature on the *in vitro* benefits of pomegranate-based substances as prevention or treatment techniques for everything from breast cancer (Syed, Afaq, and Mukhtar 2007) to influenza (Haidari et

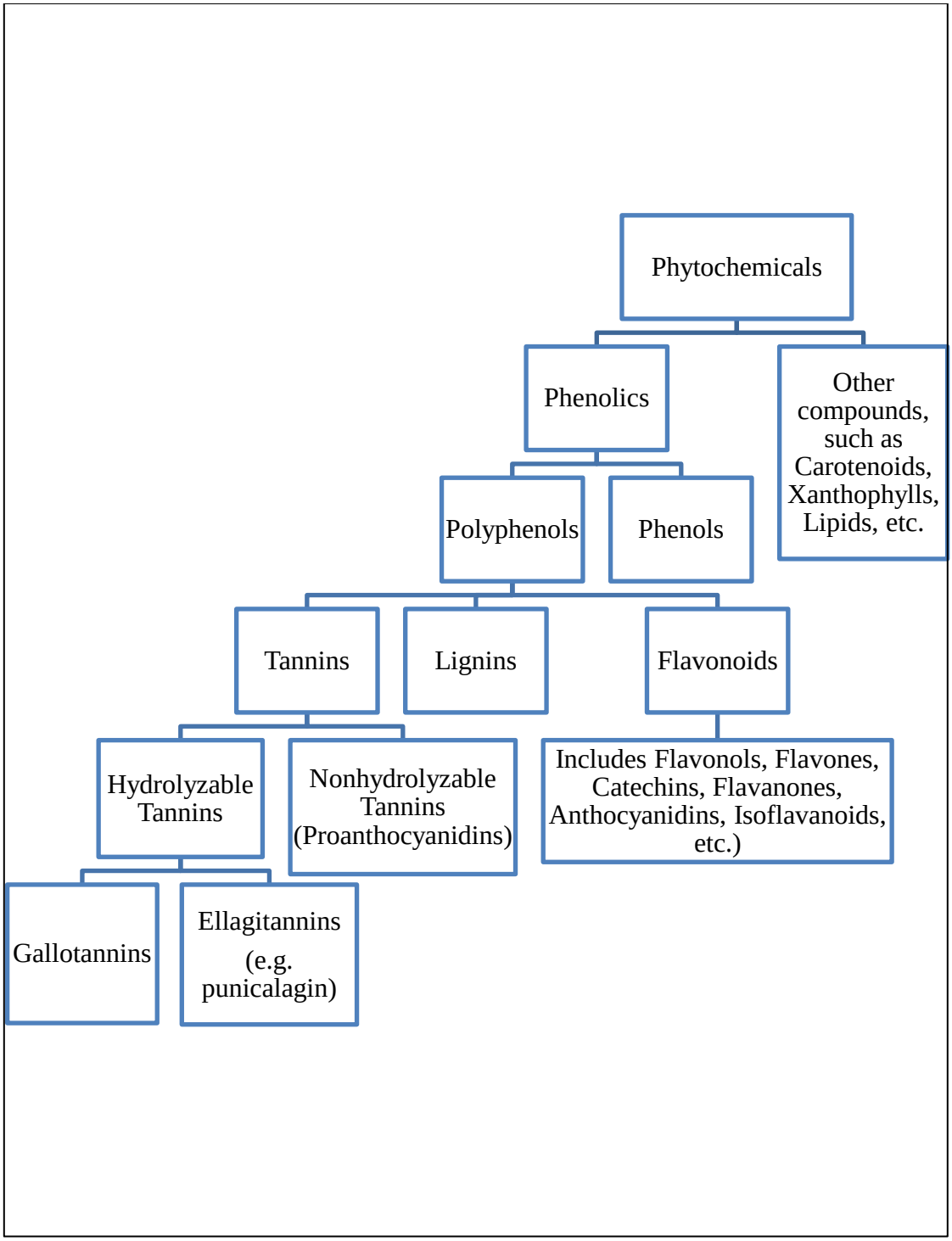

Figure 1. Relationship among Types of Phytochemicals

al. 2009). Hartman et al. (2006) suggest that the large number of compounds in pomegranate fruit and possible synergism of these compounds may yield a preference for dietary supplementation of the whole fruit or juice rather than with isolated components of pomegranate. Seeram et al. (2006a) further discuss that most *in vivo* research has focused on whole fruit or whole fruit products; therefore there is less evidence for the effects of each specific pomegranate phytochemical on health.

Pomegranate juice has been effective at decreasing amyloid load and improving behavior in mouse models of Alzheimer's Disease (a common cause of dementia in humans, particularly in older populations) (Hartman et al. 2006). The consumption of polyphenols may increase cellular signaling and neuronal communication, thus producing anti-inflammatory activity (Joseph, Shukitt-Hale, and Casadesus 2005).

Although much work remains to be done on the biological mechanisms of phytochemical activity *in vivo*, certain actions have been more commonly seen. These include increased apoptosis, decreased metastasis and invasion, and decreased inflammation (Lansky and Newman 2007).

The presence of polyphenols in pomegranates that have *in vivo* antioxidant activity does not guarantee that consumption of pomegranate products will ensure these effects in human subjects. These compounds must be absorbed in the digestive tract and moved to other parts of the body for these effects to be realized. Results on the bioavailability of ellagitannin were mixed in the detection of the free ellagic acid in human plasma four hours after consumption (Seeram, Lee, and Heber 2004; Cerdá et al. 2004). Other studies found ellagitannin metabolites in human urine following

consumption of pomegranate juice (Seeram et al. 2006b). Specific work on the bioavailability of anthocyanins and procyanidins from pomegranate products either has not been carried out or does not offer enough evidence to draw conclusions on the metabolic rate for these compounds; however, there have been studies of the bioavailability of these compounds from other sources (Tomás-Barberán, Seeram, and Espín 2006).

Although pomegranates are widely consumed and have been for thousands of years, the focus on them as beneficial to human health may cause pomegranate and pomegranate byproduct consumption to rise above historic levels. This leads to the question of toxicity to humans of pomegranate. There have been some cases of allergic reactions from eating the fruit (Hegde and Venkatesh 2004), as well as other adverse effects, such as severe gastric inflammation and congestion of internal organs (Lansky and Newman 2007 and sources therein). However, the reports of such adverse effects are rare.

Most studies regarding the effects of polyphenols are *in vitro* or in animal models, and a significant amount of research remains to be done in human subjects before the benefits of polyphenols can be predicted with certainty (Hartman et al. 2006). The precise role of antioxidants in mediating or preventing disease is still unclear, and further biological research is needed to verify the effects of polyphenols and antioxidants in pomegranates (Lansky and Newman 2007). Such research will be necessary to guarantee an increase in consumer WTP. Case in point, the juice company POM Wonderful, LLC. has launched a $34 million campaign of medical research to support its

pomegranate juice product, POM Wonderful® (POM 2010) and subjected such studies to peer review (McCutcheon, Udani, and Brown 2008).

Pomegranate Production

Pomegranate production in the world is led by Iran with 63,733 hectares (ha) in production in year 2005, followed by India, the United States, Turkey, and Spain (Islamic Republic of Iran 2009). Other estimates place China between India and the U.S. in area in production (Holland and Bar-Ya'akov 2008). Iran had an export value of $17.8 million in 2005 for approximately 27,000 metric tons of exports of pomegranates (Islamic Republic of Iran 2009). Again, these estimates vary across sources. Holland and Bar-Ya'akov (2008) estimated a global production of pomegranates of 1.5 million metric tons (1.5 billion kg); estimates for production and exports for Iran were 600,000 metric tons (600 million kg) and 60,000 metric tons (60 million kg), respectively.

The primary growing region for pomegranates in the United States is California; production in other states is currently very limited. Pomegranates were introduced into California by Spanish settlers in 1769 (Morton 1987), but they had previously been grown in the United States in Florida and Georgia (Stover and Mercure 2007). In reference to current production trends, estimates of the number of pomegranate trees in California rose from 12,000 acres (4,856 ha) in year 2006 to 29,000 acres (11,735 ha) in year 2009 ("Pomegranate Acreage" 2009).

Pre-Planting

There are a number of factors that should be considered prior to planting a pomegranate orchard, including cultivars to be grown, propagation, soil type, climate, soil preparation, pre-plant fertilization, irrigation system, weed control, and plant spacing. This is not an exhaustive list, but lists the primary factors that most pomegranate growers would need to consider.

Cultivars

The main commercial cultivar in California is 'Wonderful;' it is the industry standard by which other varieties are judged (Palou, Crisosto, and Garner 2007). Wonderful originated in Florida and was propagated in California in 1896 (Hodgson 1917). Wonderful is known for its balance of quality and yields of up to 6000 kilograms/acre (Palou, Crisosto, and Garner 2007). 'Foothill Early' and 'Early Wonderful' cultivars are widespread and mature six to eight weeks earlier than Wonderful, but these cultivars are not as sweet ("Pomegranate Acreage" 2009). Other cultivars grown in California include 'Ambrosia,' 'Eversweet,' 'Grenada,' 'Kashmir,' 'Red Silk,' and 'Sweet Pomegranate' (Glozer and Ferguson 2008), and other varieties are grown in other regions of the world. More than 500 named varieties exist, but many of these are likely the same botanically but called by different cultivar names in different areas (Stover and Mercure 2007). In particular, the same variety grown in different locations may vary in husk and aril color, making distinctions more difficult to make (Stover and Mercure 2007). Initial trials of cultivars in Texas have included varieties

such as Kandahar, Texas Pink, Sumbar, Purple, Mridula, Salavatski, and Pecos; these cultivars vary in their maturity, color, seed-hardness, and sweetness (Ashton 2010).

Figure 2. Examples of the Variability in Pomegranate Cultivars

The physical variability in fruit appearance among pomegranate cultivars that can be seen in Figure 2 is matched with additional variability in other physical, chemical, and production characteristics. Cultivars should be selected that are adapted to the climate where the orchard is to be planted. This includes differences in cold hardiness and salt tolerance among cultivars, as well as preferences in fruit color and seed hardness in the target market (Stover and Mercure 2007). Possible cultivars in Spain have been evaluated for variations in the following: seed hardness (soft preferred), sweetness, fruit size, and yield (Martínez et al. 2006). Each of these criteria should influence the market acceptability and potential profits from a pomegranate orchard.

Propagation

Pomegranate seeds will germinate and grow, but they do not come back true to type (Hodgson 1917). Hardwood cuttings are best done in late winter to early spring and

are the preferred method of propagation for general seedling production (Larue 1977). Cuttings of 6 to 8 inches in length and greater than ¼ inch in diameter should be placed directly in the ground with the top node exposed and left to grow in nursery beds for one to two years (Dubois and Williamson 2008). Glozer and Ferguson (2008) suggest that one year is generally sufficient prior to planting in a permanent orchard. Seedlings can also be grown using regeneration from cotlyedonary nodes (Naik, Pattnaik, and Chand 2000).

Soil

Pomegranates can adapt to a wider range of soils than many other types of fruit trees; deep loam is preferred but suitable yields are produced on sandy or clay soils. The tree also tolerates mildly alkali soils or mildly poor drainage; extremes of either of these two will severely affect yields (Larue 1977). Optimal growth is on deep, fairly heavy soils with a pH of 5.5-7.0 (Dubois and Williamson 2008).

Climate and Microclimate

Pomegranate is a drought tolerant plant, growing well in some desert regions; however, fruit production is very limited under such conditions (Hodgson 1917). Pomegranates grow well in full sun, and this is the preferred planting location (Glozer and Ferguson 2008). Areas with high humidity or large amounts of rain in the late summer to fall (during fruit development, ripening, and harvest) may be unsuitable for production (Özgüven and Yilmaz 2000).

Glozer and Ferguson (2008) suggest that in general, and particularly in areas at the northern and southern extremes of the pomegranate growing region, care should be taken to site the orchard so that it is protected as possible from a late frost that would damage emerging plant growth in the spring. The plants are susceptible to cold damage from the emergence of the first leaf tissue through the bloom period. The coldest planting locations are open areas with exposure to prevailing winds; trees planted in such areas are more likely to be damaged by frost. Therefore, these areas should be avoided if possible. Also, cold air settles in low-lying areas and basins; planting in these areas should also be avoided. Siting the orchard on a north-facing hill (in the northern hemisphere) reduces the direct sunlight exposure of the trees and will generally encourage the plants to bloom later in the spring, thus protecting from loss due to frost damage. Maintaining bare ground around the trees allows the soil to capture heat during the day and can thus be useful in reducing cold damage. Proper irrigation practices can also be valuable for limiting frost injury. Cold hardiness of the varieties to be planted should also be considered with respect to the siting of the orchard.

Soil Preparation, Irrigation System, and Weed Control

Soil preparation generally requires plowing and harrowing of soil to ensure that any hard pan is broken up and that soil is properly conditioned prior to planting. Previous crop matter or residual weeds should also be removed and/or harrowed under prior to planting (Day et al. 2005). These weeds, if allowed to grow, would compete with young pomegranate seedlings.

Application and incorporation of lime (calcitic or dolomitic agricultural limestone) to raise the soil pH or sulfur (elemental sulfur or aluminum sulfate) to lower the soil pH to the acceptable range should be completed prior to orchard establishment. Any pre-plant fertilization that is needed should also be completed at that time (Glozer and Ferguson 2008).

The irrigation system should be in place prior to or immediately following planting because seedlings generally require additional water at planting (Stover and Mersure 2007). Irrigation may be furrow style, overhead, or drip (e.g., Day et al. 2005, Özgüven and Yilmaz 2000). Water supply should be adequate to meet irrigation requirements when rainfall is insufficient to meet water requirements of the pomegranates. Although pomegranate is drought-tolerant in that it has an ability to survive in semi-arid regions with limited rainfall, it should certainly not be considered a drought-tolerant plant in commercial production; repeated or prolonged periods of water stress are likely to significantly reduce yields (Still 2006).

Planting Design

Pomegranate orchards may be planted to facilitate either tree growth or bush growth, depending on plant spacing. Spacing of 15 to 18 feet between rows and similar spacing between trees is common in orchards (Dubois and Williamson 2008). Bush planting spacing is a smaller distance in row, for example 14 feet by 8 feet (Cline 2008). However, spacing varies considerably by location, and may be closer than those listed even for the tree form (Bryant 2003). Suggested spacings for planting in Texas include a

14-foot in row spacing with a 17-foot between row spacing for the plants with a larger mature size but with a 10 foot-in row spacing for the smaller cultivars (Ashton 2010). Spacing also depends on the type and fertility of the soil (Morton 1987). The main objective is that trees be planted where there is adequate space to meet the light, moisture, and nutrient requirements of the specific pomegranate cultivar and allow movement of workers and equipment through the orchard with ease.

Planting

Pomegranates are planted in late winter, after the coldest temperatures have passed but prior to leaf emergence to allow for root growth. In California, the suggested planting period is January (Day et al. 2005). Others suggest a late winter to early spring planting in California to take advantage of abundant soil moisture (Stover and Mercure 2007). Pomegranates to be grown in the tree form are topped (‘headedback’) at planting (Day et al. 2005). This practice encourages the development of three to five main branches and should be done at a height of 2.5-4 feet to keep fruit from touching the ground on low hanging limbs but also prevent toppling over when the tree is heavy with fruit (Glozer and Ferguson 2008; Hodgson 1917). Damage to the bark from sunburn or freezing can be prevented or reduced by painting the trunk white at planting time (Larue 1977). The painting of the trunk is commonly used in production of other tree fruit crops and is also useful in preventing insect damage.

Pruning

To grow in a tree form, pomegranate must be pruned; otherwise the pomegranate will develop in a shrub form. In general, pruning of fruit trees develops stronger branches that can hold a heavier fruit load without breaking, brings young trees into production sooner, and allows for light and spray penetration into the canopy. Pomegranates may be trained into a single trunk, or they may be trained into multiple trunks if cold damage is of significant concern as this reduces the likelihood of total loss of the tree in a freeze (Stover and Mercure 2007). In the first year, trees are pruned at planting and suckered in early summer (Day et al. 2005). The removal of the lower branches allows for the production of a clear main stem (Morton 1987). Different specific pruning methods should be followed depending on the desired growth habit of the pomegranate (Larue 1977).

Fertilization

Pomegranate should not require large amounts of nitrogen during establishment, but recommendation range around 17 pounds N/ acre (Day et al. 2005) during the first year. Depending on the soil composition, pre-plant fertilization may be sufficient to meet the nutrient requirements of the pomegranate during establishment. Fertilization of young trees should take into account the initial size and age of the tree. If applied, fertilizer should be done in mid-spring and/or mid-summer; fertilization in the fall is discouraged (Ashton 2010).

Orchard Management

Pomegranate production once the orchard is established requires regular management. The pomegranate must be irrigated, fertilized, and pruned as needed. Problems from disease, insects, and weeds must also be prevented when possible and managed if problems arise.

Irrigation

Water requirements for pomegranate are similar to those for citrus trees at about 50-60 inches per year (Larue 1977). Dubois and Williamson (2008) suggest irrigating every seven to ten days in the absence of sufficient rainfall. Pomegranates can be irrigated with furrow, overhead, or drip irrigation; drip irrigation is the most water-efficient but also the most expensive of these methods. Research in India found drip irrigation to produce higher yield of both high and low grades of pomegranates (and thus higher total yield) than basin irrigation systems (Sulochanamma, Reddy, and Reddy 2005). Cracking and splitting of the fruit may be a result of either under- or over-watering (Özgüven and Yilmaz 2000). Another reason pomegranates may crack as they mature is cool night-time temperatures (Ashton 2010). Larue (1977) emphasizes the importance of irrigation in the period immediately prior to harvest, including late summer and early fall, as a means to reduce the number of split fruit. However, irrigation late into the fall can induce late season growth or delay the onset of dormancy, making trees more susceptible to cold damage (Day, Klonsky, and De Moura 2010; Glozer and Ferguson 2008). More recent descriptions of commercial pomegranate

production practices suggest that pomegranates need 36 acre inches of water per year, but 80 percent efficiency for furrow irrigation requires the application of 45 acre inches for orchards using that irrigation system (Day, Klonsky, and De Moura 2010).

Pruning

Regular pruning and suckering is done in the winter, with additional suckering in early summer. Pomegranates sucker aggressively from the base of the plant, and these should be removed if pomegranates are grown in the tree form (Hodgson 1917). Light annual pruning encourages growth of fruit-bearing spurs, but heavy pruning will reduce yield (Larue 1977). Pruning should be done with the intent of leaving strong, healthy branches and removing dead or diseased plant material. The canopy of the tree should be kept open for optimal fruit development (Glozer and Ferguson 2008). Some growers prune three to six weeks prior to harvest to improve fruit color (Day, Klonsky, and De Moura 2010).

Fertilization

Mature pomegranate trees have an annual nitrogen requirement of one-half to one pound of actual nitrogen per tree (Larue 1977). This may be applied in a single winter application or in a split application, depending on whether the soil is heavy or light in texture (Larue 1977). Applications of phosphorous and potassium are not necessary in most cases in California (Larue 1977; Day et al. 2005), although potassium is supplemented in some other growing areas such as Israel (Blumenfield, Shaya, and

Hillel 2000). Zinc deficiency has been noted as a rare but possible problem; it is most common in young trees or in pomegranates grown in alkaline soils (Glozer and Ferguson 2008), and this deficiency should be treated with foliar application of zinc only if needed (Larue 1977; Day et al. 2005).

Management practices that encourage vegetative growth rather than fruit set, such as excessive fertilization or irrigation, may cause fruit drop; this is true particularly in young trees. Such practices may also delay fruit maturity and affect fruit quality (Larue 1977).

Frost Protection

As a primary means of frost protection, pomegranate orchards should not be sited in frost-prone areas. However, additional management techniques can reduce the danger of late (spring) or early (fall) frost to the trees if they are not fully dormant. Dormancy should be maintained throughout the winter; thus, there should be no late summer or fall fertilization or pruning that would encourage plant growth (Glozer and Ferguson 2008). Overhead irrigation is used for watering and frost-protection in some California orchards (Morton 1987). The additional considerations mentioned previously in the description of the microclimate should also be followed. Irrigation for frost protection may be needed in early spring for frost protection of blooms and emerging leaves or in the winter if temperatures drop below 23-25°F (Day, Klonsky, and De Moura 2010).

Pest Management

Pest management issues are not typically severe in pomegranate cultivation. However, there are some considerations for disease, weeds, and insects. Proper attention to these issues can prevent or greatly reduce yield reduction from pests.

Disease

Alternaria rot (also known as 'black heart' or 'heart rot') is caused by *Alternaria* spp.; *Aspergillus niger* causes similar symptomology and can cause fruit loss to pomegranate growers (D'Aquino et al. 2009). In Alternaria rot, the interior of the fruit is partly or completely decayed and black in color, but the husk of the fruit is unaffected; the infection seems to take place in the bloom and progress to the central cavity of the fruit (Larue 1977). Significant yield losses have been reported due to Alternaria rot in Greece (Tziros, Lagopodi, and Tzavella-Klonari 2007). *Botrytis cinera* is also a disease of pomegranate, although this disease is generally not of serious economic consequence until the post-harvest stage (Day et al. 2005). However, pomegranates are not generally threatened by serious disease in production in the United States (Day, Klonsky, and De Moura 2010). Application of copper hydroxide is an option for control of fungal diseases (Ashton 2010).

Insects

With limited pomegranate production in the state of Texas, most available information on pest management is based on problems that have been reported in

California. Carroll et al. (2006) offer a review of some California pomegranate pests. Aphids are one of the most commonly discussed pests, with the cotton aphid (*Aphis gossypii*) and a yet unidentified species of aphid unofficially known as the 'pomegranate aphid' (Carroll et al. 2006). Biological control of these pests is generally effective. Grape mealybug (*Pseudoccus maritimus*) can cause damage to the fruit, and Citricola scale (*Coccus pseudomagnoliarum*) and black scale (*Saissetia oleae*) both occur on pomegranate and can cause superficial damage to the fruit that results in the quality being downgraded. The greenhouse whitefly (*Trialeurodes vaporariorum*) and the ash whitefly (*Siphoninus phillyreae*) have also been known to cause problems. They can be controlled biologically with parasites; Admire® (imidacloprid) and Lannate® (methomyl) are effective means of chemical control. Other pests of pomegranates in California include the omnivorous leaf roller (*Platynota stultana*), leaf-footed plant bugs (*Leptoglossus clypealis*), false chinch bug (*Nysius raphanus*), and flat mite (*Brevipalpus lewisi*). Both the flat mite and the leafroller cause checking and scarring on the fruit. Thrips are not commonly reported as a problem in the San Joaquin Valley, California, but they have been a cause of damage in pomegranates grown in India (Ananda, Kotikal, and Balikai 2009).

There are a few other insects that are of particular importance in other areas of pomegranate production. The pomegranate butterfly (*Virachola livia*) and the Mediterranean fruit fly (*Ceratits capitata*) cause damage to pomegranate and can be present in large numbers (Holland and Bar-Ya'akov 2008). Good general cleanliness practices such as removal of all fruit from trees and mowing of weeds in the orchard has

shown some effectiveness at managing pest populations. An example of the visual effects of insect damage on the outer husk of the pomegranate fruit can be seen on the pomegranate fruits in Figure 3. Such damage makes fruit less marketable as a whole fruit product due to limited acceptability by consumers.

Figure 3. Example of Insect-Damaged Pomegranate Fruits

Weeds

Weeds can serve as a harbor for harmful insects and plant pathogens, so management of weed populations is of economic importance. Recommendations for California orchards are to control weeds in the orchard row with pre-emergence herbicides in the winter and in the row middles throughout the summer with multiple applications of a burndown chemical (e.g., glyphosate) (Day et al. 2005). Spot treatment of in-row weeds should be completed as needed in the summer. Recommendations for use in Texas by the Texas Pomegranate Growers Cooperative include oryzalin (e.g., Surflan 4 AS®) as a pre-emergent weed control, oxyfluorfen (e.g., Goal 2 XL®) to control broadleaf weeds, and glyphosate (e.g., Roundup Ultra Max®) as a burndown

chemical (Ashton 2010). (Note that none of these or any other chemicals listed in other sections or subsections are endorsed; trade names are included only as a convenience to the reader).

Pomegranate Pest Management Issues

With pomegranates being a minor crop in California, there are very few pesticides that are labeled for use in this crop. Lannate® and Admire® (for whiteflies) are two that have met the labeling requirements in California. However, there are some reduced-risk or tolerance-exempt chemicals that can be used on any crop, including pomegranate. Those include *Bacillus thuringiensis* (Bt) sprays, insecticidal soaps such as M-Pede®, and pyrethrins (Carroll et al. 2006).

One treatment that offers benefits for control of certain insects also offers benefits for fruit quality; application of kaolin clay (i.e. Surround ®) deters fruit sunburn and results in more brightly colored fruit (Ashton 2010). An example of the result of sun scald on a pomegranate fruit can be seen in Figure 4.

Figure 4. Example of Scald on a Pomegranate Fruit Caused by Sun Damage

Harvest

On average it takes three to six months from the time of pomegranate bloom until fruit maturity (Glozer and Ferguson 2008). The harvest period for the 'Wonderful' cultivar is from September to November in California, and there has been great interest in extending the postharvest life until at least the Christmas holiday season, when demand is greater and prices are higher (Palou, Crisosto, and Garner 2007). Similar concern has been shown in Israel, where there is interest in extending the time frame of pomegranate exports to the Christmas season in Europe (Nerya et al. 2006).

Harvest of pomegranates is done by hand and should occur when the fruit is highly colored (for Wonderful cultivar, dark red) (Glozer and Ferguson 2008). At maturity, the fruit should also have a hollow, metallic sound when tapped (Morton 1987). A maturity index can be used to describe the readiness for harvest based on a calculation of total suspended solids (TSS) divided by titratable acidity (TA) (Elyatem and Kader 1984; Artés, Marín, and Martínez 1996). Pomegranate fruits should be handled carefully to prevent scarring of the skin; the skin of the pomegranate fruit is easily disfigured by scratches and blemishes, although such damage does not affect the fruit inside (Glozer and Ferguson 2008). Cutting of the fruits from the trees may be preferred to pulling the fruit off the tree (Ashton 2010) in order to prevent external blemishing of the fruit because such damage may make the fruit more susceptible to later infection by postharvest pathogens (Palou, Crisosto, and Garner 2007). Most worldwide pomegranate fruit harvest is done by hand, but a mechanical harvester for

pomegranates has been used on a trial basis in the San Joaquin Valley of California (Cline 2008).

Yield estimates for the cultivar Wonderful are from 6,000 kg per hectare (Palou, Crisosto, and Garner 2007) to over 33,000 kg per hectare (Bryant 2003); yield estimates for other cultivars vary considerably as well (Sulochanamma, Reddy, and Reddy 2005). A moderate range of yield for Wonderful cultivar in California would be 6,200 kg/ha to 11,700 kg/ha (Day et al. 2005). The average yield for Tulare County, California (a major area for US pomegranate production) in 2009 was 12,620 kg/ha (Kinoshita 2010). These estimates may depend on whether only top-quality fruits suitable for fresh-market are included in this estimate or total fruit production (suitable for juicing) is the basis. Harvest may begin by the second or third year after propagation, but mature yields are not attained until five to six years after propagation (Stover and Mercure 2007). Harvest estimates for Texas varieties are in the range of 11,208 kg/ha (10,000 pounds/acre), but this is expected to vary with growing season, location, and cultivar.

Post-Harvest

Pomegranate fruit is characterized as being nonclimacteric, meaning that the fruits do not ripen after harvest (Artés, Marín, and Martínez 1996). Pomegranates should therefore be harvested when color meets a minimum standard and titratable acidity is within the appropriate range (Elyatem and Kader 1984) since ethylene treatment is not effective at inducing ripening. The storage life of pomegranate is similar to that of the apple; estimates range from 7 months at 80% humidity and 32 to

41° F (Morton 1987) to a range of 8 weeks to 20 weeks in atmosphere controlled conditions at 45°F (Palou, Crisosto, and Garner 2007), depending on the effects of postharvest pathogens. A review of the state of the pomegranate industry in 2008 suggested a storage period of 4 to 5 months was possible with modified storage practices (Holland and Bar-Ya'akov 2008). Some post-harvest issues may arise after a long storage period as described below; still, storage has been found by some to increase the red color of pomegranate juice (Artés, Marín, and Martínez 1996), although this change was not observed by Palou, Crisosto, and Garner (2007).

Two of the most common post-harvest physiologic issues for pomegranate are husk scald and chilling injury. Both of these are external to the fruit but can greatly reduce marketability. Chilling injury is possible below temperatures of 41°F (Elyatem and Kader 1984). Symptomology of chilling injury includes skin discoloration, surface pitting, and accelerated fungal growth (Paull 1990). The severity of the injury due to chilling injury is dependent on the storage temperature, duration, and whether the pomegranate fruits are stored in air or in an atmosphere-controlled environment (Kader 2006). Husk scald is characterized by superficial browning that develops from the stem-end of the fruit; this increases the susceptibility of the fruit to decay (Defilippi et al. 2006). Husk scald appears to be more severe on fruit harvested later in the season, but treatment with a controlled atmosphere (CA) of 5 kPa O_2 + 15 kPa CO_2 (balance N_2) at 7°C (44.6°F) and 90-95% relative humidity was effective at reducing the incidence of husk scald (Defilippi et al. 2006).

The high environmental humidity which reduces chilling injury and weight loss of pomegranates also creates ideal conditions for microorganism development and decay (D'Aquino et al. 2009). Gray mold caused by *Botrytis cinera* Pers.: Fr. is a considerable economic threat to pomegranate in California (Tedford, Adaskaveg, and Ott 2005). Other common problems include heart rot (as discussed earlier) and penicillin rot caused by *Penicillin* spp. (D'Aquino et al. 2009). Fludioxonil (trade name Scholar®) was approved by the United States Environmental Protection Agency (EPA) in 2005 for use as a postharvest fungicide on pomegranate (EPA 2005). Fludioxonil has shown to be a useful tool for reducing post-harvest decay with activity against *Botrytis cinera* and *Penicillin* spp.; there are some estimates of a large impact on profitability that fludioxonil has had as a post-harvest treatment for pomegranate fruit (D'Aquino et al. 2010; Tedford, Adaskaveg, and Ott 2005).

Minimally processing and using polymeric film packaging for arils to produce a ready-to-eat product has the effect of reducing browning and allowing storage for up 14 days at 3.5-4.5°C while maintaining physical, chemical, and microbiological quality (Sepúlveda et al. 2000). Other types of packaging resulted in a storage life of 15 days for a low oxygen atmosphere packaging treatment and 18 days for air, nitrogen, and enriched oxygen atmospheres (Ayhan and Eştürk 2009). Minimal processing includes washing with sanitizing agents to reduce microbial counts, use of antioxidant agents, control of temperature, and making pH modifications, while the semi-permeable polymeric film serves to create a modified atmosphere packaging (MAP) that reduces the respiratory intensity and prevents and slows the growth of contaminating

microorganisms (Sepúlveda et al. 2000). López-Rubira et al. (2005) found differences in the storability of arils from pomegranate fruit harvested early in the season (14 days) versus pomegranate fruit harvested late in the season (10 days), both in terms of microbial counts and sensory acceptability.

Current State of the Industry

Recent developments and needed research in the pomegranate industry are related to growing, storage, and processing practices; they include the development of new cultivars and irrigation techniques to generate more yields of higher quality, technologies to market a "ready-to-eat" arils product, the addition of pomegranate as an ingredient to a wide spectrum of consumer products, and modifications to storage practices to allow longer storage times (Holland and Bar-Ya'akov 2008). Blumenfield, Shaya, and Hillel (2000) have also pointed out the need for a ready-to-eat aril product that can be mass-produced in order to increase the market for fresh pomegranate fruit.

Several companies have gotten involved in the marketing of pomegranate products. For example, POM Wonderful, LLC is a vertically integrated pomegranate marketer with a wide range of pomegranate products that are sold fresh and used to make juices, teas, bars, pills, and other supplements; the company is supplied with pomegranates from over 18,000 acres of trees in the San Joaquin Valley, California (POM Wonderful 2010). Simonian Fruit Company is also a California-based supplier of pomegranates and a member of the Pomegranate Council (Schrak 2010). Large global marketers have also gotten involved in pomegranate juice products, including Welch's®,

Tropicana® (owned by PepsiCo), and Minute Maid® (owned by The Coca-Cola Company). Pomegranate markets are driven by consumption of fresh fruit as well as processed products with pomegranate ingredients (Martínez et al. 2006). Seeram, Zhang, and Heber (2006) offer a listing of over 25 suppliers in the United States of fresh fruit, juice, and/or botanical extracts made from pomegranates.

Pomegranate movement in the United States was 13.76 million pounds from the San Joaquin Valley (California) district, according to United States Department of Agriculture estimates for the year 2009, down from 15.44 million pounds in 2008 (USDA 2009b). The movements recorded by USDA have also varied over the last several years. Since 1998, movements range from 18.63 million lbs. for the 2003 season to 7.39 million lbs. for the 1998 season, with reported movements of 14.28 million lbs. for the 2009 season (USDA 2010). The seasonal movements of pomegranates for a ten year timespan can be seen in Figure 5.

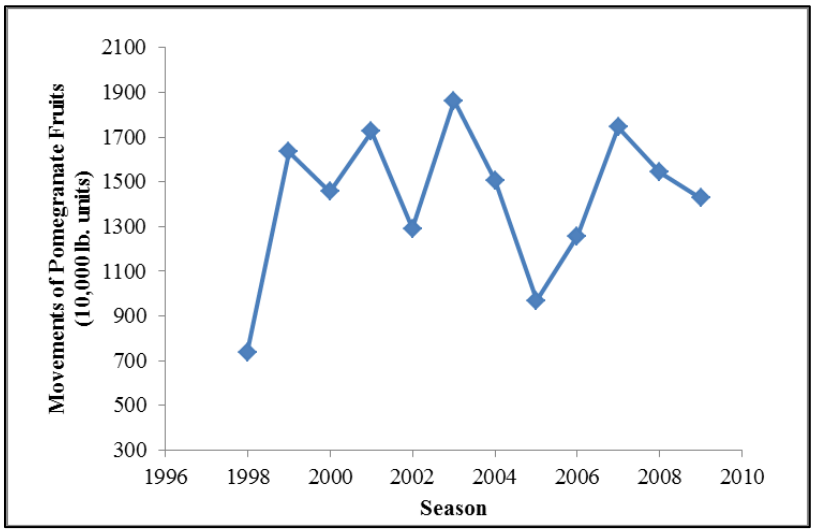

Figure 5. Total Seasonal Movements of Pomegranate Fruits within the United States. (USDA 2010)

These results are based on movements of fresh fruit within the United States. As an additional note on the status of the industry, the USDA recently moved to allow importation of pomegranates from the country of Chile (APHIS 2010a). Chile joins Argentina, Colombia, Greece, Haiti, Israel, and fruit fly free areas of Mexico as areas from which pomegranate fruit may be imported into the United States. Additionally, the import of arils from all counties is allowed subject to inspection by the Animal and Plant Health Inspection Service of the USDA (APHIS 2010b).

Average shipping point prices have varied from seasonal averages of $15.53 per 22-lb. carton in the 2001 season to $25.04 per 22 lb. carton in the 2006 season. The average price per carton for the 2009 season was $24.54 (USDA 2010). Please see Figure 6 for average shipping point prices by season. These prices varied by variety, time of year, and size.

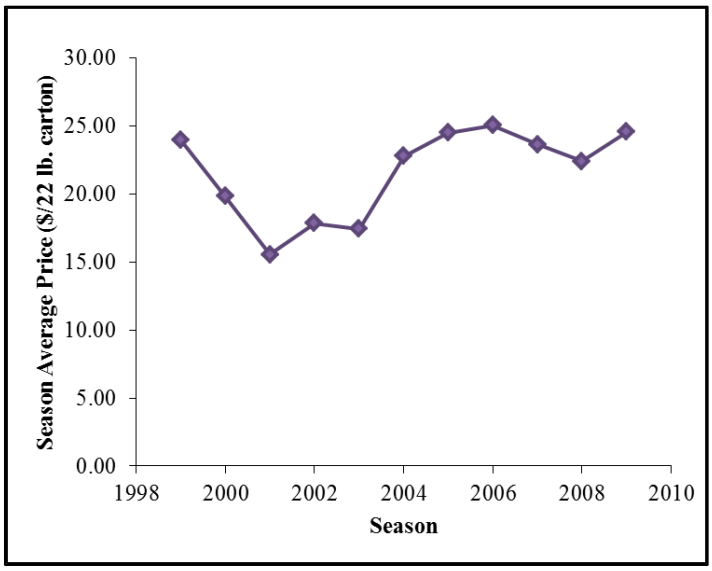

Figure 6. Season Average Shipping Point Pomegranate Fruit Prices ($/22 lb. carton). (USDA 2010)

The season average shipping point prices can be further decomposed into the weekly average shipping point prices. The plot of these prices given in Figure 7 reveals that although there has been a positive trend in shipping point prices from 1999 to 2009, there has also been considerable variation within each season. The prices are typically highest at the beginning of the season, and decline throughout the season as larger quantities of pomegranate fruits are shipped. However, the size of the range from minimum average shipping point price to maximum average shipping point price has varied from a minimum of $4.93 for the season to a maximum of $14.67 for the season for the average price for 22 lb. cartons of pomegranate fruits. The seasonal ranges in average weekly prices for 2006-2009 were all larger than $10.00, indicating that growers should expect seasonal variations in prices.

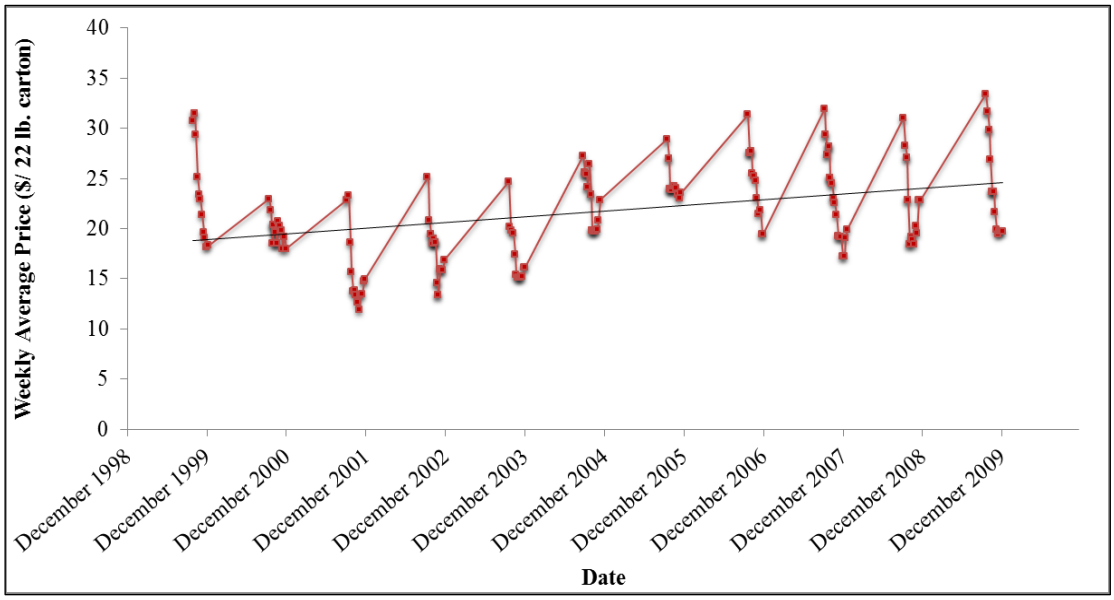

Figure 7. Weekly Shipping Point Prices for Pomegranate Fruits ($/22 lb. carton).
Note: The linear trendline over time is indicated. (USDA 2010)

Products

Pomegranates are marketed in a number of ways, including as whole fresh fruits, minimally processed as arils, and further processed into juice and a number of other products.

The introduction of minimally processed arils as a ready-to-eat marketing device in recent years has offered an opportunity to expand the market for pomegranates (Ayhan and Eştürk 2009). These products offer greater convenience for consumers than eating the fruit fresh, since, as pointed out in materials from the Pomegranate Council, it is sometimes difficult to separate the arils from the membrane and husk (PC 2007). Lopez and Rubira (2005) note that the marketing of pomegranate arils in modified atmosphere packaging also offers the opportunity to market fruit that is cracked or otherwise superficially blemished and that would not be acceptable for the fresh market as a whole fruit.

The assortment of pomegranate-based products on the marketplace is astounding. There are pomegranate husk extracts, weight-loss pills, tea, fermented wine and vinegar, seed oil, powder, body wash, dried seeds, jelly and cattle feed, to name a few. Even more pomegranate products are likely on the way. Examples of proposed pomegranate products include the use of a powder made from pomegranate rind as a natural additive to prevent oxidation of fresh ground meat (Devatkal and Naveena 2010) and pomegranate extract as a chemotherapeutic agent (Longtin 2003).

Marketing Challenges

Pomegranates as a fresh fruit are generally less familiar than many other fruits to United States consumers. Additionally, they have a tough outer husk, seeds that are somewhat difficult to eat, and juice that readily stains clothing. The Pomegranate Council even suggests a three step method for opening the pomegranate to minimize the need for cleanup. The steps are as follows: 1) Remove the crown and cut the pomegranate into sections; 2) In a bowl of water, separate the arils from the membrane and discard everything but the arils; and 3) Strain out the water and eat the arils (including the seeds) (PC 2007).

Further, pomegranate is a crop with a substantial acreage grown outside the United States, as described by Holland and Bar-Ya'akov (2008). These authors further express several factors that could help or hinder pomegranate markets. Included are mechanical aril separators for marketing of a ready-to-eat aril product, development of additional high-yielding cultivars, more efficient irrigation techniques, and longer storage periods for pomegranate fruits. Pomegranate juice concentrate can easily be imported; therefore, some members of the industry have suggested that farmgate prices for pomegranates will decline as more acres of pomegranates come into production (Cline 2008). There are now multiple companies with fully-automated mechanical aril separators on the market. Time will tell whether demand for pomegranate products will match pomegranate production.

Pomegranates are a crop that has been cultivated by humans for thousands of years; however, their popularity in the western world has grown tremendously in the last

decade. This growth has been spurred by a combination of factors, including the interest in healthful eating in general and functional foods in particular. Pomegranate fruit and other plant components of pomegranate are known to have high levels of antioxidants, particularly hydrolyzable tannins and flavonoids. A number of health benefits have been proposed for those who consume these polyphenols, particularly in the areas of reduced cardiovascular disease and reduced risk of certain cancers. Worldwide pomegranate production is expanding in order to meet the increasing demand for pomegranate fruits. The primary production area in the world is Iran, where the pomegranate is believed to have originated. Within the United States, California accounts for the overwhelming majority of production. A number of cultural practices must be considered for pomegranates, including fertilization and irrigation practices and management of insects and disease. Recent innovations have led to a boom of pomegranate products in the marketplace, including pomegranate juice, ready-to-eat fresh fruit products, and everything from lotion to energy supplements with pomegranate as an ingredient. Despite this, there are still a number of challenges within the pomegranate market. These include the need for further research to verify health claims on pomegranate, the potential for lower prices as supplies increase, further development of best production practices, and overcoming the novelty of the pomegranate fruit for many consumers. The pomegranate industry is poised for growth, but growth will not come without innovation as well as scientific and crop management developments.

CHAPTER IV

METHODOLOGY

There are a number of important considerations when applying experimental economics methods to elicit values for pomegranate fruits and other pomegranate products. Many of these were outlined in the literature review chapter. However, several of these are re-emphasized here as they apply to this experimental auction and ranking procedure, with justification for the procedure used. In general, and in keeping with the suggestions of Lusk and Shogren (2007), the methods and analysis were maintained with a balance between the control and context of the experiment. This was done with the goal of obtaining the most meaningful results that were relevant to the questions under investigation in the study.

Auction Description and Estimation Overview

The study was designed to elicit the effects of health information on willingness-to-pay (WTP) for pomegranate products. The study also proposes a value elicitation mechanism that, to the author's knowledge, has not been previously implemented in this specific form by combining incentive compatible and nonhypothetical mechanisms for both discrete choice rankings and experimental auctions. A brief overview of the procedures is included here with more detail provided later. Subjects participated in sessions in which whole pomegranate fruits, other pomegranate products, and a control fruit product were available for bidding. Subjects were given extensive instructions and

examples of auction procedures and were informed that both the ranking and auction procedures were nonhypothetical. Following the instructions, subjects participated in practice rounds of ranking and bidding for non-target products. After the instructions, subjects participated in one practice ranking round and one practice auction round each for soft drinks and for assorted snack products. Between the rounds for the two types of products, subjects were given a brief quiz on the auction procedures and were then given the correct answers. The winning (11th) price for each product was posted only in the practice rounds to ensure participants understood how winners were determined. Subjects were also provided with an opportunity to ask questions if they were uncertain about any of the ranking or auction procedures. Next, subjects completed a brief demographic survey and answered preliminary questions on buying behaviors.

Subjects then participated in a series of ranking and auction rounds for fruit products, first without any additional information and then with 3 additional information treatments. The first round (referred to as the "baseline round") was to establish a starting point for WTP and preferences based on the information that subjects had when they began the study. Each subsequent round involved some additional information treatment. The order of these treatments was randomized among sessions to control for any order effects. The three additional information treatments were: 1) an opportunity to taste all of the products in the auctions and rankings, 2) information on the nutrition and health value of each type of product, and 3) specific information on the anti-cancer properties of pomegranates that are currently the focus of medical research. Also, a portion of subjects were given a reference price; this price was based on the current

purchase price of the products in local retail stores.

Subjects were asked to both rank and bid on all products. For the fruit product rounds, subjects ranked 8 options (7 fruit products and the option of no product). The option of no product was necessary in the rankings to accommodate match the rankings procedure to the bidding behavior and bids of $0.00. The auction used was an 11th price sealed-bid modified-Vickrey auction. The 11th-price is near the median price for the auction, and thus should elicit WTP in a way similar to that of the 2nd price auction while engaging a wider range of bidders. (In an 11th price auction, the ten highest bidders all pay the 11th highest price for the product). Prices were not posted during the fruit product rounds in an effort to avoid bid affiliation problems and to avoid confounding effects with the additional information treatments.

Despite the criticisms that single-round auctions lack market feedback, if information on the winning bids had been provided it could have been difficult to distinguish among the effect of the auction price information and the other information treatments (e.g., tasting information, health and nutrition information, and anti-cancer information) that were applied between rounds. Prior to the experimental session, it was announced that only one round of the ranking and bidding for the fruit products would be binding, and it was explained to the subjects how the actual purchasers of the binding products were selected. The likelihood of a product being drawn was proportional to the subjects' ranking of that item; thus, there should be an incentive to truthfully rank the most preferred product the highest and so on until the least preferred product is ranked lowest. Subjects completed a consumer survey following the end of the rounds of

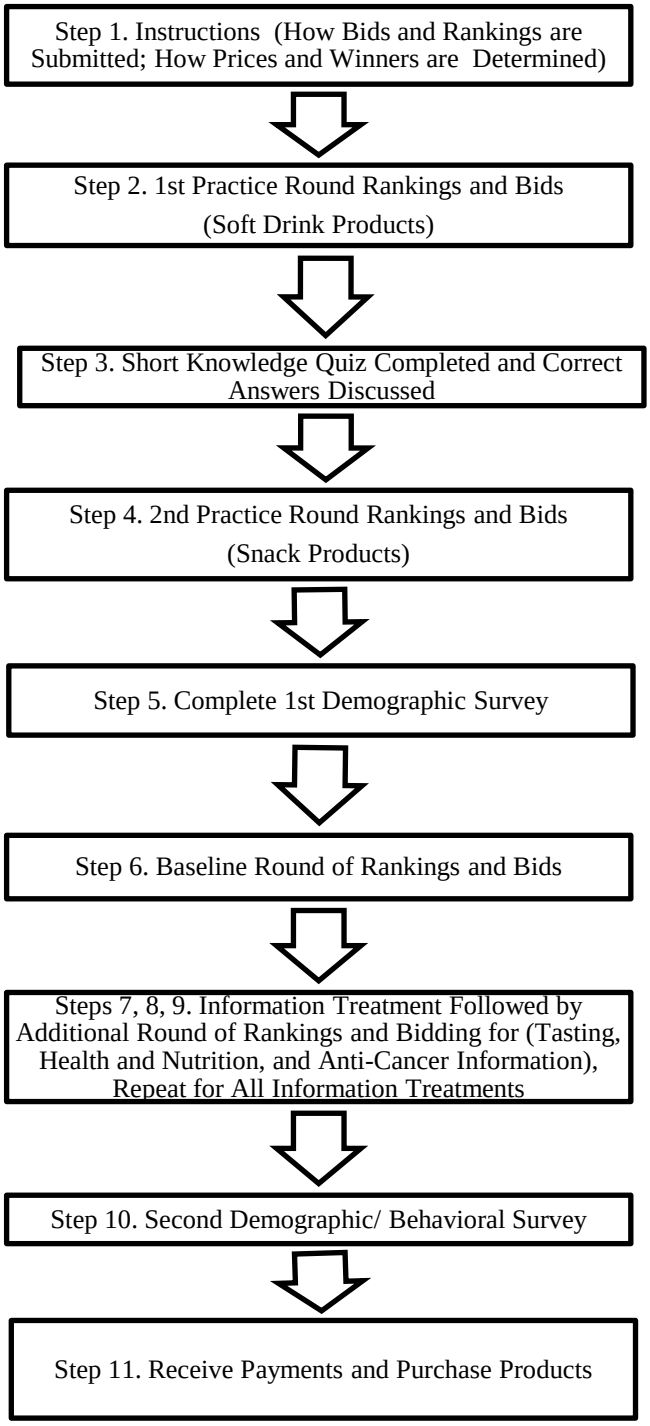

Figure 8. Experimental Procedures.
Note: Steps 7, 8, and 9 were conducted in a randomized order for each session such that every participant submitted 4 total rounds of rankings and bids

ranking and bidding on fruit products while payments were calculated. Subjects were compensated in cash with payments of $35 for their participation in the study, less any purchases they made during the auction. The series of steps that each participant followed as a part of the experimental auction are given in Figure 8. A more detailed explanation of the auction procedures is given following the theoretical framework subsection.

Theoretical Framework for Combined Experimental Auction and Ranking Mechanism

Consider an experimental auction mechanism for an individual *i* of *n* total individuals who must submit bids on *J* products with *S* information treatments applied between rounds of bidding. Assuming that no reserve price is imposed and that bidders' private values are independent (and thus follow the independent private values paradigm), the equilibrium bid function for bidder *i* who has valuation V_i has the form

(1) $$B_{ij} = \beta(V_{ij}) = V_{ij}$$

where $\beta(V_i)$ is the vector of equilibrium bid functions (Paarsch and Hong 2006).

The expected utility to an individual based on rankings can be understood using the random utility framework applied to rankings by McFadden (1974). Thus, an individual *i*'s utility from product *j* can be given by the addition of a deterministic (V_{ij}) and a random (ε_{ij}) component as given in equation 2,

(2) $$U_{ij} = V_{ij} + \varepsilon_{ij},$$

where U_{ij} can be defined as the utility experienced by an individual *i* from product *j* that is unobserved to the researcher.

Further, consider a ranking mechanism for the same individual *i* who must also submit rankings on $L = (J+1)$ product options with *S* information treatments applied between rounds of bidding. The $J+1$ product options are the same *J* products from the bidding, with the added option of no product; these products are specified as *L*. As proposed by Beggs, Cardell, and Hausman (1981), a rank-ordered logit model can be applied as follows. Individual *i* is asked to rank *L* product options that differ in terms of a vector of attributes x_l. The systematic portion of utility derived from product *l* by individual *i* is

(3) $$V_{il} = \beta_i x_l$$

where β_i is a vector of marginal utilities. In the ranking decision process, individual *i* ranks a choice set *C* with *L* products, with each product *l* ranked higher than *k* for $k = 1, 2, \ldots, l-1$ if $U_{il} > U_{ik}$.

Within the ranking procedure, the probability that any product would be chosen as binding was modeled following the procedure in Lusk, Fields, and Prevatt (2008). As these authors describe, the chance of any product *l* with ranking *r* being drawn (randomly selected as binding) can be given by the following function:

(4) $$\frac{L+1-r_l}{\sum_{l=1}^{L} l} * 100\%$$

If the product l is selected, then participants would pay the price P_l based on the binding price in the auction procedures of that product to purchase that item. This function makes it more likely that higher-ranked products are selected, and less likely that lower-ranked products are selected as the items for purchase by participants. But, there is a 100% chance that one product will be selected. Thus, each participant's expected utility (EU_i) for ranking L products option is described by:

(5) $$EU_i = \sum_{l=1}^{L} \left(\frac{L+1-r_l}{\sum_{l=1}^{L} l} \right) U_{il}$$

This shows that each individual has an expected utility from product l that is equal to the sum of the probability that a product is received multiplied with the individual utility that would be received from purchasing that product. In order to maximize expected utility, an individual should rank the products such that product l =1 is ranked highest, product l =2 is ranked next highest, and so on. As Lusk, Fields, and Prevatt (2008) detail, this implies that the individual cannot improve his or her expected utility by assigning a higher numerical rank (implying it is less preferred) to a more preferred product, and thus the mechanism is itself incentive compatible using the expected utility framework. Further, under the prospect theory of Kahneman and

Tversky (1979) in which individuals misperceive probabilities such that low probabilities are overweighted and high probabilities are underweighted, the equation above is still maximized where the most preferred product is ranked first down to the least preferred product ranked last, and therefore such a mechanism is indeed incentive compatible.

The selection of which product would be purchased may seem at first glance to be difficult to implement in a laboratory setting. However, the likelihood of any ranking being chosen was calculated prior to the experimental sessions, and the percentages were available if participants had further questions beyond the basic premise that an item ranked first would be most likely to be randomly selected as binding, an item ranked second would be next most likely to be selected, and so on until the item ranked last would be the least likely to be selected as the item to be purchased.

Procedural Details and Justification

While an introduction to the procedures used in this study was included previously, a number of specific details can help guarantee or bring into question the validity of the results of an experimental auction and/or preference ranking procedure. Therefore, more specific details of the auction procedures as well as the justification for the procedures that were used are provided.

Auction Procedures

For the study, a total of 203 participants were recruited from the Bryan-College

Station area of Texas. Participants were assigned to sessions based on age and gender demographics of U.S. grocery shoppers (please see Carpenter and Moore 2006) and the overall Texas population. Such a subject sample was preferred over the commonly-used participant base consisting exclusively of university students due to the nature of the question being addressed. Information on potential long-term health benefits would be less of a concern for a younger demographic (in general), not to mention anticipated differences in grocery purchasing behavior within a student population versus the overall Texas grocery-shopper demographic. The sessions were held at various times during the day in an attempt to capture more variability in population factors such as employment.

These participants were recruited using advertisements in the local newspaper and other local online and print media to attend one of a total of eight sessions over the course of three days to be held at the Texas A&M University Horticultural Gardens Classroom. The newspaper advertisement that was used to recruit participants is included in Appendix A. Subjects were informed that they would be participating in a study on the decision-making process for fruit purchases and were told that they would be paid $35 for their participation in a 1.5 hour long session, less any purchases that they made during the session. (The recruited sample was not intended to be representative of all possible buyers, as it was expected that only individuals who were interested in such a study would respond to the advertisement.) Individuals who agreed to participate were emailed directions to the facility, as well as a reminder of their agreement to participate within one week prior to the study. Individuals who did not have email addresses were provided directions via telephone or postal mail.

The intent was to recruit twenty-five subjects each of eight study sessions over three consecutive days, for a total of 200 participants in the experimental auction. However, there was a range (n=19 to n=35) in the number of participants who were present on the day of the auction due to last minute cancellations by participants. However, a total of 203 participants were recruited in total to participate in the eight sessions over three days.

Upon arrival to their designated session, participants were provided with an instructional packet and a packet of bid and ranking sheets. They were randomly assigned an identification number to be used throughout the experimental session to maintain anonymity. The participants were then asked to sign a consent form as required by the Texas A&M University Institutional Review Board (IRB). Participants were instructed to review the procedures for the first two stages of the auction. A session monitor read these instructions aloud, describing the auction and ranking procedures, as well as how bids and rankings were submitted. The session monitor then provided information on how winners were selected for the auctions and rankings. It was made explicitly clear that both types of preference elicitation procedures were nonhypothetical in nature and that any participant would have to pay actual money for any good that he or she purchased during the session. It was also made clear that there would be ten winners who actually purchased fruit items based on the results of the auctions and ten winners who purchased fruit products based on the results of the rankings for each session.

The instructions for the procedures were adapted from examples given in Lusk

and Shogren (2007); Lusk, Fields, and Prevatt (2008); Lusk and Schroeder (2006), Umberger, Boxall, and Lacy (2009), and Rousu et al. (2007). The verbal instructions that subjects were given included more specific details and are provided in Appendix B. Additionally, the full written instructions that subjects received for this study can be found in Appendix C. Subjects were provided with both verbal and numerical examples of auctions to help them understand the 11th-price auction mechanism and nonhypothetical ranking procedure in which they would participate. The participants then engaged in practice rounds, submitting rankings and bids for four common soft drink products: Pepsi®, Coke®, Diet Coke®, and Dr. Pepper®. After one round of ranking and one round of bidding in which the market price (the 11th-highest price) was posted, subjects completed a five-question quiz. The session monitor went over the answers to the quiz and answered any questions.

Subjects then participated in another round of practice, with one ranking and one round of bidding. The second practice round was for four snack products that varied in their familiarity: a package of chips, a package of cheese puffs, an individually-wrapped cookie, and a package of a less-common flavor of snack crackers. Following the completion of the practice rounds of the auction, the participants completed a consumer survey over their purchasing habits and demographic characteristics. The questionnaire was broken into smaller segments to be worked on at different stages to reduce participant fatigue. The 11th-price for each product in the two practice rounds were posted to ensure that participants understood how the winning price was selected.

Subjects were next given verbal and written instructions on the procedures for

the fruit product portion of the session. The fruit products were: California Wonderful Pomegranate, Texas Pomegranate 1 (Variety Salavatski), Texas Pomegranate 2 (Variety Texas Red), Ready-to-Eat California Pomegranate Arils, Ready-to-Eat Texas Pomegranate Arils, Mixed Pomegranate Juice, and Pineapple (as a control fruit product). A control fruit product was included because it was assumed that many individuals would be unfamiliar with pomegranates but would be more familiar with pineapple. Further, a product that would have a similar reference price for a single unit was preferred for use as a reference product over a product with a dissimilar price for a single unit. The cultivars of pomegranates were selected based on the industry standard variety (California Wonderful) and two varieties thought to have commercial potential in Texas (Texas Red and Texas Salavatski).

Many study designs suggest that an orthogonal approach to the different product characteristics of the products be included as one of several important components of the study design; however, in some cases such a comparison would lose sight of the question of control versus context for the experiment. For example, claiming that a pineapple product from Texas was commercially available would have been discredited by participants, and including a California and two Texas varieties of each form of the pomegranate products would have resulted in too large of a selection of products to expect subjects to accurately and carefully rank them. Also, the varieties that were included as Texas varieties are cultivars that have shown promise for commercial cultivation in Texas, and it would have been unrealistic to separate the growing location of Texas, the physical appearance of the product, and the flavor of the product just for

the purpose of estimating the specific size of these effects. These novel products were novel because of the unique combination of these attributes that they provided. Further, the appearance of the products was not identical across varietal cultivars; nevertheless, the products that subjects bid on were representative of the typical appearance of that cultivar. Images of these products can be found in Appendix D.

Subjects were given an opportunity to closely examine the fruit products and were then asked to submit ordered rankings of the 7 products and the option of "no product" (8 total product options and to also submit a sealed bid for each of the 7 products. The option of "no product" was included to allow for a comparison of the rankings and bids, since subjects also had the option of bidding $0.00 for any of the products. Examples of the ranking and bidding sheets provided to participants are included in Appendix E. Five of the eight (n=138) subject sessions were provided with a reference price of $3.50 per item as the retail price for all of the fruit products, based on the current prices of the products in College Station retail stores. This was done in order to control for the effects of reference prices in the magnitude of the submitted bids. However, all participants were informed that the products available sold at retail for the same price. Each of these sessions received three additional information treatments, with the order of these treatments randomized among sessions.

Following the "baseline round" (no information provided) of bidding, subjects were provided with a series of three randomized information treatments. All subjects received all three information treatments by the end of the session; in each of these they could gain more information on the products before submitting additional rankings and

bids. The order of the additional information treatments were randomized across sessions. These treatments were as follows: 1) Tasting: subjects tasted small (approximately 2 oz.), equally-sized samples of each product and the method for removing the husk of a whole pomegranate fruit was described, 2) Health and Nutrition Information: subjects were provided with health and nutrition information for all fruit products, and 3) Anti-Cancer Information: subjects were provided with specific information on the potential anticancer properties of pomegranates. Information on how to remove the husk of the pomegranate was included because it was assumed that in a setting outside the experimental auction, subjects would need this minimal amount of information in order to consume any of the whole fruit products. The full details of these informational treatments are included in Appendix F; in general, the health and nutrition information provided the specific nutrition facts of the products in the standard consumer nutrition label format and gave additional background on the role that antioxidants can play in human health. This text was written in plain language to facilitate subject understanding.

Similarly, the anti-cancer information that was given on pomegranates was provided on a written handout to subject participants during the appropriate round of preference ranking and bidding. The anti-cancer information that was provided was titled as “Pomegranate Health Information” to avoid unintentionally biasing the results with a title of “Pomegranate Anti-Cancer Information,” which may have alerted participants to what type of health information effects were being measured. The information included some of the information from the health and nutrition information

treatment, but also included more specifics on potential anti-cancer properties. Clear warnings were given on the need for further clinical research into specific anti-cancer effects of pomegranates in human subjects.

The anti-cancer information that was provided was based on research of the potential benefits of consuming pomegranate products as discussed in the pomegranate chapter, and every effort was made to provide information that could potentially be provided to consumers as point-of-purchase materials or in other types of advertisements. All claims made were verifiable based on scientific studies.

When consumers are exposed to a new food product, there are certain types of information that are generally gained, including both experience and credence attributes. Consumers gain information on the basic nutrition of the products, as well as any health claims that are made by marketers. Many attributes of food products can only be determined when the good is consumed, and this is often valuable information to the consumer to decide whether to purchase the item again in the future. Marketers often make claims on other attributes of products in addition to the basic nutrition, but these may or may not serve as valuable information to consumers.

Following the completion of all rounds of ranking and bidding, the round of the auction bidding (baseline, tasting, health information, or anti-cancer information) that was to be binding was drawn by a session subject with equal probability for each round and was announced to the session participants. The product that would be binding for the bidding rounds was randomly drawn prior to each session and placed in a sealed envelope. The binding product from the sealed envelope was also announced to session

participants following the completion of all rounds of ranking and bidding. Based on the 11th-price auction mechanism, there were ten subjects in each round who bid higher than the 11th-highest price and who purchased the binding product at the 11th-price for that product in the binding round of auction bids. Then, of subjects who did not win in the auction, ten subjects purchased an item based on their respective rankings. These items were purchased at the 11th-price for that good for the binding round of the auction. All ranks and bids were entered into a template in Microsoft Office Excel® that was developed to sort the bids for each product, pick the 11th price for each product, and break any ties to randomly pick winners.

Subjects received cash compensation of $35 for their participation in the study, less any purchases that they made based on the auction or ranking procedures. Any subjects who purchased any of the items received those items once all results of the auction and rankings were tabulated. The subjects signed a receipt of payment form, and the session was complete.

Experimental Auction and Preference Ranking Design Considerations

Participants were not aware that pomegranates would be a part of the study, as pomegranates are a novel good and the investigators wanted to ensure that the previous level of exposure reported by participants as a part of the consumer survey was indicative of the novelty of the product *prior* to the subjects' agreement to participate in the experimental auction. Subjects were told only that they would be participating in a study to evaluate fruit-purchase decision-making. Participants were also unaware that

there would be the opportunity to taste the products as a part of the experimental procedures. Lusk and Shogren (2007) suggest that it is critical to make efforts to enhance the validity and the independence of data from each phase; making participants unaware of additional opportunities to taste and/or gather additional information on the products was intended to assist in this effort. If participants were aware of later information-gathering opportunities, they may have discounted bids in earlier rounds and biased the experimental results.

The opportunity to taste the goods was important to make a more thorough evaluation of consumers' WTP for pomegranates after their initial purchase. This was also important for identifying differences in taste preference for the pomegranate varieties. Specifically, the novelty of pomegranates meant that participants may have been unfamiliar with the fruit, and giving them the opportunity to taste the good increased their familiarity with the good. Since the value of food products is derived at least in part, if not primarily, from the consumption value, then the opportunity to consume the good was important to the external validity of the auction results. On the opposite hand, it was just as important that participants be unaware of the opportunity to consume the good as a part of the study. This is because, given knowledge of the opportunity to obtain further information at a later time, it is likely that participants would submit initially lower bids for the goods in anticipation of gaining further information at a later time. However, since participants were previously unaware of the requirement to consume the good, individuals who refused to taste the good were still compensated for participation; they were not allowed to participate in further ranking

and bidding rounds of the study. (There were no recruited subjects who refused to consume the fruit products.)

It was determined to be impractical to require participants to consume the product they purchased onsite as was done in some previous WTP studies for food products (i.e. Shin et al. 1992; Fox et al. 1995; Gimalva, Bailey, and Redfern 1997); it requires some amount of effort to remove the husk of pomegranates and the fruits are larger than most consumers would eat in a single sitting. However, they do not require short-term refrigeration so no alternative pick-up requirements were made as in Lusk, Feldkamp, and Schroeder (2004).

Only one fruit product could be purchased by any participant, and this was emphasized to subjects. This was accomplished by randomly drawing which round of the auction and which product within that round was binding. Winners for the ranking procedure were then selected from non-winners in the auction. Such a procedure is useful in avoiding demand reduction over multiple rounds of the auction, as well as diminishing marginal utility in analysis of consumer WTP.

The effects of posting prices within experimental auctions have been debated. One faction suggests that posting of prices causes affiliation of bids among subjects, and they indicate that a single-shot auction mechanism is preferable. The opposite faction indicates that repeated rounds encourage learning of the auction mechanism and that the influence of the market effect stabilizes bids made by subjects. Further, some indicate that the problem of bid affiliation is not necessarily solved by a single-shot auction mechanism as there are other indicators besides a posted price that may cause bids to

become affiliated. Additionally, there is a lack of evidence that bids are not affiliated before subjects begin the study and that bids are not affiliated in the outside marketplace. Therefore, a single round auction mechanism was selected. The imposition of product information treatments throughout the study may have been compounded with repeated rounds, and the bidding information feedback may have made it difficult to determine if changes in measured prices were due to bid affiliation or a result of the preference updating of consumers that should occur when new information is received.

In terms of which auction mechanism was preferred, a uniform n^{th}-price auction avoids the primary emphasis on only the highest value bidders in a standard Vickrey 2nd-price auction while also avoiding the emphasis on low value bidders in a random nth-price auction. (A uniform nth-price auction selects a single nth-price for all rounds, while a random nth-price auction selects a different random nth-price for every round of the auction). For instance, in a 2nd-price auction there is only one winner, so bidders with lower individual values for the product may be "disinterested" in the auction outcome. A price in which approximately one-half of participants were winners would eliminate some of the imbalances in the incentives to under- or over-bid for participants. As described by Lusk and Shogren (2007), the expected monetary loss from "misbidding" (where an individual's bid does not equal that same individual's WTP for that product) varies depending on the specifics of the mechanism. However, none of these auction mechanisms (and no others for that matter) guarantees that subjects will bid exactly their true WTP; rather, the auction mechanisms vary in the degree to deviation from the dominant strategy is punished and the mechanisms that do this the

best are generally the ones that are selected for WTP elicitation procedures.

Lusk, Alexander, and Rousu (2007) provide a generalization on the cost of bids that deviate from a bidder's value (designated as Value_i) of the product in the auction. Following their discussion, the expected payoff for an individual (Payoff_i) is given by

$$\text{(6)} \quad \text{E}[\text{Payoff}_i] = (\text{Value}_i - \text{E}[\text{Price}|(\text{winning}|\text{bid}_i)][\text{Prob}(\text{winning })|\text{bid}_i].$$

where E is the expectations operator, Prob is the probability operator. Thus, an individual expects to earn the value of the good minus the expected purchase price (conditional on winning the auction, which is conditional on the submitted bid_i multiplied by the probability of winning the auction given bid_i. Using this notation, if an individual's bids are equal to that individual's value for each product, then the auction mechanism is incentive compatible. As several different fixed *n*th price auctions have previously been discussed, Lusk, Alexander, and Rousu (2007)authors further extend the payoff function to any *n*th price auction where the expected payoff function is defined based on the formula for the probability density function (pdf) and cumulative density function (cdf) for any given order statistic as:

(7) $\mathrm{E}[\mathrm{Payoff}_i^{nth}]$

$$= \left[V_i - \int_{-\infty}^{bid_i} \frac{\frac{(N-1)!}{(N-n)!\,(n-2)!} G(v)^{N-n}[1-G(v)]^{n-2} g(v)}{\int_{-\infty}^{bid_i} \frac{(N-1)!}{(N-n)!\,(n-2)!} G(x)^{N-n}[1-G(x)]^{n-2} g(x) x dx} v dv \right]$$

$$\left[\sum_{r=N-n+1}^{N-1} \frac{(N-1)!}{r!\,(N-1-r)!} G(bid_i)^r [1-G(bid_i)]^{N-1-r} \right]$$

where n is the designated nth winning price in the auction at which (n – 1) winning bidders of N total bidders pay the nth highest price. V_i denotes the individual value, G denotes the cumulative density function, and g denotes the probability density function. Here the function is maximized at $bid_i = V_i$ and assumes that all bidders other than bidder i are well-behaved and bid their true value.

Lusk and Shogren (2007) further define the expected cost of misbehavior, or when an individual submits a bid that is not equivalent to an individual's value, as $\mathrm{E}[\mathrm{Payoff}_i | bid_i = Value_i] - \mathrm{E}[\mathrm{Payoff}_i | bid_i \neq Value_i]$ which takes a value of zero if the bid is equal to the true value and is a positive value for the dollar loss expected from suboptimal bidding as the bid moves away from the true value. This can be used to show that the expected cost of misbehavior for a 2nd-price auction is higher when an individual's private value for the product is higher (relative to the private values of other bidders). Further comparisons can be made with other values of n for n^{th} price auctions, and the results of an (N -1)th auction would impose higher costs for underbidding than for overbidding. Note that following the convention of auction literature, here n^{th} refers to the nth highest of all the ordered bids, and (N-1)th refers to the bid that is one above the

lowest (the Nth) bid. These conclusions are more straightforward when a uniform distribution of private values is assumed, but can be shown to generally be similar for other distributions of private values (i.e. normal, pseudo-normal, left-skewed, right skewed) as well (Lusk, Alexander, and Rousu 2007). For a 5th price auction with N=10, these authors found results that varied depending on the distribution that was specified and whether bidders were underbidding or overbidding. However, the main point to be drawn from this discussion is as follows: the expected cost of deviating bids from true values was highest when a fixed price auction was specified where n was somewhere near the middle range of N.

A uniform n^{th}-price (specifically an 11th-price) modified-Vickrey auction was used for the experimental auction portion of this study. There have been a number of discussions of which price should be selected as the binding price in these types of auctions. For this study, the target products were generally novel to the participants. There has also been discussion in the literature on the use of endowed versus full-bidding methods for novel products. With a good that is unfamiliar to subjects, an approach where subjects have no opportunity for further learning is preferable. This is typically implemented as an endowed approach; however, use of the combined ranking and bidding mechanism guaranteed that most subjects would purchase a product during the sessions but avoided the inherent difficulty in assessing WTP based on bids to upgrade if full bid values are not collected.

Also, a full bidding approach is generally preferred if preferences are expected to be heterogeneous. The full-bidding approach allows for positive and negative

differences in values between two products. Lusk and Shogren (2007) indicate that the endowed approach is preferable because differences in WTP are the most reliable estimates from auction data; therefore, the implied differences in the full bidding results for each subject were also included in the analysis. However, auction procedures that ensured that subjects left with a good would have similar advantages to the endowed approach of preventing future learning about the good while at the same utilizing a full-bidding approach that allows for more realistic differences in valuation. Thus, with a targeted study size of 20-35 participants per session, an 11th-price auction would ensure that ten subjects were product purchasers based on the nonhypothetical auction, and another ten subjects were purchasers based on the nonhypothetical ranking portion of the procedure. This was done to guarantee that most participants had no future option for learning about the products when they made their bids and preference decisions.

Anonymity of subjects was ensured by the use of randomized identification numbers and the use of a sealed bid auction mechanism. Envelopes were also used to disperse payments, and care was taken not to allow other participants to see the amount of an individual's payment for participation in the study.

Practice was required in order to teach the auction procedures and mechanisms to subjects prior to the auction rounds for the target products. This was accomplished in several ways. The subjects were provided with explicit written instructions on how the auction mechanism worked. Further, subjects were given descriptive examples of the auction procedures as well as explicit numerical examples. An explanation of the dominant bidding strategy was provided and it was explicitly stated that it was in each

person's best interest to bid truthfully. Further, subjects participated in two nonhypothetical practice rounds of auctions, one for common soft drink products and one for snack products that varied in novelty. In between the two rounds of practice, subjects were given a brief quiz in which they answered questions about the auction and ranking mechanisms.

An important consideration in the experimental design is that there is a necessary tradeoff between the external validity of the auction procedures and the degree of control that can be obtained. The design of this experiment was undertaken giving careful attention to these two conflicting goals. An auction setting in a classroom or laboratory is already quite distinct from an actual purchase interaction that would occur in the day-to-day lives of most consumers. Given this, great efforts were taken to balance these differences and elicit the most accurate WTP estimates from the experimental procedure.

For example, consumers neither submit bids for goods they purchase in a retail store nor submit an actual ranking for the goods they might consider purchasing. However, consumers must implicitly answer these types of questions by selecting which price and product combination is their most preferred option. As described in the literature review, the use of auctions is generally thought to produce more conclusive WTP results than choice experiments. Combining the ranking procedure with the auction was done with the intent of providing additional information on consumer preferences.

Separation of the imposed effects from the specific goods to be auction was achieved in several ways. Since all of the goods up for auction during the procedure are

related in consumption, only one good was randomly chosen to be a binding purchase. Further, an additional product that is somewhat novel in preparation and consumption (fresh pineapple fruit) was included to account for specificity of health effects to a particular product. A pineapple fruit is similarly priced to all of the pomegranate products that were included but was anticipated to be more familiar to participants than pomegranate products.

In order to avoid specific effects of a number of components of the experimental procedures, randomization was utilized to avoid a systematic effect on the experimental results. The ordering of the additional information treatments was randomized among each of the eight sessions.

The effects of information as measured by such an experiment are subject to a focusing effect. More specifically, there is the potential for subjects to identify the effects of health information as one of the targets of the study and increase their bids because they anticipate higher bids to be the expected result of the study. Another implication of providing additional information is the potential effect of preference learning (Shogren, List, and Hayes 2000) on the outcome of the study. If participants believe that they will have the opportunity to gain information on the product by purchasing it and having the opportunity to consume it (particularly for a novel product), then this might introduce upward pressure on their bids. However, once information has been gained on the product during the course of the experiment, then this upward pressure from the information effect may be reduced or eliminated. Therefore, the final WTP bids after participants have received all information treatments should reflect a

state of full information on the good, particularly since most participants would be taking home a product as a result of either their rankings or bids.

Subjects were informed that they were allowed to submit zero or negative bids. However, no subjects actually submitted negative bids. Subjects may not have felt comfortable with submitting negative bids since they would be uncharacteristic of a traditional retail setting. There were a high percentage of zero bids, as described by the censoring results presented later. Allowing subjects to make zero or negative bids in the auction rounds was mimicked in the ranking rounds by allowing a preference for the option of "no product." Beyond allowing subjects to submit zero or negative bids, if all submitted bids are zero or above then the econometric model must be adjusted to account for this. These considerations are discussed further in the model estimation subsection.

Subjects participated in one round of ranking and one round of bidding for two sets of practice products in order to become familiar with the auction mechanism; consequently, they participated in two total rounds of practice for each of the ranking and bids. This was in addition to extensive descriptions of the procedures and opportunities to answer questions. Then, subjects submitted a total of 4 additional rankings and 4 additional rounds of bidding for the fruit products that were the target of the auction. Further rounds would have increased subject fatigue, as well as causing the total time for the session to be long relative to subjects' attention spans.

The possibility of varying the base of $35 for the participation fee was considered; however, a variation in such an endowment would have needed to be large

in size to be substantial in relation to participants' total income. This was determined to be unrealistic for the experimental auction setting. Also, all subjects received the same endowment, so the premiums that each individual would pay for one product over another should all be based relative to that endowment.

The ranking experiment included was modeled after a profile ranking procedure introduced by Lusk, Fields, and Prevatt (2008) and a nonhypothetical ranking procedure introduced by Chang, Lusk, and Norwood (2009). The rankings were included in the practice rounds to give participants additional practice with the procedures. Further, the ranking has the potential to either confirm or dispute the results of the auction mechanism. Due to the number of questions that still surround the mechanisms of experimental auctions, the addition of another mechanism to measure preferences may allow a balance between some of the problems of each approach in isolation.

Prior to the actual study sessions, the experimental auction and preference ranking procedures were tested with a group of graduate students from Texas A&M. Based on the results of the practice study, modifications to the procedures were made to increase the clarity of instructions and reduce the amount of time required to complete the bidding and ranking procedures.

Econometric Model

The experimental design described above led to a need to accommodate a number of factors in the econometric modeling of bidding and ranking behavior. The use of rankings and biddings are generally done separately. This could either be

accommodated with a single model for both procedures, or it could be accommodated with two separate models best suited for each type of data. Those types are continuous data that is censored from below for the auction bidding and a series of choice decisions for the ranking procedure.

The goal of modeling WTP was to gain a better understanding of which factors may influence consumer WTP for pomegranate fruits and other pomegranate products. If possible, such a model would also have some ability to predict consumer WTP based on these characteristics. The models that are used should, if possible, allow for comparisons of the two value elicitation mechanisms.

The models that have been used in the past in application to WTP are quite diverse, and many of these are applied to this data. Considerations are given to the benefits and drawbacks of each model in their application to this particular dataset.

Econometric Model for Experimental Auction Bids

The WTP for products in this study is modeled as a function of an individual's demographic characteristics, behavioral characteristics, the reference price, the order that information treatments are received.

Thus, each individual has a WTP that is described as the following equation:

$$WTP = f(socioeconomic\ factors, behavioral\ factors, \\ information\ treatments, product\ characteristics). \tag{8}$$

The included factors are as follows: product characteristics of the variety of fruit product (California Wonderful, Texas Red, and Texas Salavatski), the form of the product (whole fruit, ready-to-eat arils, or juice), and the type of fruit (pomegranate or pineapple). To compare the specification of the model, several models were estimated that eliminated one or more of these types of variables. If the types of variables are further broken down, the previous equation with all included independent variables of interest is given by:

$$
\begin{aligned}
WTP_{ij} = \; & C + \beta_v(Age + Education + Household\ Size \\
& + Female + \; Marital\ Status + Income \\
& + \; Fruit\ and\ Vegetable\ Spending \\
& + Fresh\ Produce\ on\ Hand \\
& + Previous\ Pomegranate\ Purchase \\
& + Serious\ Health\ Issue + Tobacco\ Use \\
& + Exercise \; + Reference\ Price \\
& + Information\ Treatment \; + \; Variety \\
& + Product\ Form)
\end{aligned} \tag{9}
$$

where each variable v is assigned its own β_v coefficient.

The dummy variables (sometimes called indicator variables) for this analysis were coded such that the levels of the variables are compared to some base level of that variable by excluding the base level variable from the estimation. For example, for three

possible age categories, the results would be coded such that there were three age variables, with a value of one being assigned to a variable if an individual was in that age category and a value of zero being assigned otherwise. Then one of the dummy variables was removed for each characteristic of interest in order to avoid the dummy variable trap. This procedure was followed for all included dummy variables.

The variable names and descriptions are given in Table 3.

Table 3. Demographic and Behavioral Variables

Type	Abbreviation	Meaning
Dummy	*DAGE2*	Dummy for ages 30 to 49 years of age
Dummy	*DAGE3*	Dummy for ages more than 50 years of age
Dummy	*DEDU2*	Dummy for education x, where: high school degree $< x \leq$ 4-year college degree
Dummy	*DEDU3*	Dummy for education of more than a 4-year college degree
Continuous	*HOUSE*	Household size (number of individuals)
Dummy	*FEMALE*	Dummy for female gender
Dummy	*DMAR*	Dummy for married individuals
Dummy	*DINC2*	Dummy for household income x, where: \$50,000 $< x <$ \$99,999
Dummy	*DINC3*	Dummy for household income greater than \$100,000
Continuous	*SPENDFV*	Weekly household spending on fruits and vegetables
Continuous	*FPOH*	Paired sum of pounds of fresh fruit and pounds of fresh vegetables on hand
Dummy	*POMFRUITP*	Dummy for previous purchase of a pomegranate fruit
Dummy	*ILLNESS*	Dummy for having a health issue considered serious by the subject
Continuous	*TOBACCO*	Percentage of days per year that the individual uses tobacco products
Continuous	*EXERCISE*	Percentage of days per year that the individual exercises for 20 minutes or more
Dummy	*PRICE*	Dummy for whether the individual was given a reference price for the fruit products

For example, age is described by two dummy variables: *DAGE2* takes a value of 1 if the individual was between 30 and 49 years of age and 0 otherwise, and *DAGE3* takes a value of 1 if the individual was over 50 years of age and 0 otherwise. These divisions of the age variable were included because it was expected that these categories of ages may be possible levels where differences in attitudes on preferences may vary.

As an example of a continuous variable, fruit and vegetable spending (*SPENDFV*) was a dollar amount of total weekly spending on fruits and vegetables. The variables listed in the table above are coded similarly to these examples.

During the course of the experiment, each individual submitted a total of 28 bids for fruit products as bids for seven products for each of four information treatments. These bids could be treated in several ways. First, the bids could be estimated separately for each product and each information treatment with a separate equation for each. In this manner, the WTP was estimated for each of the seven included products. The WTP was also estimated for the following information treatments: Baseline (*BASE*) - baseline at the beginning of the study, Tasting (*TASTE*) - subjects were allowed to taste a small sample of all products, Health (*HEALTH*) - subjects were given health and nutrition information for all products, and Anti-Cancer (*CANCER*) - subjects were given information on the anti-cancer properties of pomegranates. In addition, estimation of the WTP for the full information set (*FULL*) was conducted based on an individual's bids following all three information treatments. Thus, 35 equations were used to estimate WTP based on the full bids made by subjects in the study for this technique.

The WTP for the fruit products could also be estimated in some combination of aggregated bids (multiple bids made by an individual aggregated into one sample), either aggregated by information treatment, product, or both. Thus, several additional models were developed to do this. To accommodate the aggregated bids, other variables were needed to identify the information treatments and product characteristics. The variables for the imposed information treatments are included in parentheses above; aggregated

models did not include the bids for the full information set as these bids were reflected in one of the other information rounds. The product characteristic variables that were included are: Texas Red (*TXR)* took a value of 1 for Texas Red variety products and 0 otherwise; Texas Salavatski (*TXS*) took a value of 1 for Texas Salavatski Variety products and 0 otherwise; *RTE* took a value of 1 for all ready-to-eat product forms and 0 otherwise, *JUICE* took a value of 1 for the juice product and 0 otherwise, and *PINEAPPLE* took a value of 1 for the pineapple fruit and 0 otherwise.

There were a number of models that have been applied to auction and rankings data. Several of these were applied and the benefits and drawbacks of each are presented as they apply to the specific results of this study.

Ordinary Least Squares Model

A number of possible models were considered to evaluate the WTP for the included products based on the subjects' bids. A basic ordinary least squares model was first considered. Such a model can be estimated in a number of ways. An ordinary least squares model can be estimated as above by adding a constant term and calculating the parameters for each variable. However, given the nature of auction bidding, it was anticipated that there would be a number of censored observations. Although participants were informed that they had the option of bidding $0.00 or negative values, it was anticipated that censoring would need to be accounted for in the estimation of the parameters. Even so, an ordinary least squares model was estimated for comparison purposes.

Tobit Model

The potential for bid censoring led to consideration of using a tobit model to estimate consumer WTP for the targeted products. Although participants were informed that they could submit zero bids, the overall distribution could still be censored at $0.00. The tobit model was first introduced by Tobin (1958); since that time it has been frequently used for modeling of censored and truncated dependent variables (McDonald and Moffitt 1980). A distinction should be made between truncated and censored variables. Truncation is seen when a researcher needs to draw conclusions about a full population that is based on a sample that is drawn from only a restricted portion of the population. On the other hand, censoring occurs when values in a certain range of the distribution are reported as a single value (Greene 2003).

Greene (2003) provides a modern explanation of the tobit model (also known as the censored regression model), which is summarized below. First, to explain the need for a tobit model the distribution of the data of interest should first be assessed. Tobit models are highly useful for describing censored variables. Censored variables can (but do not have to) be understood by starting with a normal probability distribution. For convenience, the censoring will be assumed to be at zero. When data are censored, the distribution that applies to the censored data is described by a mixture of continuous and discrete distributions. In order to analyze such a distribution, a new variable can be defined such that

(10)
$$y = 0 \quad \text{if } y^* \leq 0,$$
$$y = y^* \quad \text{if } y^* > 0.$$

If it is assumed that y^* is approximately normally distributed with mean μ and variance σ^2, the distribution that applies is

(11)
$$\text{Prob}\ (y = 0) = \text{Prob}(y^* \leq 0) = \ \phi\left(-\frac{\mu}{\sigma}\right) = 1 - \phi\left(\frac{\mu}{\sigma}\right),$$

and if $y^* > 0$, then y has a density given by y^*. For this distribution, the total probability is still one, but instead of a full continuous distribution, the full probability in the censored region is assigned to the censoring point (which in this discussion is set to be zero). Tobin (1958) proposed a censored regression model which came later to be known as the tobit model. The mean in the following distribution can be defined for distributions which are censored at zero as

(12)
$$\text{E}[y|a = 0] = \phi\left(\frac{\mu}{\sigma}\right)(\mu + \sigma\lambda),$$

where

(13)
$$\lambda = \frac{\varphi\ (\mu/\sigma)}{(\mu/\sigma)}.$$

If this mean is allowed to correspond with the mean in a classical regression model, the

following equations are obtained:

$$y_i^* = x_i\beta + \varepsilon_i$$

(14) $$y_i = 0 \text{ if } y_i^* \leq 0,$$

$$y_i = y_i^* \text{ if } y_i^* > 0$$

where x_i are explanatory variables for each individual that are hypothesized to influence bids, β is a vector of coefficients, and ε_i is the error term that is randomly distributed with mean zero and variance σ^2 as described by Greene (2003). Since censoring was hypothesized at $0.00, left-censored bids and uncensored bids would be expected to be observed. Here, for the index variable (also known as the *latent variable*), the

(15) $$\mathrm{E}[y_i^*|x_i] \text{ is } x_i\beta.$$

Using the equations above, any observation randomly drawn from the population may or may not be censored; for such observations, the expected value of the observed value *y* is given by

(16) $$\mathrm{E}[y_i|x_i'] = \Phi\left(\frac{x_i\beta}{\sigma}\right)(x_i'\beta + \sigma\lambda_i)$$

where

(17) $$\lambda_i = \frac{\phi[(0 - x_i'\beta)/\sigma]}{1 - \Phi[(0 - x_i'\beta)/\sigma]} = \frac{\phi(x_i'\beta/\sigma)}{\Phi(x_i'\beta/\sigma)}$$

(Greene 2003). It is further pointed out that the marginal effects are different than in a standard regression model. The marginal effects of the index variable are given as

(18) $$\frac{\partial \mathrm{E}[y_i^* | x_i]}{\partial x_i} = \beta.$$

However, since y_i^* is unobserved, then for y_i the general result given in Greene (2003) is shown to reduce to

(19) $$\frac{\partial \mathrm{E}[y_i | x_i]}{\partial x_i} = \beta x \Phi\left(\frac{\beta x_i}{\sigma}\right)$$

for distributions censored at zero with a normal distribution. A useful interpretation of this result is provided by the decomposition done by McDonald and Moffitt (1980) that split the previous equation into two components such that

(20) $$\frac{\partial \mathrm{E}[y_i | x_i]}{\partial x_i} = \mathrm{Prob}[y_i > 0]\left(\frac{\partial \mathrm{E}[y_i | x_i\,, y_i > 0]}{\partial x_i}\right) + \mathrm{E}[y_i | x_i\,, y_i > 0]\left(\frac{\partial \mathrm{Prob}[y_i > 0]}{\partial x_i}\right)$$

where the first component is an effect on the conditional mean of y_i^* in the positive part

of the distribution and the second component is an effect on the probability that the observation will fall in that part of the distribution. Then, to estimate the model the likelihood function can be given as

$$\text{(21)} \qquad \text{LF} = \prod_{i=1}^{N} \left(\frac{1}{\sigma} \phi \left(\frac{y_i - \beta' x_i}{\sigma} \right) \right)^{Uncensored_i} \left(\Phi \left(\frac{-\beta' x_i}{\sigma} \right) \right)^{Left\ Censored_i}$$

The marginal effects from the tobit model can either be averaged across all levels of the variable, or they can be specified to be calculated at the mean of the variable. The currently accepted practice in estimating the marginal effects from the tobit model is to use the marginal effects averaged across all levels of the variable (Greene 2003).

Based on this discussion of tobit models, a number of possible variables were considered for possible inclusion in the WTP tobit models. A series of 35 separate equations were estimated for each of seven products in the baseline round, the three information treatment rounds, and the full information. Models were estimated based on the actual WTP bids made by participants. However, these will not all be described here. A set of equations for one such model (i.e. an estimation of bids for one product given one information treatment will be described in Chapter V, and the complete estimation results can be found in Appendix G. Besides a full description of one model, additional results of interest will also be highlighted in the description of the results.

Random Effects Tobit Model

However, individual preferences are likely to be heterogeneous, and full bids are also likely to be censored at zero. A number of models have been developed to account for individual heterogeneity as described by Greene (2003), including fixed effects, random effects, random parameters models, and covariance structures. In each of these, the underlying individual heterogeneity is addressed in the model in some way. A full coverage of each of these is not pertinent to the topics under investigation in this study; however, a few components of these models will be addressed. A simple pooled regression can be assumed to be biased and inconsistent if the individual effects are correlated with the included regressors, but such a problem can be addressed with a fixed effects model such that there is a constant term specific to each group in the regression (Greene 2003).

On the other hand, a random effects model assumes that the individual heterogeneity is not correlated with the included variables but that there is a random element specific to each group such that the differences between units are strictly parametric shifts of the function being estimated. A random effects model can be specified following Greene (2003) as

(22) $$y_{isj} = x'_{isj}\beta + \alpha + u_i + \varepsilon_{isj}$$

where α is a constant term and u_i is a group-specific random element that is similar to the random error term except that there is only one draw from the distribution for each

member of the group.

Greene (2003) cautions against out-of-sample applications of such a model. He suggests that estimates may be inconsistent if the assumption of the distribution for the random effects is incorrect.

Nevertheless, a random effects tobit model was investigated for application to the bids of study participants. If the random effects are thought of as differences in individuals, then the random effects model given in the preceding equation can be combined with the tobit model previously specified in Equation 14 to give

$$y_{isj}^{*} = x_i'\beta + \alpha + u_i + \varepsilon_{isj} \tag{23}$$

where y_{isj}^{*} is as before, a latent variable only observed for bids above the level of censoring that is specific to the ith individual, j^{th} product, and s^{th} information treatment.

The assumption made by a random effects model of no correlation of individual heterogeneity with the regressors in the model may be not be correct, and therefore other models to account for individual heterogeneity were also considered.

Mixed Linear Model

Another method suggested by Greene (2003) for dealing with individual heterogeneity is the random parameters model; this model is also frequently called a mixed model or a random coefficients model. The “mixed” name comes from the fact that the random parameters model is generally considered a combination of the fixed

effects model and the random effects model. The phrase "random parameters" refers to allowing the model to account for unobserved heterogeneity in the data by allowing the parameters to vary following a specified distribution. A normal distribution for the random parameters is allowed; however, the model is able to account for several other distributions. Thus, the IIA assumption can be relaxed for the estimation. To start with an explanation of the mixed linear model, subject bids can be modeled as

$$y_{isj} = x_{isj}\mathrm{b} + \alpha + u_i + \eta_i x_{isj} + \varepsilon_{isj} \tag{24}$$

where b is a set of coefficients for the regressors that are constant for all bids, α is the intercept for all bidders, u_i allows for variation in the individual intercept, $\eta_i x_{isj}$ allows for variation in the values of the regressors for each individual, and ε_{isj} is distributed as before. This gives an equation that is similar to that in the random effects model while also allowing for changes across individuals for any specified regressors through the $\eta_i x_{isj}$ term. The error introduced by the terms that are correlated with each individual are independently distributed of the overall error termε_{isj}. Notice that here the mixed linear model is not specified with the subject bid as a latent variable as in the previous tobit models, so bids below zero would be possible.

Models for Bid Differences across Goods and Treatments

Recent attention has been given to the value of the differences in paired bids (multiple bids by an individual) before and after information treatments or across similar

goods in experimental auctions (i.e., Alfnes 2009; Kanter, Messer, and Kaiser 2009). The use of novel products in experimental auctions allows greater opportunity for bids of \$0.00 than for more familiar products since the bidders may have no experience, positive or negative, with the product being auctioned.

Differences in WTP across information treatments but within each individual are labeled following the terminology of Lusk, Feldkamp, and Schroeder (2004); these calculated differences are called "implied differences." That is, for any individual *i* the "implied difference" would be defined as

(25) $$DeltaWTP_{isj} = WTP_{isj} - WTP_{i(Base)j}$$

where $s \neq Base$. For example, the "implied difference" in WTP by individual with identification number 4 for product 1 between a baseline round bid of \$2.00 and a tasting information round of \$3.00 would be calculated as $DeltaWTP_{4(Taste)1} = \$3.00 - \$2.00 = \$1.00$.

In estimating any model based on the implied differences, the interpretation of the parameter estimates must be undertaken cautiously. The equation for the implied difference in WTP can also be written as

(26) $$DeltaWTP_{isj} = (C_s - C_{Base}) + [\beta_s(X) - \beta_{Base}(X)]$$

where C is a constant and X is a vector of product characteristics, demographic and behavioral features, and information treatments. The constant can be re-specified as a single constant value, and factoring out the explanatory variables gives

$$DeltaWTP_{isj} = C + (\beta_s - \beta_{Base})(X). \tag{27}$$

Any parameters estimated based on implied differences for products are actually the changes in the parameters from the baseline to the later information treatment.

Unlike the full bids for the products, the implied differences in WTP are not censored at a value of $0.00, as participants were free to vary their bids positively or negatively from the baseline round following the information treatments. (For example, it was expected that some individuals might have an increase in WTP following the tasting information round if they enjoyed the taste of the product, but if an individual disliked the taste of the product they might have a decrease in WTP for that product in the tasting information round.) Thus, the tobit models used for the full bids were no longer appropriate to apply here.

The "implied differences" across rounds could be of four types, as described by Rousu et al. (2007). These types of differences and the information each provides are included in Table 4. Thus, any instances of zero bids by an individual for both the baseline round and the later round could be removed from the analysis of the implied differences because those bids, described as Case 4 in the table, do not provide any information on the differences in WTP from one round to another.

Table 4. Four Cases for Differences in Bids

	Bid for Baseline (Round or Product)	Bid for Comparison (Round or Product)	Sign of Bid Difference	Presence of Censoring	Effect on Bid Difference
Case 1	Positive (+) Bid	Positive (+) Bid	Negative (-) or Positive (+)	Uncensored	Difference in value is equal to the difference measured
Case 2	Zero (0) Bid	Positive (+) Bid	Positive (+)	Censored from Below	Difference is absolutely larger than the difference measured
Case 3	Positive (+) Bid	Zero (0) Bid	Negative (-)	Censored From Above	Difference is absolutely larger than the difference measured
Case 4	Zero (0) Bid	Zero (0) Bid	Zero (0)	Not Defined	Does not provide any information on difference

Further, the analysis of models based on the implied differences in bids is of particular value when the question to be answered involves questions of the size of those differences. For example, and particularly in the case of a novel product where there is likely to be individual heterogeneity not only in individual bids but also in the size of the changes in those bids across products and information treatments, consider an individual bidder for several products. If those products have similar outside substitutes and are similarly valued, then these differences will cancel out when the difference of the two bids is taken. This is true for the within-subject differences in bids for each product, as the relevant outside substitutes are assumed to remain constant for each product across multiple rounds. On the other hand, this is not the case for calculating differences in overall bids for each product because the outside alternatives for a product for one individual are not necessarily the same as those for any other individual. Alfnes (2009) previously discussed this issue in relation to a full-bidding or endowed approach.

However, the dialogue can be extended to the value elicitation procedures for novel products. In the case of a novel product, individuals lack familiarity with the characteristics of the product, and there are likely to be even greater differences among individuals in regards to which products are considered relevant outside substitutes. These substitutes will differ in product characteristics and are likely to differ in price as well; both of these types of information can then influence the bids that are submitted by an individual.

However, the use of bid differences for estimation of WTP models allows the outside substitutes for each product to cancel out when the difference in the two are taken. Therefore, the differences in WTP should provide additional useful comparisons because the difference in value across two consumers is not necessarily the same as the difference in value within a single consumer due to differences in what each individual perceives as the outside substitutes for each product.

Since the overall set of implied differences is not restricted to values that are only positive or negative, the model for the implied differences was estimated using a mixed linear model that was previously described.

Econometric Model for Preference Rankings

Discrete choices are often modeled using a logit model. As pointed out by Train (2003), the functional form for the choice probabilities in a logit model has a closed form. In addition, the interpretation of the logit model is more straightforward than that of some alternative models. (For the purposes of clarity, we specify L products here to

avoid confusion with the product options presented in the models for the auction bids.) Using $U_{il} = V_{il} + \varepsilon_{il}$, each ε_{il} is assumed to be independently and identically distributed (IID) extreme value. Train (2003) also points out that the key assumption of the logit model is not so much the shape of the distribution, but rather the independence of the errors. Econometric methods to analyze choice experiments include conditional logit and mixed logit models to estimate WTP (e.g., Teratanavat and Hooker 2006; Hu, Woods, and Bastin 2009).

In the standard logit model, it is assumed that any unobserved utility from one product is independent of the unobserved utility from any other product. This can be avoided with a well specified model in which V_{il} is sufficient to describe the majority of variation in the utility that the individual obtains, and the error term for one product does not provide additional information on the error term for any other product. If this cannot be achieved, then some other model which allows for correlated errors should be used. A multinomial logit, which allows for more than two discrete choice outcomes, is not a good candidate for the rankings data due to the fact that it fails to account for the ordinal nature of the rankings data (Greene 2003). Rather, the choice decisions made by each individual that result in ordered data provide more information to the researcher than a single choice of the most preferred option. The rank-ordered logit model, which is in essence a series of multinomial logit models multiplied together, can be applied to the rankings data (Lusk, Fields, and Prevatt 2008).

Rank-Ordered Logit Model

In using ordered models, the model is built around a latent regression described by Greene (2003). In this case, a general model of the form given in

(28) $$U_{il} = V_{il} + \varepsilon_{il}$$

where U_{il} is unobserved and ε_{il} are unobserved factors (alternatively interpreted as random disturbances); this equation can be used as a starting point for building a model that accounts for the ordered nature of the data. Following Calfee, Winston, and Stempski (2001), let each individual i submit a response $r_i = \{r_{i1}, r_{i2}, r_{i3}, \ldots, r_{iL}\}$, which is a ranking of the choice set in order of descending preference. Then, each survey response would have a probability given by

(29) $$\text{Prob}(r_i) = \text{Prob}[U_i(r_{i1}) > U_i(r_{i2}) > \ldots > U_i(r_{iL})]\,;$$

this can be further expanded to the probability expression

(30) $$\begin{aligned}\text{Prob}[U_i(r_{i1}) > U_i(r_{i2}) > \ldots > U_i(r_{iL})] \\ &= \text{Prob}\big[U_i(r_{i1}) > U_i\big(r_{ij}\big) \text{ for } l \\ &= 2, \ldots, L\big] * \text{Prob}[U_i(r_{i2}) > U_i(r_{il}) \text{ for } l \\ &= 3, \ldots, L] * \ldots * \text{Prob}\big[U_i\big(r_{i,L-1}\big) > U_i(r_{iL})\big].\end{aligned}$$

This illustrates that a ranking response for L alternatives has an equivalent expression as (L – 1) binary choice decisions. Thus, more preferred elements of the choice set are censored as subsequent ranks are assigned. This application of the model is sometimes referred to as "exploding" the data, allowing the researcher to make full use of all information by repeatedly applying whichever model is used (i.e. probit, standard logit, mixed logit). As these authors suggest, a standard ordered probit or a rank-ordered logit model are easier to estimate due to their closed form solutions. If the products are indexed such that

(31) $$V_{i1} > V_{i2} > \cdots > V_{i(L-1)} > V_{iL}.$$

then for a rank-ordered logit, the logit probability is

(32) $$F_l = \text{Prob}(Y = l) = \frac{e^{V_{il}}}{\sum_{k=1}^{L} e^{V_{ik}}}.$$

Then, by "exploding" the series of L -1 ranking decisions and assuming the error terms ε_{il} are distributed type I extreme value (Gumbel) distribution (Greene 2003), the probability for the entire ranking of L – 1 decisions is simply the product of L – 1 multinomial logit models (Lusk, Fields, and Prevatt 2008) and is given by

(33) $$\text{Prob}[U(r_1) > U(r_2) > \ldots > U(r_L)] = \text{Prob}_i = \prod_{l=1}^{L-1} \frac{e^{V_{il}}}{\sum_{k=l}^{L} e^{V_{ik}}}.$$

With *N* individuals in the sample where each individual's ε_l is independent and identically distributed, the log-likelihood function maximized is then given by

(34) $$\begin{aligned} LL(\beta) &= \sum_{i=1}^{n} \ln \left[\prod_{l=1}^{L-1} \frac{e^{V_{il}}}{\sum_{k=l}^{L} e^{V_{ik}}} \right] \\ &= \sum_{i=1}^{n} \sum_{l=1}^{L-1} \ln \left[\frac{e^{V_{il}}}{\sum_{k=1}^{L} e^{V_{ik}}} \right] = \sum_{i=1}^{n} \sum_{l=1}^{L-1} \Big(V_{il} \\ &\quad - \ln \sum_{l=k}^{L} e^{V_{il}} \Big) \end{aligned}$$

With parameter variation across individuals (heterogeneity), the model estimated by rank-ordered logit is subject to misspecification. Hensher and Jones (2007) suggest that the multinomial model should be estimated first as a baseline comparison to other models; in the case of rank-ordered data, the baseline model is simply the product of several multinomial logit models.

More specifically, the rank-ordered logit makes an assumption of uncorrelated stochastic components across alternatives; therefore if these errors are correlated estimates of the parameters and WTP are inconsistent. In this case, a mixed (random parameters) logit would be a good candidate. The mixed logit model is more flexible than, and avoids certain limitations of, the standard logit model. A mixed logit model

allows for correlation in unobserved factors (an issue discussed above), has unrestricted substitution patterns, and allows for random taste variation (Train 2003).

Mixed Multinomial Logit Model

McFadden and Train (2000) develop the properties of the mixed multinomial logit as a model for discrete response, particularly as applied to random utility theory and the use of maximum simulated likelihood (MSL) estimation. Train (2003) further provides a thorough discussion of the mixed logit model and readers are referred there for additional information. However, a brief summary is included here to describe the model that will be used for estimation of the ranking data. When the standard logit model is integrated over a density of parameters, a mixed logit model is obtained. More specifically, mixed logits are any models where the choice probabilities can be described as

(35) $$P_{ik} = \int L_{ik}(\beta) f(\beta) d\beta$$

where L_{ik} is the logit probability evaluated at β as given by

(36) $$L_{ik}(\beta) = \frac{e^{V_{ik}(\beta)}}{\sum_{k=1}^{K} e^{V_{ik}(\beta)}},$$

$f(\beta)$ is the density function, and V_{ik} is the observed utility which depends on the

parameters β for a particular product *k*. If utility is assumed to be linear in parameters, then

(37) $$V_{ik}(\beta) = \beta' x_{ik}$$

and the probability takes the form

(38) $$P_{ik} = \int \frac{e^{\beta' x_{ik}}}{\sum_k e^{\beta' x_{ik}}} f(\beta) d\beta.$$

Thus, the mixed logit probability is based on weighting the average of the logit formula at various parameter values β using the density *f(β)* to describe the weights. Statistics literature would call *f(β)* the mixing distribution. In the case where a mixed logit is specified, but none of the exclusions from the three assumptions key to a standard logit are needed, the probability function of the mixed logit simplifies to that of the standard logit. The mixed logit is most commonly interpreted from a random coefficients theory, where the random coefficients refer to a vector of coefficients representing an individual's taste and are allowed to vary across individuals in the population. The mixed logit model can also be used based on an error components theory, with a representation of the correlations among utilities for different alternatives as the error components. Under such an interpretation, the stochastic portion of the utility can be interpreted as a random coefficient plus the product of a vector of random

terms that sum to zero and the error components. Mixed logit is also free from the IIA assumption discussed earlier in the literature review. Mixed logit models can be estimated using simulated maximum likelihood estimation or Bayesian procedures. Greene (2003) suggests that the mixed logit model be estimated using simulation of the log-likelihood function rather than direct integration, as the mixture distribution based on the error term and the random part of the coefficient is unknown to the researcher.

On this basis, a mixed logit model can be applied to the ranking decisions made by individual participants in the study. However, the mixed logit model alone is not equipped to handle to ordering issues presented in the description of the rank-ordered logit model. Hence, estimation under a rank-ordered framework with a mixed logit model allows errors to be correlated.

The preceding discussion points towards the use of a rank-ordered mixed logit model that accounts for the ordinal nature of the data as well as avoiding the IIA assumptions of the standard logit model. In such a model, if the stochastic terms are used to represent deviations from the mean tastes, then the errors can be allowed to be correlated across product alternatives. Returning to the random utility model, again let l correspond to the alternatives to be ranked, with $L - 1$ choice decisions to be made. The model can now be specified as

(39) $$U_{isl} = \beta_i x_{isl} + \varepsilon_{isl}$$

where $V_{isl} = \beta_i x_{isl}$. In order to allow the correlation across multiple products, the

random utility function can be modified with further specification of β_i. Recall that β_i is the unobserved vector of coefficients for each individual that is randomly distributed with a conditional probability density function given by $f(\beta_i|\theta^*)$ where θ* represents the true parameters of the distribution (Calfee, Winston, and Stempski 2001); θ* can also be understood as the vector of parameters of the density function (Wong, Wong, and Sze 2008). The stochastic source of error ε_{isl} remains uncorrelated with β_i and x_{isl} and is distributed i.i.d. extreme value as before. The β coefficient vector more specifically takes on a form of $\beta = \mathrm{b} + \eta_i$ where b is the population mean and η_i are individual deviations from the average tastes for the population (Calfee, Winston, and Stempski 2001). Now, utility can be specified as

$$V_{isl} = \mathrm{b}x_{isl} + \eta_i x_{isl}$$

(40) and

$$U_{isl} = V_{isl} + \varepsilon_{isl}$$

where the stochastic portion of utility is now correlated across alternatives through the attributes in the model. Thus, the model no longer imposes IIA. The conditional probability that individual *i* will choose alternative *k* is

(41) $$F_{il}(\beta_i) = \frac{e^{(\beta_i x_{isj})}}{\sum_{l=1}^{L} e^{(\beta_i x_{isl})}}.$$

The conditional probability of assigning a given full ranking of all possible alternatives of $l^1,\ l^2,\ l^3, \ldots, l^{L-1}$ such that, for example, alternative l^1 is ranked first, l^2 is ranked second, and so on for a given set of information *s* can be calculated as the product of the conditional probability for all choice decisions:

$$\text{(42)} \qquad \text{Prob}_{is}(l^1,\ l^2,\ l^3, \ldots, l^{L-1}|\theta^*) = \prod_{l=1}^{L-1} \frac{e^{(\beta_i x_{isl})}}{\sum_{l=k}^{L} e^{(\beta_i x_{isk})}};$$

this is the probability of the series of binary choice decisions that are "exploded" from the full rankings in order to take advantage of all possible information (Srinivasan, Bhat, and Holguin-Veras 2006). As a final step, to obtain the unconditional probability that a given alternative *l* will be selected, the conditional probability must be integrated over all possible values of β_i, where the parameters θ^* define the distribution of β_i. Then, the unconditional probability is given by

$$\text{(43)} \qquad \text{Prob}_{is}(l_1\ , l_2\ , l_3\ , \ldots, l_{L-1}|\theta^*) = \int \prod_{l=1}^{L-1} \frac{e^{(\beta_i x_{isl})}}{\sum_{k=1}^{L} e^{(\beta_i sk)}} f(\beta_i|\theta^*) d\beta_i.$$

Thus, with an objective of estimating θ^*, which are the parameters defining the distribution of coefficients β_i, the log-likelihood function to be maximized is

(44) $$LL(\theta) = \sum_{i=1}^{n} \ln \int \prod_{l=1}^{L-1} \frac{e^{(\beta_i x_{isl})}}{\sum_{k=1}^{L} e^{(\beta_i sk)}} f(\beta_i|\theta^*) d\beta_i.$$

[A monotonic transformation of the likelihood function preserves the maximum, so taking the logarithm of the likelihood function is the method that is generally preferred for estimation (Paarsch and Hong 2006)].

The integral to be maximized has no closed-form solution (Calfee, Winston, and Stempski 2001). Therefore, it is not possible to maximize the log-likelihood function in its true form (Greene 2003). Thus, as further described by Greene (2003), a procedure for random sampling from the vector that describes individual heterogeneity can be applied in conjunction with an appropriate law of large numbers. This permits substitution of this approximation for the expectation into the log-likelihood function. With a sufficient number of draws, the estimation procedure is able to approximate the true function. Therefore, estimation is most often done by using simulation techniques. In the output of the maximum simulated likelihood estimation and as a result of the model used, the marginal effects of the regressors *x* as given in $U^* = \beta x' + \varepsilon$ are not equivalent to the coefficients β, but the marginal effects are the measures which should have explanatory power in this model. (Please see Calfee, Winston, and Stempski 2001 and Srinviasan, Bhat, and Holguin-Veras 2006 for further development of the rank-ordered mixed logit model).

The rankings data were expanded in STATA/ IC 11.0 © to create a series of (*L* - 1) decisions for each individual, where in each decision one product was chosen over all

remaining choices. This procedure has been described by others using a mixed rank-ordered logit model, including Srinivasan, Bhat, and Holguin-Veras (2006) and in the example given by Rabe-Hesketh, Pickles, and Skrondal (2001).

Consider an example of the following rankings given in Table 5. This was the format of the data prior to "exploding" it, and this format indicates a single instance of ranking each product by one individual with one information treatment.

Table 5. Example of Rankings Data before "Exploding" Data

ID	Information	Product Key	Ranking
101	Baseline	Cal Wonderful	6
101	Baseline	TX Red	4
101	Baseline	TX Sal.	3
101	Baseline	RTE CA	5
101	Baseline	RTE TX	2
101	Baseline	Juice	1
101	Baseline	Pineapple	7
101	Baseline	No Product	8

The rankings of each product are indicated by the column titled "Ranking." Thus, the mixed pomegranate juice was ranked first, the RTE Texas product was ranked second, and so on, until the option of no product was ranked last.

Now consider the exploded data as given in Table 6. The data now show the implied decisions made in assigning each rank. First, the subject decided that he preferred the mixed pomegranate juice to all other options. Then, the subject decided that he preferred the RTE Texas product out of all the remaining product options. This

continued until there were only two product options remaining, and the subject chose the option of pineapple over the option of no product. Note that only (L - 1) decisions need to be included because the ranking of the final product is implied in the $(L - 1)^{th}$ decision.

Table 6. Example of Rankings Data after "Exploding" Data

ID	Information	Product Key	Ranking	Chosen
101	Baseline	Cal Wonderful	1	0
101	Baseline	TX Red	1	0
101	Baseline	TX Sal.	1	0
101	Baseline	RTE CA	1	0
101	Baseline	RTE TX	1	0
101	Baseline	Juice	1	1
101	Baseline	Pineapple	1	0
101	Baseline	No Product	1	0
101	Baseline	Cal Wonderful	2	0
101	Baseline	TX Red	2	0
101	Baseline	TX Sal.	2	0
101	Baseline	RTE CA	2	0
101	Baseline	RTE TX	2	1
101	Baseline	Pineapple	2	0
101	Baseline	No Product	2	0
101	Baseline	Cal Wonderful	3	0
101	Baseline	TX Red	3	0
101	Baseline	TX Sal.	3	1
101	Baseline	RTE CA	3	0
101	Baseline	Pineapple	3	0
101	Baseline	No Product	3	0
101	Baseline	Cal Wonderful	4	0
101	Baseline	TX Red	4	1
101	Baseline	RTE CA	4	0
101	Baseline	Pineapple	4	0
101	Baseline	No Product	4	0
101	Baseline	Cal Wonderful	5	0
101	Baseline	RTE CA	5	1
101	Baseline	Pineapple	5	0
101	Baseline	No Product	5	0
101	Baseline	Cal Wonderful	6	1
101	Baseline	Pineapple	6	0
101	Baseline	No Product	6	0
101	Baseline	Pineapple	7	1
101	Baseline	No Product	7	0

The rankings models were then estimated using the --mixlogit-- command in STATA/ IC 11.0 ©. The --mixlogit-- command was developed by A. R. Hole (2007).

The mixed logit model is estimated using maximum simulated likelihood. Simulations sometimes use a pseudo-random number generator as the basis for the simulation. However, this method has relatively high discrepancy, which refers to the fact that the draw is far from the uniform distribution. To address this and use an alternative that has a better "worst discrepancy" from a series of draws, Halton draws are used as a more uniform alternative (Wanscher and Sørensen 2006). Henscher and Train (2003) describe the usefulness of Halton draws as applied to mixed models, and suggest that with greater complexity (more random parameters and treatment of preference heterogeneity) increases the number of draws required. Train (1999) finds a lower simulated variance in the estimated parameters when using 100 Halton numbers than when using 1,000 Halton numbers. This result is important because the estimation procedure is faster when fewer Halton draws are used. One hundred Halton draws were used for the model estimation.

One important note of caution is provided by Greene (2003) for discrete choice modeling. Both logit and probit models are susceptible to two important specification issues, which were previously described by Yatchew and Griliches (1985). First, if a variable is omitted from the model when it should not be, even if the omitted variable is uncorrelated with the included variables the coefficients on the included variables will be inconsistent. Second, if the disturbances in the underlying regression are heteroskedastic then maximum likelihood estimators will be inconsistent.

However, despite the constraints and distributional assumptions of the logit model and its modified versions, as pointed out by Greene and Hensher (2010), the use

of fully nonparametric in applications is rare. While nonparametric techniques avoid the distributional assumptions of parametric models for ordered choices, they are also therefore less informative to the practitioner in terms of estimation results. Semi-parametric approaches are something of a compromise between the two in which the estimator of the probability function is done using a kernel density estimator. Greene and Hensher (2010) further call attention to the fact that although the application of semi-parametric methods from single choice models to ordered choice models has taken place almost entirely in the 21st century.

Comparison of Preferences Based on Bids and Rankings

It is likely that consumers prefer to avoid instances of cognitive dissonance as described by Alfnes, Yue, and Jensen (2010). However, a comparison of the preference rankings and the ordered bids collected in this study lead to some questions about such an assertion. The auction and bidding mechanisms used here are a novel combination; however, since both were incentive compatible and nonhypothetical, it was hypothesized that the two mechanisms would produce similar results. Olsen, Donaldson, and Shackley (2005) addressed the issue of *explicit* versus *implicit* rankings data in terms of public preference for health care programs. In this case, the implied rankings are the ordered bids, and the explicit rankings are the actual preference rankings submitted by subjects. Economic theory suggests that rational subjects would respond to either of these ranking situations in the same way. The experimental design for this study offers a unique opportunity to compare the two methodologies and look at the issue of

consistency; that is, whether the implied and explicit rankings produce convergent results. The opportunity to analyze this issue differs in this case from that of Olsen, Donaldson, and Shackley (2005) because subjects for this study were asked to submit bids and rankings for a product which is typically purchased on an individual level and has a private value unique to each individual; the Olsen, Donaldson, and Shackley (2005) paper addressed preference ranking and partial WTP values for health care programs that benefit the general public.

Economic theory suggests the two methodologies should produce similar results on the basis that as a product increases in desirability to an individual from less preferred to more preferred, that individual would be willing to give up larger and larger sums (have a higher WTP) in exchange for that item. However, the question to be addressed is whether this economic theory of two types of preference elicitation that are related in their general purpose and in their theoretical underpinnings are related in practical settings.

Two distinct methods of preference elicitation were utilized as a part of this study, each of which lends itself to a different type of analysis. However, one primary goal of the study was to compare the results of each of the two preference elicitation procedures. This was done by ordering the bids (given in dollars) such that the product with the highest bid was assigned a rank of one, the next highest bid was assigned a rank of two, and so forth until the lowest bid was assigned a rank of 8. Two particular issues were addressed in assigning these rankings. First, let equivalent bids (ties) be considered participant indifference between two or more products. In the event of a tie, the products

with the tied bids were assigned the same ranking and the product with the next highest bid was assigned the rank of the number of products that were above it plus one. For example, if a subject submitted bids for four products of \$2.00, \$1.75, \$1.75, and \$1.50, the rankings assigned to the ordered bids would be 1, 2, 2, and 4, respectively. For the rank-ordered logit model, ties in the rankings were addressed using the exact marginal likelihood for indifference in alternatives (StataCorp 2009). Second, as a part of the experiment subjects submitted bids for seven fruit products during the experimental auction rounds, but for the ranking they were asked to rank their preferences for seven products and the option of no product, with 1 being the most preferred product and 8 being the least preferred product. Thus, there was one less product bid than there was product option ranking. Nevertheless, while submitting bids, subjects had the option of submitting bids of \$0.00. For the ordered bids, the option of no product was assigned the appropriate ranking based on the ordered bids (OB) as $OB\ Rank_{No\ Product} = \max(OB\ Rank\ for\ Product\ with\ Bid > \$0.00) + 1$. Any products that had bids of \$0.00 were assigned ordered ranks based on $OB\ Rank_{Product\ with\ Bid=\$0.00} = OB\ Rank_{No\ Product} + 1$. The preference models for the ordered bids were then estimated using the same model used for the preference rankings.

Variation in Ranking Ability

Both the preference rankings and the ordered bids were modeled using the full information set for all eight product options. However, Calfee, Winston, and Stempski (2001) follow Hausman and Ruud (1987) in considering the possibility of respondents

who rank more preferred alternatives more carefully than less preferred ones. If this is the case, there should be less variance in the rankings for the most preferred alternatives and vice versa, and the parameter estimates based on such models should be affected by the change in the model from including all rankings to including only the top half of the rankings. The model with only the top half of the rankings will be referred to here as the *partially-ranked* model. This was done first for the preference rankings data. The ordered bid rankings were also estimated using the partially-ranked model for the top four rankings to check the models for heterogeneity in ranking ability.

If the preference ranking parameters are sensitive to estimation with a full- versus partially-ranked model, then a scaling parameter can be estimated based on the specific dataset. This procedure would be useful if there is more noise in the rankings for the less preferred products than the more preferred products. One example of such a technique is demonstrated by Lusk, Fields, and Prevatt (2008).

In summation, the econometric techniques applied to the dataset collected from the experimental procedures were determined at least in part by the nature of the data itself. This allows for accommodation of any issues which may not have been anticipated in the experimental design.

CHAPTER V

RESULTS AND DISCUSSION

The study design was somewhat complex in order to allow for testing a number of different hypotheses; still, attention to detail during the study design process yielded results on a number of issues of interest. These results can be broadly categorized as a discussion of the demographic and behavioral characteristics of those included in the sample, results of the various models used to estimated WTP based on the experimental auction, and results of the preference rankings. Further comparisons among these results were also made, and specific characteristics of this particular data set were addressed.

Demographics and Behavioral Characteristics

A total of 203 individuals participated in the study. Of these, 198 submitted complete and usable demographic information and auction bids. The socioeconomic characteristics of the study sample are described in Table 7. Participants were assigned to sessions to ensure that there was a similar demographic representation in each of the eight sessions. It was assumed that this sample would be reflective of those who were interested in the advertised topic of the study and who were also willing and able to participate in the designated study sessions for the designated compensation amount.

Table 7. Socioeconomic and Behavioral Characteristics of Experiment Subjects

Variable	Category	Mean	Std. Dev.
Age (years)		42.84	17.51
	Under 29	34.83%	
	30-39	11.94%	
	40-49	14.43%	
	50-59	21.89%	
	60-69	7.46%	
	70 and over	9.45%	
Household Size (individuals)		2.24	1.15
Education	High School Diploma or Less	11.44%	
	More than High School up to 4-year College Degree	60.70%	
	Graduate Courses or More	27.86%	
Gender	Female	68.66%	
	Male	31.34%	
Marital Status	Married	54.23%	
	Not Married	45.77%	
Annual Household Income	Less than $50,000/year	53.77%	
	$50,000- $99,999/year	35.18%	
	More than $100,000/year	11.06%	
Primary Shopper	Primary Shopper	88.00%	
	Secondary Shopper	12.00%	
Household Spending on Food ($/week)		109.13	75.49
Household Spending on Fruits and Vegetables ($/week)		25.13	17.72
Fresh Fruits and Vegetables on Hand (lbs.)		6.37	4.65
Previous Purchase of Pomegranate Fruit	Yes	24.62%	
	No	75.38%	
Have a Serious Health Issue	Yes	28.50%	
	No	71.50%	
Tobacco Use (% of days per year smoked)		20.79	57.77
Exercise (% of days per year exercised)		43.52	38.97

In analyzing the demographics of the population sample, it should first be noted that 88.00% of participants reported themselves to be the primary shopper for their household. Per the recruitment conditions of the study, all other participants reported that they carried out at least a portion of the household shopping responsibilities. The

mean age for the sample was 42.84 years of age, younger than the age of the average shopper (47 years of age) in the United States (Goodman 2008). Over 68% of the respondents were female, and participants reported an average annual household income of $53,693. Of this income, the weekly household spending on all food purchases (including restaurants and other purchases outside the home) was reported by participants with a mean of $109. Of that weekly household spending on food, participants reported a mean of $25 per week spending on all fruits and vegetables. Also, participants reported to have an average of 6.4 pounds of fresh produce (including fruits and vegetables) on hand at home at the time of the study. This was measured to judge any effects that current home stocks may have had on WTP for additional fruit as measured by the experimental auctions. As anticipated, most participants were unaccustomed to purchasing pomegranate fruits, with just 24.5% of subjects reporting that they had previously purchased a pomegranate fruit. This lends itself to the interpretation of pomegranates as a novel product for the majority of participants in the study.

A series of health questions were also posed to participants after they had submitted all rankings and bids. Of all the study participants, 28.5% reported having a health issue that they considered to be serious. The average tobacco use by subjects was 77 days (or 21%) of the year, while the average percentage of days exercised per year was 161 (or 44%). These health characteristics were measured to allow for further investigation into possible relationships between the effects of such behaviors and the information treatments imposed throughout the course of the study.

The number of participants per session and the assigned treatments for each session are included in Table 8. The number of subjects per session ranged from 19 to 35 due to a large number of no-show participants in some of the sessions.

Table 8. Sessions, Information Treatments, and Reference Price

	N (Total N=198)	1st Information Treatment	2nd Information Treatment	3rd Information Treatment	Given Reference Price
Session 1	22	Tasting	Health and Nutrition	Anti-Cancer	No
Session 2	19	Health and Nutrition	Tasting	Anti-Cancer	Yes
Session 3	22	Health and Nutrition	Tasting	Anti-Cancer	No
Session 4	21	Anti-Cancer	Tasting	Health and Nutrition	Yes
Session 5	19	Health and Nutrition	Anti-Cancer	Tasting	No
Session 6	27	Tasting	Anti-Cancer	Health and Nutrition	Yes
Session 7	34	Anti-Cancer	Health and Nutrition	Tasting	Yes
Session 8	34	Anti-Cancer	Tasting	Health and Nutrition	Yes

Note: Five participants failed to submit complete bids and demographic information, and were not included in the analysis. The total number of participants recruited for the study was 203.

Each of these sessions received the three additional information treatments, with the order of these treatments randomized; five of these sessions (n=138; 70% of participants) were given a reference price for the current retail price of the fruit products. However, all participants were informed that the products available sold at retail for the same price.

The general buying behaviors, particularly for fruits and vegetables, of participants were surveyed in order to gather more information on possible behaviors or beliefs that could influence purchases. The buying behaviors of participants are given in Table 9. Although the more general of these were pointed out in subject characteristics, a few others will be pointed out here. The average percent of all fruit and vegetable

purchases that were for *fresh* fruits and vegetables was 71%. For this response, participants were asked to exclude purchases of canned fruit, frozen fruit, fruit juices, and fruit-flavored products. The *primary* purchase location for fruit and vegetable purchases was reported to be a grocery store or supermarket by 86.4% of participants, with just 8.5% of consumers doing the majority of their shopping at a mass merchandiser or supercenter. These figures are somewhat disproportionate with the national averages reported by the USDA's Economic Research Service for the types of stores where consumers do their grocery shopping, with values of 67.1% at grocery store and supermarkets versus 19.7% for warehouse clubs, supercenters, and mass merchandisers for the year 2009 (Kaufman and Kumco 2010). This could be an artifact of the subject selection procedures or attributed to regional variation in retail availability of groceries.

Table 9. Participant Survey Responses on Fruit and Vegetable Buying Behaviors

	Mean	Std. Dev.	%
Primary Shopper			88.00%
Weekly Food Expenditures	109.13	75.49	
Weekly Fruit and Vegetable Expenditures	25.13	17.72	
Percent *Fresh* Fruits and Vegetables of All Fruit and Vegetable Purchases	0.71	0.37	
Location of Fruit and Vegetable Purchases			
Grocery Store/ Supermarket			86.43%
Mass Merchandiser/ Supercenters			8.54%
Farmers Market or Other Location			5.03%
Length of Time Since Last Visit (days)	3.00	2.81	
Frequency of Fruit and Vegetable Purchases (Days Between Purchases)	8.63	6.28	
Fresh Fruit on Hand (lbs.)	3.29	2.72	
Fresh Vegetables on Hand (lbs.)	2.39	1.09	
Fresh Produce on Hand (Paired Sums of Fruits and Vegetables) (lbs.)	6.37	4.65	

The mean length of time since a participant's last visit to the retail establishment where he or she purchased groceries was 3.00 days, with a reported typical length of time between fruit and vegetable purchases of 8.63 days. These were both hypothesized to influence a subject's bidding behavior and his or her perception of outside substitutes and the transactions costs of delaying a purchase in the laboratory setting until the time of their next trip to purchase groceries.

In terms of the quantity of fruits and vegetables on hand at the time of the study, a few items are notable. First, the mean weight of fruit on hand for subjects was 3.29 pounds, and the mean pounds of vegetables on hand was somewhat lower, at 2.39 pounds. However, the paired sums of fruits and vegetables on hand for each subject were 6.37 pounds, which is larger than the 5.67 pounds that the sum of the unpaired means gives. This can be interpreted to mean that although there may be some outliers in terms of either the fruit or vegetables on hand for each individual, the total fresh produce on hand was higher than would be predicted by either of these measures alone. These amounts were elicited from consumers in order to test whether current "stocks" of fruits and vegetables on hand would have any influence on the WTP for pomegranate products.

The pomegranate has received a great deal of recent attention as a so-called "functional food" due to the health benefits beyond basic nutritional value that the fruit have been reported to have. One goal of the study was to gain a general understanding of the product awareness that participants had for functional food products. Thus, subjects were surveyed on their familiarity with functional foods, as well as their

familiarity with some common and some less-common functional food products. Somewhat surprising was the result that only 16% of participants were familiar with the term "functional foods." Nevertheless, a much larger percentage of subjects reported previously purchasing a variety of functional food products; ranging from 21.5% for wine with added polyphenols to 85.5% for breakfast cereal for heart health. These results, further detailed in Table 10, suggest that although consumers may not be readily familiar with the terminology that is used for such products, they are aware of these products in the marketplace, and in many cases they are purchasing these functional food products.

Table 10. Subject Familiarity with Functional Foods

	Percentage (%)
Heard of Functional Foods	
Yes	16.00%
No	65.50%
Unsure	18.50%
Previously Purchased Functional Food Products:	
Breakfast Cereal for Heart Health	85.50%
Yogurt with Probiotics	79.00%
Green Tea	68.00%
Fish with Omega-3 Fatty Acids	65.00%
Tomatoes for Lycopene	64.50%
Wine with Added Polyphenols	21.50%

Since the preferences for pomegranate fruits and other pomegranate products were elicited on the basis of the pomegranate as a novel product, subjects were also asked about their familiarity with these products. As shown in Figure 9, there were

similarities among the two forms of pomegranate juice and the whole pomegranate fruit; however, participants were generally unfamiliar with the RTE pomegranate products and the pomegranate-flavored products. This was expected considering that RTE pomegranate products are relatively new and much less common in the marketplace than juice or whole fruit products. Only 7.53% of participants indicated that they currently had any pomegranates on hand.

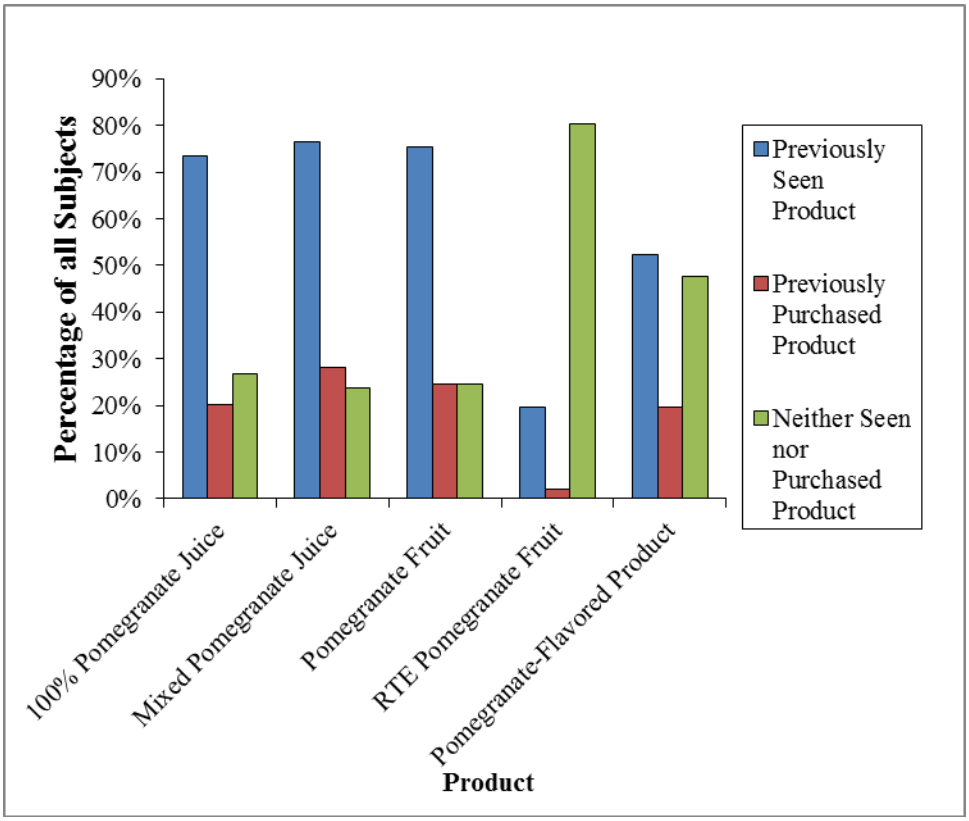

Figure 9. Familiarity with Pomegranate Products

Participants who indicated that they had previously purchased whole pomegranate fruits were asked to indicate when those purchases were made. The

responses to these questions, given in Figure 10, further indicated that either participants were unfamiliar with the pomegranate products or that they were not highly aware of the times of year that pomegranates were in season and thus available for purchase. Over 70% of individuals who had previously made a purchase of the whole pomegranate fruit products indicated that they did not know or did not remember when those purchases had been made. Admittedly, for those who indicated knowledge of when pomegranates were purchased, this knowledge could have been affected by the month of the year when the study was held.

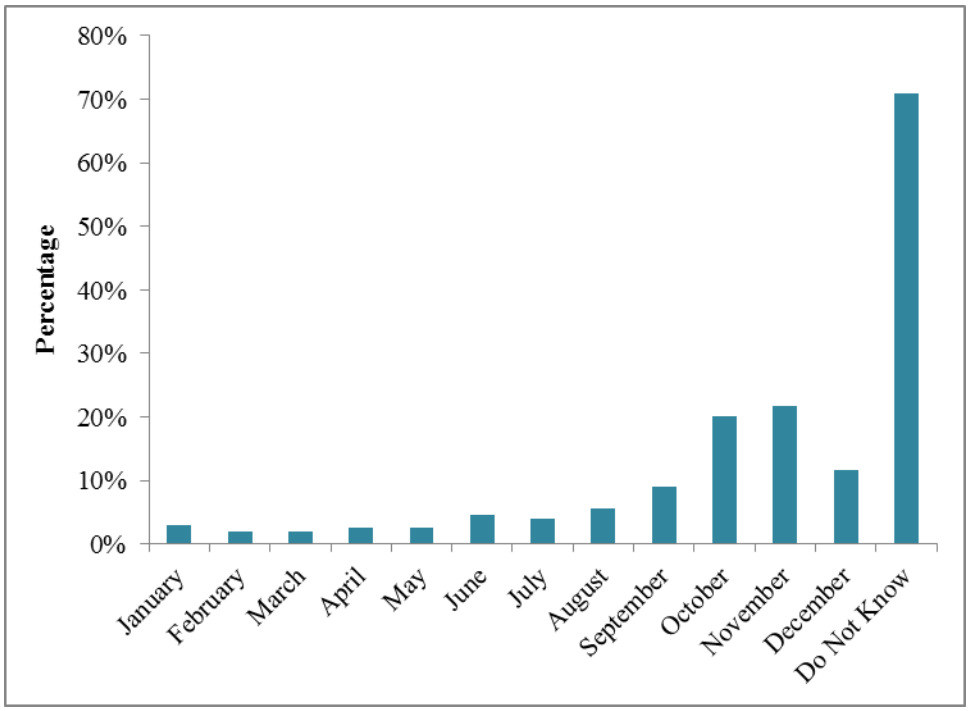

Figure 10. Of Participants Who Previously Purchased Whole Pomegranate Fruits, Percentages Who Purchased Pomegranate Fruits in a Particular Month

The subjects in the study were also surveyed as to which of the following factors were most important in making fruit and vegetable purchases: convenience, freshness, growing location, nutrition, price, production practices, size, and visual appearance. Production practices refer to any of several growing methods that are advertised at the point-of-sale for the item, such as organic, no pesticides, or any other production practices. These factors were measured in two separate question formats. Several items in the responses to these questions should be noted. First, the factors that were important in fruit and vegetable decision-making were measured in an effort to capture the qualities that play a role in consumer decision-making in regards to fruit and vegetable purchases. These factors were also measured to provide a comparison to the behaviors of participants in the nonhypothetical experimental auctions and ranking procedures. For the first measurement of these factors, subjects selected which of three factors were the most important in their fruit and vegetable purchasing decisions. However, one caution with this type of analysis is that a subject's answers could be influenced by what he or she perceives as social norms or the socially acceptable answer; a bias of this sort is termed as "social desirability bias" by Lusk and Norwood (2009). For instance, a subject may claim that he had a strong preference for growing location, but his bidding and ranking behavior should indicate whether the factors he cited as important actually had an influence on his bidding behavior.

In an effort to capture some portion of the possible social desirability bias, subjects were asked which factors were important to them as well as which factors they perceived to be important to the average American. An example of how this was

phrased in the survey questions is as follows: "Which of these factors do *you* consider most important in making fruit and vegetable purchase decisions? (Please select up to 3 options)." This was followed by the question, "Which of these factors do you believe *the average American* considers most important in making fruit and vegetable purchase decisions? (Please select up to 3 options)." Thus, subjects were freed from an obligation to report an answer that they saw as socially desirable by answering the second question.

Of the provided factors, the most commonly cited factor was *Price* for both individuals and for the predictions for average Americans. Thus, regardless of the health benefits or other experience attributes of a product, the cost items was confirmed to still play an important role in purchasing decisions.

However, the results differed for the remainder of the factors between the individual vs. average American predictions, with predictions for average Americans being more common for visual appearance, size, convenience, and production practices. The most striking of these was for convenience, being cited 2.75 times more often for the prediction for average Americans than for the individual's reported behavior. More individuals indicated that their own purchase decisions were based on freshness, growing location, and nutrition than what was predicted for average Americans. This lends support to the hypothesis by Lusk and Norwood (2009) that behaviors considered by some to be more socially acceptable behaviors, such as choosing fresh produce based on a growing location, freshness, or nutrition were more commonly cited for individual behavior than for the prediction for the average American. This behavior could also be because an individual believes he or she is more knowledgeable or has more information

than the “average American” that he or she is being compared against. Still, the overriding factor in purchase decision-making was price, indicating that any product offering should be done with this factor in mind. Also, the fact that the results of the two questions are not identical does not indicate that either set of results is wrong; if study participants differ in some way from the average American in terms of these characteristics, then the results of the two questions would be expected to differ.

Table 11. Factors Cited as Important in Fruit and Vegetable Purchasing Decisions

	Individuals	Individual Anticipations for "Average Americans"
Factor	Percentage Citing as Important [(a)]	Percentage Citing as Important
Price	78.97%	84.93%
Freshness	69.74%	43.72%
Visual Appearance	50.26%	62.31%
Nutrition	34.87%	21.11%
Growing Location	18.46%	4.52%
Size	16.41%	22.61%
Convenience	15.90%	43.72%
Production Practices	6.67%	7.54%

[(a)] Based on top 3 factors selected by participants.

In an alternative method of gauging the factors that might influence price, subjects were also asked to rate a similar list of factors on a rating scale from 1 to 4, ranging from 1 = Not important at all to 4 = Very Important. There was an important difference between the previous list and this list of factors; a factor for *Taste* was included. The previous list included only information that could be gained by consumers by information observed during the buying process. This could include

information they assessed themselves (i.e. visual appearance, size, and freshness) or information that might be provided at the point-of-sale (i.e. growing location, production practices, and nutrition). In the rating scale question, subjects were also asked to rate an experience attribute factor that can only be determined with consumption of the product: taste. On this rating scale, taste and freshness were cited as the top two factors in purchase decision making for fruits and vegetables; these were followed by price and then nutrition as the next highest in importance.

Table 12. Relative Importance of Factors in Fruit and Vegetable Purchase Decisions Based on a Rating Scale

Factor	Mean [(a)]	Std. Dev.	Interpretation of Importance[(a)]
Taste	3.835	0.385	Very Important
Freshness	3.835	0.411	Very Important
Price	3.465	0.686	Somewhat Important
Nutrition	3.345	0.706	Somewhat Important
Visual Appearance	3.265	0.767	Somewhat Important
Size	2.739	0.760	Somewhat Important
Convenience	2.693	0.773	Somewhat Important
Production Practices	2.470	0.951	Not Very Important
Growing Location	2.360	0.998	Not Very Important

[(a)] Subjects were asked to rank all of these factors on a scale of 1 to 4; 1 = Not important at all, 2 = Not Very Important, 3 = Somewhat Important, and 4 = Very Important.

In the rankings, the mean for importance for individuals was lowest for growing location, and then slightly higher for production practices and convenience. Although

these results are similar to the results measured based on selecting the top 3 factors, they confirm that the taste value gained from consuming the food is one of the most important factors influencing purchasing decisions for fruits and vegetables. There was also less variability in this response than in the responses for the two lowest rated factors. The results from the two measures of the factors involved in fruit purchasing decisions are summarized in Table 11 and Table 12.

The responses to these survey questions can be used to make interesting predictions about what the responses to the information treatments that are imposed during the study will be. Also, if the results of these factor selection and ratings responses are convergent with the results of the ranking and/or bidding model, then they will provide confirmation of subject awareness of factors that influence their utility maximization. If the results are divergent, then the issue of which responses are of value in predicting economic behavior may be explored in greater detail.

WTP Models for Full Experimental Auction Bids

The full bids for the products included in the experimental auction and ranking procedure are summarized in Table 13. Note that there were zero bids for all products in all rounds, but that the maximum bid also exceeded the current retail price of $3.50 for all products in all rounds, regardless of whether participants were provided with this reference price.

Table 13. Summary Statistics: Full Bids for Pomegranate and Other Fruit Products

Product Type	Mean Bid	Std. Dev.	Minimum	Median	Maximum	Difference in Mean Bid From Baseline Product [(a)]
A. Bids - Baseline Round						
California Wonderful Pomegranate Fruit	0.83	0.85	0.00	0.50	4.00	0.00 (Baseline Product)
Texas Red Pomegranate Fruit	0.80	0.84	0.00	0.50	4.05	-0.03
Texas Salavatski Pomegranate Fruit	0.81	0.80	0.00	0.63	4.00	-0.02
Ready-to-Eat Pomegranate Arils - California Wonderful	1.14	1.07	0.00	1.00	6.00	+0.31
Ready-to-Eat Pomegranate Arils - Texas Salavatski	1.16	1.06	0.00	1.00	6.00	+0.33
Mixed Pomegranate Juice	1.60	1.14	0.00	1.50	5.00	+0.77
Pineapple	1.87	1.15	0.00	2.00	5.00	+1.05
B. Bids - Tasting Round						
California Wonderful Pomegranate Fruit	1.06	1.06	0.00	0.77	6.40	+0.23
Texas Red Pomegranate Fruit	1.13	1.10	0.00	1.00	6.35	+0.30
Texas Salavatski Pomegranate Fruit	1.07	1.06	0.00	0.88	6.50	+0.24
Ready-to-Eat Pomegranate Arils - California Wonderful	1.22	1.16	0.00	1.00	6.25	+0.39
Ready-to-Eat Pomegranate Arils - Texas Salavatski	1.30	1.18	0.00	1.00	6.00	+0.47
Mixed Pomegranate Juice	1.41	1.13	0.00	1.00	7.00	+0.58
Pineapple	1.89	1.17	0.00	2.00	6.00	+1.06
C. Bids - Health and Nutrition Information Round						
California Wonderful Pomegranate Fruit	1.00	1.02	0.00	0.75	6.35	+0.17
Texas Red Pomegranate Fruit	1.04	1.06	0.00	0.75	6.25	+0.21
Texas Salavatski Pomegranate Fruit	1.02	1.10	0.00	0.78	8.00	+0.19
Ready-to-Eat Pomegranate Arils - California Wonderful	1.20	1.11	0.00	1.00	6.50	+0.37
Ready-to-Eat Pomegranate Arils - Texas Salavatski	1.26	1.12	0.00	1.00	6.75	+0.43
Mixed Pomegranate Juice	1.44	1.16	0.00	1.25	6.95	+0.61
Pineapple	1.93	1.20	0.00	2.00	7.00	+1.10
D. Bids - Anti-Cancer Information Round						
California Wonderful Pomegranate Fruit	0.94	0.98	0.00	0.70	6.75	+0.12
Texas Red Pomegranate Fruit	0.99	1.01	0.00	0.75	6.50	+0.16
Texas Salavatski Pomegranate Fruit	0.98	0.98	0.00	0.75	6.25	+0.15
Ready-to-Eat Pomegranate Arils - California Wonderful	1.27	1.19	0.00	1.00	8.00	+0.44
Ready-to-Eat Pomegranate Arils - Texas Salavatski	1.33	1.12	0.00	1.00	7.00	+0.50
Mixed Pomegranate Juice	1.57	1.14	0.00	1.50	6.00	+0.74
Pineapple	1.86	1.13	0.00	2.00	5.00	+1.03
E. Bids - Full Information						
California Wonderful Pomegranate Fruit	1.05	1.06	0.00	0.75	6.35	+0.22
Texas Red Pomegranate Fruit	1.13	1.09	0.00	1.00	6.25	+0.30
Texas Salavatski Pomegranate Fruit	1.07	1.06	0.00	0.83	6.00	+0.24
Ready-to-Eat Pomegranate Arils - California Wonderful	1.24	1.17	0.00	1.00	6.50	+0.41
Ready-to-Eat Pomegranate Arils - Texas Salavatski	1.30	1.20	0.00	1.00	6.75	+0.47
Mixed Pomegranate Juice	1.39	1.11	0.00	1.05	6.95	+0.56
Pineapple	1.99	1.19	0.00	2.00	7.00	+1.16

[(a)] The baseline product is assigned to the California Wonderful Pomegranate Fruit from the Baseline Information Round.

There was a large degree of variance in the bids that were submitted. In some cases the standard deviations of the bids for a product are as large as the bids for the products themselves; this is even more noticeable given the censoring that was anticipated at zero for the novel products.

The mean bids for all products in all rounds are lower than the retail price of the included products. All included products sold at retail for approximately $3.50 per item. For products that were not as readily available, the price that the item would sell for was approximated based on items available in other markets. The two more familiar products, mixed pomegranate juice and pineapple, had higher mean and median bids for all rounds. Further, there were large variations in the mean bids for all products; the 95% confidence interval for all products would include a bid of $0.00. Also included in this table are the differences in the mean bids from the baseline product of the California Wonderful pomegranate fruit in the Baseline information round. This is also the baseline product that will be used in the later estimation of WTP for the fruit products. This makes it clear that based on the mean bids, individuals had a higher WTP for both RTE products in comparison to the baseline product and the whole pomegranate fruit products. The control product that was included, the pineapple fruit, had the highest mean WTP of the included fruit products for every round. This could be true based on familiarity with the product for the baseline round, but the persistence of this premium even when additional information (on taste, nutrition and health, and additional health benefits) for the pineapple suggests possible differences in the underlying tastes and preferences for the fruit products as well.

The information for the median bids and conditional mean bids can be visualized in Figure 11 and Figure 12, respectively. In comparing these, slightly different stories of the effects of information treatments on the bids for each of the products emerge, as do differences in consumer preferences for each type of product. The mean bids are conditional on the bid not equaling zero; therefore, the censored bids are removed in this plot.

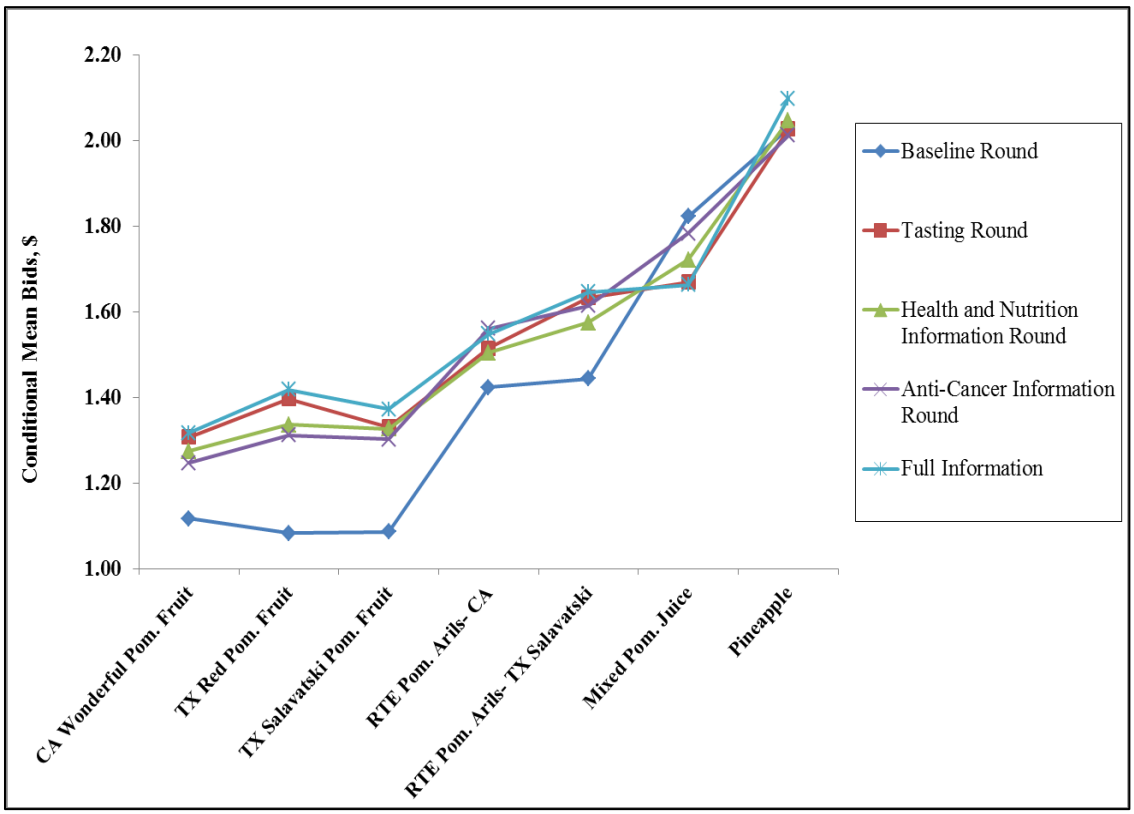

Figure 11. Conditional Mean Bids for Fruit Products by Information Treatment

Although there are some exceptions, the mean bids in the baseline information round were generally lower than the mean bids in the subsequent information rounds.

This was true for all of the entirely pomegranate products. Secondly, the full information mean bids closely mirror the mean bids for the tasting round for all products except the mixed pomegranate juice and pineapple. The largest range in mean bids across information treatments were for the three whole pomegranate fruits and the mixed pomegranate juice. However, the direction of the change in mean bid across information treatments was opposite for the whole pomegranate fruit products (positive change) and the mixed pomegranate juice (negative change). This suggests that one of the biggest hurdles in pomegranate marketing may be just getting consumers to initially try the products.

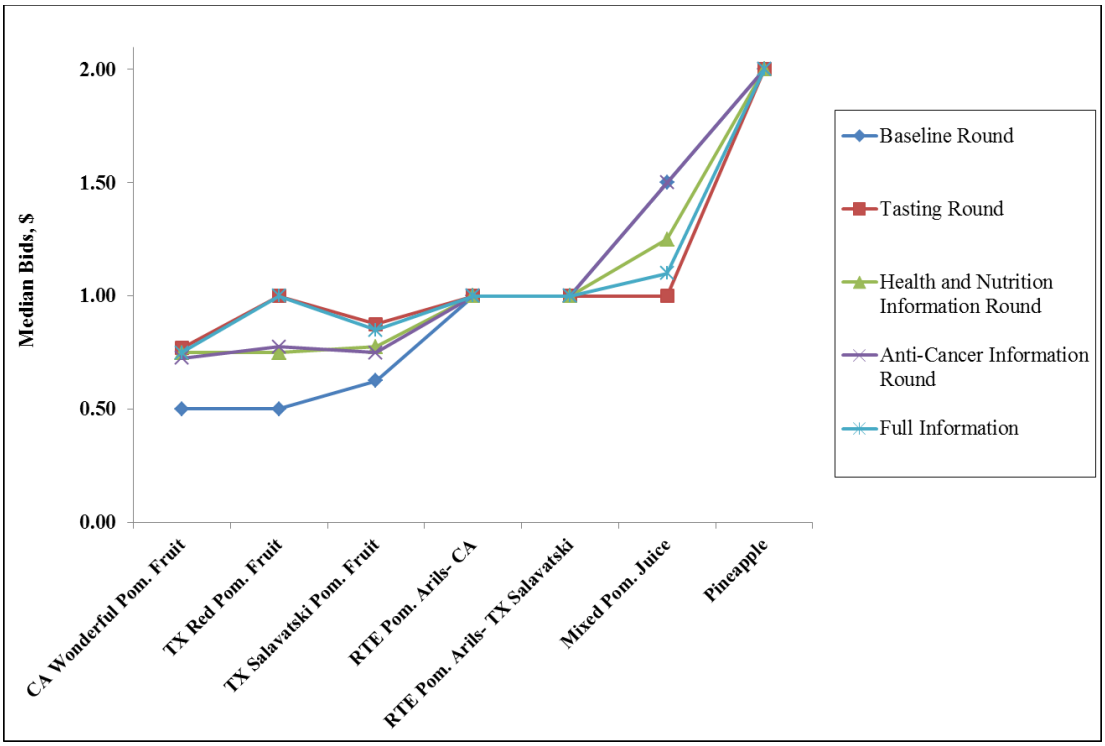

Figure 12. Median Bids for All Fruit Products by Information Treatment (Baseline, Tasting Information, Health and Nutrition Information, Anti-Cancer Information, and Full Information)

As can be seen in Figure 12, there are differences in the median bids for the fruit products across information treatments as well as in comparison to the mean bids previously presented. Three things should be highlighted about this plot. First, the median bid for the baseline round is the lowest of all information treatments for the whole pomegranate products and the highest for the juice and pineapple; the two RTE products have the same median bid for all rounds. Second, the bids for the full information closely follow the tasting information as in the plot of the means. Finally, while there was an initial price premium for the RTE products, this price premium decreased as study participants gained information on the products.

While the summary statistics for each set of products and information treatments are useful, it is also instructive to look at the distributions of the bids. Two ways this can be done are with histograms or with kernel density smoothed probability density functions. For added simplicity, the bids are plotted on separate graphs for each information treatment, allowing for visual comparison of the distributions of bids for each product. The probability density functions shown were estimated using a Gaussian kernel density distribution in Simetar©.

Kernel density estimation is a nonparametric way to estimate the probability density function. The plot of the estimated kernel density function is similar to a histogram in that it allows the researcher to visualize the distribution of the data; however, in an estimated kernel density distribution each observed point in the data is assigned a specified distribution, and the sum of all of the distribution for all observed points is used to reflect the overall distribution. By using a Gaussian (normal) kernel

density distribution, if the bids are normally distributed they should appear normally distributed in the probability density function estimates.

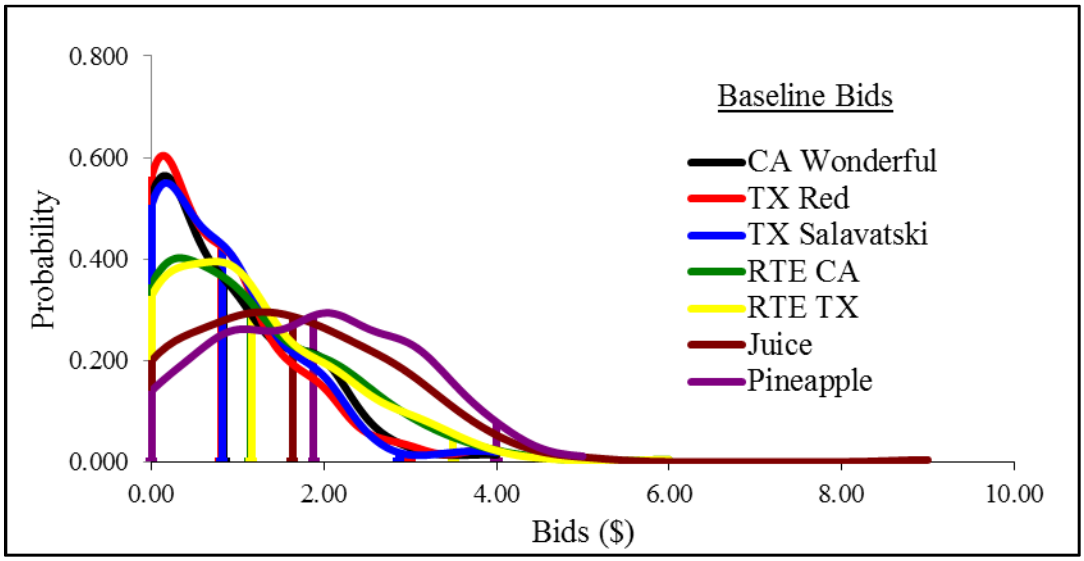

Figure 13. Distribution of Baseline Round Bids for Fruit Products in Dollars as Estimated with a Gaussian Kernel Density Distribution

There are three basic groups of distributions with similar characteristics that can be distinguished in Figure 13. The three whole fruit pomegranate products appear to have the highest degree of censoring at zero, with another clustering for the bids for the two ready-to-eat pomegranate products with somewhat less censoring at zero, and then the least amount of censoring for the juice and pineapple products.

The clustering effect that was seen for the baseline information round in Figure 13 is much less visible in Figure 14 in the bids for the tasting information treatment. However, the most frequent bids are still well under $1.00 for all of the products except the juice and the pineapple.

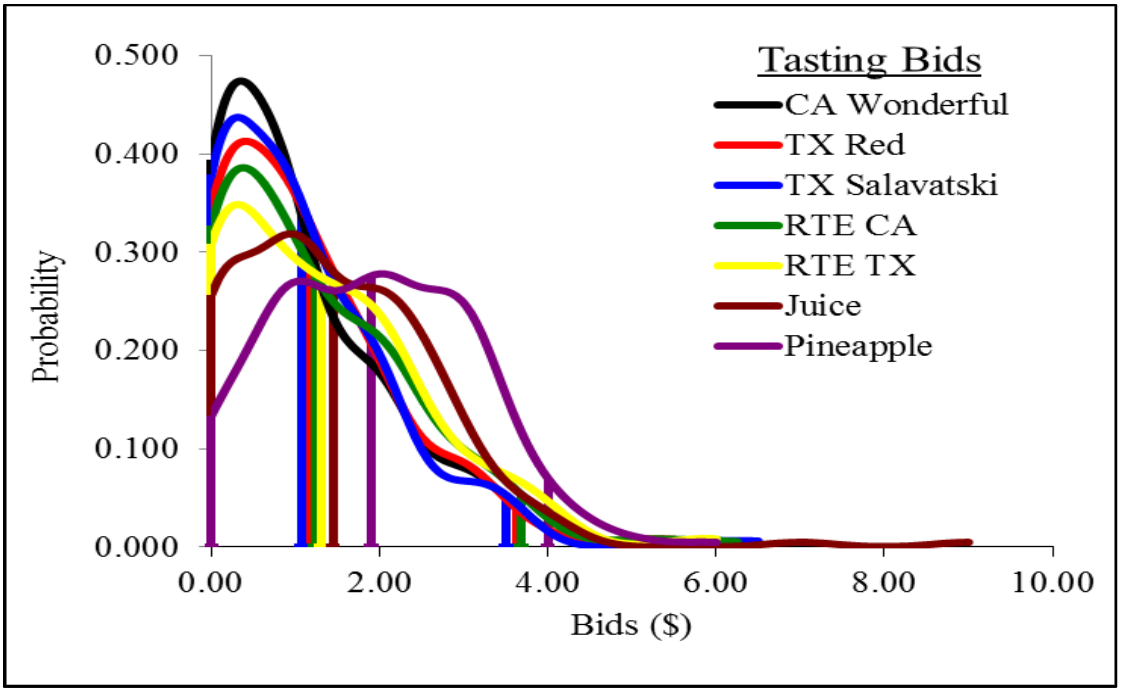

Figure 14. Distribution of Tasting Information Round Bids for Fruit Products in Dollars as Estimated with a Gaussian Kernel Density Distribution

While the estimated probability density functions are similar across information treatments, it was necessary to compare all distributions for all products. It would have been imprudent to assume that the distribution of bids for each product across the information treatment remained unchanged; it was possible that the information treatment would affect not only the location of the bids, but also the shape of the bid distribution.

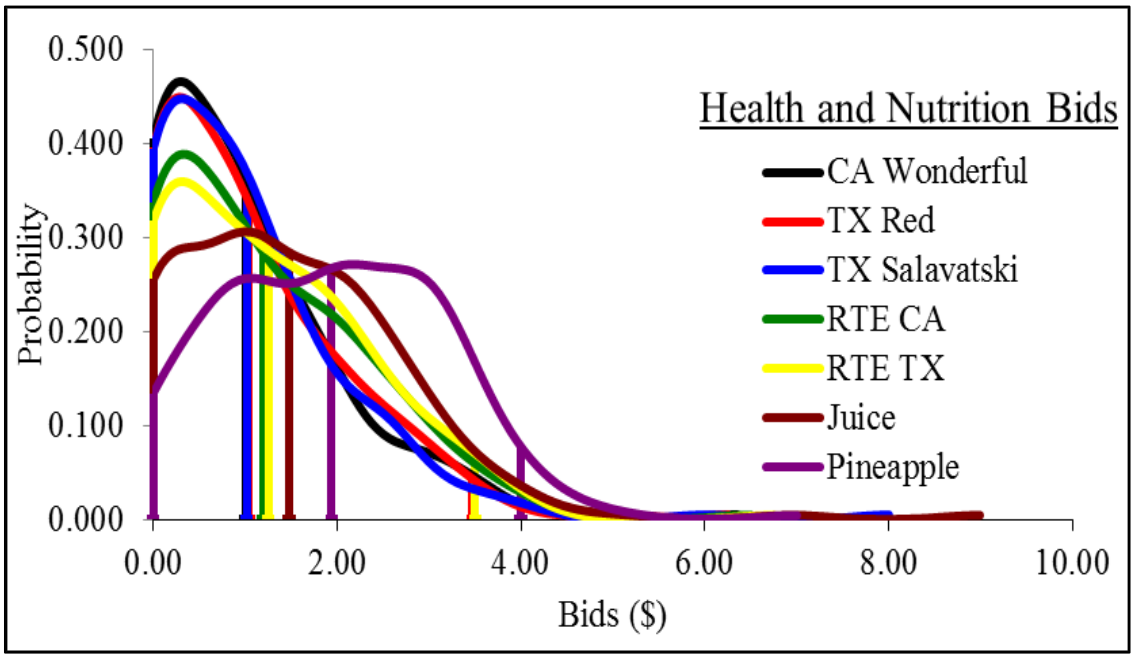

Figure 15. Distribution of Health and Nutrition Information Round Bids for Fruit Products in Dollars as Estimated with a Gaussian Kernel Density Distribution

The distribution of the bids when compared across products reveals several points of interest. First, the two products that subjects were expected to be more familiar with, juice and pineapple, are generally seen to have less censoring at zero than the other pomegranate fruit products; the means for these two products are shifted to the right relative to the other products. It is also clear that the distribution of bids is not centered at the reference price of $3.50 for any of the products.

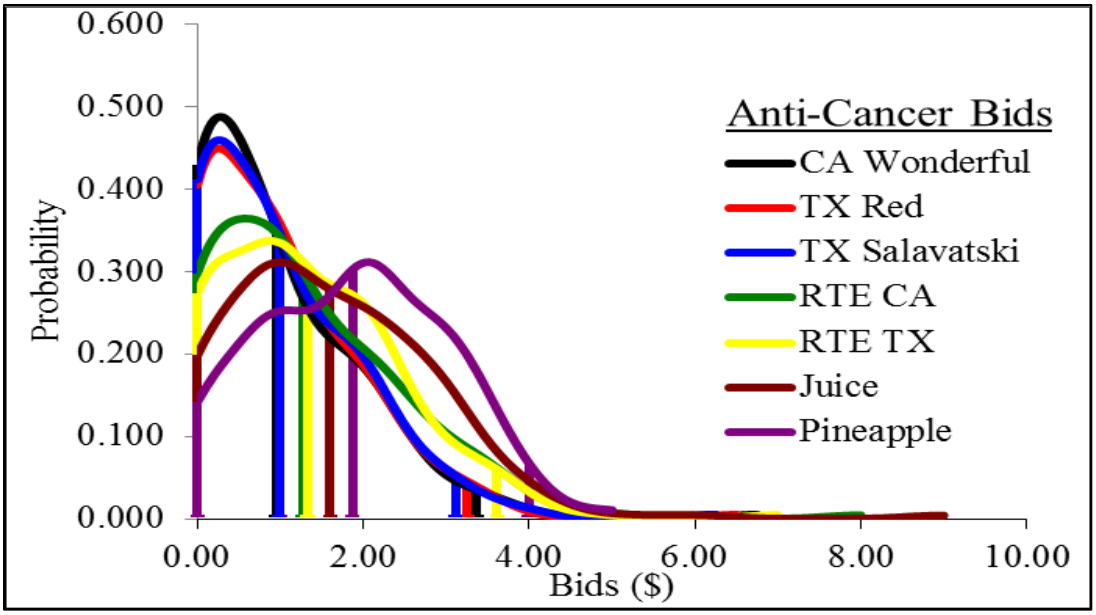

Figure 16. Distribution of Anti-Cancer Information Round Bids for Fruit Products in Dollars as Estimated with a Gaussian Kernel Density Distribution

The clustering of the estimated probability density functions among classes of products appears again in the health and information treatment and the anti-cancer information treatment plots (Figure 15 and Figure 16, respectively). There is also some clustering in the estimated probability density functions for the full information set; these distributions can be seen in Figure 17. However, more differences in the estimated distribution shapes are seen when participants had the full information set than in the other individual information treatments. The shapes of the distributions also led to the question of whether the bids are normally distributed. The question of the shape of the bid distribution will be addressed in further detail later.

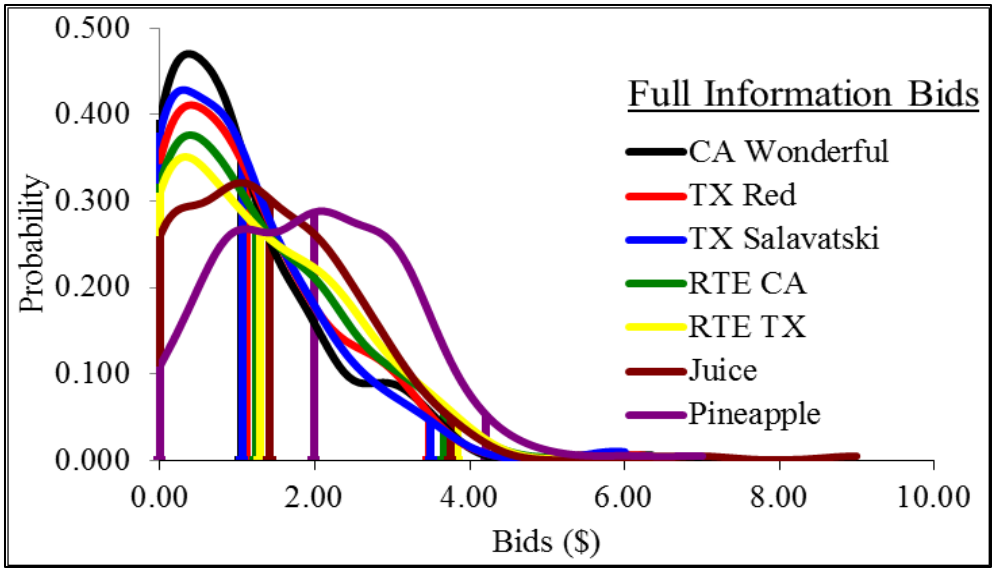

Figure 17. Distribution of Full Information Bids for Fruit Products in Dollars as Estimated with a Gaussian Kernel Density Distribution

Bid Censoring

These figures visualize the bid censoring that occurred for the bids of the auction participants. The percentages of the bids that are censored are included in Table 14. This result was not unexpected; it would have been extremely foreign for study participants to submit negative values for a good that would regularly be purchased for a positive value from a retail establishment. Negative bids by subjects would have implied that they would require payment to accept the product in question. This type of behavior would be expected in studies of products which varied significantly in subject reaction, such as irradiated meat or genetically modified food products (Parkhurst, Shogren, and Dickinson 2004). Many studies which anticipate large percentages of negative values utilize either an endowed approach where subjects are endowed with a product with negative traits and asked to bid to upgrade (i.e. Lusk et al. 2001b).

Alternatively, products with potential negative values can be valued using willingness-to-accept procedures rather than WTP (e.g. NOAA 1994).

Table 14. Bids Censored at $0.00 and Bids above Reference Price, by Round

	Information Treatment			
	Baseline	Tasting	Health and Nutrition	Anti-Cancer
Percentage of bids censored at $0.00	19.59%	17.19%	18.46%	17.71%
Percentage of bids ≥ $3.50, if participants given reference price	6.03%	7.30%	7.30%	6.67%
Percentage of bids ≥ $3.50, if participants NOT given reference price	0.91%	1.13%	0.91%	1.36%

Also included in Table 14 are the percentage of bids over the given reference price. Five of the eight study sessions (n = 135) received reference price information for the current retail price (Price = $3.50) of all of the included products. Economic theory would suggest that a rational consumer would not submit a bid for the product that exceeded the sum of the retail price of the good and any associated transaction costs less any additional utility received from obtaining additional information on a novel product immediately. Fewer participants in the sessions that were not given reference prices (n=63) reported bids higher than the retail price of the products in local stores ($3.50) at the time of the study. However, the lack of familiarity with pomegranate products would not indicate that there were few bids above this particular price because of a bid censoring effect. Rather, it suggests that those subjects who received reference price information were influenced by that value. Therefore, given the percentages of

participants that submitted auction bids above the given reference price, it was concluded that an upper limit for the tobit model would not be appropriately based on the retail price of the products. Thus, a lower-limit only tobit model was applied to the full bids for all products and all rounds of information. Also, despite subjects being provided with a reference price, the mean bids were much lower for the fruit products than that reference price. This suggests that in the marketplace the average participant would not purchase the product at the market price. However, additional estimation was needed to determine what product, demographic, and behavioral characteristics might influence this WTP, regardless of whether it was lower than the reference price.

Tobit Models for Each Product and Round

As discussed in the methods chapter, the WTP for pomegranates and other fruit products was estimated using 35 tobit models, with each model being specific to a particular product as well as to a particular information set received by subjects. For purposes of brevity, each of these will not be fully detailed here. Rather, the results from one set of models will be explained in detail, and the results of interest from the other models will be noted. Full parameter estimates and marginal effects from the separate tobit models from these models can be found in Appendix G. The results for the full information set are presented here and only the results for one product (Texas Red pomegranate fruit) for the full information set are interpreted here.

First, the demographic variables that were included are explained in Table 3. These variables were introduced to account for possible differences in WTP for the

pomegranate and other fruit products based on differences in socioeconomic or behavioral characteristics.

The estimates provided in Table 15 suggest that the second education level dummy variable (education of more than high school up to and including a four-year college degree) is significant ($P < 0.05$) in predicting an increase in WTP for the Texas Red pomegranate fruit. In a similar manner, previous purchase of a pomegranate product and being provided with a reference price also increased WTP for the Texas Red pomegranate fruit. The estimated standard error of the regression is indicated by σ.

However, the β coefficients that are estimated in the tobit model should not be interpreted in the same way as the β coefficients in a standard ordinary least squares (OLS) model estimation. Rather, as pointed out by McDonald and Moffitt (1980), β actually reflects two components: 1) the change in the dependent variable (here, y_i) of those values above the censoring limit and weighted by the probability of being above the censoring limit, and 2) the change in the probability of being above the limit, weighted by the expected value of y_i if above the limit. A change in β is only equal to the effect of a change in x on y_i when x is equal to infinity. Therefore, the results that are of economic interest from the tobit model are the marginal effects for each independent variable. Estimation of marginal effects allows for comparison of the effects of the included regressors on the observed bids.

As discussed in Chapter IV, the tobit model that is estimated is based on a censored distribution of bids; thus, the marginal effects of interest are the expected changes in bids given bid censoring at the specified level (here, for censoring at $0.00)

for a one unit change in the parameter of interest. Marginal effects were calculated using the Delta method. Estimates for marginal effects are given in Table 16. (Note that marginal effects for dummy variables are calculated as a change from the base level of zero to a value of one.)

In looking at the predicted marginal effects for changes in the variables in the tobit model for the Texas Red pomegranate, we conclude that an individual who has more than a high school education but less than a graduate education would be willing to pay a $0.42 premium over someone with a high school degree or less. Similarly, an individual who had previously purchased a pomegranate fruit would pay $0.48 more for the Texas Red pomegranate fruit, and individuals who were provided with a reference price were willing to pay a $0.49 premium over those not given a reference price. The results in this table for other products as well as those for other information treatments can be interpreted similarly.

The tobit model estimations presented are useful in that they allow for comparisons of the parameter estimates and marginal effects for each product under each information treatment. However, this limits generalizing the results to less specific products and to make comparisons across information treatments and products. By pooling all of the bids made by each individual with indicator variables for the information treatment and product that each bid was made for, further models may be estimated to provide additional insight.

Table 15. Tobit Models for WTP by Product, Full Information

	Full Information						
	California Wonderful Pom. Fruit	Texas Red Pom. Fruit	Texas Salavatski Pom. Fruit	Ready-to-Eat California Pom. Arils	Ready-to-Eat Texas Pom. Arils	Mixed Pom. Juice	Pineapple
	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)
Constant	-0.244	-0.076	-0.080	0.309	0.318	0.603	0.830**
	(0.389)	(0.399)	(0.401)	(0.436)	(0.460)	(0.405)	(0.382)
Demographics/ Behaviors							
DAGE2	0.312	0.203	0.064	0.092	0.002	0.028	0.523**
	(0.243)	(0.249)	(0.250)	(0.273)	(0.288)	(0.255)	(0.240)
DAGE3	0.158	0.126	0.035	-0.147	-0.033	0.256	0.069
	(0.231)	(0.235)	(0.236)	(0.258)	(0.272)	(0.241)	(0.228)
DEDU2	0.430	0.651**	0.579**	0.444	0.604*	0.320	0.427
	(0.275)	(0.279)	(0.280)	(0.306)	(0.321)	(0.286)	(0.268)
DEDU3	0.410**	0.314	0.384*	0.409*	0.403*	0.004	0.117
	(0.199)	(0.204)	(0.204)	(0.223)	(0.235)	(0.207)	(0.197)
HOUSE	-0.093	-0.116	-0.113	-0.245**	-0.193*	-0.204**	-0.223***
	(0.085)	(0.086)	(0.087)	(0.096)	(0.100)	(0.088)	(0.082)
FEMALE	0.203	0.008	0.027	0.364*	0.128	0.214	0.236
	(0.193)	(0.197)	(0.198)	(0.216)	(0.226)	(0.201)	(0.189)
DMAR	0.131	0.166	0.102	0.179	0.132	0.178	0.018
	(0.227)	(0.230)	(0.232)	(0.254)	(0.265)	(0.237)	(0.222)
DINC2	-0.022	-0.016	0.083	0.040	0.129	0.164	0.369*
	(0.219)	(0.223)	(0.224)	(0.245)	(0.257)	(0.228)	(0.215)
DINC3	0.138	-0.053	0.073	0.337	0.187	0.193	0.584*
	(0.310)	(0.317)	(0.318)	(0.347)	(0.364)	(0.324)	(0.303)
SPENDFV	0.003	0.004	0.004	0.005	0.005	0.002	0.006
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
FPOH	0.004	0.013	0.017	0.017	0.030	0.028	0.014
	(0.021)	(0.021)	(0.021)	(0.023)	(0.024)	(0.021)	(0.020)
POMFRUITP	0.855***	0.752***	0.757***	0.713***	0.594***	0.485**	0.392**
	(0.193)	(0.198)	(0.199)	(0.217)	(0.229)	(0.203)	(0.193)
ILLNESS	-0.125	-0.044	-0.104	-0.268	-0.250	0.237	0.238
	(0.200)	(0.203)	(0.205)	(0.224)	(0.236)	(0.206)	(0.195)
TOBACCO	0.400	0.310	0.301	0.204	0.318	0.641**	0.460*
	(0.266)	(0.272)	(0.273)	(0.299)	(0.314)	(0.277)	(0.262)
EXERCISE	-0.051	-0.130	-0.128	-0.002	-0.252	-0.277	0.165
	(0.280)	(0.284)	(0.286)	(0.312)	(0.327)	(0.289)	(0.274)
Price Information	0.749***	0.896***	0.840***	0.641***	0.770***	0.438**	0.684***
	(0.183)	(0.188)	(0.189)	(0.204)	(0.215)	(0.189)	(0.178)
σ	1.117***	1.142***	1.143***	1.249***	1.316***	1.174***	1.123***
	(0.065)	(0.067)	(0.068)	(0.073)	(0.078)	(0.067)	(0.059)
Log-Likelihood	-277.626	-282.051	-278.682	-297.095	-304.215	-294.845	-300.604

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are given in parentheses.

Table 16. Tobit Models by Product Marginal Effects on WTP, Full Information

	Full Information						
	California Wonderful Pom. Fruit	Texas Red Pom. Fruit	Texas Salavatski Pom. Fruit	Ready-to-Eat California Pom. Arils	Ready-to-Eat Texas Pom. Arils	Mixed Pom. Juice	Pineapple
	∂y/∂x (Std. Error)	∂y/∂x (Std. Error)	∂y/∂x (Std. Error)	∂y/∂x (Std. Error)	∂y/∂x (Std. Error)	∂y/∂x (Std. Error)	∂y/∂x (Std. Error)
Demographics/ Behaviors							
DAGE2	0.183	0.121	0.037	0.055	0.001	0.019	0.434**
	(0.146)	(0.151)	(0.144)	(0.164)	(0.170)	(0.167)	(0.201)
DAGE3	0.092	0.075	0.020	-0.087	-0.019	0.169	0.057
	(0.135)	(0.141)	(0.135)	(0.151)	(0.160)	(0.161)	(0.187)
DEDU2	0.265	0.423**	0.361*	0.280	0.385*	0.218	0.362
	(0.180)	(0.197)	(0.189)	(0.204)	(0.221)	(0.203)	(0.234)
DEDU3	0.246**	0.191	0.228*	0.252*	0.245*	0.003	0.096
	(0.124)	(0.128)	(0.126)	(0.142)	(0.148)	(0.136)	(0.163)
HOUSE	-0.054	-0.069	-0.065	-0.145**	-0.114*	-0.133**	-0.183***
	(0.049)	(0.051)	(0.050)	(0.057)	(0.059)	(0.058)	(0.067)
FEMALE	0.115	0.005	0.016	0.211*	0.075	0.138	0.191
	(0.108)	(0.116)	(0.113)	(0.122)	(0.131)	(0.128)	(0.152)
DMAR	0.076	0.098	0.058	0.106	0.078	0.116	0.015
	(0.130)	(0.136)	(0.132)	(0.150)	(0.156)	(0.154)	(0.181)
DINC2	-0.013	-0.009	0.048	0.024	0.077	0.108	0.305*
	(0.126)	(0.132)	(0.129)	(0.146)	(0.153)	(0.151)	(0.179)
DINC3	0.082	-0.031	0.042	0.210	0.113	0.129	0.500*
	(0.187)	(0.185)	(0.186)	(0.226)	(0.226)	(0.223)	(0.270)
SPENDFV	0.002	0.002	0.002	0.003	0.003	0.001	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
FPOH	0.002	0.008	0.010	0.010	0.018	0.018	0.011
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)	(0.017)
POMFRUITP	0.539***	0.480***	0.468***	0.452***	0.369**	0.330**	0.328**
	(0.133)	(0.135)	(0.132)	(0.146)	(0.149)	(0.144)	(0.165)
ILLNESS	-0.071	-0.026	-0.059	-0.156	-0.145	0.158	0.197
	(0.113)	(0.120)	(0.115)	(0.127)	(0.134)	(0.140)	(0.163)
TOBACCO	0.231	0.184	0.172	0.121	0.188	0.418**	0.376*
	(0.154)	(0.162)	(0.156)	(0.177)	(0.185)	(0.181)	(0.214)
EXERCISE	-0.029	-0.077	-0.073	-0.001	-0.149	-0.181	0.135
	(0.162)	(0.168)	(0.164)	(0.185)	(0.193)	(0.189)	(0.224)
Price Information	0.407***	0.494***	0.449***	0.364***	0.431***	0.278**	0.545***
	(0.095)	(0.098)	(0.096)	(0.112)	(0.115)	(0.117)	(0.137)

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are given in parentheses.

However, it is noteworthy that the individual tobit models avoid some of the issues that arise from pooling the bids made by an individual for multiple products and under multiple information treatments. One such problem is a lack of independence among the multiple bids submitted by an individual subject. Relationships that an individual's bids have among different product characteristics in the same round (same information treatment) or for the same product with different information treatments are included. A model that is for a single product and a single information treatment circumvents this by only making estimates based on one bid for each individual.

Ordinary Least Squares Model

The pooled bids for the pomegranate and other fruit products are first modeled using an ordinary least squares (OLS) model to provide a baseline for comparison for the other models. Using an OLS model for all of the bids by all individuals for all products ignores the problem of censoring of bids at $0.00 that was discussed earlier. Further, it ignores possible relationships between an individual's bids across products and across information treatments. Therefore, it was hypothesized that the bids for the OLS model would be biased and that the models discussed later would address some of the causes of that bias. However, OLS models are frequently estimated as a baseline comparison for the models presented later.

The results for the OLS model are presented in Table 17. The table includes the results of five sets of variable specifications for comparison purposes. A total of 5,544 observations were included in the OLS models. The R^2 values ranged from 0.08 to 0.22,

but each of the regressions gave an F-test value of 0.000, rejecting the null hypothesis that all the model coefficients in a single regression equation were equal to zero.

Several points about these results are notable. First, the variety of the two Texas pomegranate varieties was never significant in relation to the baseline variety of California Wonderful, regardless of the other regressors that are included in the model. Second, the product forms as well as the information treatments are significant ($P < 0.01$) for all the models in which they are included. The demographic results are the same for the two models that contain them; however, not all of the demographic variables are predicted to have a significant effect on the bids for the products included in the experimental auctions. In including the demographic variables, an attempt was made to create a model that would have greater explanatory power.

Many of the hypothesized factors that influence bidding behavior were not found to be significant in the OLS regression. Those that were not significant include the older age grouping, the middle income bracket, whether an individual had an illness that he or she considered serious, and the frequency with which an individual exercised. However, given the lack of familiarity with several of the products in the auction, it was surprising that so many of the demographic factors were significant. Finally, the estimates for Models 4 and 5 may look similar. However, the estimated parameter for the constant is found to be negative in the final model, although it is not significant (and therefore can be excluded); the constant value is positive for all other OLS estimations.

Table 17. Ordinary Least Squares Model Results for WTP for Fruit Products Using Pooled Experimental Auction Bids

	Model 1 : Product Characteristics Only		Model 2: Product Characteristics and Price Info		Model 3: Product Characteristics, Price Information, Additional Information		Model 4: Product Characteristics, Price Information, Demographics		Model 5: Product Characteristics, Price Information, Additional Information, Demographics	
	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
Constant	0.948***	0.033	0.515***	0.038	0.433***	0.045	0.079	0.069	-0.002	0.073
Variety										
1: Texas Red	0.041	0.051	0.041	0.049	0.041	0.049	0.041	0.047	0.041	0.047
2: Texas Salavatski	0.031	0.038	0.031	0.037	0.031	0.037	0.031	0.035	0.031	0.035
Product Form										
Ready-To-Eat (RTE)	0.272***	0.038	0.272***	0.037	0.272***	0.037	0.272***	0.035	0.272***	0.035
Juice	0.557***	0.051	0.557***	0.049	0.557***	0.049	0.557***	0.047	0.557***	0.047
Pineapple	0.942***	0.051	0.942***	0.049	0.942***	0.049	0.942***	0.047	0.942***	0.047
Price Information			0.635***	0.030	0.635***	0.030	0.603***	0.030	0.603***	0.029
Additional Information										
Tasting					0.124***	0.039			0.124***	0.038
Health and Nutrition					0.097**	0.039			0.097***	0.038
Anti-Cancer					0.103***	0.039			0.103***	0.038
Demographics/ Behaviors										
DAGE2							0.169***	0.040	0.169***	0.040
DAGE3							0.044	0.038	0.044	0.038
DEDU2							0.351***	0.045	0.351***	0.045
DEDU3							0.191***	0.033	0.191***	0.033
HOUSE							-0.117***	0.014	-0.117***	0.014
FEMALE							0.187***	0.031	0.187***	0.031
DMAR							0.076**	0.037	0.076**	0.037
DINC2							0.056	0.036	0.056	0.036
DINC3							0.247***	0.050	0.247***	0.050
SPENDFV							0.004***	0.001	0.004***	0.001
FPOH							0.012***	0.003	0.012***	0.003
POMFRUITP							0.517***	0.032	0.517***	0.032
ILLNESS							0.043	0.032	0.043	0.032
TOBACCO							0.231***	0.044	0.231***	0.044
EXERCISE							-0.036	0.045	-0.036	0.045

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Tobit Model for Pooled Bids

The censoring that is ignored in the OLS regressions is included in the tobit models presented in Table 18. The same five models that are estimated in the OLS regressions are used. The estimated standard deviation of the residual is given by the σ value indicated, and the maximized log-likelihood value is also given. The likelihood ratio test suggests whether each model fits better than a model with no predictors. Additionally, the marginal effects for the tobit models are presented in Table 19.

The differences between the two types of models presented thus far, OLS and tobit, are reflected in the parameter estimations. A few contrasts are pointed out here, and the tables can be used for further comparisons. In terms of the parameter estimates, the constant is significant for all tobit models, even with a negative value for the two models with demographic variables included. This may initially be a cause for concern; still, if the characteristics of the average consumer are fit to the model then the estimated WTP for the baseline product is given by evaluating the respective model at the means for the demographic characteristics, then the WTP for the baseline product is positive. This can be done using the actual mean values for each variable and using only the variables that are significant at $P < 0.05$. If this is done, the estimated value is $1.10 for both Model 4 and Model 5. The value at the means can also be evaluated by calculating the means for each variable and then assigning values of 0 or 1 based on the means to the dummy variables in the model.

Table 18. Standard Tobit Model Parameter Estimates for WTP for Fruit Products Using Experimental Auction Pooled Bids

	Model 1 : Product Characteristics Only		Model 2: Product Characteristics and Price Info		Model 3: Product Characteristics, Price Information, Additional Information		Model 4: Product Characteristics, Price Information, Demographics		Model 5: Product Characteristics, Price Information, Additional Information, Demographics	
	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
Constant	0.770***	0.040	0.304***	0.046	0.211***	0.055	-0.265***	0.083	-0.360***	0.088
Variety										
1: Texas Red	0.040	0.062	0.039	0.059	0.039	0.059	0.041	0.056	0.041	0.056
2: Texas Salavatski	0.030	0.046	0.029	0.045	0.029	0.044	0.030	0.042	0.030	0.042
Product Form										
Ready-To-Eat (RTE)	0.314***	0.046	0.314***	0.045	0.314***	0.045	0.316***	0.042	0.317***	0.042
Juice	0.645***	0.061	0.644***	0.059	0.644***	0.059	0.648***	0.056	0.649***	0.056
Pineapple	1.081***	0.061	1.077***	0.058	1.077***	0.058	1.082***	0.055	1.082***	0.055
Price Information			0.691***	0.036	0.691***	0.036	0.668***	0.036	0.667***	0.036
Additional Information										
Tasting					0.149***	0.047			0.150***	0.045
Health and Nutrition					0.111**	0.047			0.112**	0.045
Anti-Cancer					0.114**	0.047			0.116***	0.045
Demographics/ Behaviors										
DAGE2							0.202***	0.048	0.202***	0.048
DAGE3							0.069	0.045	0.069	0.045
DEDU2							0.433***	0.053	0.433***	0.053
DEDU3							0.256***	0.039	0.256***	0.039
HOUSE							-0.147***	0.016	-0.147***	0.016
FEMALE							0.232***	0.038	0.233***	0.038
DMAR							0.095**	0.044	0.095**	0.044
DINC2							0.133***	0.043	0.132***	0.043
DINC3							0.260***	0.060	0.260***	0.060
SPENDFV							0.005***	0.001	0.005***	0.001
FPOH							0.016***	0.004	0.016***	0.004
POMFRUITP							0.640***	0.038	0.640***	0.038
ILLNESS							0.014	0.039	0.014	0.039
TOBACCO							0.285***	0.052	0.285***	0.052
EXERCISE							-0.051	0.054	-0.051	0.054
σ	1.271***	0.014	1.222***	0.013	1.220***	0.013	1.159***	0.013	1.158***	0.013
Log-Likelihood	-8526.628		-8350.207		-8344.637		-8057.457		-8051.162	
Likelihood Ratio Test	433.390***		786.240***		797.370***		1371.740***		1384.330***	
Degrees of Freedom for LR Test	5		6		9		21		24	

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

If this alternative method is followed, the values predicted are $1.32 for the baseline product of California Wonderful pomegranate fruit based on Model 4 and $1.23

based on Model 5. Thus, we would not generally expect the model to predict negative WTP for products once individual demographics are included in Models 4 and 5. However, when the lowest possible values for the demographic characteristics are included in this model, the estimated value is negative, implying that an individual would have to be paid to take a California Wonderful pomegranate fruit. Even so, since the tobit model is estimated to allow for conclusions to be drawn about utility based on willingness-to-pay, a negative value indicates that an individual with the lowest values would have a negative utility for the baseline product (California Wonderful pomegranate fruit). Furthermore, we are more interested in the results of the marginal effects estimations (which do not include the constant) than in the actual parameter estimates for the tobit model.

The demographic effects that are significant from the OLS model are also significant for the pooled tobit models. Further, the Texas varieties are not shown to be significant in any of the tobit models, indicating subjects were indifferent between the California and Texas varieties on the basis of this model. There was a significant and positive effect from the two further-processed fruit forms (RTE and juice), as well as for the pineapple fruit and the price information. Individually each of these indicates a positive relationship between WTP and each respective product characteristic. Taken together, this suggests that the lack of familiarity of subjects with the pomegranate fruit may have influenced bids for the products. For example, if a subject lacked knowledge on how to remove the husk from a whole pomegranate fruit, he or she may have preferred the product forms that were easier to consume. Of course, this positive

correlation between each product form and WTP could have also been a result of preference for ease of consumption, shelf life, or any number of other factors.

Table 19. Marginal Effects for Standard Tobit Model for WTP for Fruit Products Using Pooled Experimental Auction Bids

	Model 1 : Product Characteristics Only		Model 2: Product Characteristics and Price Info		Model 3: Product Characteristics, Price Information, Additional Information		Model 4: Product Characteristics, Price Information, Demographics		Model 5: Product Characteristics, Price Information, Additional Information, Demographics	
	∂y/∂x	Standard Error	∂y/∂x	Standard Error	∂y/∂x	Standard Error	∂y/∂x	Standard Error	∂y/∂x	Standard Error
Variety										
1: Texas Red	0.024	0.037	0.024	0.036	0.024	0.036	0.025	0.035	0.025	0.035
2: Texas Salavatski	0.018	0.028	0.018	0.027	0.018	0.027	0.019	0.026	0.019	0.026
Product Form										
Ready-To-Eat (RTE)	0.187***	0.028	0.190***	0.027	0.191***	0.027	0.196***	0.026	0.196***	0.026
Juice	0.383***	0.036	0.391***	0.036	0.391***	0.036	0.402***	0.035	0.402***	0.035
Pineapple	0.643***	0.036	0.654***	0.036	0.654***	0.036	0.670***	0.034	0.671***	0.034
Price Information			0.399***	0.020	0.399***	0.020	0.395***	0.020	0.395***	0.020
Additional Information										
Tasting					0.090***	0.029			0.093***	0.028
Health and Nutrition					0.067**	0.028			0.068**	0.028
Anti-Cancer					0.069**	0.028			0.071***	0.028
Demographics/ Behaviors										
DAGE2							0.126***	0.030	0.126***	0.030
DAGE3							0.043	0.028	0.043	0.028
DEDU2							0.285***	0.037	0.285***	0.037
DEDU3							0.162***	0.025	0.162***	0.025
HOUSE							-0.091***	0.010	-0.091***	0.010
FEMALE							0.142***	0.023	0.142***	0.023
DMAR							0.059**	0.027	0.059**	0.027
DINC2							0.083***	0.027	0.083***	0.027
DINC3							0.167***	0.040	0.167***	0.040
SPENDFV							0.003***	0.001	0.003***	0.001
FPOH							0.010***	0.002	0.010***	0.002
POMFRUITP							0.421***	0.026	0.421***	0.026
ILLNESS							0.009	0.024	0.009	0.024
TOBACCO							0.177***	0.032	0.177***	0.032
EXERCISE							-0.031	0.034	-0.031	0.034

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

[b] All of the tobit models had 1,020 observations that were left censored at $0.00, and 4,524 observations that were not censored, where $Percentage\ of\ Censored\ Bids\ = 0.184$.

Pineapple was included as a control product because it is a substitute for pomegranates that subjects were expected to be more familiar with; the higher WTP for the pineapple fruit could have been a result of greater product familiarity or other differences in the products, such as flavor and size preferences. The positive marginal effect of the price information variable (with a value of 0.40) indicates that providing a reference price to consumers significantly influenced the bids that they submitted. Providing a reference price would not be give valuable or significant information to individuals who were familiar with the current retail price of the good; however, the survey of buying behavior indicated that most subjects had not purchased a pomegranate fruit before and therefore may have been unaware of the market price.

In comparing the marginal effects based on the tobit model estimation, the differences between the marginal effects and the parameter estimates are indicative of why the parameter estimates should not be used for comparisons of changes in the values of the regressors. Only one of the demographic/ behavioral characteristics has a negative marginal effect on bids: household size. However, this result is not necessarily unexpected; larger households may be making purchases based on quantity and be seeking less expensive fruit substitutes. The results across the 5 tobit models similar in terms of the size of the effects, and are generally robust to controls for the demographic and behavioral attributes of subjects. The only notable exception to this is the constant term, but this was addressed previously.

In order to determine which of the specifications of the tobit model would be preferred, three tests were considered. First, a likelihood ratio test was conducted to

compare Model 1 through Model 4 to Model 5. The likelihood of a function gives the probability of the data given the parameter estimates. A likelihood ratio test is based on the assumption that one of the models is a restricted form of the other model (the "unrestricted" model). Alternatively, the test assumes that the restricted model can be nested within the unrestricted model by assuming that the coefficients on the variables not included in the restricted model follow a smooth constant pattern. The likelihood ratio test statistic is calculated as

$$LRT = -2\ln\left(\frac{L_R}{L_U}\right) = -2\left[\ln(L_R) - \ln(L_U)\right] \tag{45}$$

where L_U is the likelihood function value of the unrestricted model and L_R is the likelihood function value of the restricted model. The null hypothesis of the test is that the restrictions imposed on the model do not significantly impact the overall fit of the model. The likelihood ratio test statistic is distributed χ^2 with degrees of freedom equal to the number of restrictions placed on the model. The results of the likelihood ratio tests comparing each restricted model to Model 5 are given in Table 20.

The results of two additional specification tests are also provided. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are given for comparison. These two measures of goodness of fit are similar except that the Bayesian Information Criterion includes a more severe penalty for including additional variables in order to help prevent overspecification of the model.

Table 20. Specification Test Values, Standard Tobit Models Using Pooled Experimental Auction Bids

	Model 1	Model 2	Model 3	Model 4	Model 5
Likelihood Ratio Test Statistic [(a)]	950.93	598.09	586.95	12.59	---
P-Value	0.0000	0.0000	0.0000	0.0056	---
Degrees of Freedom	19	18	15	3	---
AIC	17,067.26	16,716.41	16,711.27	16,160.91	16,154.32
BIC	17,113.60	16,769.38	16,784.10	16,313.18	16,326.46

[(a)] Likelihood ratio test statistics are all calculated compared to Model 5.

The likelihood ratio test rejects the restrictions of Models 1-4 ($P < 0.01$). Using the results of the AIC and BIC, Models 4 and 5 should both be considered based on economic theory. Combining these results indicates that both Models 1-3 should not be used for a tobit model of the pooled bids. Finally, the comparison of the tobit model versus the OLS model shows a high number of observations (1,020 censored observations of 5,544 total bids) at the censoring level of $0.00, which indicates that an OLS model is inappropriate for the bids.

Random Effects Tobit Models

The random effects tobit model is then applied to the auction bids to address another problem with original OLS and tobit regression models. The pooled bids contain 28 bids submitted by each individual: bids for seven fruit products across the baseline and three additional information treatments. It is likely that these bids are

related across products and across rounds. The random effects tobit model that was discussed previously can be applied to the bids submitted by study participants in order to account for a random effect from each individual. Thus, the model specified as $y_{isj}^{*} = x_i'\beta + \alpha + u_i + \varepsilon_{isj}$ (Equation 22) in the discussion of the random effects tobit model is fit, allowing random variation for each individual with a Gaussian (normal) distribution. The random effects tobit model parameter estimates for each of the five sets of explanatory variables are included in Table 21. There are several results of interest from these models, particularly in comparison with the standard tobit model specification.

The first is that the only model that has a significant and negative value for the constant is the model with all of the included explanatory variables (Model 5). However, this can be addressed as mentioned in the discussion of the tobit model, and the linear value of the function can be calculated at the means. The estimated WTP from the random effects tobit model at the means are less than those from the pooled tobit model, with a value of $0.67 for Model 4 and $0.77 for Model 5 for the prediction at the mean values. When values of 0 or 1 are assigned to the dummy variables based on the means, the predicted WTP for the baseline product of the California Wonderful pomegranate is $0.80 in both Model 4 and Model 5. The significance of the product forms and the information treatments is robust to any of the presented model specifications for regressors; however, the two Texas varieties still did not have a significant impact on the bids that were submitted for the fruit products.

Table 21. Random Effects Tobit Model Results for WTP for Fruit Products Using Pooled Experimental Auction Bids

	Model 1 : Product Characteristics Only		Model 2: Product Characteristics and Price Info		Model 3: Product Characteristics, Price Information, Additional Information		Model 4: Product Characteristics, Price Information, Demographics		Model 5: Product Characteristics, Price Information, Additional Information, Demographics	
	Parameter[a]	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
Constant	0.725***	0.082	0.243*	0.135	0.149	0.137	-0.450	0.329	-0.544*	0.330
Variety										
1: Texas Red	0.043	0.037	0.043	0.037	0.043	0.037	0.043	0.037	0.043	0.037
2: Texas Salavatski	0.035	0.028	0.035	0.028	0.035	0.028	0.035	0.028	0.035	0.028
Product Form										
Ready-To-Eat (RTE)	0.330***	0.028	0.330***	0.028	0.330***	0.028	0.330***	0.028	0.330***	0.028
Juice	0.681***	0.036	0.680***	0.036	0.681***	0.036	0.680***	0.036	0.681***	0.036
Pineapple	1.116***	0.036	1.115***	0.036	1.116***	0.036	1.116***	0.036	1.116***	0.036
Price Information			0.709***	0.162	0.709***	0.162	0.679***	0.153	0.679***	0.153
Additional Information										
Tasting					0.149***	0.029			0.150***	0.029
Health and Nutrition					0.110***	0.029			0.110***	0.029
Anti-Cancer					0.117***	0.029			0.117***	0.029
Demographics/ Behaviors										
DAGE2							0.306	0.206	0.307	0.206
DAGE3							0.104	0.196	0.104	0.196
DEDU2							0.485**	0.230	0.486**	0.230
DEDU3							0.276	0.169	0.276	0.168
HOUSE							-0.163**	0.071	-0.163**	0.071
FEMALE							0.259	0.163	0.259	0.163
DMAR							0.120	0.190	0.120	0.190
DINC2							0.190	0.184	0.190	0.184
DINC3							0.287	0.260	0.287	0.260
SPENDFV							0.006	0.004	0.006	0.004
FPOH							0.017	0.017	0.017	0.017
POMFRUITP							0.688***	0.165	0.688***	0.165
ILLNESS							0.017	0.167	0.018	0.167
TOBACCO							0.336	0.225	0.336	0.225
EXERCISE							-0.002	0.235	-0.002	0.235
σ(u) [b]	1.099***	0.059	1.046***	0.056	1.046***	0.056	0.955***	0.051	0.954***	0.051
σ(e) [c]	0.735***	0.008	0.735***	0.008	0.733***	0.008	0.735***	0.008	0.733***	0.008
ρ	0.691***	0.023	0.669***	0.024	0.671***	0.024	0.628***	0.025	0.629***	0.025
Log-Likelihood	-5998.493		-5989.326		-5974.5369		-5971.4906		-5956.687	
Likelihood ratio test [d]	5066.64***		4797.20***		4746.83***		4171.93***		4188.95***	

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

[b] Standard deviation of individual-specific error.

[c] Standard deviation of overall error.

[d] Likelihood ratio test that σ(u) = 0.

Furthermore, there were differences in the significance of the demographic variables when the tobit model was specified to allow for random effects. When demographic variables were included (Models 4 and 5), the random effects model only suggests an influence on subject bids from the demographic/ behavioral characteristics of having a 4-year college degree, household size, and previous purchase of a pomegranate fruit. This suggests that for the novel fruit product of pomegranate there may have been less of an influence on WTP of standard demographic characteristics than would be expected for more familiar products.

Specification of the random effects tobit model also provides additional regression statistics which can be useful in determining whether the model is appropriate. The standard deviation of the individual specific error as $\sigma(u)$ is provided, and this can be tested against a standard tobit model in which $\sigma(u) = 0$ using a likelihood ratio test. The results of the likelihood ratio test are given in the final row of Table 21. Also provided is the value labeled ρ; this value is the percent of the overall variance that is contributed by the individual variance. Therefore, ρ takes on values from zero to one, with a value of zero indicating that none of the variance comes from the individual random effects and a value of one indicating that all of the variance in the overall model comes from the individual effects.

The likelihood ratio test rejects a specification of no individual specific error for all five variable specifications ($P < 0.001$). Thus, if the assumptions of the model are correct, the conclusion is that there are individual specific effects and that the standard tobit model would be inappropriate.

As with the tobit model, the marginal effects of the random effects tobit are useful in comparing one-unit changes for any regressor. The marginal effects are presented in Table 22.

The random effects tobit model indicates a slightly greater increase in bids based on the tasting information treatment when compared to the other two additional information treatments. However, each information treatment indicates an increase of less than $0.10 from the baseline bid. The product forms and price information had larger marginal effects on the bid that was submitted. In looking at the demographic and behavioral characteristics, a subject with a four-year university degree is estimated to be willing to pay $0.31 more than an individual without a 4-year university degree. However, this effect is still smaller than that of previous purchase of a pomegranate fruit, which is estimated to increase the bid of a subject by $0.44 versus someone who has not previously purchased a pomegranate fruit product. The final relevant demographic/ behavioral marginal effect is for household size, which is estimated to decrease bids by $0.10 for each additional member of the household. This could be interpreted as a relationship of the tastes and preferences of individuals with larger families, or a tradeoff in the quantity versus quality of food products that a larger household with an income constraint must purchase.

Table 22. Marginal Effects for Random Effects Tobit Model for WTP for Fruit Products Using Pooled Experimental Auction Bids

	Model 1 : Product Characteristics Only		Model 2: Product Characteristics and Price Info		Model 3: Product Characteristics, Price Information, Additional Information		Model 4: Product Characteristics, Price Information, Demographics		Model 5: Product Characteristics, Price Information, Additional Information, Demographics	
	∂y/∂x	Standard Error	∂y/∂x	Standard Error	∂y/∂x	Standard Error	∂y/∂x	Standard Error	∂y/∂x	Standard Error
Variety										
1: Texas Red	0.025	0.021	0.025	0.022	0.025	0.022	0.026	0.022	0.026	0.022
2: Texas Salavatski	0.020	0.016	0.021	0.016	0.021	0.016	0.021	0.017	0.021	0.017
Product Form										
Ready-To-Eat (RTE)	0.191***	0.017	0.194***	0.017	0.195***	0.017	0.199***	0.018	0.199***	0.018
Juice	0.394***	0.025	0.401***	0.025	0.401***	0.025	0.410***	0.025	0.411***	0.025
Pineapple	0.646***	0.030	0.657***	0.029	0.657***	0.029	0.673***	0.029	0.673***	0.029
Price Information			0.397***	0.087	0.397***	0.087	0.391***	0.084	0.391***	0.084
Additional Information										
Tasting					0.087***	0.017			0.090***	0.018
Health and Nutrition					0.064***	0.017			0.065***	0.018
Anti-Cancer					0.068***	0.017			0.070***	0.018
Demographics/ Behaviors										
DAGE2							0.188	0.128	0.188	0.128
DAGE3							0.063	0.119	0.063	0.119
DEDU2							0.313**	0.158	0.313**	0.158
DEDU3							0.170	0.106	0.170	0.106
HOUSE							-0.098**	0.043	-0.098**	0.043
FEMALE							0.153	0.095	0.153	0.095
DMAR							0.072	0.114	0.072	0.114
DINC2							0.116	0.114	0.116	0.114
DINC3							0.180	0.170	0.180	0.170
SPENDFV							0.003	0.003	0.003	0.003
FPOH							0.010	0.010	0.010	0.010
POMFRUITP							0.442***	0.113	0.442***	0.113
ILLNESS							0.011	0.101	0.011	0.101
TOBACCO							0.203	0.136	0.203	0.136
EXERCISE							-0.001	0.142	-0.001	0.142

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

A comparison of the random effects tobit models for pooled bids is presented in Table 23. The likelihood ratio test statistics can be calculated in a similar manner as with the standard tobit models. Thus, the likelihood ratio test indicates that Models 1, 2, and 4 should be rejected for Model 5. We fail to reject the null hypothesis for Model 3. However, in this case the AIC and BIC do not entirely confirm that conclusion. The

AIC still suggests that Model 3 and 5 should both be considered, but the BIC actually suggests that Models 1-3 would be preferred because the additional variables included in Models 4-5 are not shown to substantially improve the fit of the model. However, this result is not unexpected since the random effects tobit model controls for the characteristics of each individual and the demographic and behavioral characteristics are specific to each individual.

Table 23. Specification Test Values, Random Effects Tobit Models for Pooled Auction Bids

	Model 1	Model 2	Model 3	Model 4	Model 5
Likelihood Ratio Test Statistic [(a)]	54.01	35.67	6.09	29.61	---
P-Value	0.0000	0.0020	0.9113	0.0000	---
Degrees of Freedom	19	18	15	3	---
AIC	12,012.99	11,996.65	11,973.07	11,990.98	11,967.37
BIC	12,065.95	12,056.24	12,052.52	12,149.87	12,146.13

[(a)] Likelihood ratio test statistics are all calculated compared to Model 5.

Mixed Linear Models

The mixed (random parameters) linear model was applied to the participant bids to account for possible correlations in the repeated bids of each individual (individual heterogeneity). It is perhaps an unjustified assumption to presume that there is no individual heterogeneity across products and across rounds. The mixed linear models were estimated using maximum likelihood estimation.

In examining the results for Models 1-5 as specified in the previous models reported in Table 24, there are a number of points of comparison with the models already reported. The results for the two Texas varieties are robust to this model specification in that they are not significant in a mixed linear model. Again, the product forms are all significant ($P < 0.01$) regardless of whether the demographic and/or information variables are included in the model. While there is a tendency for an influence of a college degree on bids, the only effects on the bids that we can expect are a negative effect for household size and a positive effect on bids from previous purchases of pomegranate fruit. The likelihood of this can be given by the log-likelihood value. Also included in Table 24 are the estimated standard deviations for the random effects specified at the individual level, reported as $\hat{\sigma}_u^2$.

A likelihood ratio test of the null hypothesis H_0 (linear regression model) versus H_A (mixed linear model) was conducted for each set of regressors. The results are listed as the last line in Table 24. The null hypothesis of a linear regression model was rejected for all sets of explanatory variables. This indicates that there are effects within the model which can be accounted for by using a random parameters specification better than can be accounted for using a standard linear regression.

For the mixed linear model, an additional specification was also estimated to allow for further comparisons. In Model 6 given in Table 24, the model was extended to allow for random effects on the terms for the information treatments. This can be interpreted as variation in the effect that any particular information treatment might have had on an individual. Thus, while an individual's preferences may have given him a

different intercept than another individual in the study, the information treatments may have influenced his subsequent bids differently as well.

Table 24. Mixed Linear Model Results for WTP for Fruit Products Using Experimental Auction Bids

	Model 1 : Product Characteristics Only		Model 2: Product Characteristics and Price Info		Model 3: Product Characteristics, Price Information, Additional Information		Model 4: Product Characteristics, Price Information, Demographics		Model 5: Product Characteristics, Price Information, Additional Information, Demographics		Model 6: Product Characteristics, Price Information, Additional Information, Demographics, with Random Effects by Information Treatment	
	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
Constant	0.948***	0.065	0.515***	0.105	0.433***	0.106	0.079	0.256	-0.002	0.257	-0.002	0.144
Variety												
1: Texas Red	0.041	0.030	0.041	0.030	0.041	0.030	0.041	0.030	0.041	0.030	0.041	0.030
2: Texas Salavatski	0.031	0.023	0.031	0.023	0.031	0.023	0.031	0.023	0.031	0.023	0.031	0.022
Product Form												
Ready-To-Eat (RTE)	0.272***	0.023	0.272***	0.023	0.272***	0.023	0.272***	0.023	0.272***	0.023	0.272***	0.022
Juice	0.557***	0.030	0.557***	0.030	0.557***	0.030	0.557***	0.030	0.557***	0.030	0.557***	0.030
Pineapple	0.942***	0.030	0.942***	0.030	0.942***	0.030	0.942***	0.030	0.942***	0.030	0.942***	0.030
Price Information			0.635***	0.125	0.635***	0.125	0.603***	0.119	0.603***	0.119	0.603***	0.063
Additional Information												
Tasting					0.124***	0.025			0.124***	0.025	0.124	0.080
Health and Nutrition					0.097***	0.025			0.097***	0.025	0.097	0.080
Anti-Cancer					0.103***	0.025			0.103***	0.025	0.103	0.080
Demographics/ Behaviors												
DAGE2							0.169	0.161	0.169	0.161	0.169**	0.085
DAGE3							0.044	0.153	0.044	0.153	0.044	0.081
DEDU2							0.351*	0.181	0.351*	0.181	0.351***	0.095
DEDU3							0.191	0.132	0.191	0.132	0.191***	0.069
HOUSE							-0.117**	0.055	-0.117**	0.055	-0.117***	0.029
FEMALE							0.187	0.127	0.187	0.127	0.187***	0.067
DMAR							0.076	0.149	0.076	0.149	0.076	0.078
DINC2							0.056	0.144	0.056	0.144	0.056	0.076
DINC3							0.247	0.203	0.247	0.203	0.247**	0.107
SPENDFV							0.004	0.003	0.004	0.003	0.004**	0.002
FPOH							0.012	0.014	0.012	0.014	0.012	0.007
POMFRUITP							0.517***	0.130	0.517***	0.130	0.517***	0.068
ILLNESS							0.043	0.131	0.043	0.131	0.043	0.069
TOBACCO							0.231	0.176	0.231	0.176	0.231**	0.093
EXERCISE							-0.036	0.184	-0.036	0.184	-0.036	0.097
$\hat{\sigma}_u^2$ (b)	0.862***	0.044	0.809***	0.042	0.809***	0.042	0.748***	0.039	0.748***	0.039	0.579*** (d)	0.032
Log-Likelihood	-5856.337		-5582.911		-5829.101		-5828.554		-5813.421		-6278.248	
LR Test : (c)	4874.4***		4462.69***		4481.60***		3967.35***		3984.65***		3054.99***	

(a) Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

(b) Estimated standard deviation for the random effects specified at the individual level.

(c) Likelihood Ratio Test of Mixed Linear Model versus Linear Regression.

(d) Estimated standard deviation for random effects for information treatment nested within each individual.

For example, it was anticipated that the anti-cancer information might have a greater effect on individuals with serious health conditions or who smoked on a regular basis than those who did not. As another example, it was considered probable that the tasting treatment would have a range of effects on the bids submitted, from strongly negative to strongly positive, depending on whether that individual found the taste of each product desirable or undesirable.

The values of the estimated parameters for the demographic model with a random intercept only (Model 5) and the demographic model with a random intercept and random coefficients (Model 6) for the information treatments are equal in this case. However, looking at only the estimated parameters does not tell the full story of the differences between these two models. The explanatory variables that would actually be included in predictions of WTP would be very different for the two models. When the information effect is allowed to vary for each individual, the additional information treatments no longer has predictive ability in this model. However, the demographic characteristics gain additional significance. Here, the 30-49 year old age group, a college degree, completion of at least some graduate school, being a female, having a household income greater than $100,000, having higher spending on fruits and vegetables, and using tobacco products all increased the bids for the fruit products; only a larger household size decreased the WTP for the fruit products.

This begs the question of which model specification for the mixed linear models is more correct, given that either could be based on a relevant economic interpretation of the results. First, a comparison of the Akaike Information Criterion (AIC) and the

Bayesian Information Criterion (BIC) for goodness of fit for the model for all 6 mixed linear models favored selection of Model 3 over the others; these results are included in Table 25. BIC imposes a greater penalty based on the number of variables included in the model to correct for overspecification of the model.

Table 25. Goodness of Fit Comparison for Specifications of Mixed Linear Models

	Degrees of Freedom	Akaike Information Criterion	Bayesian Information Criterion
Model 1 : Product Characteristics Only	8	11,728.67	11,781.64
Model 2: Product Characteristics and Price Info	9	11,706.47	11,766.05
Model 3: Product Characteristics, Price Information, Additional Information	12	11,682.20	11,761.65
Model 4: Product Characteristics, Price Information, Demographics	27	11,680.84	11,859.59
Model 5: Product Characteristics, Price Information, Additional Information, Demographics	24	11,705.11	11,864.00
Model 6: Product Characteristics, Price Information, Additional Information, Demographics, with Random Effects by Information Treatment	27	12,610.50	12,789.25

Additionally, a likelihood ratio test can indicate differences in mixed models that have the same fixed effects specifications. Of the models that were estimated, Models 4 and 6 can be compared as they have the same fixed effects (Model 6 has the addition of a random effect for each information treatment). Conducting a likelihood ratio test under the assumption of Model 6 nested within Model 4, the likelihood ratio χ^2 has a value of -899.39 with 3 degrees of freedom; therefore the null hypothesis of Model 4

(the simpler model) cannot be rejected. These two tests would indicate that using AIC, Model 4 is preferred to Model 6. Further results of AIC indicate that Models 1, 2, and 6 are not preferred. Models 3 and 4 are close in their values and so should both be considered. Alternatively, using the Bayesian Information Criterion suggests that the first 3 models are all similar but that Model 6 is less desirable. Based on consideration of the purposes of this study in describing the product characteristics, information treatments, and demographic variables that may have a role in the WTP for pomegranate fruit products, Model 5 allows for additional relationships with demographics to be included and will be used for further comparisons.

If the model including all variables and all information treatments (Model 5) is chosen based on expected differences in relevant demographic behavioral characteristics and information treatments, then this model can be used to address other interesting questions based on the bids submitted by study participants.

Unengaged vs. Engaged Bidders

The novelty of the fruit products investigated in this study led to the hypothesis that there would be a number of bidders who were completely unengaged in the auction process. That is, these "unengaged bidders," despite being recruited for a study that expressly dealt with fruit purchase decisionmaking, were disinterested in the bidding for one or more of the fruit products, or the entire study. These subjects were identified as those who submitted bids of $0.00 for a particular product for all four (Baseline, Tasting, Health and Nutrition, and Anti-Cancer) information treatment rounds. The treatment of

unengaged bidders has been previously described by Lusk and Fox (2003) and Roosen, Marette, and Blanchemanche (2010), who both report results for estimations based on both engaged and unengaged bidders.

The underlying theory for which population of bidders, engaged or unengaged, are the ones that provide economic information of interest is of value. The results presented thus far have referred to the entire population of bidders, both those who are engaged and those who are unengaged. Estimates based on the entire population of bidders may be more reflective of the general population; given the novelty of the included fruit products, it was unlikely that all bidders actually purchase all included products in a real world setting on a regular basis. Therefore, further comparisons of the previous model estimates suggest that they are likely to be more representative of the general population of *shoppers*.

However, the population of potential *buyers* of fruit products is also of economic interest. It should be useful to review what portion of the study participants were unengaged in each product, as well as the implications of removing the unengaged bidders from the sample prior to estimation of the models described earlier. The counts and percentages of unengaged bidders for each fruit product are included in Table 26.

The numbers of unengaged bidders varies considerably from ten for the control product of pineapple to 3.5 times as many unengaged bidders for the two Texas pomegranate fruits. This supports our hypothesis on the greater familiarity of the pineapple, and in a secondary manner the juice product, versus the whole pomegranate fruits. In comparing these products, the number of bidders who were unengaged for any

seven of the fruit products (“Any Product”) was counted at *n* = 44 and the number of bidders who were unengaged for every product in every round (“All Products”) was much lower, at *n*= 6.

Table 26. Count of Unengaged Bidders for Each Fruit Product

Product	Count of Unengaged Bidders [(a)]	Percentage of Unengaged Bidders [(a)]
California Wonderful Pomegranate Fruit	33	16.67%
Texas Red Pomegranate Fruit	35	17.68%
Texas Salavatski Pomegranate Fruit	35	17.68%
Ready-to-Eat Pomegranate Arils - California Wonderful	28	14.14%
Ready-to-Eat Pomegranate Arils - Texas Salavatski	28	14.14%
Mixed Pomegranate Juice	16	8.08%
Pineapple	10	5.05%
Any Product [(b)]	44	22.22%
All Products [(c)]	6	3.03%

[(a)] Unengaged bidders are those who submitted bids of $0.00 for all rounds for the specified fruit product.

[(b)] "Any product" refers to bidders who were unengaged for *any* one of the seven included fruit products.

[(c)] "All products" refers to bidders who were unengaged for *all* seven of the seven included fruit products.

Several of the models presented for the WTP based on the bids were re-estimated and compared for the entire sample versus only the engaged bidders; these results are included in the following pages. The rank-ordered tobit model parameter estimates are presented first in Table 27.

Table 27. Comparison of Random Effects Tobit Model WTP Parameter Estimates for Levels of Bidder Engagement

	All Bidders		Excluding Bidders Who Are Unengaged for *All* Products [b] [c]		Excluding Bidders Who Are Unengaged for *Any* Product [b] [d]	
	Parameter[a]	Standard Error	Parameter	Standard Error	Parameter	Standard Error
Constant	-0.544*	0.330	-0.156	0.311	0.419	0.272
Variety						
1: Texas Red	0.043	0.037	0.043	0.037	0.056	0.036
2: Texas Salavatski	0.035	0.028	0.035	0.028	0.057**	0.027
Product Form						
Ready-To-Eat (RTE)	0.330***	0.028	0.331***	0.028	0.320***	0.027
Juice	0.681***	0.036	0.682***	0.036	0.567***	0.036
Pineapple	1.116***	0.036	1.119***	0.036	0.948***	0.036
Price Information	0.679***	0.153	0.637***	0.141	0.723***	0.134
Additional Information						
Tasting	0.150***	0.029	0.150***	0.029	0.172***	0.029
Health and Nutrition	0.110***	0.029	0.110***	0.029	0.137***	0.029
Anti-Cancer	0.117***	0.029	0.118***	0.029	0.145***	0.029
Demographics/ Behaviors						
DAGE2	0.307	0.206	0.105	0.191	0.038	0.171
DAGE3	0.104	0.196	0.042	0.182	-0.062	0.161
DEDU2	0.486**	0.230	0.356*	0.211	0.281	0.192
DEDU3	0.276	0.168	0.192	0.155	0.219	0.141
HOUSE	-0.163**	0.071	-0.124*	0.065	-0.120**	0.059
FEMALE	0.259	0.163	0.186	0.151	0.115	0.138
DMAR	0.120	0.190	0.127	0.176	0.016	0.162
DINC2	0.190	0.184	0.045	0.171	-0.047	0.155
DINC3	0.287	0.260	0.214	0.243	0.469**	0.231
SPENDFV	0.006	0.004	0.005	0.004	0.001	0.003
FPOH	0.017	0.017	0.014	0.016	0.002	0.014
POMFRUITP	0.688***	0.165	0.580***	0.151	0.376***	0.133
ILLNESS	0.018	0.167	0.037	0.155	0.094	0.142
TOBACCO	0.336	0.225	0.204	0.206	0.058	0.183
EXERCISE	-0.002	0.235	-0.158	0.217	-0.015	0.198
$\sigma(u)$ [e]	0.954***	0.051	0.867***	0.046	0.706***	0.042
$\sigma(e)$ [f]	0.733***	0.008	0.733***	0.008	0.670***	0.008
ρ	0.629***	0.025	0.583***	0.026	0.526***	0.030
Log-Likelihood	-5956.687		-5928.639		-4681.491	
Likelihood ratio test [g]	4188.95***		3796.60***		2652.20***	
N (individuals)	198		192		154	

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

[b] Unengaged bidders are those who submitted bids of $0.00 for all rounds for the specified fruit product.

[c] "Any product" refers to bidders who were unengaged for *any* one of the seven included fruit products.

[d] "All products" refers to bidders who were unengaged for *all* seven of the seven included fruit products.

[e] Standard deviation of individual-specific error.

[f] Standard deviation of overall error.

[g] Likelihood ratio test that $\sigma(u) = 0$.

The results for “all bidders” are the same as those for Model 5 in the original rank-ordered tobit model estimates. These are compared to models where either individuals who were unengaged for all products are removed or where individuals who were unengaged for any product are removed. In the former case, those individuals who were unengaged for all products indicated with their bids that they would be unwilling to purchase any of the fruit products, regardless of the product characteristics and regardless of the additional information that was provided. There is a lack of information provided by these bids in terms of understanding whether the information treatments or individual characteristics influenced their preferences for the products since all bids were reported as zero.

On the other hand, excluding bidders who were unengaged for “any product” removes a larger portion of the sample, but also removes those individuals who were unengaged for any of the bids that are included in the regression. Thus, there should be no bidders who were unengaged for any product included in the latter model.

In the model excluding bidders who were unengaged for all products, the only demographic or behavioral characteristic that still has predictive power is whether or not the individual has made previous purchases of pomegranate fruits. As a consequence, the model including all bidders may have a suggestion as to which bidders will submit zero bids, regardless of whether they are engaged; this may not be true of bidders that were engaged for at least one product.

The models in which bidders who were unengaged for any product were removed are a more interesting comparison. These models can be thought of as models

of those individuals who would actually purchase each product in at least one round of the experimental auctions. There is a significant effect ($P < 0.05$) for the Texas Salavatski Pomegranate variety.

This is the only model discussed so far in which there has been any effect due to the growing location of any of the pomegranate fruit products. If individuals are willing to buy the pomegranate products, then the random effects model that accounts for unengaged bidders suggests there is a positive price premium for the Texas Salavatski variety.

To determine the size of such an effect, the marginal effects are again used and are presented in Table 28. Thus, although it is not a large sum, there is expected to be a $0.04 premium in WTP for the Texas Salavatski pomegranate over the California Wonderful baseline product. Also in looking at the marginal effects, the magnitude of the effect of the information treatments is larger when unengaged bidders are removed, as would be expected; all of the bidders whose bids were removed had no change in bids (from $0.00) across any information treatments. Similarly, there is a larger effect from the product characteristics on WTP because the individuals whose bids were excluded may have been unengaged for more than one product, and thus differences in WTP predicted by product characteristics would be masked to some extent. The effect of price information is also larger on engaged versus unengaged bidders.

Table 28. Comparison of Random Effects Tobit Model WTP Marginal Effects Estimates for Levels of Bidder Engagement

	All Bidders		Excluding Bidders Who Are Unengaged for *All* Products [b] [c]		Excluding Bidders Who Are Unengaged for *Any* Product [b] [d]	
	∂y/∂x[a]	Standard Error	∂y/∂x	Standard Error	∂y/∂x	Standard Error
Variety						
1: Texas Red	0.026	0.022	0.028	0.024	0.043	0.027
2: Texas Salavatski	0.021	0.017	0.023	0.018	0.043**	0.021
Product Form						
Ready-To-Eat (RTE)	0.199***	0.018	0.211***	0.019	0.243***	0.021
Juice	0.411***	0.025	0.436***	0.026	0.431***	0.029
Pineapple	0.673***	0.029	0.716***	0.030	0.720***	0.032
Price Information	0.391***	0.084	0.389***	0.083	0.525***	0.093
Additional Information						
Tasting	0.090***	0.018	0.095***	0.019	0.130***	0.022
Health and Nutrition	0.065***	0.018	0.070***	0.019	0.103***	0.022
Anti-Cancer	0.070***	0.018	0.074***	0.019	0.109***	0.022
Demographics/ Behaviors						
DAGE2	0.188	0.128	0.068	0.123	0.029	0.130
DAGE3	0.063	0.119	0.027	0.117	-0.047	0.122
DEDU2	0.313**	0.158	0.239	0.148	0.221	0.155
DEDU3	0.170	0.106	0.125	0.102	0.169	0.110
HOUSE	-0.098**	0.043	-0.080*	0.042	-0.091**	0.045
FEMALE	0.153	0.095	0.118	0.094	0.087	0.103
DMAR	0.072	0.114	0.081	0.112	0.012	0.123
DINC2	0.116	0.114	0.029	0.110	-0.036	0.118
DINC3	0.180	0.170	0.141	0.165	0.378*	0.195
SPENDFV	0.003	0.003	0.003	0.003	0.001	0.003
FPOH	0.010	0.010	0.009	0.010	0.001	0.011
POMFRUITP	0.442***	0.113	0.390***	0.107	0.294***	0.106
ILLNESS	0.011	0.101	0.024	0.100	0.072	0.109
TOBACCO	0.203	0.136	0.131	0.132	0.044	0.139
EXERCISE	-0.001	0.142	-0.101	0.139	-0.011	0.150

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.
[b] Unengaged bidders are those who submitted bids of $0.00 for all rounds for the specified fruit product.
[c] "Any product" refers to bidders who were unengaged for *any* one of the seven included fruit products.
[d] "All products" refers to bidders who were unengaged for *all* seven of the seven included fruit products.

A comparison of the effect of prior experience with the product as measured by the previous pomegranate fruit purpose variable showed a decrease in the size of the marginal effect as more unengaged bidders were removed, from premiums of $0.44 to

$0.39 to $0.29. Of those bidders who were engaged, the marginal effect of the additional information treatments was relatively larger and the marginal effect of previous purchase of pomegranate fruit products was relatively smaller when compared to models including all bidders. This model also suggested a tendency ($P < 0.10$) of a bid premium of $0.38 for subjects who had annual household incomes of greater than $100,000 over individuals with an annual household income of less than $50,000.

The mixed linear model including the pooled product bids was also re-estimated to account for unengaged bidders; please see Table 29. Again, the product forms, price information, and additional information treatments all have a significant effect ($P < 0.01$) on estimated WTP, with the size of these effects increasing in the model for entirely engaged bidders for the information variables.

In a similar manner to the previously estimated models, there is an inverse relationship between household size and observed bids for the fruit products. Further, the influence of previous experience with the products also decreases as more unengaged bidders are removed from the sample. Consequently, the previous experience with the product (as indicated by *POMFRUITP*) should be a predictor of whether the individual will be engaged in the experimental auction.

Table 29. Comparison of Mixed Linear Model WTP Parameter Estimates for Levels of Bidder Engagement

	All Bidders		Excluding Bidders Who Are Unengaged for *All* Products [b] [c]		Excluding Bidders Who Are Unengaged for *Any* Product [b] [d]	
	Parameter [a]	Standard Error	Parameter	Standard Error	Parameter	Standard Error
Constant	-0.002	0.257	0.129	0.266	0.438	0.268
Variety						
1: Texas Red	0.041	0.030	0.042	0.031	0.053	0.035
2: Texas Salavatski	0.031	0.023	0.032	0.024	0.054**	0.026
Product Form						
Ready-To-Eat (RTE)	0.272***	0.023	0.280***	0.024	0.308***	0.026
Juice	0.557***	0.030	0.574***	0.031	0.555***	0.035
Pineapple	0.942***	0.030	0.972***	0.031	0.930***	0.035
Price Information	0.603***	0.119	0.604***	0.121	0.725***	0.132
Additional Information						
Tasting	0.124***	0.025	0.128***	0.025	0.158***	0.028
Health and Nutrition	0.097***	0.025	0.100***	0.025	0.128***	0.028
Anti-Cancer	0.103***	0.025	0.106***	0.025	0.136***	0.028
Demographics/ Behaviors						
DAGE2	0.169	0.161	0.100	0.164	0.057	0.168
DAGE3	0.044	0.153	0.026	0.156	-0.057	0.159
DEDU2	0.351*	0.181	0.309*	0.180	0.278	0.189
DEDU3	0.191	0.132	0.159	0.132	0.210	0.139
HOUSE	-0.117**	0.055	-0.109*	0.056	-0.116**	0.059
FEMALE	0.187	0.127	0.159	0.129	0.104	0.136
DMAR	0.076	0.149	0.090	0.150	0.015	0.159
DINC2	0.056	0.144	0.005	0.147	-0.038	0.153
DINC3	0.247	0.203	0.239	0.208	0.469**	0.227
SPENDFV	0.004	0.003	0.004	0.003	0.001	0.003
FPOH	0.012	0.014	0.009	0.014	0.002	0.014
POMFRUITP	0.517***	0.130	0.480***	0.130	0.367***	0.131
ILLNESS	0.043	0.131	0.044	0.133	0.106	0.140
TOBACCO	0.231	0.176	0.185	0.176	0.067	0.180
EXERCISE	-0.036	0.184	-0.096	0.185	-0.015	0.195
$\hat{\sigma}_u^2$ [e]	0.748***	0.039	0.551***	0.058	0.483***	0.057
Log-Likelihood	-5813.421		-5694.734		-4523.360	
LR Test [f]	3984.65***		3753.29***		2756.57***	
N (individuals)	198		192		154	

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

[b] Unengaged bidders are those who submitted bids of $0.00 for all rounds for the specified fruit product.

[c] "Any product" refers to bidders who were unengaged for *any* one of the seven included fruit products.

[d] "All products" refers to bidders who were unengaged for *all* seven of the seven included fruit products.

[e] Estimated standard deviation for the random effects specified at the individual level.

[f] Likelihood Ratio Test of Mixed Linear Model versus Linear Regression.

There are three additional results that are of primary interest in the mixed linear model that includes only engaged bids by engaged bidders: those for the Texas varieties, those for the upper income dummy variable, and those for the constant. This model predicts a $0.05 premium for the Texas Salavatski variety as compared to the baseline California Wonderful variety. The *P*-value for the Texas Red variety in the model that excluded any individual who was unengaged was $P = 0.12$.

With an estimated size of the effect that is the same for either Texas variety over California Wonderful, the difference in significance was hypothesized to likely be due to the fact that there were two products included in the experimental auction that were the Texas Salavatski variety and only one product that was Texas Red, so there would be twice as many bid observations for the Texas Salavatski variety. (Some of the original standard tobit models including all demographic and behavioral variables were estimated using a single variable for the Texas varieties and they generally produced results that were not significant for an effect of the Texas varieties.)

The random effects tobit and the mixed linear model that removed any unengaged bidders were re-estimated to test such a hypothesis, and the results for those two models are included in Appendix H in Table 56 -Table 58. The estimations of these models give coefficients that are the same for all other included variables, excepting the Texas varieties. However, the value for the single “Grown in Texas” variable is the same as that previously estimated for the Texas Salavatski variety, but the standard error is smaller. This would lead us to conclude that there is an effect of the Texas variety in general but that effect can be further divided into a specific contribution from the Texas

Salavatski variety in this experiment. However, this does not reject the idea that there could be an increase in WTP for the Texas Red variety as well; rather, we fail to reject the hypothesis that there is no change in WTP for the Texas Red variety.

The next point of interest from the comparison of engaged versus unengaged bidders is the result for the upper income (annual household income greater than $100,000) dummy variable. In the model for bidders who were engaged for every product, a $0.47 increase in WTP was predicted for the included fruit products by individuals who fit this demographic category. Thus, of individuals who were engaged for every product, the expected positive relationship between higher income and higher WTP was seen, but this distinction could not be made when unengaged bidders were included.

The third result of interest is that in the estimations that include bidders who were engaged for every product, the constant estimates (although still not significant at $P < 0.05$) are now positive for the baseline product. This is expected, since engaged bidders were those who had a positive value for the product regardless of their demographic characteristics.

The comparisons of the models for all bidders, bidders who were engaged for at least one product, and bidders who were engaged for all products allow for valuable comparisons of the general population of shoppers versus bidders who would actually make purchases of pomegranate fruit products. This is akin to the exclusion of non-shoppers from WTP and discrete choice studies in terms of the relevance of results. Nonetheless, a number of the included products were novel (unfamiliar) in nature and

excluding bidders who were not fully engaged for every product in every round could result in reports of effects of information treatments and product characteristics that do not account for those consumers who purchase a novel product either before or after gaining new information on that product. This information can also be useful to marketers of novel products who want to know the maximum that currently engaged buyers would be willing to pay for a product. Such information can also indicate the factors that influence the decisions of consumers who are not current purchasers of a product but would be willing to purchase a novel product once they have gained more information on the novel product. In effect, these differences in the models for unengaged versus partially engaged versus fully engaged bidders suggest that there is value in all three types of sample selection, depending on the question that is to be addressed by researchers. Also, considering all these estimates is particularly important for an unfamiliar product.

Comparison of Models for Full Bids

Each of the models described previously has some benefit in regards to understanding the relative value placed on the included products by consumers. However, each is also paired with drawbacks in terms of predicting WTP and subsequent buying behavior. The individual tobit models are perhaps the most straightforward in their interpretation; however, the ability to generalize them across information treatments and products is limited in comparison to a model that includes all bids. However, although the OLS and mixed linear models include all products and

information treatments, they ignore bid censoring; on the other hand, the tobit and random effects tobit models include bid censoring in the model but do not account for individual variation in the effects of each product characteristic and/or information treatment.

However, even given these drawbacks there are results that are robust across models. The product forms of RTE, juice, and the type of fruit (pineapple versus pomegranate) were generally significant predictors of WTP. However, the Texas varieties versus the industry standard variety were not always significant, indicating that the product form was more important in predicting WTP than the location of origin or the specific variety. Also, having a reference price for the products and previous experience with the products were generally indicators of an increase in WTP for the fruit products included in this study. The rest of the demographic and behavioral characteristics varied in whether they were good predictors of WTP, depending on the model that was used.

It is not entirely surprising that this analysis does not suggest a strong ability of demographic characteristics to predict willingness-to-pay. The usefulness of demographics in predicting consumer willingness-to-pay has been found to be limited or insignificant by other studies, including by Umberger and Feuz (2004) in predicting WTP for quality-differentiated beef and by Lusk et al. (2001b) in evaluating beef tenderness. Other studies have excluded demographic attributes from the modeling of WTP (e.g., Abidoye et al. 2011). However, overall the results on the importance of demographic factors in predicting WTP have been mixed. For example, in a recent

study on WTP for grass-fed beef Xue et al. (2010) found that several demographic factors, including household size, nutritional knowledge, consumption behavior, and health status were all predictors of WTP. Thus, consideration of demographic characteristics is useful, but there is no guarantee that they will be predictors of WTP for every product.

In terms of specific model comparisons, the evaluation of which of the random effects tobit models and the mixed linear models are preferred is not straightforward. Comparisons of the log-likelihood values are not valid because the models are not nested inside one another. A Hausman test could be used to compare two models; however this test assumes that one of the models is efficient while the other model is consistent. The choice of which model is consistent should be based on the use of whichever model is expected to converge at the true value of the parameters. However, the Hausman test is not necessarily appropriate for the comparison of these two types of models. This leaves the consideration of which model is more theoretically appropriate. This can be debated as each of the random effects tobit models and mixed linear models have their own drawbacks.

Bid Differences across Information Treatments

One important question to be answered regarding the information treatments is whether there was a difference in the bids subjects submitted for each product following each information treatment. The difference in the bids across treatments were compared using paired t-tests and two-tailed non-parametric Wilcoxon signed-rank tests on the

differences in bids for each product from the baseline round to the specified information round. (Wilcoxon signed-rank tests are also known as Mann-Whitney-U tests and are specified here for paired differences among individuals.) These tests have been used in previous experimental auction studies with information treatments to compare the results for different treatments (e.g., Huffman et al. 2003; Lusk et al. 2004, Corrigan and Rousu 2006a). The Wilcoxon signed rank test is used based on the assumption that the values for individual WTP are often non-parametrically distributed. The results for the paired t-tests are given in Table 30, and the results of the Wilcoxon signed-rank tests are given in Table 31.

Table 30. Test of Information Treatment Effects: Paired t-Tests

	California Wonderful Pomegranate Fruit	Texas Red Pomegranate Fruit	Texas Salavatski Pomegranate Fruit	Ready-to-Eat California Pomegranate Arils	Ready-to Eat Texas Pomegranate Arils	Mixed Pomegranate Juice	Pineapple
	p-values	p-values	p-values	p-values	p-values	p-values	p-values
Tasting Information	0.0001[(a)]	0.0000	0.0000	0.1469	0.0093	0.0033	0.6816
Health and Nutrition Information	0.0008	0.0000	0.0002	0.2900	0.0552	0.0040	0.2116
Anti-Cancer Information	0.0166	0.0000	0.0001	0.0166	0.0009	0.5291	0.6983
Full Information	0.0001	0.0000	0.0000	0.0789	0.0136	0.0013	0.0203

[(a)] Tests are paired t-tests of the null hypothesis H_0: $WTP_{baseline} = WTP_{treatment}$

Using a conservative assumption of non-parametric data, the majority of the product and treatment combinations showed a significant effect ($P \leq 0.001$) for the Wilcoxon signed-rank tests. This was true for all three varieties of whole pomegranate

fruits for all rounds. However, there were only significant differences ($P \leq 0.05$) in WTP for the California ready-to-eat pomegranate arils for the anti-cancer information round, but for the ready-to-eat Texas products all information treatments were significant ($P \leq 0.05$). The results for the mixed pomegranate juice were somewhat different with significance for all information treatments other than the anti-cancer information. As expected, there was no significant effect for each of the information treatments for pineapple, but there was significance ($P \leq 0.01$) for the full information set versus the baseline.

Table 31. Test of Information Treatment Effects: Wilcoxon Signed-Rank Tests

	California Wonderful Pomegranate Fruit	Texas Red Pomegranate Fruit	Texas Salavatski Pomegranate Fruit	Ready-to-Eat California Pomegranate Arils	Ready-to Eat Texas Pomegranate Arils	Mixed Pomegranate Juice	Pineapple
	p-values	p-values	p-values	p-values	p-values	p-values	p-values
Tasting Information	0.0001[(a)]	0.0000	0.0000	0.1258	0.0072	0.0016	0.2252
Health and Nutrition Information	0.0003	0.0000	0.0000	0.1734	0.0259	0.0004	0.0612
Anti-Cancer Information	0.0095	0.0000	0.0000	0.0013	0.0004	0.6322	0.6101
Full Information	0.0001	0.0000	0.0000	0.0752	0.0181	0.0001	0.0043

[(a)] Tests are two-tailed Wilcoxon Signed-Rank Tests of the null hypothesis H_0: $WTP_{baseline} = WTP_{treatment}$

The Wilcoxon signed-rank tests (Table 31) suggest that there was generally an information effect for all the products that were labeled as being grown in Texas, while this was not the case for similar products that were grown in California. Given that the participants were residents of College Station, Texas and surrounding areas, providing

additional information on “Texas-grown” products may have a greater impact than products not labeled as being grown in Texas. However, this needs to be further tested in other geographic locations to determine if such an effect is applicable to other growing locations and consumers. If the subject responses to the survey questions on purchasing preferences are reviewed, this result comes as a surprise; the average subject indicated that the growing location of a product was “not very important” and that growing location was not one of the top three factors that were considered in making fruit purchasing decisions.

In the discussion thus far, only WTP based on the “full bids” for the fruit products in the study have been estimated using econometric models. While the “full bids” for the products in the auction were of interest, it is perhaps more instructive to compare differences in WTP across information treatments but within each individual.

One surprising result of a comparison of individual bids for a single product across information treatments is the number of bids that decreased for a product when an individual had more information on the item. These results are included in Table 32. While it was hypothesized that some individuals may dislike the taste of an item and therefore discount the amount that they would be willing to pay for them product in subsequent rounds, it was unexpected that a large portion of the participants also decreased the amount that they were willing to pay for products following the health and information treatment and the anti-cancer information treatment. Also, of the possibilities to increase, decrease, or have no change in WTP for a product, the most common result for each of the information treatments was to have no change. This

would indicate that the additional information subjects were provided with regarding the products did not influence the utility they would receive from purchasing and consuming the product. However, despite the number of bids that showed no change from the baseline to the later round, almost 60% of bids submitted by participants were either an increase or decrease (positive or negative change) from the baseline bid for that same product. Thus, for the majority of participants the information treatment had some effect on WTP.

Table 32. Proportions of Positive, Negative, and Zero Differences for Changes in WTP from Baseline Information Treatment, Summed for All Products

Type of Bid Difference	Calculation	Percentage of Negative Differences	Percentage of Zero Differences	Percentage of Positive Differences
DeltaBidTaste	$WTP_{Tasting} - WTP_{Baseline}$	22.03%	40.75%	37.23%
DeltaBidHealth	$WTP_{Health\ Information} - WTP_{Baseline}$	19.99%	48.35%	31.67%
DeltaBidCancer	$WTP_{Anti\text{-}Cancer\ Information} - WTP_{Baseline}$	19.28%	48.28%	32.44%
DeltaFullBid	$WTP_{Full\ Information} - WTP_{Baseline}$	22.38%	40.18%	37.44%

The summary statistics for the implied bid differences are presented in Table 33. While the mean results could actually be calculated using the values given in the summary statistics for the full bids, the median results and the comparisons among the effects on bid differences of each information treatment are useful.

Table 33. Summary Statistics for Implied Bid Differences

Product Type	Mean Bid Difference	Std. Dev.	Minimum	Median	Maximum	Difference in Mean Bid From Baseline Product within a Round, Based on Implied Bid Differences[a]
A. Implied Bid Differences - Tasting Round						
California Wonderful Pomegranate Fruit	0.23	0.80	-2.45	0.00	5.40	(Baseline Product)
Texas Red Pomegranate Fruit	0.33	0.68	-2.25	0.15	3.50	+0.10
Texas Salavatski Pomegranate Fruit	0.26	0.72	-2.75	0.00	3.75	+0.03
Ready-to-Eat Pomegranate Arils - California Wonderful	0.09	0.83	-3.95	0.00	3.90	-0.15
Ready-to-Eat Pomegranate Arils - Texas Salavatski	0.14	0.78	-3.90	0.00	3.95	-0.09
Mixed Pomegranate Juice	-0.19	0.91	-3.75	0.00	3.00	-0.43
Pineapple	0.02	0.69	-3.00	0.00	3.10	-0.21
B. Implied Bid Differences - Health and Nutrition Information Round						
California Wonderful Pomegranate Fruit	0.17	0.70	-2.45	0.00	5.35	(Baseline Product)
Texas Red Pomegranate Fruit	0.24	0.61	-2.50	0.00	3.00	+0.07
Texas Salavatski Pomegranate Fruit	0.21	0.74	-2.75	0.00	7.10	+0.04
Ready-to-Eat Pomegranate Arils - California Wonderful	0.06	0.71	-3.95	0.00	3.90	-0.12
Ready-to-Eat Pomegranate Arils - Texas Salavatski	0.10	0.70	-3.90	0.00	3.95	-0.08
Mixed Pomegranate Juice	-0.16	0.78	-3.75	0.00	2.95	-0.33
Pineapple	0.06	0.64	-3.00	0.00	3.15	-0.12
C. Implied Bid Differences - Anti-Cancer Information Round						
California Wonderful Pomegranate Fruit	0.12	0.69	-2.45	0.00	5.75	(Baseline Product)
Texas Red Pomegranate Fruit	0.19	0.62	-2.50	0.00	3.00	+0.07
Texas Salavatski Pomegranate Fruit	0.17	0.58	-2.75	0.00	3.00	+0.06
Ready-to-Eat Pomegranate Arils - California Wonderful	0.13	0.73	-3.95	0.00	3.95	+0.01
Ready-to-Eat Pomegranate Arils - Texas Salavatski	0.17	0.72	-3.90	0.00	3.90	+0.06
Mixed Pomegranate Juice	-0.03	0.76	-3.75	0.00	2.50	-0.15
Pineapple	-0.02	0.58	-3.00	0.00	3.00	-0.13
D. Implied Bid Differences - Full Information Round						
California Wonderful Pomegranate Fruit	0.22	0.79	-2.45	0.00	5.35	(Baseline Product)
Texas Red Pomegranate Fruit	0.33	0.69	-2.50	0.10	3.50	+0.11
Texas Salavatski Pomegranate Fruit	0.26	0.70	-2.75	0.00	3.75	+0.04
Ready-to-Eat Pomegranate Arils - California Wonderful	0.10	0.82	-3.95	0.00	3.90	-0.12
Ready-to-Eat Pomegranate Arils - Texas Salavatski	0.14	0.81	-3.90	0.00	3.95	-0.08
Mixed Pomegranate Juice	-0.21	0.93	-3.75	0.00	2.95	-0.44
Pineapple	0.12	0.70	-3.00	0.00	3.15	-0.11

[a] The baseline product is assigned to the California Wonderful Pomegranate Fruit but is specific to each information treatment.

There is only one product that has a median that does not have a value of zero: the Texas Red whole pomegranate fruit. This implies that for the median subject, the information treatments did not cause a change in WTP except for that particular product with the tasting information treatment. However, regardless of whether the median consumer showed a change in WTP, there may still be valuable information in analyzing factors that indicate which consumers show changes in the levels of their bids. The minimum and maximum values make it clear that there were some individuals who had significant changes in bids for a product from the baseline round to one of the additional information rounds. This was particularly true for what is referred to as the "full information;" that is, the round in which participants had received all 3 of the other information treatments. Thus, the results for the full information would be expected to show some combination of the previous three results.

These results can also be plotted using a boxplot to visualize and compare the general densities of the distributions. Such a plot is provided in Figure 18.

Although the distributions are generally centered at a difference of $0.00 from the baseline to the information treatment, the box plot shows that some of the distributions are either skewed negatively (e.g., mixed pomegranate juice) or skewed positively (e.g., Texas Red pomegranate fruit). The plots also show that while there were larger and smaller values for the implied bid differences, the majority of values had a much smaller range.

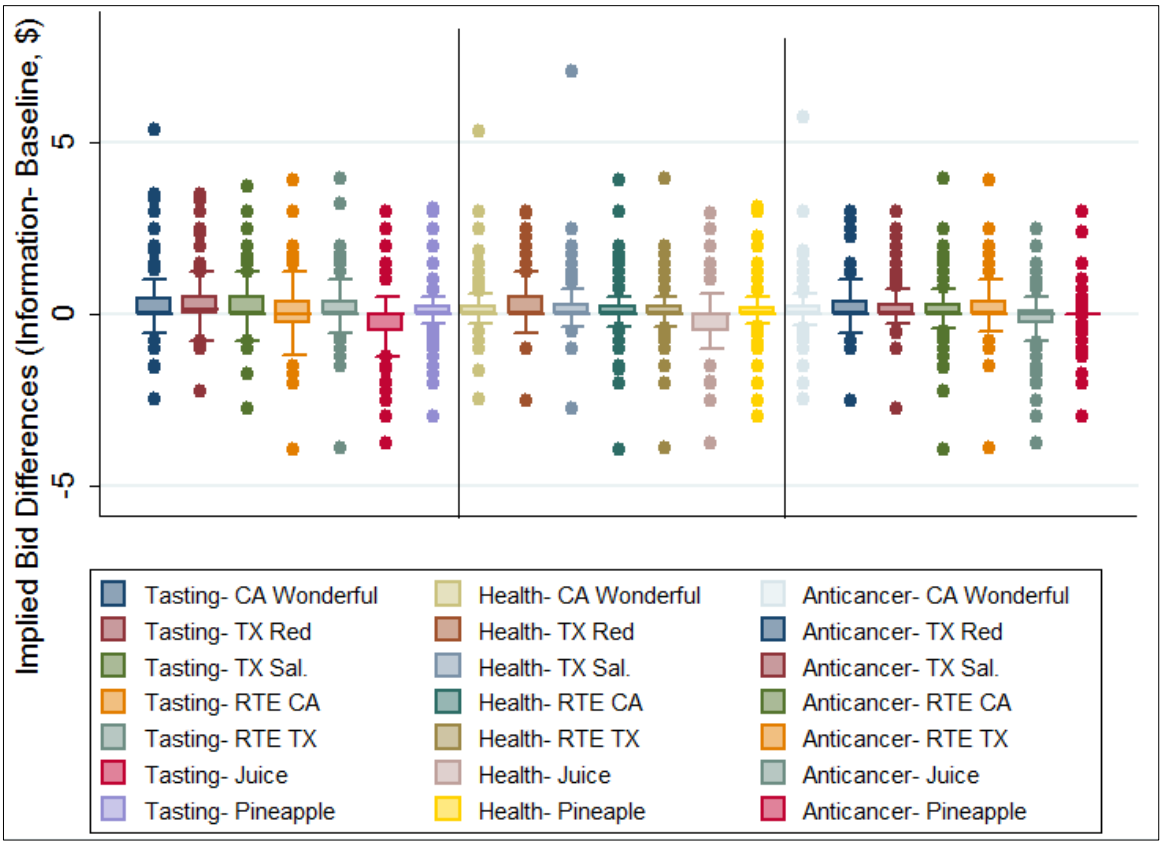

Figure 18. Box Plot of Implied Bid Differences

The approach taken in modeling the "implied differences" for the products in the experimental auction started with an approach of simplicity and as models were rejected for various reasons, the model required to properly model the data became more complex. First, an ordinary least squares model was estimated for each of the seven products and for each of the three information treatments, as well as the full information round (four total). These estimations were conducted using the same dependent variables as in the original estimations of the full bids. However, results of these estimations led to the conclusion that the residuals from the regression were non-normal

on the basis of the skewness and kurtosis of the residuals, as determined by a Jarque-Bera test shown in Table 34.

Table 34. Jarque-Bera Test Statistics for Normality of Residuals from OLS Estimates of Implied Differences

	Product						
Information Treatment	California Wonderful Pomegranate Fruit	Texas Red Pomegranate Fruit	Texas Salavatski Pomegranate Fruit	Ready-to-Eat California Pomegranate Arils	Ready-to Eat Texas Pomegranate Arils	Mixed Pomegranate Juice	Pineapple
Tasting	462.824***	153.689***	162.356***	196.583***	259.617***	37.665***	379.245***
Health and Nutrition	1100.46***	225.642***	8764.41***	705.518***	465.112***	123.618***	494.833***
Anti-Cancer	2833.59***	396.934***	215.261***	394.636***	435.314***	209.335***	246.622***
Full Information	527.248***	161.63***	205.857***	254.079***	200.906***	27.951***	226.391***

*** indicates significance at the P = 0.001 level

The implied differences were also tested using Kolmogorov-Smirnov tests for normality of the distributions. This is a nonparametric test of the null hypothesis that the implied differences are normally distributed. The results for this test are in Table 35. To summarize, the results of both the Jarque-Bera tests and the Kolmogorov-Smirnov tests indicate that the implied differences are not normally distributed ($P \leq 0.001$) for any of the products or across any of the information treatments.

Table 35. Kolmogorov-Smirnov Tests for Normality of Errors for OLS Regression of Bid Differences

	p-values						
	California Wonderful Pomegranate Fruit	Texas Red Pomegranate Fruit	Texas Salavatski Pomegranate Fruit	Ready-to-Eat California Pomegranate Arils	Ready-to Eat Texas Pomegranate Arils	Mixed Pomegranate Juice	Pineapple
Tasting Information	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Health and Nutrition Information	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Anti-Cancer Information	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Full Information	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0000

Note: All values in this table are significant at the $P < 0.001$ level.

The number of unengaged *bids* (vs. bidders) can also be calculated for the differences in bids. Extending the framework discussed previously, any implied differences in bids should be excluded from the model if the individual submitted a bid of zero in the baseline round as well as bidding zero in the respective treatment round. This is because although the implied difference is zero, both the baseline and the treatment bids may be censored and thus do not provide any information on the direction or magnitude of any possible change in WTP that occurred across information treatments. Therefore, for the estimation of the implied bid differences models, any observations that were “case four” for that product and round were excluded. The count of the number of excluded bids for each product and round are included in Table 36.

Table 36. Counts of Unengaged Bids for Implied Bid Differences, by Product and by Information Treatment

Product	Information Round			Total Unengaged Bids by Product	Full Information
	Tasting Information	Health and Nutrition Information	Anti-Cancer Information		
California Wonderful Pomegranate Fruit	33	39	43	115	34
Texas Red Pomegranate Fruit	35	43	46	124	37
Texas Salavatski Pomegranate Fruit	35	44	44	123	38
Ready-to-Eat Pomegranate Arils - California Wonderful	30	32	32	94	30
Ready-to-Eat Pomegranate Arils - Texas Salavatski	31	31	30	92	31
Mixed Pomegranate Juice	20	22	18	60	20
Pineapple	12	10	12	34	10
Total Unenegaged Bids by Information Treatment	196	221	225	642	200
Total of Engaged and Unengaged Bids	1386	1386	1386	4158	

Note: For each product and round, there were a total of 198 bids per product per round.

These results indicate that overall 15.36% of the bids submitted were unengaged ranging from 5.02% for the health and nutrition information treatment for pineapple up to 23.12% for the anti-cancer information for the Texas Red Fruit. This result indicates that there were more unengaged bidders depending on the familiarity of the product, and this must therefore be accounted for when analyzing bid differences for novel products. The mean number of implied bids that were considered unengaged (bids of zero in baseline and in the information treatment round are given in Figure 19.

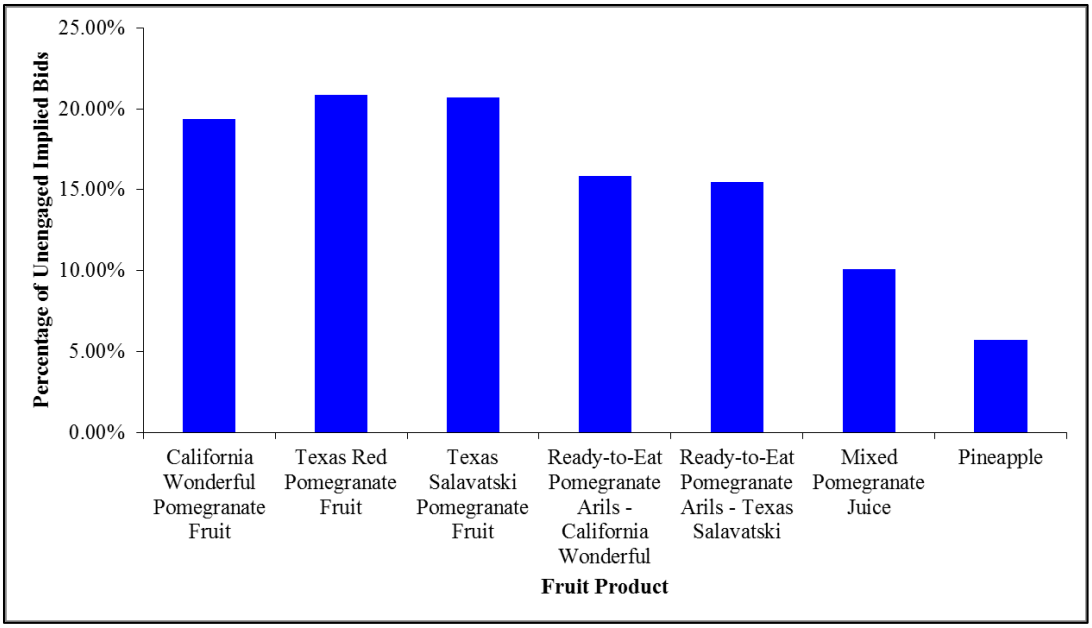

Figure 19. Unengaged Implied Bids: Averages across Tasting, Health and Nutrition, and Anti-Cancer Information Treatments

A mixed linear model was applied to account for individual heterogeneity in preferences using the implied bid differences. Once bids where a single individual submitted bids of zero for a particular product in both the baseline and subsequent information treatment were excluded, the estimation of the mixed linear model gave the results in Table 37. This exclusion is somewhat different from that discussed previously in that in this case only the actual bids that are unengaged are excluded, rather than all results for that bidder. Thus, the number of observations per individual varied from 3 to 21, depending on how many products (of 7 total products) and rounds (of 3 information treatments) for which they have engaged implied bid differences.

Table 37. Mixed Linear Model Results for Experimental Auction Data, Implied Differences in WTP for Fruit Products

	Model 1 : Product Characteristics Only		Model 2: Product Characteristics and Price Info		Model 3: Product Characteristics, Price Information, Additional Information		Model 4: Product Characteristics, Price Information, Demographics		Model 5: Product Characteristics, Price Information, Additional Information, Demographics	
	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
Variety										
1: Texas Red	0.147*** (a)	0.033	0.108***	0.035	0.096***	0.035	0.100***	0.035	0.098***	0.035
2: Texas Salavatski	0.090***	0.025	0.064**	0.026	0.057**	0.026	0.060**	0.026	0.059**	0.026
Product Form										
Ready-To-Eat (RTE)	-0.071***	0.025	-0.098***	0.026	-0.106***	0.026	-0.105***	0.026	-0.106***	0.027
Juice	-0.294***	0.032	-0.335***	0.034	-0.347***	0.034	-0.344***	0.034	-0.346***	0.035
Pineapple	-0.133***	0.032	-0.175***	0.033	-0.187***	0.034	-0.183***	0.034	-0.185***	0.034
Price Information			0.235***	0.051	0.124	0.084	0.150*	0.080	0.135	0.084
Additional Information										
Tasting					0.132*	0.074			0.121	0.185
Health and Nutrition					0.109	0.074			0.100	0.185
Anti-Cancer					0.123*	0.074			0.112	0.185
Demographics/ Behaviors										
DAGE2							0.104	0.091	0.063	0.114
DAGE3							0.070	0.096	0.041	0.108
DEDU2							0.075	0.124	0.065	0.125
DEDU3							0.149*	0.088	0.132	0.092
HOUSE							0.013	0.036	0.005	0.039
FEMALE							-0.069	0.080	-0.093	0.090
DMAR							0.040	0.104	0.038	0.104
DINC2							-0.068	0.100	-0.078	0.102
DINC3							-0.103	0.144	-0.105	0.144
SPENDFV							-0.001	0.002	-0.001	0.002
FPOH							0.009	0.010	0.009	0.010
POMFRUITP							-0.017	0.089	-0.023	0.089
ILLNESS							-0.003	0.091	-0.013	0.092
TOBACCO							0.322***	0.119	0.303**	0.123
EXERCISE							-0.165	0.123	-0.188	0.129
$\hat{\sigma}_u^2$ (b)	0.300***	0.033	0.273***	0.030	0.269***	0.030	0.251***	0.028	0.251***	0.028
Log-Likelihood	-3372.180		-3361.992		-3360.105		-3338.803		-3338.257	
LR Test : (c)	1542.18***		1499.89***		1491.620***		1359.71***		1358.02***	
AIC	6758.359		6739.984		6742.21		6723.605		6728.515	
BIC	6801.556		6789.353		6810.092		6865.402		6888.807	

(a) Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.
(b) Estimated standard deviation for the random effects specified at the individual level.
(c) Likelihood Ratio Test of Mixed Linear Model versus Linear Regression.

The results of the mixed linear model for the implied bid differences gives results that must be interpreted differently than the mixed linear model estimated for the full bids. Since the dependent variable is the difference in bids from the baseline round to

the respective information treatment round, the parameter estimates are also the differences in the parameters for the information treatment round and the baseline round. For example, the first estimate in Table 37 indicates that in Model 1, the estimated difference in the effect of the Texas Red variety from the baseline to the information treatment is an increase of 14.7¢ in value. The interpretation follows similarly for all other dummy variables in the model; for continuous variables such as tobacco use the estimated change in WTP for a product for any individual attributed to that variable would be the value of that variable times the estimated parameter. Thus, the trend in Model 4 for tobacco use would indicate a $0.14 increase in WTP for an individual who used tobacco products every day, but only a $0.07 increase in WTP for an individual who uses tobacco on average every other day.

Comparing the results of the mixed linear model for the implied differences in bids to the mixed linear models for the full bids in Table 24, there are a number of differences in the results. This would indicate that the predictors for the levels of the actual bids for an individual under a certain information treatment are not necessarily the same as the predictors for how an individual's bids will change when an information treatment is applied. Thus, the model for the implied differences should indicate the product and/or demographic factors that are relevant when information treatments are applied. This type of information is economically relevant when information treatments (i.e. advertisement, product promotional materials, etc.) are applied with the aim of increasing WTP for a product. For the implied differences models, all product characteristics were significant ($P < 0.05$), and this result was robust across all Models 1

to 5. However, the sign of these effects for the product form characteristics (RTE, juice, and pineapple) was negative for the models based on implied differences. This indicates that for any of these product form characteristics, the change in WTP attributed to that characteristic decreased from the baseline round to the information treatment rounds, while the positive values on the two Texas varieties variables indicates that the effect of those product varieties on WTP increased from the baseline to the information treatment rounds.

Depending on whether AIC or BIC is used in comparing the model specifications, Model 2 or 4 would be preferred of these model options. In contrast to the other models examined for predicting WTP, the price information effect was not robust across all specifications of this model. This indicates that although price information had an effect on the level of individual bids, it did not necessarily have an effect on the size of the change in bids due to an information treatment. This result is of interest for two reasons. First, reference prices and their effects on the level of bids have been the topic of much discussion in the literature, but the application of a model based on implied bid differences may avoid some of the problems that the presence or absence of a reference price may cause. However, since this result was dependent on which variables were included in the model of the change in WTP, further investigation will be needed to confirm or disprove this result. Second, and again in contrast to the models based on the full bids, there was generally not significance for the implied differences in bids for the information treatment indicator variables. This is interpreted to mean there was not a specific effect due to any one of the particular information treatments, and the

changes in WTP could be more correctly attributed to the product characteristics. Also, note that in these mixed linear models a constant was not estimated in order to allow for the calculation of differences due to all three information treatments, which were the tasting, health and nutrition, and anti-cancer information treatments included in the model. In the models for implied bid differences that included demographic variables, the only effect that was significant was for tobacco-users the size of the effect due to the information treatments was larger than for nonsmokers.

For the various test statistics for the model, based on the size and standard error of the estimated standard deviation for the individual there were significant random effects specified at the individual level. Note that it is less surprising that the demographic and behavioral characteristics were not estimated to be relevant because the random effects were specified as individual-specific effects. The likelihood ratio test of the mixed linear model versus an ordinary least squares linear model also rejected the null hypothesis of the OLS model.

The use of the implied bid differences instead of the full bids gives quite different results in terms of which variables are statistically significant. If researchers and marketers are interested in predicting what type of information on which products will cause consumers to be willing to pay more for novel products, the use of full bids could lead to dramatically different results than using the paired differences in bids. It may not be sufficient to compare the differences in the means for the products and information treatments and may therefore be preferable to utilize paired differences in bids before and after additional information on the novel product is provided. If paired

differences are not used for such comparisons, then the conclusions that are drawn may be contradictory to those from full bids. With no paired responses, the outside substitutes for each product for each individual may not cancel with those of others, and the differences in bids may not be the same as the differences in value. Of course, the differences in value are why the study was originally undertaken.

Preference Models for Rankings

Each participant submitted a ranking of seven products and the option of no product, for a total of eight possibilities that were to be ranked. For the rankings, the frequency and percentage of each ranking for each product for the full information are described in Figure 20; the percentage of participants who assigned a given ranking for each information treatment and each product are given in Table 38.

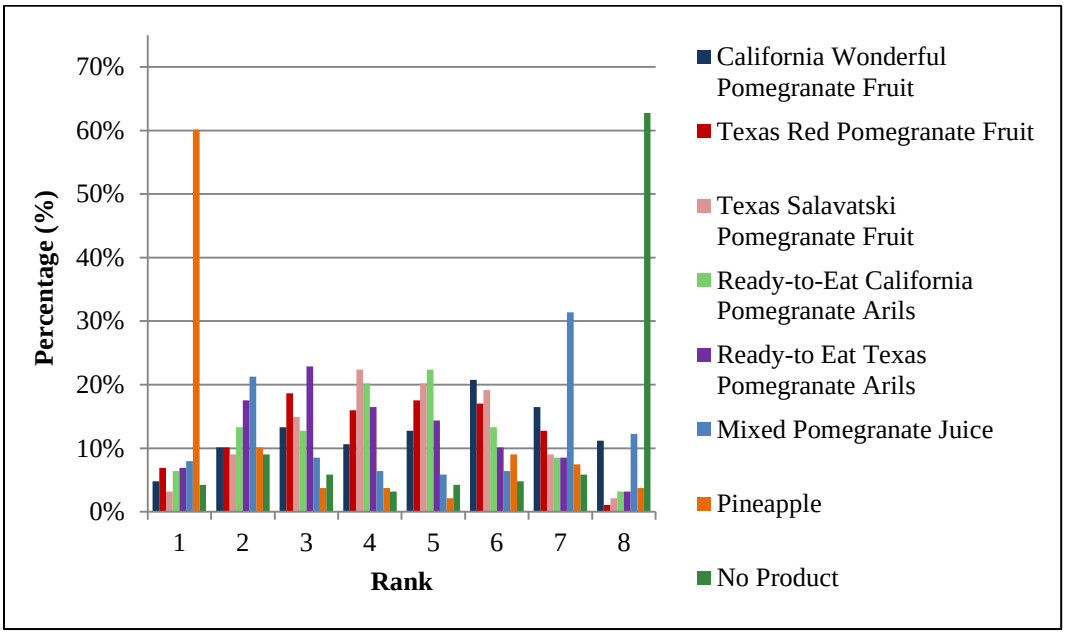

Figure 20. Frequency of Each Ranking for Each Product, Full Information

Table 38. Percentages of Participants Who Assigned Each Ranking to Each Product in Each Round

Rank	California Wonderful Pomegranate Fruit	Texas Red Pomegranate Fruit	Texas Salavatski Pomegranate Fruit	Ready-to-Eat California Pomegranate Arils	Ready-to Eat Texas Pomegranate Arils	Mixed Pomegranate Juice	Pineapple	No Product
	Baseline Information							
1	6.91%	1.60%	2.66%	5.85%	4.26%	16.49%	53.19%	9.04%
2	6.38%	6.91%	6.38%	10.11%	12.77%	27.66%	18.62%	11.17%
3	9.04%	11.17%	10.64%	14.36%	25.00%	16.49%	4.26%	9.04%
4	11.70%	9.04%	13.83%	25.00%	21.28%	7.98%	5.32%	5.85%
5	18.62%	17.55%	15.43%	19.15%	11.17%	7.45%	3.19%	7.45%
6	17.02%	19.68%	28.72%	11.70%	10.64%	3.19%	5.85%	3.19%
7	12.77%	28.72%	17.02%	9.57%	10.11%	14.89%	3.72%	3.19%
8	17.55%	5.32%	5.32%	4.26%	4.79%	5.85%	5.85%	51.06%
	Tasting Information Treatment							
1	5.32%	7.98%	3.19%	4.79%	4.79%	10.11%	60.11%	3.74%
2	9.57%	12.23%	9.04%	12.23%	18.62%	21.81%	9.57%	8.56%
3	14.36%	20.21%	14.89%	14.36%	18.62%	9.04%	3.72%	5.35%
4	11.17%	14.89%	26.60%	14.89%	18.09%	6.38%	5.32%	1.60%
5	12.77%	17.02%	16.49%	23.40%	14.36%	6.38%	3.72%	5.35%
6	18.62%	14.89%	17.55%	15.43%	13.30%	6.38%	7.98%	5.35%
7	15.96%	11.70%	10.64%	10.11%	9.04%	31.91%	6.91%	3.21%
8	12.23%	1.06%	1.60%	4.79%	3.19%	7.98%	2.66%	66.84%
	Health and Nutrition Information Treatment							
1	5.32%	4.79%	3.19%	5.32%	7.98%	7.98%	61.17%	4.79%
2	11.17%	11.17%	5.85%	13.83%	13.83%	23.94%	7.98%	12.23%
3	10.11%	13.30%	13.83%	17.55%	25.53%	9.04%	5.32%	4.79%
4	11.70%	14.36%	17.55%	19.68%	20.21%	10.11%	3.19%	3.19%
5	16.49%	19.15%	19.15%	18.09%	8.51%	8.51%	2.13%	7.98%
6	18.09%	14.89%	24.47%	13.83%	10.11%	6.91%	8.51%	3.72%
7	14.36%	20.21%	11.70%	7.98%	10.64%	21.28%	7.45%	6.38%
8	12.77%	2.13%	4.26%	3.72%	3.19%	12.23%	4.26%	56.91%
	Anti-Cancer Information Treatment							
1	5.32%	6.38%	2.13%	9.04%	5.85%	18.09%	46.81%	6.38%
2	6.91%	9.04%	6.38%	11.17%	21.81%	22.34%	14.89%	7.45%
3	14.36%	12.23%	14.36%	14.89%	22.87%	11.17%	4.79%	5.32%
4	6.91%	17.55%	17.55%	20.21%	18.09%	9.04%	6.38%	4.26%
5	15.43%	15.96%	22.87%	14.89%	13.83%	4.79%	4.26%	7.98%
6	21.28%	17.55%	20.74%	15.96%	4.79%	6.91%	8.51%	4.26%
7	15.43%	18.62%	12.23%	9.04%	10.64%	19.15%	9.57%	5.32%
8	14.36%	2.66%	3.72%	4.79%	2.13%	8.51%	4.79%	59.04%
	Full Information							
1	4.79%	6.91%	3.19%	6.38%	6.91%	7.98%	60.11%	4.26%
2	10.11%	10.11%	9.04%	13.30%	17.55%	21.28%	10.11%	9.04%
3	13.30%	18.62%	14.89%	12.77%	22.87%	8.51%	3.72%	5.85%
4	10.64%	15.96%	22.34%	20.21%	16.49%	6.38%	3.72%	3.19%
5	12.77%	17.55%	20.21%	22.34%	14.36%	5.85%	2.13%	4.26%
6	20.74%	17.02%	19.15%	13.30%	10.11%	6.38%	9.04%	4.79%
7	16.49%	12.77%	9.04%	8.51%	8.51%	31.38%	7.45%	5.85%
8	11.17%	1.06%	2.13%	3.19%	3.19%	12.23%	3.72%	62.77%

Note: The percentages of participants who assigned a particular ranking to a particular product in a particular round are given here.

For the rankings models, the number of individuals who submitted usable responses was 188 due to several individuals who failed to rank one or more products in one or more rounds.

A comparison of the preference rankings may be somewhat simplified by comparing whether a product was ranked in the top half of bids. Although this does not directly depict the lower half of the data, it allows for a simpler visualization of whether the product was likely to be one of the more favored products in the study. The bids that were ranked in the lower half (5th-8th) of the rankings are implied by the difference $Percentage\ ranked\ in\ bottom\ half = 1 - Percentage\ ranked\ in\ top\ half$. These results are shown in Figure 21. It is clear that the information treatments had little effect on the overall frequencies of the rankings for some products while the effect was greater for other products. In comparing this plot to the plot of the individual rankings given in Figure 20, the changes from one information treatment to another are more clearly revealed, as is a more direct comparison of overall preference for a particular product.

To address the rankings data further, the average rank for each product for each information treatment is given in Figure 22. Note that on average, pineapple was the most preferred product for all information treatments and the no product option was the least preferred for all information treatments. Also, when the control product and the no product option are excluded, the Texas Salavatski RTE arils were the most preferred for any additional information treatment and the California Wonderful pomegranate fruit was the least preferred product for any of the additional information treatments.

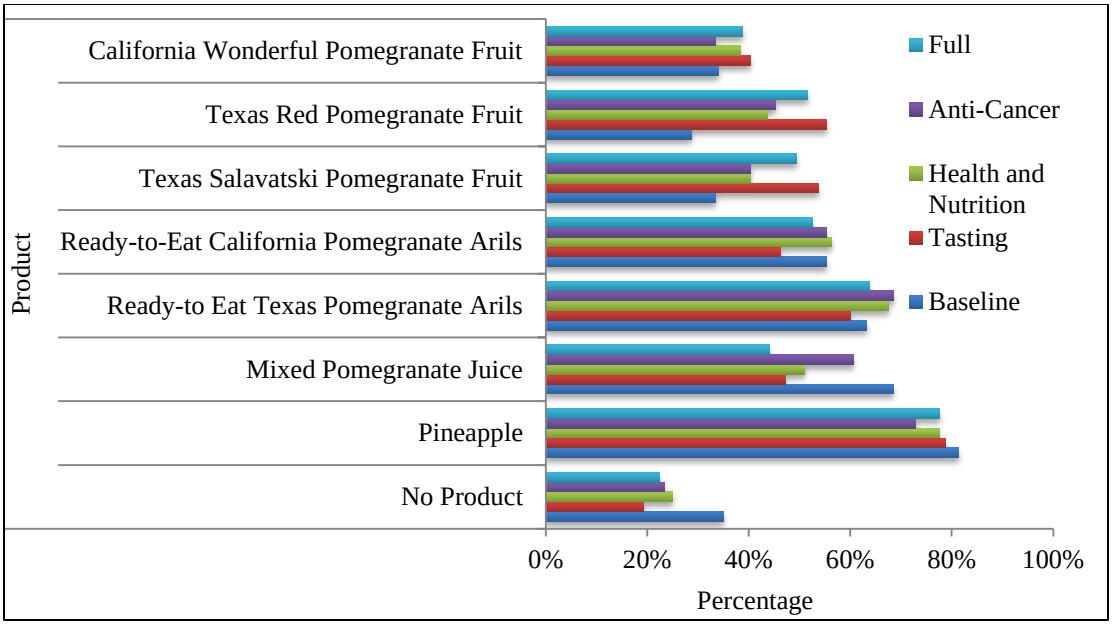

Figure 21. Percentage of Subjects Who Ranked a Particular Product in the Top Half of All Products

Also notable is that for the anti-cancer information round, the ranking for the pineapple dropped; this result confirmed the suggestion that the anti-cancer information regarding one product ingredient (pomegranate) would have an effect relative to products without those health benefits (pineapple).

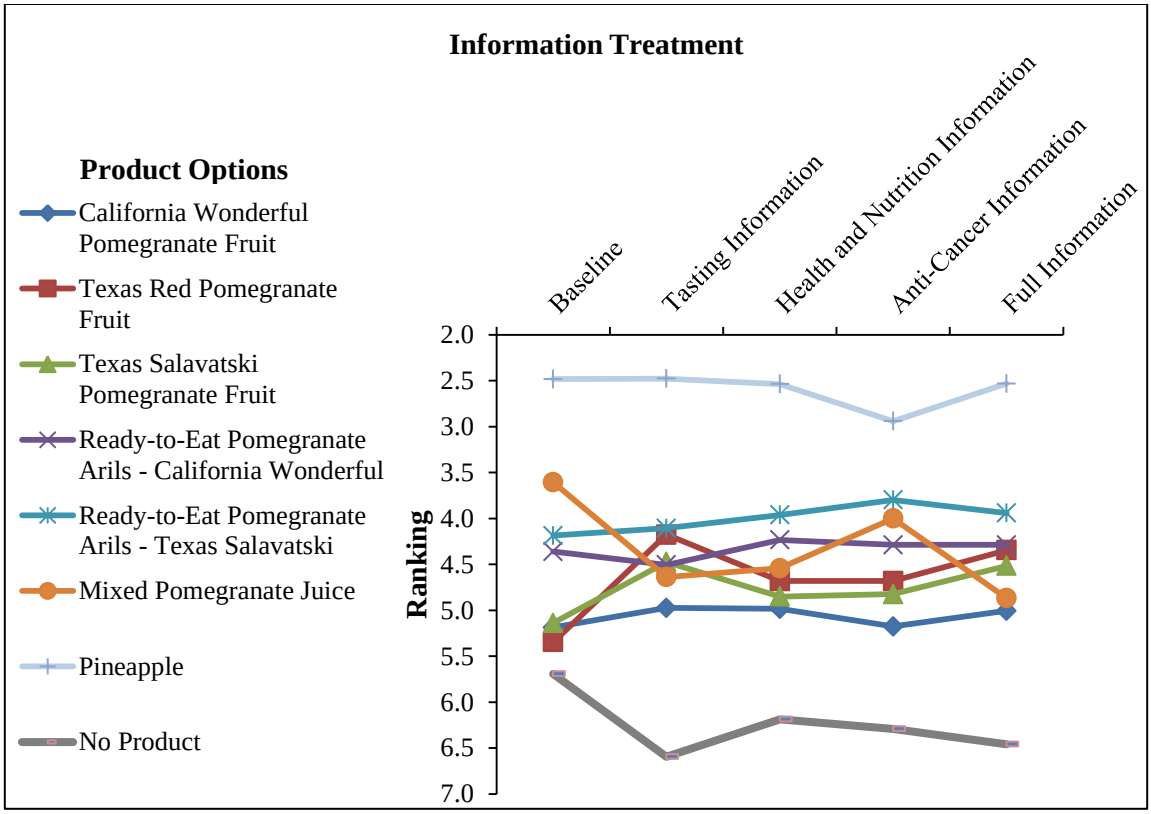

Figure 22. Average Preference Ranking by Product and by Information Treatment. Note: Preferences were ranked from 1-8 for the product option, with a ranking of 1 being the most desirable and a ranking of 8 being the least desirable

Rank-Ordered Logit Model

The rank-ordered logit model estimations were done in STATA/ IC 11.0 ©. Prior to estimation the rankings data were "exploded" as described previously, giving an implied L-1 choice decisions for each participant. The respondents were asked to rank the products in order of descending preference, but the rank-ordered logit model is not symmetrical in the estimation of ascending versus descending preferences; therefore simply reversing the sign of the marginal effects for a rank-ordered logit for ascending ranks would not give equivalent estimates. However, the software includes an option in

the rank-ordered logit estimation procedure to handle such “reversed” ranks (StataCorp 2009). The product characteristics that were included for the rank-ordered mixed logit models are the cultivar of the product (California Wonderful, Texas Red, and Texas Salavatski) and the product form (RTE, juice, pineapple, and no product).

After the traditional fully-ranked models were estimated, the models were re-estimated using partial rankings to check for possible differences in ability to rank less-preferred versus more-preferred product options. The results of this estimation are given in Table 39.

The first portion of the table includes estimates for the changes in ranking due to the product characteristics. Each model was estimated separately for each information treatment. In interpreting the parameter estimates, a product would be more preferred due to a characteristic if it has a positive value, and less preferred due to that characteristic if there is a negative value for the parameter estimate. Thus, in the baseline ranking round, there was no effect on preference for a product if the product was either of the two Texas varieties, but items were more preferred if they were RTE, juice, or pineapple. Of these, the largest relative effect on preference was pineapple, followed by juice, and then RTE. The option of no product was discounted in the rankings.

The estimates of the models for tasting, health and nutrition, anti-cancer, and full information will not be described individually. However, points of interest in each and across models will be discussed. In the Tasting Information round, the ranking of the juice product no longer differed significantly from the baseline. However, once subjects

tasted all of the products there was a greater preference for the Texas varieties of pomegranate fruit products as compared to the California product; the Texas Red variety was more preferred than the Texas Salavatski variety. In general, all products were more preferred over the option of "no product," which was discounted even more with the full information set than in the baseline round.

Table 39. Rank-Ordered Logit Models for Explicit Preference Rankings for Fruit Products by Information Treatment, Fully- and Partially-Ranked Models

	Rankings, Fully Ranked (1-8)									
	Baseline Information		Tasting Information		Health and Nutrition Information		Anti-Cancer Information		Full Information	
Product Characteristics	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
Variety										
1: Texas Red	0.039	0.106	0.444***	0.108	0.212**	0.106	0.284***	0.106	0.363***	0.106
2: Texas Salavatski	0.116	0.081	0.282***	0.084	0.149*	0.081	0.258***	0.082	0.257***	0.083
Product Form										
Ready-To-Eat (RTE)	0.520***	0.088	0.216***	0.083	0.407***	0.086	0.474***	0.085	0.316***	0.084
Juice	0.747***	0.117	-0.118	0.118	0.016	0.118	0.379***	0.117	-0.243**	0.119
Pineapple	1.431***	0.123	1.181***	0.121	1.142***	0.121	0.952***	0.120	1.085***	0.122
No Product	-0.692***	0.132	-1.536***	0.151	-1.108***	0.137	-1.058***	0.139	-1.409***	0.145
	Rankings, Partially Ranked (1-4)									
Variety										
1: Texas Red	-0.086	0.172	0.426***	0.139	0.258*	0.149	0.376**	0.151	0.364***	0.142
2: Texas Salavatski	0.127	0.108	0.313***	0.105	0.182*	0.104	0.253**	0.106	0.270***	0.104
Product Form										
Ready-To-Eat (RTE)	0.691***	0.113	0.190*	0.105	0.594***	0.108	0.686***	0.109	0.389***	0.105
Juice	1.215***	0.144	0.288**	0.147	0.522***	0.146	0.930***	0.144	0.236	0.150
Pineapple	1.957***	0.147	1.583***	0.139	1.722***	0.143	1.515***	0.143	1.622***	0.141
No Product	0.180	0.166	-0.804***	0.195	-0.390**	0.181	-0.338*	0.185	-0.591***	0.185

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

In the health and nutrition information round, the Texas Red variety was still preferred over the Texas Salavatski variety, and there was also still a preference for RTE products over whole fruit products. There was less of a preference for the two Texas

varieties of pomegranate over the California pomegranate fruit under this information treatment; however, this result was expected because the health and nutrition information was for the fruit products in general and was not variety specific.

In the anti-cancer Information round, the changes in preference ranking due to the Texas variety product characteristics was nearly the same for Texas Red and Texas Salavatski. This is in contrast to the results of the Tasting Information treatment; suggesting that although there may be a consumer preference for the taste of the Texas Red variety over the Texas Salavatski variety, the preference for either one can be increased by providing information on the anti-cancer properties of the fruit products. Also, in this round the preference for the pineapple fruit in comparison to the pomegranate products was less than in other rounds, which was expected since pineapple is not known for having the same potential anti-cancer benefits as pomegranates and pomegranate products. The juice product was still not as preferred in the anti-cancer round as in the baseline, but it was more preferred than in the other two information rounds.

The full information estimation provides insight into the net sum effect of all of the information treatments on individual preferences. The results suggest that on the whole, there is a greater preference for the Texas Red than the Texas Salavatski variety. Also, with the full information set there was a preference for RTE products over whole fruit products and a discount for the mixed pomegranate juice product in relation to the fresh fruit products. However, the “no product” option was discounted the most heavily, indicating that most subjects preferred to have any one of the included products over the

option of having no product. The largest effect for the full information set was due to the product characteristic of pineapple (versus pomegranate); this indicates that even when subjects were given additional information on the pomegranate products to decrease the novelty of the good, the more familiar pineapple product was still preferred. However, the difference in the pomegranate versus pineapple products was not as large as in the baseline round, and thus to relative degree to which the more familiar pineapple product was preferred over the novel pomegranate products was decreased.

Table 39 includes the estimations for both the fully-ranked and partially-ranked models. The parameter estimates are different across treatments, with generally more variance in the partially-ranked model. In the partially-ranked model, the parameter for the "no product" option was not significant for the baseline round, nor were the Texas varieties. Although the rankings are all on a relative scale, the magnitude of the parameter estimates does indicate a relative degree of preference among product characteristics. The largest preference in the baseline round for the partial rankings is clearly for the pineapple. Therefore, in comparison to the fully-ranked model, it was clear that the partially ranked-model has more predictive ability for the products that were most frequently ranked at the top of the rankings and less predictive ability for the products that were more commonly at the bottom of the rankings.

The differences in the parameter estimates could be interpreted in two ways, depending on whether it is believed that individuals are less able to accurately rank the less-preferred products or, alternatively, it is assumed that individuals devote equal amounts of attention to ranking all products from the least preferred to the most

preferred. The former situation would be interpreted as heterogeneity in an individual's ability to rank the products, while the latter assumes that the rankings are done homogeneously across all preference levels by all respondents.

Mixed Rank-Ordered Logit Model

Combining the mixed logit and rank-ordered logit framework provides the following results. The preference data were exploded as described by Rabe-Hesketh, Pickles, and Skrondal (2001) and Rabe-Hesketh and Skrondal (2005) and the mixed rank-ordered logit model was then estimated using the –mixlogit– command in STATA/ IC 11.0 © developed by Hole (2007). A series of different specifications are provided for comparison of these models. A model similar to the first rank-ordered logit model was first estimated. As seen in Table 40, such a model provides estimated parameters and standard errors for those parameters, but it also provides estimated standard deviations and standard errors for the standard deviations. This is because the model allows each individual to have their own slope for each parameter in the model. Thus, if the standard deviation is significant then we would expect that there are differences in each variable that depend on each individual. More precisely, the standard deviations of the β parameters accommodate the presence of preference heterogeneity in the sample (Hensher and Greene 2003).

Table 40. Mixed Rank-Ordered Logit Models for Preference Rankings, Estimated Coefficients and Standard Deviations of Coefficients

	Preference Rankings, Fully Ranked (1-8)									
	No Interactions[b]		Tasting Information Interactions[b]		Health and Nutrition Information Interactions[b]		Anti-Cancer Information Interactions[b]		Full Information Interactions[c]	
	Parameter[a]	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
Variety										
1: Texas Red	0.369***	(0.058)	0.281***	(0.066)	0.379***	(0.067)	0.337***	(0.067)	0.071	(0.114)
Std. Deviation	0.062	(0.068)	0.058	(0.082)	0.055	(0.077)	0.042	(0.076)	0.037	(0.099)
2: Texas Salavatski	0.286***	(0.046)	0.259***	(0.053)	0.318***	(0.053)	0.257***	(0.053)	0.195**	(0.088)
Std. Deviation	0.059	(0.131)	0.171*	(0.095)	0.163*	(0.099)	0.205**	(0.083)	0.060	(0.090)
Product Form										
Ready-To-Eat (RTE)	0.704***	(0.096)	0.828***	(0.094)	0.715***	(0.092)	0.675***	(0.101)	0.959***	(0.132)
Std. Deviation	1.748***	(0.088)	1.567***	(0.084)	1.625***	(0.092)	1.625***	(0.126)	1.500***	(0.112)
Juice	0.542***	(0.160)	0.695***	(0.124)	0.571***	(0.126)	0.289**	(0.127)	1.536***	(0.216)
Std. Deviation	2.900***	(0.201)	3.121***	(0.163)	3.100***	(0.180)	3.002***	(0.167)	3.320***	(0.235)
Pineapple	2.921***	(0.189)	3.026***	(0.182)	2.919***	(0.171)	3.166***	(0.172)	4.286***	(0.403)
Std. Deviation	4.499***	(0.206)	3.630***	(0.153)	3.606***	(0.165)	3.614***	(0.171)	4.062***	(0.266)
No Product	-1.739***	(0.209)	-1.198***	(0.168)	-1.451***	(0.165)	-1.471***	(0.162)	-0.527*	(0.304)
Std. Deviation	5.250***	(0.320)	4.844***	(0.218)	4.822***	(0.223)	4.838***	(0.226)	5.795***	(0.516)
Information Treatment Interactions										
Info Trt. x Variety 1: Texas Red			0.461***	(0.138)	-0.039	(0.133)	0.127	(0.134)	0.583***	(0.165)
Std. Deviation			0.164	(0.118)	0.088	(0.114)	0.083	(0.110)	0.061	(0.115)
Info Trt. x Variety 2: Texas Salavatski			0.169	(0.107)	-0.085	(0.104)	0.143	(0.104)	0.262**	(0.129)
Std. Deviation			0.054	(0.096)	0.038	(0.086)	0.093	(0.085)	0.215*	(0.118)
Info Trt. x Ready-To-Eat (RTE)			-0.403***	(0.114)	0.023	(0.116)	0.271**	(0.117)	-0.353**	(0.146)
Std. Deviation			0.182	(0.115)	0.081	(0.114)	0.256**	(0.119)	0.004	(0.148)
Info Trt. x Juice			-0.945***	(0.175)	-0.482***	(0.174)	0.587***	(0.171)	-2.080***	(0.241)
Std. Deviation			0.507***	(0.160)	0.334	(0.207)	0.057	(0.188)	0.837***	(0.213)
Info Trt. x Pineapple			0.096	(0.196)	0.237	(0.191)	-0.648***	(0.191)	-0.746***	(0.264)
Std. Deviation			0.393**	(0.200)	0.091	(0.258)	0.079	(0.213)	0.510**	(0.223)
Info Trt. x No Product			-1.025***	(0.216)	-0.044	(0.204)	0.062	(0.202)	-2.353***	(0.305)
Std. Deviation			0.159	(0.213)	0.051	(0.196)	0.250	(0.187)	0.690*	(0.415)
Log Likelihood	-5845.995		-5847.638		-5894.849		-5877.829		-3090.089[c]	

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

[b] The models for the baseline, tasting, health and nutrition, and anti-cancer information treatments are based on the observations for all four rounds of preference rankings.

[c] The model for the full information is based on only observations in the first and last rounds of preference rankings.

Thus, in the first model which includes no interactions, all included product characteristics are significant predictors of preference rankings ($P < 0.001$). However, the comparison of the two Texas varieties and their standard deviations indicates that in this model there is not a significant individual component to the prediction and these were generally uniform across the population when differences in individual characteristics for the other product characteristics were controlled.

These models were also estimated to include interaction effects of each information treatment with each product characteristic. These estimations should indicate whether receiving the additional information had an individual interaction with the product characteristics. It would not be expected that all individuals would have the same response to all product characteristics since it was possible that they would enjoy the taste of one product and dislike the taste of another product. This could similarly hold for the other information treatments. In comparing the models for each of the three additional information treatments, the product forms and varieties were all still significant ($P <0.001$) predictors of the preference rankings.

However, these models suggest that the presence of individual-level interaction terms varied from one type of information treatment to the next. The tasting information treatment had a positive significant effect on the Texas Red variety but a negative effect on the RTE and juice product forms. For the juice this information interaction was also significant on the individual level. This was not entirely surprising as the RTE form is in comparison to the baseline of the whole fruit product, so the tasting information reduced the premium for the RTE product in comparison to the whole fruit product. Since

participants were also told how to remove the husk from the whole fruit product, this is not an unreasonable result. There was not a significant interaction effect of tasting information on the pineapple product, which was expected since most participants were expected to be familiar with pineapple.

For the health information, the effects were generally not a result of an interaction of product characteristics with the information other than for the juice product. Additionally, none of the interactions terms had a significant effect at the individual level. For the anti-cancer information, there were effects for all of the product forms and varieties, and all of these varied significantly with the individual except for the Texas Red variety. There were interaction effects between the anti-cancer information and RTE, juice, and pineapple product forms, but only the RTE form had significant preference heterogeneity for the interaction term.

The final model presented in Table 40 was a comparison of the baseline information treatment and the full information treatment. This model generally predicts more individual variation in preferences and greater effects from the interaction of the product characteristics and having the full information set. Although only the Texas Salavatski variety was important alone, both Texas pomegranate varieties were important when the interaction of those varieties and the full information was considered.

Changes in Rankings

The rankings that were submitted by subjects following each information treatment offer an opportunity to quantify effects of the information treatments. Although comparisons of aggregated rankings before and after an information treatment are useful, it is perhaps more instructive to compare the change that each individual has in his or her preference rankings for the product, and then to compare those changes. For example, large changes in preference by one individual may be lost in the overall comparisons if they are offset by equally large changes in the opposite direction by another individual. Thus, the changes for each product across each information treatment are included in the subsequent pages.

First, in looking at Table 41, the effects of the tasting information treatment on the relative preference rankings, more of the participants showed an improvement in the ranking for the two Texas varieties of whole pomegranate fruits than the California variety of pomegranate fruit. This could have been a result of less familiarity with the Texas varieties prior to the tasting actual differences in the tastes of the three whole fruit products. On the other hand, the changes in rankings for the ready-to-eat products were very similar for the RTE California arils and the RTE Texas arils. Of all the products, the mixed pomegranate juice had the most participants who ranked it worse following the tasting round. Confirmation of the hypothesis that participants would be more familiar with the pineapple product is seen in the much higher proportion of participants whose ranking stayed the same relative to the other products. The means and standard deviations for the ranking changes are provided here, but the standard deviation is large

for all products included and therefore the median change is also provided. In comparing the medians, the only product that showed a change in the product ranking is the Texas Red Pomegranate Fruit which improved by one rank.

Table 41. Changes in Explicit Preference Rankings by Product (Tasting Information Rank – Baseline Rank)

	California Wonderful Pomegranate Fruit	Texas Red Pomegranate Fruit	Texas Salavatski Pomegranate Fruit	Ready-to-Eat California Pomegranate Arils	Ready-to Eat Texas Pomegranate Arils	Mixed Pomegranate Juice	Pineapple	No Product
Ranking improved (lower ranking number)	69	114	92	61	65	34	38	13
%	36.70%	60.64%	48.94%	32.45%	34.57%	18.09%	20.21%	6.91%
Ranking worsened (higher ranking number)	66	30	46	69	66	86	35	57
%	35.11%	15.96%	24.47%	36.70%	35.11%	45.74%	18.62%	30.32%
Ranking the same	53	52	54	63	62	76	122	126
%	28.19%	27.66%	28.72%	33.51%	32.98%	40.43%	64.89%	67.02%
Mean	-0.2340	-1.1915	-0.6543	0.1223	-0.0479	1.1011	0.0053	0.8883
Std. Error	2.2225	1.9029	1.8651	1.9184	1.8217	2.5845	1.6851	2.2116
Interpretation	improved	improved	improved	worsened	improved	worsened	worsened	worsened
Median	0	-1	0	0	0	0	0	0
Interpretation	no change	improved	no change	no change	no change	no change	no change	no change

The next information treatment interactions to be addressed are for the health and nutrition information treatment; these results are in Table 42. The changes in the ranking across this information indicate fewer improved rankings and more rankings that stayed the same as the baseline for the three whole pomegranate fruit products. This was

also the case for the ready-to-eat aril products. More individuals worsened their ranking for the mixed pomegranate juice than either improved or maintained their ranking. Again in this information treatment the standard errors of the sample is larger than the mean, but regardless of which product is considered, the median value indicates no change in preference ranking for any product.

Table 42. Changes in Explicit Preference Rankings by Product (Health and Nutrition Information Rank − Baseline Rank)

	California Wonderful Pomegranate Fruit	Texas Red Pomegranate Fruit	Texas Salavatski Pomegranate Fruit	Ready-to-Eat California Pomegranate Arils	Ready-to Eat Texas Pomegranate Arils	Mixed Pomegranate Juice	Pineapple	No Product
Ranking improved (lower ranking number)	57	76	60	51	63	28	39	18
%	30.32%	40.43%	31.91%	27.13%	33.51%	14.89%	20.74%	9.57%
Ranking worsened (higher ranking number)	50	29	38	47	45	88	28	45
%	26.60%	15.43%	20.21%	25.00%	23.94%	46.81%	14.89%	23.94%
Ranking the same	81	52	54	63	62	76	122	126
%	43.09%	27.66%	28.72%	33.51%	32.98%	40.43%	64.89%	67.02%
Mean	-0.2074	-0.6915	-0.2872	-0.1170	-0.2181	0.9894	0.0532	0.4947
Std. Error	1.8743	1.6156	1.5417	1.6045	1.6644	2.1693	1.7934	2.0040
Interpretation	improved	improved	improved	improved	improved	worsened	worsened	worsened
Median	0	0	0	0	0	0	0	0
Interpretation	no change	no change	no change	no change	no change	no change	no change	no change

The anti-cancer information treatment results are included in Table 43. The results for the whole pomegranate fruits are very similar to those for the health and

nutrition information in terms of proportions that improved, worsened, or maintained their ranking. There was less change (more rankings that stayed the same) for the Texas ready-to-eat pomegranate arils than for the two previously discussed treatments, and the number of participants that worsened their relative ranking for the Texas RTE pomegranate arils was less than for the tasting treatment in particular.

Table 43. Changes in Explicit Preference Rankings by Product (Anti-Cancer Information Rank − Baseline Rank)

	California Wonderful Pomegranate Fruit	Texas Red Pomegranate Fruit	Texas Salavatski Pomegranate Fruit	Ready-to-Eat California Pomegranate Arils	Ready-to Eat Texas Pomegranate Arils	Mixed Pomegranate Juice	Pineapple	No Product
Ranking improved (lower ranking number)	56	78	68	54	60	41	16	10
%	29.79%	41.49%	36.17%	28.72%	31.91%	21.81%	8.51%	5.32%
Ranking worsened (higher ranking number)	52	28	39	47	33	49	43	48
%	27.66%	14.89%	20.74%	25.00%	17.55%	26.06%	22.87%	25.53%
Ranking the same	80	52	54	63	62	76	122	126
%	42.55%	27.66%	28.72%	33.51%	32.98%	40.43%	64.89%	67.02%
Mean	-0.0266	-0.6702	-0.2872	-0.0904	-0.3617	0.4255	0.4734	0.6170
Std. Error	1.7411	1.7049	1.5996	1.5878	1.5433	2.2083	1.8426	2.0271
Interpretation	worsened	improved	improved	improved	improved	worsened	worsened	worsened
Median	0	0	0	0	0	0	0	0
Interpretation	no change	no change	no change	no change	no change	no change	no change	no change

The percentage of rankings that decreased was less for the mixed pomegranate juice than for the Tasting Information and Health and Nutrition Information treatments.

This could possibly be attributed to differences in what types of prior information subjects had for the product. Finally, for the control product (pineapple), the anti-cancer information was provided only for pomegranate products. This was done in order to simulate an advertising campaign or news report that focused on the positive health attributes of one type of product while giving no mention (neither positive nor negative) of substitute products. This suggests that additional information on the anti-cancer attributes of pomegranates improved the preference ranking for many subjects relative to a substitute product. However, as previously, the median indicates no change in preference ranking for any product.

The full information set relative to the baseline information interactions are provided in Table 44. Here more participants improved their preference ranking for the two Texas varieties of whole pomegranate fruits relative to the California pomegranate fruit. Two things should be re-emphasized here: 1) the full information set designation refers to whichever round of information was the last information presented (alternatively, the ranking reported by subjects when they had received all three information treatments) and 2) that the study sample was not intended to give results that would reflect the same opinions across the United States, as it is possible that the opposite result would be true in other states.

There was less improvement and more worsening for both of the ready-to-eat products relative to the Texas whole fruit products with the full information set. Mixed pomegranate juice showed the most worsening of relative preference rankings. There were more rankings that did not change from the baseline round for two products

relative to the rest of the products: pineapple and no product. It is instructive to look at the sum effect of all the information treatments that participants are exposed to in order to get a better gauge of what their response to gaining several types of information on a single product might be. The only products with a median that showed any change in ranking is the Texas Red pomegranate fruit with an improvement and the mixed pomegranate juice with a worsening in rank.

Table 44. Changes in Explicit Preference Rankings by Product (Full Information Rank – Baseline Rank)

	California Wonderful Pomegranate Fruit	Texas Red Pomegranate Fruit	Texas Salavatski Pomegranate Fruit	Ready-to-Eat California Pomegranate Arils	Ready-to Eat Texas Pomegranate Arils	Mixed Pomegranate Juice	Pineapple	No Product
Ranking improved (lower ranking number)	68	105	91	66	77	31	40	18
%	36.17%	55.85%	48.40%	35.11%	40.96%	16.49%	21.28%	9.57%
Ranking worsened (higher ranking	69	30	40	60	56	96	33	57
%	36.70%	15.96%	21.28%	31.91%	29.79%	51.06%	17.55%	30.32%
Ranking the same	51	52	54	63	62	76	122	126
%	27.13%	27.66%	28.72%	33.51%	32.98%	40.43%	64.89%	67.02%
Mean	-0.2021	-1.0213	-0.6011	-0.0851	-0.2234	1.3191	0.0638	0.7394
Std. Error	2.2088	1.7458	1.8107	1.8682	1.7802	2.4019	1.8575	2.2111
Interpretation	improved	improved	improved	improved	improved	worsened	worsened	worsened
Median	0	-1	0	0	0	1	0	0
Interpretation	no change	improved	no change	no change	no change	worsened	no change	no change

Comparison of Bidding and Ranking Results

Subjects expressed their preferences for the fruit products in two distinct yet conceptually-related ways. Did these two methods of preference elicitation yield compatible results, and if not, which method is preferred? It was expected that the two methods would produce similar, yet not identical results due to inconsistencies or human error in decision processes, failure to remember previous responses, and so on. Even so, a rational decisionmaker would be predicted to submit rankings and bids that expressed the same order of preferences.

However, results on the convergence of the two methods for preference elicitation were mixed. There were a total of 142 individuals expressing at least one preference reversal. Preference reversals have been previously discussed by Tversky and Thaler (1990). For this description, preference reversals are defined as a difference between rankings and ordered bids for the same round. This suggests that the preferences expressed in the rankings indicate different preferences than the preferences expressed by the same subjects' actual bids. The term preference reversal will specifically exclude changes in rankings or biddings across rounds, as it is expected that those could occur due to preference updating based on the additional information that subjects received across rounds. The numbers of individuals with at least one preference reversal among the product alternatives within any single round are listed in Table 45.

Table 45. Count of Individuals per Round with at Least One Preference Reversal between Explicit Rankings and Implied Ordered Bids

	Baseline	Tasting Information	Health and Nutrition Information	Anti-Cancer Information	Full Information
Individuals with at least one reversal	142 [(a)]	141	132	133	137

[(a)] Preference reversals are defined here as instances when an individual ranked the goods in an order for the preference ranking portion of the experiment which differed from the ranking implied by his or her ordered bids.

There are several possible reasons for the high incidence of preference reversals between the rankings and ordered bids. There were several product options, so there was greater complexity in the decision-making process than there would have been for fewer products. Also, the "no product" option which has been commonly used in the literature for rankings may not have cognitively equated with bids of $0.00 for subjects. Another hypothesized reason for the preference reversals is that the products in question were novel products. If subjects were unfamiliar with the products, they may have been less able to consistently rank and bid on products. However, the degree of differences is surprising since subjects did not have to submit bids and rankings at different times. All subjects ranked the products and submitted bids on those products at the same time, and had the opportunity to check that all their implied ordered bid rankings and their actual preference rankings were the same. While there has been extensive review in the literature of similarities and differences among discrete choice rankings and bids submitted in experimental auctions, the presence of so many preference reversals suggests that at least in this case, the two methods of preference elicitation do not

provide identical results. This hypothesis was further tested by estimating the ordered bid rankings models using the two Texas product varieties, the form of the product (RTE arils or juice), and the type of product (pomegranate, pineapple, or no product); these were the same product characteristics used in the previous estimation of the preference rankings models. These results were given in Table 39.

There were two models estimated for the ordered bids following the estimation of a fully-ranked and partially-ranked model for the rankings data. The estimates for the ordered bids are included in Table 46.

Table 46. Rank-Ordered Logit Models for Implied Preference Rankings Using Ordered Bids for Fruit Products, by Information Treatment, Fully-Ranked and Partially-Ranked Models

	Information Treatment									
	Baseline		Tasting		Health and Nutrition		Anti-Cancer		Full	
	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
	Ordered Bids, Fully Ranked (1-8)									
Variety										
1: Texas Red	-0.112	0.137	0.169	0.130	0.032	0.132	0.087	0.135	0.210	0.131
2: Texas Salavatski	0.024	0.099	0.175*	0.097	0.106	0.098	0.129	0.099	0.129	0.098
Product Form										
Ready-To-Eat (RTE)	0.739***	0.105	0.424***	0.098	0.538***	0.101	0.741***	0.103	0.460***	0.100
Juice	1.323***	0.138	0.496***	0.130	0.632***	0.133	1.028***	0.136	0.409***	0.132
Pineapple	1.997***	0.144	1.566***	0.136	1.766***	0.141	1.544***	0.138	1.776***	0.140
No Product	-1.342***	0.151	-1.515***	0.152	-1.452***	0.151	-1.309***	0.149	-1.466***	0.149
	Ordered Bids, Partially Ranked (1-4)									
Variety										
1: Texas Red	-0.153	0.174	0.261*	0.150	0.094	0.156	0.217	0.162	0.244	0.149
2: Texas Salavatski	0.036	0.112	0.241**	0.108	0.098	0.109	0.157	0.111	0.170	0.108
Product Form										
Ready-To-Eat (RTE)	0.906***	0.117	0.582***	0.109	0.692***	0.111	0.913***	0.115	0.567***	0.110
Juice	1.597***	0.150	0.799***	0.143	0.848***	0.145	1.351***	0.150	0.699***	0.145
Pineapple	2.298***	0.156	1.929***	0.148	2.021***	0.151	1.876***	0.151	2.019***	0.150
No Product	-0.823***	0.194	-1.123***	0.198	-1.057***	0.197	-0.912***	0.198	-1.102***	0.193

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

For the fully ranked ordered bids, the magnitude of the estimated parameters for the rank-ordered logit model differs from that of the estimated parameters for the rankings model. However, for the baseline information round, in both models there was no preference effect for either Texas variety. In order of increasing preference, there were positive effects for RTE, juice, and pineapple. In both cases there was a negative effect for the no product option. In the tasting round, the implied rankings from the ordered bids indicate a tendency for a preference for the Texas Salavatski variety ($P < 0.10$); the Texas Red variety was preferred by the explicit rankings (Table 39) over either Texas Salavatski or California Wonderful. Not only is this a difference in magnitude of the parameters, this difference would lead to opposite conclusions in selecting one variety or the other. This is a cause for concern in marketing research in terms of which product is the one that is *actually* preferred and would be purchased by consumers. The preferences for the remaining product characteristics are similar for RTE, pineapple, and no product, but there was no significant effect in the preference ranking for the juice while there was a preference for juice over the whole fruit products. In fact, other than the product fruit cultivars, the ordered bids indicated increasing preference, in order, for RTE, juice, and pineapple, with a discounted preference for no product for the baseline and all information treatment rounds. In contrast, when subjects had full information the RTE product was preferred to juice for the full ranked implied rankings. For the Texas varieties, there was a trend towards a preference for the Texas Red variety over the Texas Salavatski variety. This result is similar to the estimates of the rank-ordered logit model for the explicit preference rankings; however, in this case

the result is a change from tasting round of the experimental auction bidding. It would be unusual but not impossible for the implied preference to vary from the tasting round to the full information set, since subjects had already tasted the product for the full information round.

Again, although the values of the estimated parameters are not identical for the partially-ranked implied rankings, there was a slight preference for the Texas Salavatski variety. Overall a comparison of the implied preferences from the baseline round to the full information set showed an increase in the relative discount for option of no product along with less strong preferences for RTE, juice, and pineapple. This was most noticeable for the juice, where the decrease in relative preference was approximately 1.5 times less in the full information set.

Comparing the fully ranked ordered bid model to the partially-ranked model reveals several patterns and trends. The relative size of the effects is generally larger for the product characteristics in the partially ranked model. However, as pointed out in the comparison of the explicit ranking decisions, the size of the discount for no product is much less than that in the fully ranked model. Based on the distributions of the preference rankings, this result is not unexpected. With the majority of the “no product” options ranked as the lowest rank, discarding the four lowest ranks was almost guaranteed to underestimate the parameters for the no product option and any other product that was consistently among the lowest ranked products; in discarding the lowest ranks, relevant information on some of the products is discarded. Calfee, Winston, and Stempski (2001) state that if subjects have paid less attention to the lower ranked

products, noise will be introduced into the data and give inconsistent estimates if a fully ranked model is used. However, the results here suggest that this is not the only reason that there may be differences in results from the two types of models, and products that are consistently in the lower portion of the rankings may be incorrectly discarded using partially ranked models. In this case, the fully ranked model should provide greater insight into the rankings for *all* products, not just those that are consistently preferred.

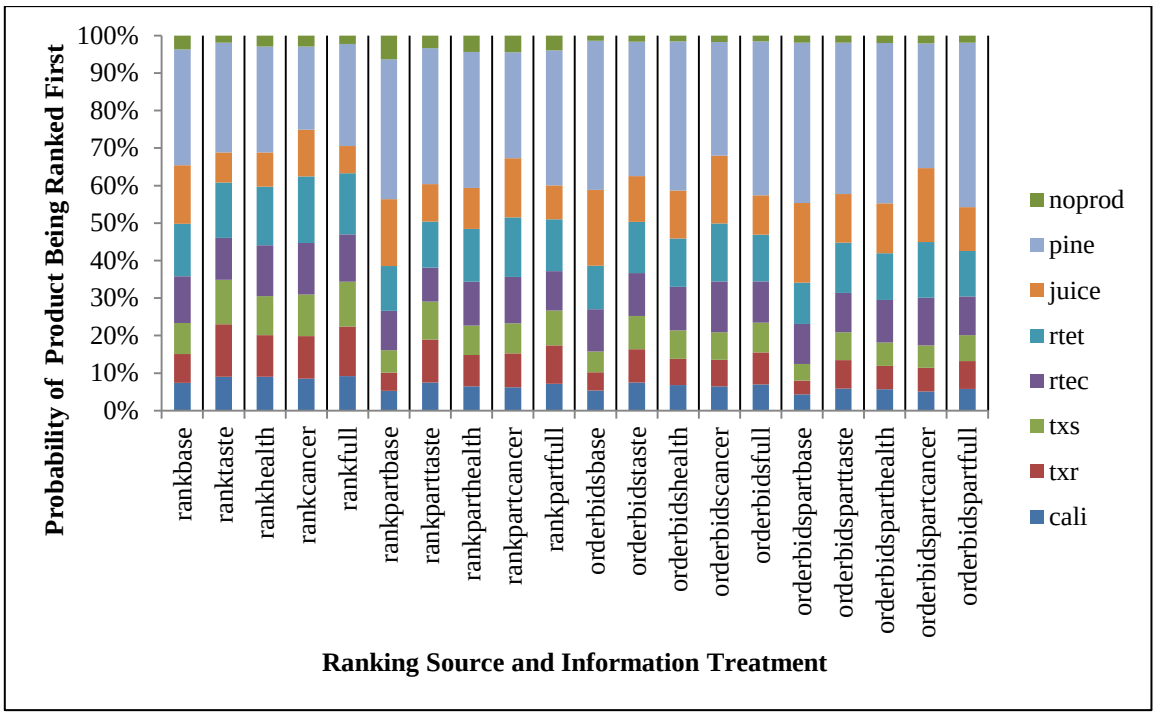

Figure 23. Probability of a Particular Fruit Product Being Ranked Most Preferred Based on Rank-Ordered Logit Model Estimates.
Note: The probability of a product being ranked first was calculated based on the rank-ordered logit models for 5 information treatments (baseline, tasting information, health and nutrition information, anti-cancer information, and full information) for each of 4 selections of rankings data (fully-ranked preference rankings, partially-ranked preference rankings, fully-ranked ordered bids, and partially-ranked ordered bids)

The rank-ordered logit model can also be used to predict the probabilities that a particular product will be ranked first based on the product characteristics. These probabilities are graphed in Figure 23, and the values of each probability are included in Appendix I.

The general trends in these probabilities is that the probability of the California Wonderful whole fruits was consistent across information treatments, while for the Texas varieties of whole pomegranate fruits there was the greatest likelihood of being ranked first in the tasting information treatment. For the baseline rounds the likelihood of any of the fresh pomegranate products being ranked first was the lowest of all the information levels. Also, there is a general increase in the probability of the mixed pomegranate juice being ranked first in the anti-cancer information round. Thus, it is useful to consider the multiple ways in which a product may be novel to a consumer. A product may be novel in terms of its taste characteristics, its nutritional value, the production practices that are used, and a number of other categories. Thus, these differences indicate the potential for differences in the novelty of products in regards to the information that was presented. Most consumers were expected to be unfamiliar with the taste of the Texas varieties of pomegranates. Relative to the novelty of the taste of the juice product, consumers may have been more unfamiliar with the health benefits of the juice product. This could have led to differences in changes that were seen across information treatments. For the fresh fruit products, there was very little difference between the results for anti-cancer information and for health and nutrition information.

Table 47. Mixed Rank-Ordered Logit Models for Ordered Bids, Estimated Coefficients and Standard Deviations of Coefficients

	Ordered Bids, Fully Ranked (1-8)									
	No Interactions[b]		Tasting Information Interactions[b]		Health and Nutrition Information Interactions[b]		Anti-Cancer Information Interactions[b]		Full Information Interactions[c]	
	Parameter[a]	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
Variety										
1: Texas Red	-0.136	(0.123)	-0.246	(0.150)	-0.059	(0.148)	-0.206	(0.152)	-0.508*	(0.271)
Std. Deviation	0.156	(0.148)	0.207	(0.165)	0.289*	(0.174)	0.610***	(0.179)	0.831***	(0.245)
2: Texas Salavatski	-0.024	(0.096)	-0.126	(0.116)	-0.027	(0.111)	-0.057	(0.119)	-0.146	(0.189)
Std. Deviation	0.096	(0.130)	0.525***	(0.127)	0.329***	(0.110)	0.364**	(0.182)	0.454***	(0.170)
Product Form										
Ready-To-Eat (RTE)	0.963***	(0.147)	0.500***	(0.171)	0.134	(0.162)	0.692***	(0.174)	0.970***	(0.262)
Std. Deviation	2.239***	(0.155)	2.563***	(0.285)	2.272***	(0.164)	1.773***	(0.146)	1.878***	(0.219)
Juice	2.771***	(0.194)	1.325***	(0.341)	1.425***	(0.254)	2.902***	(0.242)	4.144***	(0.478)
Std. Deviation	3.485***	(0.202)	5.669***	(0.453)	5.596***	(0.373)	4.396***	(0.276)	6.738***	(0.684)
Pineapple	3.758***	(0.266)	5.820***	(0.390)	5.799***	(0.346)	5.435***	(0.343)	7.701***	(0.809)
Std. Deviation	6.061***	(0.354)	5.526***	(0.350)	5.339***	(0.323)	6.630***	(0.425)	8.618***	(0.930)
No Product	-1.129***	(0.206)	-3.609***	(0.419)	-2.755***	(0.356)	-4.875***	(0.469)	-3.007***	(0.526)
Std. Deviation	4.867***	(0.330)	4.673***	(0.315)	5.227***	(0.351)	7.123***	(0.595)	7.429***	(0.958)
Information Treatment Interactions										
Info Trt. x Variety 1: Texas Red			0.463	(0.285)	0.059	(0.287)	-0.058	(0.295)	0.656*	(0.366)
Std. Deviation			0.440	(0.365)	0.024	(0.290)	0.105	(0.266)	0.268	(0.295)
Info Trt. x Variety 2: Texas Salavatski			0.200	(0.213)	-0.001	(0.216)	-0.032	(0.217)	0.275	(0.268)
Std. Deviation			0.182	(0.186)	0.072	(0.219)	0.416**	(0.205)	0.287	(0.223)
Info Trt. x Ready-To-Eat (RTE)			-0.237	(0.252)	-0.089	(0.262)	0.024	(0.255)	-0.497	(0.371)
Std. Deviation			0.272	(0.213)	0.392*	(0.237)	0.087	(0.237)	1.432***	(0.415)
Info Trt. x Juice			-1.247***	(0.353)	0.055	(0.343)	0.312	(0.333)	-1.300***	(0.495)
Std. Deviation			1.648***	(0.369)	0.276	(0.381)	0.044	(0.336)	2.192***	(0.342)
Info Trt. x Pineapple			-0.260	(0.379)	0.476	(0.387)	-0.470	(0.369)	0.487	(0.573)
Std. Deviation			1.500***	(0.462)	0.956**	(0.376)	0.971**	(0.387)	2.982***	(0.512)
Info Trt. x No Product			-0.618*	(0.348)	0.326	(0.350)	0.079	(0.352)	-0.001	(0.480)
Std. Deviation			0.438	(0.330)	0.151	(0.322)	0.422	(0.346)	0.634*	(0.360)
Log Likelihood	-1957.470		-1859.692		-1873.132		-1868.864		-1072.361[c]	

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

[b] The models for the baseline, tasting, health and nutrition, and anti-cancer information treatments are based on the observations for each of the four rounds of preference rankings.

[c] The model for the full information is based on only observations in the first and last rounds of preference rankings.

Also, the fully-ranked preference rankings generally indicated the greatest probability that the fresh pomegranate fruit products would be ranked first, while the

partially-ranked explicit preference rankings were closer to the predictions of the estimations based on implied rankings. In all cases, the whole pomegranate fruits were more likely to be ranked first given the full information set than for the baseline round. This was not always true for the RTE pomegranate products. The likelihood of the juice product being ranked first is lower in all cases from the baseline to the full information.

The rank-ordered bid models have been discussed thus far, and the focus now shifts to the rank-ordered mixed logit models for the ordered bids. The results for the implied preference rankings (ordered bids) are given in Table 47; the preference rankings models were shown previously in Table 40.

The results of the application of the mixed rank-ordered logit model to the ordered bids provide somewhat similar results to the explicit preference rankings models. The trend is for significance of both the coefficient and the individual preference heterogeneity for the product form attributes. For the interaction effects, in the tasting information model there were interactions and preference heterogeneity for the interaction of juice and tasting information, and the juice was less preferred as a result of the tasting information. For the health and nutrition information and anti-cancer information rounds, the interaction terms did not have predictive ability but they led to an interesting contrast with the model in which only the baseline and full information rounds were included, and interaction effects between those two were compared.

When the full information set was compared to the baseline by using interaction effects of the information treatment and the product characteristics, there was trend for a penalty on the Texas Red variety but a trend for an individual specific interaction effect

with the full information in which the Texas Red variety was more preferred. Participants indicated a decreased preference for the juice product when they had received the full information set. The signs on the product form characteristics with no interaction terms were as expected: preferences for RTE, juice, and pineapple with a negative preference for the no product option. One note of caution is needed in comparing these results to the rank-ordered logit models estimated previously. The rank-ordered logit model is equipped to handle ties in the rankings; however, in the process that was followed for "exploding" the data, ties imply that the same choice was made at the same time when in fact there were most likely equal probabilities that the subject would select either of the two options.

The choice of which method, discrete choice preference ranking or experimental auctions, is more relevant for use in preference elicitation is one for which economic theory does not provide a direct answer. Particularly since both methods were incentive compatible in nature, the bias that those differences in hypothetical versus nonhypothetical responses should be eliminated and subjects would be expected to provide more convergent answers. Olsen, Donaldson, and Shackley (2005) used a measure of "convergent validity" as a percentage of respondents who equally preferred different options over explicit and implied rankings.

For the pomegranate fruit products study, there were a few differences between the preference rankings and WTP elicitation to be considered in a comparison of the two results. One, although participants were informed that all of the products were currently marketed for the same price, it is possible that subjects either chose not to believe this or

knew of outside options and price levels which may have influenced their rankings of all of the products for the same price (the rankings) differently than it influenced their preferences for the products when they could specify their own maximum price (auctions). However, subjects did not actually pay the price they bid, and therefore rationality would still suggest that the products be ordered in the same way, regardless of which method was used. Secondly, although detailed explanations, quizzes, multiple practice rounds, and question and answer sessions took place, it is impossible to rule out the possibility that there were differences in the understandings of the two preference elicitation mechanisms that were used; this could have subsequently produced differences in the explicit and implied ordered results. For example, subjects may have different preferences when the product options have a single specified price than when those goods vary in price. However, the use of products with similar retail prices should have eliminated this possibility in this comparison of rankings and bids.

There were a number of similarities in the trends among information levels between the sets of ranking data that were used, and this robustness is reassuring in terms of drawing conclusions on the direction of the effects of the information treatments. However, the differences in the parameter estimates based on using partially- or fully-ranked models and implied or explicit rankings is a cause for concern in predicting the magnitude of these changes based on product characteristics. Further, the number of preference reversals between the ordered bids and the rankings, along with the differences in the estimated preference models, suggests that one of the two mechanisms may not be an accurate reflection of true consumer preference. Which of

these is more useful should depend on the context of the research question. If researchers are trying to determine the price that consumers would pay for a product in a retail setting, the experimental auction procedures may provide more relevant results, but if the question of interest is what type of product should even be offered for sale in a retail setting, then the preference ranking procedures may be more relevant. Therefore, caution in designing and implementing experiments is necessary to ensure that the question of interest can accurately be addressed with the results that are obtained. To obtain the full STATA coding for the estimates presented in this chapter, please refer to Appendix J.

CHAPTER VI

SUMMARY AND CONCLUSIONS

This study provided meaningful results on many levels. First, the information regarding pomegranates and the pomegranate industry can be used by those who are considering growing or marketing pomegranates. Second, the procedures for a combined nonhypothetical ranking and bidding preference elicitation mechanism developed and used here allow for other applications of the field of experimental economics. Third, the results of the econometric estimations provide insights into not only the econometric differences in the models but also the implications of the differences in product characteristics and information treatments. Each of these will be briefly summarized, and several key conclusions based on the summation of this information will also be presented. This discussion also leaves a number of research questions that could be the subject of additional research, and some of these are mentioned briefly.

Summary

Pomegranates and the Pomegranate Industry

Pomegranate (*Punica granatum* L.) typically grows best in warm, semiarid environments, with most scholars attributing its location of origin to the region in and around Iran. The large shrubs to small trees begin full production at an age of around 3 to 5 years, with an orchard lifespan of around 25 years. The pomegranate fruit are round

to oblate with a prominent calyx and with a color range of deep yellow to dark red, depending on the cultivar. The tough outer husk is filled with small juice sacs called arils that are separated into compartments within the fruit by septal membranes. Estimates of the nutritional value of pomegranates as well as the chemical composition of the different plant components have been made, but these characteristics have also been shown to vary considerably with cultivar and growing location.

Pomegranates contain a number of plant-specific compounds known as phytochemicals, and these are the compounds that give the fruits their unique flavor as well as their potential health implications. One group of phytochemicals, the polyphenols, is present in a number of forms including flavonoids, hydrolyzable tannins, and condensed tannins. These compounds are more concentrated in certain parts of the fruit and plant depending on the compound, with those that have antioxidant properties being the most commonly cited as having potential human health implications. Diseases that have been described to have a free radical method of action include general inflammation and aging, along with diseases that affect the brain, heart, kidney, liver, lungs, gastrointestinal tract, blood, eyes, skin, and muscles; antioxidants act to interfere with destructive pathways that free radicals are involved in. Although it has been difficult to establish causality links for these properties in humans, these properties have been tested extensively in laboratory settings with non-human subjects. Nevertheless, the diseases that pomegranates in particular have been linked to reducing based on either *in vitro* or in the laboratory include reductions in inflammation, cancer, and Alzheimer's disease symptoms. The effectiveness of pomegranate fruits as disease-

reducing mechanisms may also depend on the form of the fruit, as much research remains to be done on whether the benefits of pomegranates can be obtained from the individual chemical compounds or if greater benefits may be obtained by consuming the whole fruit. Reports of toxicity from pomegranate fruits are rare.

The functional food market in the United States alone had a value of $27 billion in 2007 with an anticipated growth rate of 10% per annum. This market has been targeted by both food manufacturers and pharmaceutical companies with products that are suggested to have additional health benefits beyond their basic nutritional value. Much research has been conducted regarding factors that may affect consumer purchases of these products; most results indicate differences based on the type of product, the credibility of the information source for information on the product, the taste of the products, and underlying consumer attitudes as important determinants of purchases.

Pomegranate production worldwide is led by Iran, followed by India and the United States; some reports place China third worldwide in production followed by the U.S. Within the United States, production is predominantly in the state of California, where 29,000 acres were estimated to be grown in 2009. The typical harvest period in the United States is October to January, depending on weather conditions and the particular cultivar.

Pomegranates can best be grown in deep, fairly heavy soils with irrigation and selecting a cultivar that is appropriate for the growing climate. Adequate attention should be given to soil preparation, planting design, pruning, fertilization, and disease, insect, and weed control. Harvest of pomegranate fruits is typically done by hand but

mechanical harvesters are beginning to be developed. Post-harvest, pomegranates may be stored for a typical range of four to five months; post-harvest issues to avoid include husk scaled and chilling injury. Ready-to-eat pomegranate arils have a much shorter shelf life, estimated at anywhere from ten to eighteen days using modified-atmosphere packaging.

USDA provides several estimates of the size of the pomegranate industry, including estimated movements within the U.S. for the 2009 season of over 14 million pounds, with a season average shipping point price of $24.54 per 22-lb. carton. However, these prices were generally higher at the beginning of the season and dropped as more pomegranate fruit became available; prices also varied based on fruit size, variety, and location. However, worldwide production is growing in order to meet the increased demand for pomegranate products and price trends that have been seen in recent years may be altered as prices adapt to these new levels of supply and demand for pomegranate fruits and other pomegranate products.

Nonhypothetical Preference Ranking and Experimental Auction Procedures

In this study, two common techniques in experimental economics were combined into one nonhypothetical procedure to provide paired comparisons of the information provided by participants. The participants in this study were asked to participate in repeated rounds of preference rankings and uniform nth-price modified Vickrey auctions for a baseline and three subsequent information treatments. There has been extensive discussion in the literature for WTP estimation and preference elicitation on what type of

methods provide the most accurate measures of preference. Despite this discussion, there is no overarching conclusion as to which methodology is the best; rather, there are a number of tools available to economists in the form of different types of experiments and these tools should be targeted at the particular question of interest. The application of these two basic methods of preference elicitation (ranking and bidding) for a set of products allows preferences to be gauged in two ways, and thus the results of these two methods compared. Given that participants were informed that all of the products sold at retail for the same price, the expectation would be that the two methods provide equivalent measures of preference.

In particular, the application of this combined ranking and bidding preference elicitation mechanism provided a useful means of gaining information on preferences for novel products and the effects of information treatments. For any good that is not currently available on the market, there will be a greater challenge in determining WTP for products; this is particularly true for those products that derive a large portion of their value from consumption of the item. To mimic the gain of information on a novel product, a baseline set of preferences and bids was collected on the assumption that the relative knowledge base on the products would vary across consumers. Seven products were included in the study: California Wonderful whole pomegranate fruit, Texas Red whole pomegranate fruit, Texas Salavatski pomegranate fruit, ready-to-eat California Wonderful pomegranate arils, ready-to-eat Texas Salavatski pomegranate arils, mixed pomegranate juice, and pineapple. Subjects were asked to submit bids on these seven products in the experimental auction portion of the study, and to also rank the seven

products and the option of no product on a scale of one to eight. The preference for the items was expected be individual-specific. Marketers of novel products must carefully consider what types of information they target at which types of consumers if they have the aim of increasing WTP for their products. Thus, a series of information treatments were implemented to make comparisons about three possible types of information that consumers might gain about the products of interest in this study. Those three information treatments were: 1) Tasting Information, 2) Health and Nutrition Information, and 3) Anti-Cancer Information.

Consumers who were unfamiliar with a pomegranate product were expected to experience some effect on their WTP for that product once they have tasted the product and/or learned how to prepare it to eat. It was also anticipated that consumers in Texas would be generally unfamiliar with the product prior to participation in the study. This was confirmed by the survey results on whether the products had previously been consumed or purchased. However, particularly given the recent interest in health benefits of food from a nutritional standpoint as well as in consideration of interest in functional foods, marketers often make claims regarding the nutrition and health benefits of novel food products. The question remained as to whether this information would have any effect on WTP or indicated preferences for pomegranate and other fruit products. To test this hypothesis, subjects were provided with the nutrition facts and a description of potential health benefits for each type of included product. Third, recent developments in terms of functional foods have indicated that some foods may have specific anti-cancer properties. These effects are very difficult to trace on an individual

basis, and making accurate scientific conclusions typically requires expensive and lengthy clinical trials. Thus, the relevance of such claims for these products and estimation of the effects of such information on WTP are relevant for those considering the time-consuming and expensive process of gathering this information and obtaining government approval to make these claims about products. Further, the use of several products allows for comparison of whether the effect of information treatments is the same for all products or whether it varies by product.

The bidding procedure and ranking procedures were designed to elicit these preferences for a novel product (as opposed to a familiar one) where individual valuation of the product may be influenced by later opportunities to learn more about the product characteristics. A full bidding technique was used, but each participant was informed that most of the study participants would purchase a product, based either on being a winning bidder or based on a weighted selection of his or her preference rankings. Thus, it was unlikely that participants would have an opportunity to purchase the product at a later time. By allowing the result of whether a product was purchased or not to depend on both the experimental auction bids and preference rankings, the two main components of the procedures were nonhypothetical in nature and participants would be expected to express their true preferences for the products in either portion of the study. A survey of consumer demographics and behavioral characteristics provided other variables for comparison to the preference rankings and experimental auction bids.

Analytical Procedures and Results Summary

The mechanism described above was utilized to obtain results based on behavioral and demographic characteristics reported by participants as well as make estimates of factors that influence WTP and preferences for the included products. A summary of these results follows.

Survey Procedures and Results

There are a few key demographics and behavioral characteristics of interest that were measured by the survey portion of the experiment. The average weekly household spending of participants was $109, and the average weekly household spending on fruits and vegetables was $25. The average participant had 6.37 pounds of fruits and vegetables on hand; this result was measured to determine if there was a potential effect from current stocks of similar products on the WTP for the products in the study. Subjects reported that on average 71% of their fruit and vegetable purchases were for fresh (not frozen, dried, or canned) fruits and vegetables. Study participants were asked about their relative position in their buying cycle in order to account for possible effects of whether they had just gone to the store to make purchases or whether they were about to go to make those purchases; it had been an average of 3 days since participants had last been to the store and they indicated an average length of time between trips to buy fruits and vegetables of 8 days.

To determine the relative novelty of the pomegranate products, participants were surveyed as to their previous experience with the products. Only 24.6% of participants

had previously purchased a pomegranate, and just 7.5% of study participants had a pomegranate fruit on hand. The portion of the subjects who had previously heard the term functional foods was small (16%), but the proportion who had purchased a functional food product when examples were provided was much larger (i.e. 85% for breakfast cereal for heart health). Taste, freshness, and price were all cited as being very important to subjects on an individual basis as factors in making fresh produce purchasing decisions. However, when asked about the factors that they expected most Americans to be concerned with, price and convenience became more important and nutrition and growing location became less important. This result would be expected since the factors that were more important when subjects were asked about their individual behaviors were also those factors that would be expected to have a positive social connotation ("social desirability bias"), while that bias should have been avoided when subjects were asked about the typical American.

Of course, caution should be used in extrapolating all of these results to the general population, as the study sample was recruited with the explicit purpose of being a study on fruit purchase decision-making. For example, if the individuals in the sample differed from the average American in a way that systematically affected the factors that influence fruit and vegetable purchasing decisions, then the result that the average of the included individuals and "average Americans" were predicted to be different would be expected. Nevertheless, the sample should serve the purpose of providing general trends and results for the relevant population.

However, the mean experimental auction bids for the included products ranged

from $0.84 to $1.99, all well below the retail price of $3.50 for all the included products. A portion of this result could be attributed to a lack of familiarity with the products, and perhaps more important than the absolute price levels are the relative differences in WTP for the products, as the retail price of the products is expected to vary with the season, geographic region, size of the individual products, and other factors.

Caution should also be exercised in extending any results for the products included in this study to products outside the study. Even so, it would be expected that some of the behavioral and demographic characteristics measured in this study may be useful for other products in predicting factors that influence buying behavior, particularly for a product that is less novel than pomegranate fruits.

Estimation Procedures and Results

Individual WTP for a product was censored at $0.00 when measured using this experimental auction, with 18% of all submitted bids being censored. To model these results, a number of approaches were considered. Individual models for each product and information treatment were first applied with a tobit model to account for the bid censoring. Using the separate tobit models, demographic and behavioral characteristics were as a whole poor predictors of WTP for the included pomegranate and other fruit products, with the exception of whether pomegranates had previously been purchased. For some products there were other factors that were predicted to influence WTP, including household size, income use, and tobacco use. Also, whether participants were given a reference price (current retail price) for the product was generally significant.

The bids were then pooled across individuals, information treatments, and products to suggest characteristics of the products that might influence WTP. The following models were considered: ordinary least squares, standard tobit, random effects tobit, and mixed linear. Each of these models was found to have benefits and drawbacks. These models were each considered with several independent variable specifications, including models with only the product characteristics, the product characteristics along with information treatments, and both of the previous coupled with the demographic and behavioral characteristics. While the results varied depending on the specific model used for estimation and the variables that were included, the product characteristics of ready-to-eat product form, juice product form, and pineapple product often increased WTP for the products; the distinction between the California Wonderful, Texas Red, and Texas Salavatski varieties was often not significant for the estimations based on the full bids. Also, the random effects tobit model predicted a significant presence of a random effect due to the individual, and the mixed linear model also predicted an effect for each individual. The ordinary least square model and standard tobit model were thus rejected as models for the experimental auction bids in this study; however, both models were still included as a baseline comparison.

Although the censoring and individual effects were discussed in the model results, there were several other effects of importance. First, there were a number of bidders who were found to be either unengaged as individuals or unengaged for a particular product. The models were re-estimated excluding the unengaged bidders; excluding unengaged bidders changed the parameter estimates and resulted in a

prediction that the Texas Salavatski variety positively affected WTP. Second, while comparisons using full bids across individuals are useful in predicting relative WTP for products, they do not account for differences in product substitutes, and thus the bids were reanalyzed by comparing the implied bid differences from one information treatment to the next; in this way the outside substitutes for a product and individual should cancel out. In this case it is particularly important to exclude any bids that were unengaged (that is, where an individual submitted a bid of zero in the treatment round and the baseline round for a product). The results from these models suggest that over the information treatments the change in WTP for the two Texas varieties increased but the change in WTP for RTE, juice, and pineapple decreased. Also, if demographic variables were included, tobacco use caused an increase in the change in WTP.

Although several different models were estimated to predict WTP, the effect of the information treatments was tested directly using two types of tests: the paired t-test, which assumes normality of the bid distributions, and the Wilcoxon signed rank test to compare bids with nonparametric distributions. For the three whole pomegranate fruits and the Texas RTE arils, all the information treatments as well as the full information set resulted in bids that were different from the baseline; results for the other products were mixed depending on the product and information treatment.

The rankings data were also analyzed to gather information on preferences for the included products. The preference for each product using a rank-ordered logit model was estimated first for the products for each information treatment. Thus, product characteristics within a given round of bids could be compared to predict which product

characteristics were likely to result in the product being more preferred. Using the complete set of rankings, the relative effect of the product characteristics varied across information treatments. In the baseline round there was no effect for the Texas variety, items that were RTE, juice, or pineapple were more preferred, and the option of no product was discounted. However, in considering the other information treatments and the full information set, the two Texas varieties were preferred to the California variety, the option of no product was discounted more severely relative to the other products, and juice and pineapple were not as strongly preferred. The improvement in ranking for the Texas varieties was largest in the tasting information treatment; and for all rounds where subjects had received any information the Texas Red variety was preferred to the Texas Salavatski variety. Due to the possibility of heterogeneity in ranking ability (more precisely, the possibility of subjects being less careful when ranking less preferred products than more preferred products), the rank-ordered logit model was re-estimated using the partial rankings (ranks 1-4). The estimates of this model were not identical to the estimations based on the complete rankings, which is indicative of possible heterogeneity in ranking ability.

The explicit preference rankings were compared to the implied preferences based on the ordered bids. The bids submitted by subjects were sorted from highest to lowest and rankings were assigned for the values of 1-8. The option of no product was assigned the next lowest rank after the last non-zero bid. Checking for reversals in preferences (instances when the explicit orderings and implied orderings did not “match”) within the same information treatment indicated that this was a concern for comparing preference

rankings and ordered bids. Thus, although both mechanisms were designed to be incentive compatible in nature with weakly dominant strategies of submitting true preferences and bids, respectively, an estimation of the rank-ordered logit models based on the implied rankings was not expected to provide identical results for this study. For the full information treatment relative to the baseline, the Texas varieties were neither preferred nor discounted, the no product option was less preferred at the baseline and became even less preferred across the information treatments, and ready-to-eat, juice, and pineapple all had a positive relationship with preference but this became less true across the information treatments, indicating a stronger preference for the excluded dummy variable (whole fruit for the product form and pomegranate for the product type).

The individual preferences for the pomegranate and other fruit product options were also analyzed with the use of the mixed rank-ordered logit model. Such models were estimated using both explicit preference rankings and implied rankings based on ordered bids. These models suggest the presence of individual preference heterogeneity for the product form characteristics, as well as for the interaction of some product characteristics with the additional information treatments. These results varied depending on which information treatment was considered, providing the insight that for explicit rankings tasting information increased the preference for the Texas Red variety over the California Wonderful variety but decreased it for RTE products relative to whole fruit products. We would not expect the exact parameter estimates for these two models to be equal; however, the fruit variety was generally not significant in the

bidding models but was significant in several of the preference ranking models. This suggests that there may be differences in the way that subjects viewed the consequences of misbehavior in each procedure or the individual variability that was expressed through either rankings or bidding.

Conclusions

The summary of the pomegranate industry and experimental results based on both the nonhypothetical auction and preference ranking procedures lead to both conclusions and further questions. These are discussed further here.

Key Challenges for Expansion of Pomegranate Production

There are a number of challenges that must be addressed in order for pomegranate production to expand both in terms of acreage and profitability. The registration of fungicides, insecticides, and herbicides for application in pomegranate production will be necessary in order to address disease, insect, and weed management issues. As far back as 1917, Robert Hodgson, author of a text on pomegranate history and production in California, recognized that one of the keys for the growth of the pomegranate industry was successful education of the public about this fruit.

Several individuals involved with pomegranate production also suggest that as global supply of pomegranates expands, prices may decrease (e.g., Cline 2008; “Pomegranate Acreage” 2009). This is particularly true for storable (and thus more easily transportable) forms of pomegranate such as concentrated juice or other

pomegranate by-products which may be sourced from other regions or other countries. Thus, those considering expanding production should consider marketing opportunities at a range of price points when determining the feasibility of expansion.

Also, expanded production plans might also take into account the seasonality of pomegranate production and what product forms will be marketed. Fresh pomegranates cannot be stored long enough to sustain sales from one growing season to the next with current post-harvest technology, whereas juice or other processed products may be stored for such a length of time. However, particularly for growers who intend to market a product as a regionally-grown product, the price premium received may vary for each of these different types of products. Also, there may be different cultivars of pomegranates that are ideally suited for one of the juice, RTE, or whole fruit products but be less than desirable for use for others.

In terms of further considerations for expansion of the pomegranate industry, the following issues may be potential opportunities or concerns. First, considerable media as well as research attention has been devoted to health claims about antioxidants in general and pomegranates specifically. However, many of these claims are made based on laboratory results and have not been verified in large, long-term studies of human populations. As these health claims are one component of the growth in the pomegranate industry, if these health claims cannot be verified then the projected growth in sales of pomegranate products may not come to fruition. Until those studies can be completed, a short-term alternative would be to emphasize the positive taste and nutritional benefits of pomegranates.

Further, although health claims about functional foods are not as strictly regulated in the United States as in some other places, the risk to producers remains that stricter regulations may be imposed. However, such regulation may increase WTP for any products for which regulatory approval is obtained and thereby increase consumer confidence in the health claims that are made.

Although the acreage of pomegranates planted in the United States is growing, the total acreage is still small relative to other commodities and more common fruit and vegetable crops. In terms of insect, weed, and disease management, chemical products that are available for use on other crops may not be registered for use on pomegranates or in the state where pomegranate production may be considered. Thus, these products may not be available for use or may be expensive if they are later registered for use.

One final issue with expansion of pomegranate production is labor considerations for harvest. At present, use of mechanical harvesters for the crop is not widespread. However, as with many other fruit and vegetable crops the availability and consistency of labor for harvesting seasonal fruits and vegetables can be an uncertain component of the process from planting to sales of pomegranates. Thus, the industry as a whole would stand to benefit from an effective mechanical harvester that does not damage the fruit and provides greater certainty for the supply of harvest labor.

Information provided by this study and conclusions drawn from results may not hold absolutely; this conclusion is based on the extensive discussion of the validity of WTP from auction mechanisms. Further, the exact levels of the WTP estimates from this model may not be exact and should not be assumed to be easily extrapolated to exact

premiums in a market setting. However, there does appear to be value in the relative importance of the factors analyzed.

Novel Products and Value Elicitation Mechanisms

The pomegranate products included in the study were generally novel to participants, and this was an important consideration in the design of the WTP elicitation procedures. A mechanism was needed that would limit opportunities for future learning about the products, so that all participants would submit values that were a "snapshot" of a point-in-time valuation for all of the products and not biased by future opportunities to gather information on the products or transaction costs of doing so. As a result, in the estimation of WTP many of the demographic variables that may have influenced valuations for more familiar products had little influence on the novel product, particularly for the baseline round where participants were not given any additional information. Prior experience with pomegranate products had a larger effect on an individual's valuation of the products. This result indicates the importance of gauging prior experience with a novel product if value elicitation procedures will be used to estimate WTP. Also, given the lack of familiarity with the products, participant bids in the experimental auction were affected based on whether or not a reference price was provided as a part of the study mechanism.

Individual values varied considerably for the products, and comparisons of within subject differences for a product across information treatments allows the possible differences in outside substitutes to cancel out and should provide more

information on how the information treatments affected the change in WTP. Further, bids and rankings on all products were collected; theory would suggest that for two incentive compatible preference elicitation mechanisms the results would be similar. However, the two procedures yielded results that were similar for some product characteristics and divergent for others; the results for the two procedures were not identical. This leads to the question of which results are more reflective of the purchases that consumers will actually make in the future; this is the economic result of interest. Perhaps the best way to address this would be with a paired experiment that involved collection of both sets of results in comparison with actual sales at a retail establishment to answer the question of which results have more external validity.

This leads to an important point: the design of the study must be done in such a way that not only can the questions of interest outside of the experimental setting be answered with the results, but the results would hold if the experiments were repeated. The results of this study suggest that experimental economics may offer interesting opportunities to evaluate new products before they are introduced to a large marketplace. The results also suggest that outside substitutes and product attributes of the products to be included in the study could affect the results of the preference elicitation procedures.

This study was designed to examine consumer preferences for pomegranate products and for Texas varieties of pomegranates in particular. The results indicate that the biggest hurdle in increasing WTP for the pomegranate products may be increasing consumer familiarity with the product. Of the information treatments that were provided, the one that generally had the largest effect on WTP for the Texas

pomegranate varieties was the tasting treatment, but this is not to say that the health and nutrition information or the anti-cancer information did not have an effect. Producers or retailers could increase this sort of awareness in consumers for the taste attributes of pomegranate fruits and other pomegranate products by giving away samples of the product, either for consumers to take home or as point-of-purchase promotions.

Directions for Further Research

While this research answered a number of questions, it has also opened up a wealth of other questions yet to be answered. For comparing the rankings and auction portions of the study, more research is needed into what the possible reasons for the differences between the two preference elicitation methods are and if there is a method that can be developed so that the results of the two are consistent.

Also, further work is needed to make the actual values obtained by the WTP procedures more meaningful, particularly for novel products. Consumers would be unlikely to know the suggested retail price for a product that was not currently available in stores, yet the results of this study suggest that providing a reference price had a significant effect on WTP for the items in this study. This is also necessary since the standard buying environment in the United States would be one where prices are posted on products and consumers do not have to generate their own prices for their products; rather, they only have to decide whether they want to purchase the product at the given price. If the results of experimental auctions could reliably be transferred to quantitative measures of the marketplace, they would become an even more indispensible tool for

economists and marketers. Although results of auctions have been applied to make welfare estimations previously, if this could be reliably done with *new* products or even *new* government policies and regulations of those products, then policymakers could use such results as a consideration of the costs and benefits of new regulations.

Extending the results of auctions and /or rankings procedures to make predictions about market trends and consumption patterns would be a logical next step. If the mechanisms and results estimations can be calibrated in order to allow marketers to make larger assumptions about regional or national trends then they could be an important component in new product development. Also, if marketers could compare WTP for a new product with existing products in the marketplace they would have the ability to gauge the effect that a new product introduction would have on the WTP for the other products in that product sector.

The results of the auction procedure and preference ranking procedure in this experiment were not identical. This leads to the question of whether arbitrage procedures that have been implemented in some other auctions (e.g., Cherry and Shogren 2007) would be an effective way to correct this problem and lead to convergent results for the two procedures. Comparing the two procedures using induced rather than homegrown values might provide additional insight into more specific procedural questions.

Further research is also needed on the relationship among the size of the endowment, the retail value of the products, and the relative income effect. Mixed results have been obtained by other experiments, and in some experimental designs it is

not practical to implement a payment procedure that requires payments to vary across subjects. In most instances the value of the endowment for participation in an experimental auction or other preference elicitation procedure will be a small proportion of total income. However, the endowment may be a much larger portion of a subject's expenditures for that type of product or in relation to the retail value of that product. Experiments that varied the size of the endowment as well as the values of the products would be needed to further develop the impact that such an effect has on the experimental results.

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APPENDIX A

NEWSPAPER ADVERTISEMENT

ATTENTION GROCERY SHOPPERS!

The Dept. of Agricultural Economics at Texas A&M University is looking for individuals to participate in a **study on fruit purchasing decisions**. Participants are needed for either **November 2, 3, or 4, 2010**. The study will be held on the campus of Texas A&M University.

Besides an opportunity to contribute to scientific understanding, participants will be awarded a payment of $35 for their participation. To participate, you must be at least 18 years of age. Participation in the study will take approximately 1.5 hours.

There are no foreseeable risks for participation in the study, and participants will have the option to end their participation at any time without penalty. Participation in the study is entirely voluntary.

If you are interested in participating in this study, please contact **(979)845-3171** or **TAMUFruitStudy@gmail.com** to sign up for a session.

Figure 24. Newspaper Advertisement for Fruit Purchasing Decisions Study

APPENDIX B

VERBAL AUCTION INSTRUCTIONS

A portion of the verbal instructions that subjects received are included below. These instructions were read by the session moderator for each session of the study.

> "Today's session will involve two types of procedures: ranking of your preferred goods, and placing bids on goods in an auction setting. We will now go over the information provided to you in stages 1 and 2.
>
> **Ranking Procedure**. Today you will be asked to rank your preferences for several products. You will also complete several rounds of these rankings. The rankings will work as follows:
>
> First, you will all be given the opportunity to carefully examine each item. Second, you should mark your numerical ranking for each item, with 1 being the item you would most like to purchase and the highest number being the item you would least like to purchase. Use each number only once. Turn in your ranking sheet when you finish your rankings.
>
> We have a few examples of rankings for four items. Which of these look acceptable to you? "1, 2, 3, 4"- Yes; "4, 3, 2, 1"- Yes; 0, 2, 1, 3- No, "1, 1, 2, 4"- No; 1, 3, 4, blank- No. There are three keys to remember with the rankings. No zeroes, no duplicates, and no blanks. [Emphasis added].
>
> **The 11th-Price Auction**. We will also conduct several rounds of auctions today. The auction we conduct will likely be different from any auction you have had experience with previously. You are probably familiar with the traditional English auctions where the auctioneer calls for higher and higher prices and concludes with something like "Do I hear $90?, Do I hear $95?, Do I hear $100?, going once, going twice, SOLD for $95 to the bidder on my right." However, the auctions we will hold today will be sealed bid auctions where you write down your bid rather than calling it out verbally.
>
> The auction that you will participate in today is called an "11th price" auction. The auction will work like this: You will be given the opportunity to re-examine the products. You will then write down your bid for the most you would be willing to pay for each product. Your bid sheets will be collected. After all the bids for the items have been collected from all participants, the bids will be sorted from highest to

lowest. The 11th highest bid will be the market price.

Remember that the auctions are different than the rankings. You should still submit a bid for every item, but you are allowed to bid the same amount for more than one item and you are allowed to bid zero for any item you would like.

How Winners are Determined. You will participate in more than one round of auctions today. However, we will randomly choose which one of these auctions will be binding. Only the results of that round will be used to determine the ACTUAL WINNERS who will purchase the items in the auction. Within that round only one product will be the one that is binding. Therefore, you will only have a chance to purchase one fruit product from today's session.

For the round that is binding, the 10 people who bid higher than the market price (the 11th price) will be the buyers. These 10 buyers will pay the market price for that round and will take home the product in exchange for paying the market price.

Then, of those who did not purchase an item in the auction, 10 participants will randomly be drawn to have the ranking procedure be binding. We will draw which rank will be the one purchased. The likelihood of an item being drawn is proportional to the ranking. The highest ranked product is most likely to be drawn. The lowest ranked product is least likely to be drawn. We will draw one rank and 10 individuals who were not winners from the auction bids to purchase the product at the market price.

The price for these winners will be the market price from the auction for that round. Ten randomly selected individuals who did not purchase a fruit item by winning the auction will purchase a fruit item based on the binding ranking.

Important Reminders: For both the ranking and the auction, it is in your best interest to be truthful about your preferences.

For the ranking portion, you should rank the items as you actually prefer them. Put the item that you actually prefer the most as first, your next most preferred item second, and so on. This is because it is most likely that whichever item you select as first will be chosen as the item you buy and least likely that the item you rank as last will be chosen. *In the auction, it is also in your best interest to submit a bid of your TRUE value for the good. If you submit a bid for less than you value the item, then other bidders may win the item at a price equal to your value and you miss out on having the item at your price. If you submit a bid for more than you value the item, then you may win the auction for that price and pay more than you wanted to pay for the item.

These are not hypothetical experiments. The winner will actually pay money to obtain the item. The market price for any purchased items will be deducted from your participation payment for today's session.

You may bid any value for the item, including $0.00.

When deciding on your bid, consider the alternatives for what you could spend that much money on. For example, if you did not buy the product up for auction, how many gallons of gas could you purchase with the amount you bid? Consider your other options when deciding what your true value is for that good.

You will not win more than one item from each of these markets. We ensure this by randomly drawing one round and one item to be the ones that are binding.

Many session participants will take home ONE fruit product today. There will be 10 session participants who buy a product based on their auction bids and 10 session participants who buy a fruit product based on their rankings. Therefore, you should think carefully about your ranking and bidding decisions."

Examples of preferences and the rankings and bids that would be submitted are given as follows.

"I will now give you a couple of examples to help explain the auction and the ranking procedures. Consider this general example of ranking and auctions. Suppose that you are going to purchase a rug for your living room. You like blue rugs the best, followed by red, followed by green, and you like brown rugs the least. You would rank the rugs in this order for the ranking procedure. You would also bid on the products in the auction, bidding the maximum amount you are willing to pay for each item. Most likely, you would bid the greatest dollar amount for the color rug you like the best and the smallest dollar amount for the rug of the color you like the least.

Now, consider these numerical examples of ranking and bidding. First, suppose that your favorite soda is Pepsi®. Suppose that you are willing to pay $2 to consume a Pepsi®. Your next favorite soda is Diet Coke®, which you will pay $1.50 to consume. Following Diet Coke®, you next prefer Coke®, and would pay $1 to consume Coke®. You really do not enjoy Dr. Pepper® very much, so you would pay just $0.50 to consume it. For the ranking part of the session, you would mark a 1 beside Pepsi®, 2 beside Diet Coke®, 3 beside Coke®, and 4 beside Dr. Pepper®. This indicates that you like Pepsi® the most and Dr. Pepper® the least of the 4 options, with Diet Coke® and Coke® in between.

Then you will move on to the auction portion of the experiment.

> You still prefer all of the soft drinks in the way that we just described. However, in this portion of the session you are asked to submit a bid for each soda. Here it is in your best interest to submit a bid for exactly your value for the good. So, on the auction bid sheet, you would write $2.00 beside Pepsi®, $1.50 for Diet Coke®, $1.00 for Coke®, and $0.50 for Dr. Pepper®. The winning bids will then be determined for each round. We will then determine who the buyers of the soft drinks are based on the bids and then based on the rankings."

After subjects were given an opportunity to read and answer the five questions for the practice quiz, they were provided with answers to the quiz questions and any other questions they had about procedures. The quiz questions and scripted answers are given here.

> "We will now review the answers to the practice quiz. The first two questions in the quiz were about the ranking procedure.
>
> 1. *The best strategy for the ranking is to rank only the first item that you would prefer to purchase, true or false*?
>
> The correct answer to this question is FALSE. You should rank all of the items in each round by marking a one for the item you would most like to purchase on through to marking the highest number for the item you would least like to purchase.
>
> 2. *The results of the ranking could determine which product you will purchase, true or false?*
>
> The correct answer to this question is TRUE. Your rankings will be used to determine which product you buy if you are not one of the winners of the auction, as we just saw in the case of the soft drink practice auction.
>
> Questions 3 and 4 were about the auction procedure.
>
> 3. *In an 11th price auction, the 10 highest bidders win the auctioned item, true or false?*
>
> The correct answer is TRUE. In an 11th-price auction, the ten highest bidders are the buyers, and they pay a market price equal to the next highest bid, i.e. the 11th highest bid.
>
> 4. *The people who win the auction will pay the amount they bid for the item, true or false?*
>
> The correct answer is FALSE. You will not pay the amount that you bid for an item; you will pay the amount that someone else bid. Therefore, it is in your best interest to bid the exact value of the amount of the most you are willing to pay for each product.

> The last question was about both the auction and the ranking procedures.
>
> 5. *There will be the opportunity to purchase more than one fruit product today, true or false?*
>
> The correct answer is FALSE. You will only purchase one fruit product today because we will only draw one round of the auction to be binding. If you are not a winner in the fruit product auction, we will still only have one set of rankings as binding. Therefore, you cannot purchase more than one fruit product from today's auctions.
>
> Does anyone have any additional questions about the ranking or auction procedures?"

These portions of the moderator's script are highlighted, and the majority of the additional instructions were very similar to those seen in the written instructions provided to subjects.

APPENDIX C

WRITTEN AUCTION INSTRUCTIONS AND SURVEY

Contained in this appendix is the text of the instructions participants received during participation in the study:

DECISION-MAKING FOR FRUIT PURCHASES

INSTRUCTIONS

Please do not look at instruction pages until directed to do so.

Failure to follow the instructions outlined here may result in a session monitor asking you to leave. If this occurs, any money you may have received and any products you may have purchased will be forfeited.

INTRODUCTORY INSTRUCTIONS

Welcome! Thank you for agreeing to participate in today's session.

When you entered the room you received a packet of information. You should have also been assigned an ID number, located on the packet of information you received. You should use this ID number to identify yourself throughout the session today. The use of identification numbers ensures individual confidentiality.
As a reminder before we start today's session, your participation is completely voluntary. At any time you may elect to end your participation in the session. Non-participants will not be penalized. All information collected today will be kept confidential and will not be used for any purpose other than this research.
The purpose of today's session is to gather some general information on the decision making process for purchasing fruit. The first thing you should do is open your packet. Inside you will find a packet of instructions along with several other papers. Please take a few minutes to read the overview page and the instructions provided as stages 1 and 2. We will now go through a series of instructions for what will happen in the remainder of the session. These instructions will be read from a script to ensure the procedures are accurately described. There will be an opportunity for questions once we go through

the instructions. Please do not read ahead in the instruction packet or you may be asked to leave.
For the rest of today's session, it is very important that there be no further talking or other communication between participants. If you have questions or comments, please inform a session monitor. If you are not able to comply with these requests you will be disqualified from the experiment.

If you have any questions, please direct them to a session monitor who will answer them.

OVERVIEW

***Please follow all instructions presented in this booklet carefully. If you have any questions, please ask a session monitor.

The purpose of today's experiment is to better understand purchasing decisions for fruit and fruit products. To accomplish this purpose, you will be asked to complete two surveys, rank which items you like most, and submit bids on several items. If you are one of the winners of these auctions, you will pay the auction price and in exchange you will receive the item. You will receive more information on the auction procedures shortly.

The experiment will proceed in several stages as described below.

STAGE 1: Learn How Bids and Rankings Are Submitted
STAGE 2: Learn How Prices and Winners Are Determined
STAGE 3: Submit First Practice Round Rankings/Bids
STAGE 4: Complete Short Knowledge Quiz on Auction Format
STAGE 5: Submit Second Practice Round Rankings/Bids
STAGE 6: Complete the First Survey
STAGE 7: Submit Rankings/Bids for Products
STAGE 8: Complete the Second Survey
STAGE 9: Determine Auction Winners
STAGE 10: Receive Payment

However, first please review the Consent Form if you have not already done so. Once you have read the form, you should print your name and sign and date on the second page. Please leave the portion for the "Signature of the Person Obtaining Consent" blank. You will be provided with a copy of this document.

STAGE 1: LEARN HOW RANKINGS AND BIDS ARE SUBMITTED

Ranking What You Like: Today you will be asked to rank your preferences for several products.

1. Examine the products that will be evaluated.

All participants will be given the opportunity to carefully examine each item.

2. Write down your numerical ranking.

You should mark your numerical ranking for each item, with 1 being the item you would most like to purchase and the highest number being the item you would least like to purchase.

The Auction: The auction that you will participate in today is called an "11th price" auction.

1. Re-examine the products that will be auctioned.

You will be given the opportunity to re-evaluate each item if you would like to do so.

2. Write down your bid.

After you examine the items, please write down the amount that you would pay for each one on the "Bid Sheet."

IMPORTANT REMINDERS: For both the ranking and the auction, it is in your best interest to be truthful about your preferences.

* For the ranking portion, you should rank the items as you actually prefer them. Put the item that you actually prefer the most as first, your next most preferred item second, and so on. This is because it is most likely that whichever item you select as first will be chosen as the item you buy and least likely that the item you rank as last will be chosen.

* In the auction, it is also in your best interest to submit a bid of your true value for the good. If you submit a bid for less than your value, then other bidders may win the item at a price equal to your value and you may miss out on having the item at a price you would be willing to pay. If you submit a bid for more than you value the item, then you may win the auction for that price and pay more than you wanted to pay for the item.

* These are not hypothetical experiments. The winner will actually pay money to obtain the item.

* You may bid any value for the item, including $0.00.

* When deciding on your bid, consider the alternatives for what you could spend that much money on. For example, if you did not buy the product up for auction, how many gallons of gas could you purchase with the amount you bid? Consider other options

when deciding what your true value is for that good.

* You will not win more than one item from this market. We have already selected one product to be binding, and it is in a sealed envelope that will be opened at the conclusion of today's session.

STAGE 2: LEARN HOW PRICES AND WINNERS ARE DETERMINED

How The Auction Price is Determined:
Today you will be participating in an 11th-price auction.
1. Choosing the 11th Price.
After all the bids for the items have been collected from all participants, the bids will be sorted from highest to lowest. The 11th highest bid will be the market price.

How Buyers are Determined:
1. Auction Buyers
You will participate in more than one round of auctions today. However, we will choose only one of these rounds which will be binding. Only the results of that round will be used to determine the actual buyers who will purchase the items in the auction. Within that round only one product will be the one that is binding. Therefore, you will only have a chance to purchase one fruit item from today's session.

For the round that is binding, the 10 people who bid higher than the market price (the 11th price) will be the buyers. These 10 buyers will pay the market price for that round.

2. Ranking Buyers
Four individuals who did not purchase an item as a result of the bidding will buy a product based on the ranking portion of the session. Only one product will be selected. This item will be purchased at the specified price.

IMPORTANT REMINDERS:
*Remember, in both the ranking and auction it is in your best interest to submit a bid of EXACTLY your true value for the good. It is not in your best interest to bid more or less than the price you would pay for the good or to rank the items differently than how you actually prefer them.
*Many session participants will take home ONE fruit product today. There will be 10 session participants who buy a product based on their auction bids and 10 session participants who buy a fruit product based on their rankings. Therefore, you should think carefully about your ranking and bidding decisions.

Please do not read any further in this booklet until instructed to do so by the session monitor. Your cooperation is greatly appreciated.

STAGE 3: FIRST PRACTICE ROUND OF RANKING/ AUCTION

INSTRUCTIONS:
In this stage you will participate in the first practice round. First you will be asked to rank and bid on four types of soft drinks. The stage will proceed as follows.

1. When instructed by a session monitor, go to the tables with the soft drinks on them and examine each product.
2. On the practice ranking sheet, rank each soft drink from 1 to 4, with 1 being the one you would most like to purchase and 4 being the soft drink you would least like to purchase. Turn in your practice ranking sheet to the session monitor.
3. On the practice bidding sheet, write down your bid for each item. Turn in your practice bidding sheet to the session monitor.

Please take your practice ranking sheet and practice bidding sheets with you to the table with the items on it. Please do not talk with each other during bidding. The monitor will be happy to answer any of your questions.
Once you have completed the practice bidding and ranking on the soft drinks, please return to your seat and wait while the price and buyers are determined. Following the auction you will complete a short knowledge quiz on your understanding of the auction procedures.

You may now take your practice ranking and bidding sheets to the table with the sodas on it and begin the practice round.

STAGE 4: SHORT KNOWLEDGE QUIZ ON RANKING AND AUCTION FORMAT

INSTRUCTIONS:
This is a brief quiz designed for you to check your understanding of how the ranking and auctions you will participate in today will operate. Please choose the answer you feel is correct. Once all participants have completed the quiz, we will go over the answers together.

About the Ranking:
1. The best strategy for the ranking is to rank ONLY the first item that you would prefer to purchase.
a. True
b. False

2. The results of the ranking could determine which product you will purchase.
a. True
b. False

About the Auction:
3. In an 11th price auction, the 10 highest bidders win the auctioned item.
a. True
b. False

4. For the binding round, the people who win the auction will pay the amount they bid for the item.
a. True
b. False

About Both the Ranking and the Auction:
5. There will be the opportunity to actually purchase and take home more than one fruit product today.
a. True
b. False

Please do not read any further in this booklet until instructed to do so by the session monitor. Your cooperation is greatly appreciated.

STAGE 5: SECOND PRACTICE ROUND OF RANKING/ AUCTION

INSTRUCTIONS:
You have completed half of the practice. Now you will be asked to rank and bid on four types of snack products. The stage will proceed as follows.

1. When instructed by a session monitor, go to the tables with the snack products on them and examine each product.
2. On the practice ranking sheet, rank each item from 1 to 4, with 1 being the one you would most like to purchase and 4 being the item you would least like to purchase. Turn in your practice ranking sheet to the session monitor.
3. On the practice bidding sheet, write down your bid for each item. Turn in your practice bidding sheet to the session monitor.

Please take your practice ranking sheet and practice bidding sheets with you to the table with the items on it. Please do not talk with each other during bidding. The monitor will be happy to answer any of your questions.
After you have completed the practice bidding and ranking on the snack products, please return to your seat. You will complete the first survey while the market price and the buyers are determined.

You may now take your practice ranking and bidding sheets to the table with the snack products on it and begin the second set of practice rounds.

STAGE 6: SURVEY NUMBER ONE

INSTRUCTIONS: Please answer the survey questions that follow. There are no right or wrong answers. Please think carefully about your answers, and then please mark an "X" beside the letter of your response. Your survey responses are very important to the results of today's sessions. Please remember that all responses will be kept confidential. Please select only one answer by marking an "X" in the blank unless otherwise indicated.

1. AGE: Please indicate your age in years:

a. ___ 18- 19
b. ___ 20-29
c. ___ 30-39
d. ___ 40-49
e. ___ 50-59
f. ___60-69
g. ___ 70 or over

2. EDUCATION: Please indicate the highest level of education you have completed:

a. ___ Some high school or less
b. ___ High School Diploma
c. ___ Some College
d. ___ 2 year/ Associates Degree
e. ___ 4 year/ Bachelors Degree
f. ___ Some Graduate School
g. ___ Graduate Degree

3. HOUSEHOLD SIZE: Including yourself, how many people live in your household? Include yourself, your spouse, and any dependents. Please do NOT include your roommates.

a. ___ 1
b. ___ 2
c. ___ 3
d. ___ 4
e. ___ 5
f. ___ 6
g. ___ 7
h. ___ 8
i. ___ 9
j. ___ 10 or more

4. GENDER: Please indicate your gender:

a. ___ Female
b. ___ Male

5. RACE: Please indicate your race:

a. ___ Asian/Pacific Islander
b. ___ African American
c. ___ Caucasian/White
d. ___ Native American/ Indigenous
e. ___ Hispanic
f. ___ Other (Please List: _____)

6. MARITAL STATUS: What is your current marital status?

a. ___ Single, never married
b. ___ Married
c. ___ Separated or Divorced
d. ___ Widowed

7. INCOME: Please indicate your household yearly income for 2009 for all the people in your household. (Include all forms of income, including salary, interest and dividend payments, tips, scholarship support, student loans, parental support, social security, child support, and alimony.

a. ___ Less than $30,000
b. ___ $30,000-$39,999
c. ___ $40,000-$49,999
d. ___ $50,000-$59,999
e. ___ $60,000-$69,999
f. ___ $70,000-$79,999
g. ___ $80,000-$89,999
h. ___ $90,000-$99,999
i. ___ $100,000-$149,999
j. ___ More than $150,000

8. EMPLOYMENT: Which of these best describes your employment status?

a. ___ Student
b. ___ Stay-at-Home Parent
c. ___ Part-time Employed
d. ___ Full-time Employed
e. ___ Retired
f. ___ Disabled
g. ___ Unemployed

9. PRIMARY SHOPPER: Are you the PRIMARY grocery shopper for your household?

a. ___ Yes
b. ___ No

10. WEEKLY FOOD EXPENDITURES: How much, on average, does your household spend on food PER WEEK? (Include grocery, snacks, restaurants, and any other food purchases).

a. ___ $0-$49
b. ___ $50 - $99
c. ___ $100 - $149
d. ___ $150 - $199
e. ___ $200 - $249
f. ___ $250 - $299
g. ___ $300 - $399
h. ___ $400 - $499
i. ___ $500 - $749
j. ___ $750 or more

11. WEEKLY FRUIT AND VEGETABLE EXPENDITURES: How much, on average, does your household spend on fruits and vegetables PER WEEK?
a. ___ $0 - $24
b. ___ $25 - $49
c. ___ $50 - $74
d. ___ $75 - $99
e. ___ $100 or more

12. FRESH FRUIT AND VEGETABLE EXPENDITURES: Approximately what portion of your fruit and vegetable purchases are for FRESH fruits and vegetables (Please exclude any canned, frozen, and/or processed fruits and vegetables).
a. ___ None of the fruits and vegetables purchased are fresh.
b. ___ ¼ of the fruits and vegetables purchased are fresh.
c. ___ ½ of the fruits and vegetables purchased are fresh.
d. ___ ¾ of the fruits and vegetables purchased are fresh.
e. ___ All of the fruits and vegetables purchased are fresh.

13. LOCATION OF FRUIT AND VEGETABLE PURCHASES: Of the following options, where does your household make the LARGEST PERCENTAGE of its fruit and vegetable purchases?
a. ___ Mass-merchandiser (e.g., Wal-mart, Target)
b. ___ Supermarket/ Grocery Store (e.g. HEB, Kroger, Albertsons)
c. ___ Roadside Fruit and Vegetable Stand
d. ___ Farmers' Market
e. ___ Other (Please Indicate:_____)

14. LAST VISIT TO PURCHASE FRUIT AND VEGETABLES: When did someone in your household last visit the establishment where you usually purchase fruits and vegetables?
a. ___ Less than 2 days ago
b. ___ 2-4 days ago
c. ___ 4-6 days ago
d. ___ 7- 10 days ago
e. ___ 11-14 days ago
f. ___ More than 2 weeks ago

15. FREQUENCY OF FRUIT AND VEGETABLE PURCHASES: How often does your household purchase fresh fruits and vegetables?
a. ___ Less than once a month
b. ___ Once a month
c. ___ Two to three times / month
d. ___ Once a week
e. ___ More than once a week

16. FRESH FRUIT ON HAND: Please estimate the amount of FRESH FRUIT that you currently have on hand in your home.

a. ___ Less than 1 pound
b. ___ 1-2 pounds
c. ___ 2-5 pounds
d. ___ 5-10 pounds
e. ___ More than 10 pounds

17. FRESH VEGETABLES ON HAND: Please estimate the amount of FRESH VEGETABLES that you currently have on hand in your home.

a. ___ Less than 1 pound
b. ___ 1-2 pounds
c. ___ 2-5 pounds
d. ___ 5-10 pounds
e. ___ More than 10 pounds

Please do not read any further in this booklet until instructed to do so by the session monitor. Your cooperation is greatly appreciated.

STAGE 7: RANKING AND AUCTIONS

Thank you for participating in the practice rounds. The next rounds will be for fruit products. They will proceed in a similar way to the practice rounds.

INSTRUCTIONS: You will be ranking and bidding on several fruit products. The stage will proceed as follows.

1. When instructed by a session monitor, go to the tables with the fruit products on them and examine each product.
2. On the ranking sheet, rank each item from 1 to 8, with 1 being the one you would most like to purchase and 8 being the item you would least like to purchase. Note that there are 7 products and one additional option of "No Product." Please turn in your ranking sheet to the session monitor.

3. On the bidding sheet, write down your bid for each item. Turn in your practice bidding sheet to the session monitor.
4. Return to your seat. The market price will be not be posted until the end of today's session.

Please take your ranking sheet and bidding sheet with you to the table with the items on it. Please do not talk with each other during bidding. The monitor will be happy to answer any of your questions.

You may now take your ranking and bidding sheet to the table with the fruit products on it and begin.

STAGE 8: SURVEY NUMBER TWO

INSTRUCTIONS: Please answer the survey questions that follow. There are no right or wrong answers. Please think carefully about your answers, and then please mark an "X" beside the letter of your response. Your survey responses are very important to the results of today's sessions. Please remember that all responses will be kept confidential. Please select only one answer by marking an "X" in the blank unless otherwise indicated.

18. In the store where you purchase your fruits and vegetables, have you ever seen a pomegranate for sale?

a. ____Yes
b. ____No
c. ____Don't Know/ Don't Remember

19. Have you ever eaten a pomegranate prior to today's session?
a. ____Yes
b. ____No
c. ____Don't Know/ Don't Remember

20. Have you ever purchased a pomegranate fruit prior to today's session?
a. ____Yes
b. ____No
c. ____Don't Know/ Don't Remember

21. If you answered yes to the previous question, which months of the year do you typically purchase pomegranate fruits? (Mark all that apply)
a. ___ January
b. ___ February
c. ___ March
d. ___ April
e. ___ May
f. ___ June
g. ___ July
h. ___ August
i. ___ September
j. ___ October
k. ___ November
l. ___ December
m. ___ Don't Remember/ Not Applicable

22. Do you have any pomegranate fruits on hand at home? If so, how many?
a. ___ No
b. ___ Yes, 1-2 pomegranate fruit on hand
c. ___ Yes, 3 or more pomegranate fruits on hand

Which of the following pomegranate products have you seen in stores and/or purchased within the last year? (please mark all that apply; N/A is Not Applicable)

23. 100% Pomegranate Juice:
a. ___Seen in stores b. ___ Purchased c. ___N/A

24. Mixed Pomegranate Juice
a. ___Seen in stores b. ___ Purchased c. ___N/A

25. Pomegranate Fruit:
a. ___Seen in stores b. ___ Purchased c. ___N/A

26. Ready-to-Eat Pomegranate Product:
a. ___Seen in stores b. ___ Purchased c. ___N/A

27. Pomegranate-Flavored Product(s):
a. ___Seen in stores b. ___ Purchased c. ___N/A

28. Which of these factors do you consider most important in making fruit and vegetable purchasing decisions? (please select up to 3)
a. ___ Visual appearance
b. ___ Size
c. ___ Convenience
d. ___ Price
e. ___ Freshness
f. ___ Growing Location (e.g., Texas, United States)
g. ___ Production Practices (e.g., sustainable, organic)
h. ___ Nutrition

29. Which of these factors do you believe the average American considers most important in making fruit and vegetable purchasing decisions? (please select up to 3)
a. ___ Visual appearance
b. ___ Size
c. ___ Convenience
d. ___ Price
e. ___ Freshness
f. ___ Growing Location (e.g., Texas, United States)
g. ___ Production Practices (e.g., sustainable, organic)
h. ___ Nutrition

How important are the following factors to you when making a fruit purchase decision? (Please select only one level of importance per factor).
30. PRICE
a. ____Not Important At All
b. ____Not Very Important
c. ____Somewhat Important
d. ____Very Important

31. TASTE
a. ____Not Important At All
b. ____Not Very Important
c. ____Somewhat Important
d. ____Very Important

32. NUTRITION
a. ____Not Important At All
b. ____Not Very Important
c. ____Somewhat Important
d. ____Very Important

33. CONVENIENCE
a. ____Not Important At All
b. ____Not Very Important
c. ____Somewhat Important
d. ____Very Important

34. VISUAL APPEARANCE
a. ____Not Important At All
b. ____Not Very Important
c. ____Somewhat Important
d. ____Very Important

35. SIZE
a. ____Not Important At All
b. ____Not Very Important
c. ____Somewhat Important
d. ____Very Important

36. FRESHNESS
a. ____Not Important At All
b. ____Not Very Important
c. ____Somewhat Important
d. ____Very Important

37. GROWING LOCATION
a. ____Not Important At All
b. ____Not Very Important
c. ____Somewhat Important
d. ____Very Important

38. PRODUCTION PRACTICES
a. ____Not Important At All
b. ____Not Very Important
c. ____Somewhat Important
d. ____Very Important

39. Prior to today's session, had you heard the term "functional foods" before?
a. ___ Yes
b. ___ No
c. ___ Don't Know/ Don't Remember

40. How important do you think the average American thinks his or her own health is?
a. ___ Not important at all
b. ___ Not very important
c. ___ Somewhat Important
d. ___ Very Important

41. Do you currently have any serious health issues (including any conditions which require regular doctors visits and/or prescription medication)?
a. ___ Yes
b. ___ No (If No, please also answer "Not Applicable" to the next two questions)

42. If you have health issues that you would consider serious, are any of them nutrition related?
a. ___ Yes
b. ___ No
c. ___ Not Applicable

43. If you have health issues that you would consider serious, do any of them have specific diet requirements?
a. ___ Yes
b. ___ No
c. ___ Not Applicable

44. Have you or an immediate family member (mother, father, brother, sister and/or child) ever been diagnosed with cancer?
a. ___ Yes
b. ___ No

45. Do you believe there to be health benefits of consuming fruits and vegetables?
a. ___ Yes
b. ___ No
c. ___ Don't Know/ Not Sure

46. On average, how often do you smoke and/or use other tobacco products?
a. ___ Never
b. ___ Less than 10 times per year
c. ___ Once a month
d. ___ Once a week
e. ___ Once a day
f. ___ More than once a day

47. How often do you exercise? (Include only periods of exercise longer than 20 minutes).
a. ___ Never
b. ___ Less than 10 times per year
c. ___ Once a month
d. ___ Once a week
e. ___ 2-3 times per week
f. ___ 4-6 times per week
g. ___ Once a day
h. ___ More than once a day

48. Do you read labels on new food products before you purchase them?
a. ___ Never
b. ___ Rarely
c. ___ Sometimes
d. ___ Most of the time
e. ___ Always

49. Do you think MOST AMERICANS read labels on new food products before they purchase them?
a. ___ Never
b. ___ Rarely
c. ___ Sometimes
d. ___ Most of the time
e. ___ Always

50. Have you ever purchased any of the following foods? (Please check all that apply).
a. ___ Yogurt or other dairy products with probiotics to promote digestion
b. ___ Green tea with antioxidants
c. ___ Wine with added polyphenols
d. ___ Fish high in omega-3 fatty acids
e. ___ Breakfast cereal with oat ingredients to improve heart health
f. ___ Tomato products high in lycopene

Thank you for your participation in today's study over decision-making for fruit purchases. A session monitor will collect your survey.

Please do not discuss the procedures of today's study with anyone who will be participating in later rounds of the study until after they have completed their session. This will help ensure the validity of our results.

Shortly, you will receive your payment for participation, less whatever amount you spent on purchases in today's session. Please wait for further instructions.

APPENDIX D

INCLUDED FRUIT PRODUCTS

The products pictured in Figure 25 and Figure 26 below were included in the experimental auction and preference ranking procedures.

Figure 25. Photographs of Whole Pomegranate Fruit Products.
Note: From left to right, California Wonderful Pomegranate Fruit, Texas Red Pomegranate Fruit, and Texas Salavatski Pomegranate Fruit

Figure 26. Photographs of Ready-to-Eat (RTE) Pomegranate Fruit Products.
Note: From left to right, California Wonderful Ready-to-Eat Pomegranate Arils, Texas Salavatski Ready-to-Eat Pomegranate Arils

Figure 27. Mixed Pomegranate Juice

Figure 28. Pineapple

The pictures in the next three figures (Figure 29, Figure 30, Figure 31) show the arils of the three varieties of pomegranate fruits that were used, as well as a picture of the samples that were distributed for tasting to the experimental auction participants.

Figure 29. Photograph of California Wonderful Pomegranate Arils

Figure 30. Photograph of Texas Red Pomegranate Arils

Figure 31. Photograph of Texas Salavatski Pomegranate Arils

Figure 32. Pomegranate Fruit Tasting Samples

APPENDIX E

AUCTION BID AND RANKING SHEETS EXAMPLES

STAGE 7: ROUND 3-A: Fruit Product Ranking

INSTRUCTIONS: Please rank the fruit products from the one you would prefer the most to the one you would like the least. Use a 1 to indicate your most preferred fruit product, and a 7 to indicate your least preferred fruit product. Note that you should also include the option of "no fruit product" in your rankings. Please use each ranking 1 to 8 once and only once.

PRODUCTS	RANK (1 to 8)
A. California Wonderful Pomegranate	
B. Texas Red Pomegranate	
C. Texas Salavatski Pomegranate	
D. Ready-To-Eat Pomegranate Arils- California	
E. Ready-To-Eat Pomegranate Arils- Texas Salavatski	
F. Pomegranate Juice	
G. Pineapple	
H. No Product	

Figure 33. Example Fruit Product Ranking Sheet

STAGE 7: ROUND 3-B: Fruit Product Bidding

INSTRUCTIONS: Please indicate the amount of the most that you would be willing to pay for each of these fruit products. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below. Be sure to write a bid for ALL products listed.

A. California Pomegranate	B. Texas Red Pomegranate	C. Texas Salavatski Pomegranate	D. Ready-to-Eat California Pomegranate	E. Ready-to-Eat Texas Salavatski Pomegranate	F. Pomegranate Juice	G. Pineapple
BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$____

Figure 34. Example Fruit Product Bidding Sheet

APPENDIX F

STUDY INFORMATION TREATMENTS

Each information treatment script and/or printed handouts are described below. The information treatments are presented here in the order of tasting information, health and nutrition information, and anti-cancer information; however, the order in which the information treatments were applied was randomized.

Tasting Information

For the tasting information treatment, subjects were provided with a small sample (approximately 1.5 to 2 oz.) of each type of fruit product. They were further provided with information on how to prepare the pomegranate fruits. Subjects were also given the following verbal instructions.

> "At this time we will now provide additional information on the fruit products here. You will learn how to prepare a whole pomegranate fruit as well as have an opportunity to taste the products you just submitted bids for.
>
> To prepare a pomegranate for eating, you should first remove both ends and cut the pomegranate fruit into quarters. Then remove the small juice sacs inside by breaking apart each quarter of the pomegranate fruit. If desired, this part of the process can be done with the pomegranate submerged in a bowl of water to keep the pomegranate juice from getting on your clothes. If you follow this method, drain the water from the juice sacs, and your pomegranate fruit is ready to eat.
>
> You will now have the opportunity to taste the products that you just ranked and bid on. If you do not wish to participate in this portion of today's session, you may indicate that at this time. You will not be able to participate in the remainder of the session if you do not participate in the tasting. You will be asked to complete the second survey when the

> other participants complete that survey. However, deciding to not participate will not affect your payment for participating in today's session, provided you remain here until the other participants finish with today's session.
>
> For the tasting, please take only one sample of each product. Once you have tasted the products, you will have the opportunity to rank the products and bid on the products again. Does anyone have any questions?"

Please note that subjects were only provided with verbal instructions for the tasting information treatment, subjects were not provided with any written information for this round.

Health and Nutrition Information

For the health and nutrition information rounds, subjects were provided with the nutrition facts for fresh pomegranate fruit, juice, and pineapple. Subjects were also provided with information on the additional health benefits of pomegranates and the additional health benefits of pineapple. Subjects were provided with the following verbal instructions.

> "You will now have an opportunity to look at some of the health and nutrition information for the products you bid on in previous rounds. You may also re-examine the products if you wish to do so. Once you have reviewed all the products and information, you will have an opportunity to resubmit your rankings and bids on these products."

Subjects were also provided with the written information.

Pomegranate Health and Nutrition Information (Fruit and Juice)

Pomegranates are rich in a variety of compounds that act as antioxidants. Antioxidants in the body protect against oxidative stress that can damage cells. Specifically, pomegranates contain a number of compounds called polyphenols that are very active antioxidants that may play an important role in its suggested health effects.

Much scientific research suggests that there may be health benefits to consuming pomegranate, either as a fresh fruit, as juice, or in other products. The health benefits that have been suggested include reduction in disease risk for certain cancers, reduction of inflammatory diseases, and reduction of cardiovascular disease.

Below to the left are the nutrition facts for a ½ cup serving of pomegranate arils, the small sacks inside a pomegranate fruit that contain juice, pulp, and seeds. Below to the right are the nutrition facts for a 1 cup serving of mixed pomegranate juice.

Nutrition Facts

Serving Size 1/2 cup arils (87g)

Amount Per Serving	
Calories 70	Calories from Fat 10
	%Daily Value*
Total Fat 1g	**2%**
Sodium 0mg	**0%**
Total Carbohydrate 16g	**5%**
Dietary Fiber 4g	**14%**
Sugars 12g	
Protein 1g	

Vitamin A 0% • Vitamin C 15%

Not a significant source of saturated fat, *trans* fat, cholesterol, calcium, iron.

* Percent Daily Values are based on a 2,000 calorie diet.

Nutrition Facts

Serving Size 1 cup (249g)

Amount Per Serving	
Calories 130	Calories from Fat 5
	%Daily Value*
Total Fat 0.5g	**1%**
Sodium 20mg	**1%**
Total Carbohydrate 33g	**11%**
Sugars 32g	
Protein 0g	

Vitamin A 0% • Calcium 2%

Not a significant source of saturated fat, *trans* fat, cholesterol, dietary fiber, vitamin C, iron.

* Percent Daily Values are based on a 2,000 calorie diet.

Pineapple Health and Nutrition Information

Pineapples are rich in a variety of compounds that act as antioxidants. Antioxidants in the body protect against oxidative stress that can damage cells. Specifically, pineapples contain a number of compounds called polyphenols that are very active antioxidants that may play an important role in its suggested health effects.

Much scientific research suggests that there may be health benefits to consuming pineapple, either as a fresh fruit, as juice, or in other products. The health benefits that have been suggested include reduction in disease risk for certain cancers, reduction of inflammatory diseases, and reduction of cardiovascular disease.

Below are the nutrition facts for a ½ cup serving of pineapple chunks.

Nutrition Facts

Serving Size 1/2 cup (83g)

Amount Per Serving	
Calories 40	
	%Daily Value*
Total Fat 0g	**0%**
Sodium 0mg	**0%**
Total Carbohydrate 11g	**4%**
Dietary Fiber 1g	**5%**
Sugars 8g	
Protein 0g	

Vitamin A 0% • Vitamin C 70%

Not a significant source of calories from fat, saturated fat, *trans* fat, cholesterol, calcium, iron.

* Percent Daily Values are based on a 2,000 calorie diet.

Anti-Cancer Information

For the anti-cancer information rounds, subjects were provided with written information on the anti-cancer properties of pomegranates. In a similar manner to the health and nutrition information treatment, subjects were provided with the following verbal instructions.

> "You will now have an opportunity to look at some health information for the products you bid on in previous rounds. You may also re-examine the products if you wish to do so. Once you have reviewed all the products and information, you will have an opportunity to resubmit your rankings and bids on these products."

Subjects were also provided with the written information given below.

Pomegranate Health Information 2

Pomegranates are rich in a variety of compounds that act as antioxidants. Antioxidants in the body protect against oxidative stress that can damage cells. Much scientific research suggests that there may be health benefits to consuming pomegranate, either as a fresh fruit, as juice, or in other products.

The health benefits that have been suggested include reduction in disease risk for certain cancers, reduction of inflammatory diseases, and reduction of cardiovascular disease. The effects of pomegranate and its components were seen in laboratory studies on cancer cell lines; cancer cell lines where effects were seen include breast, colon, leukemia, prostate, and skin cancer cell lines. However, these results were observed in laboratory experiments and need to be further investigated in humans before such claims can be fully verified.

APPENDIX G

TOBIT MODEL RESULTS

Table 48. Tobit Model Estimates, Baseline Round

	Baseline Round						
	California Wonderful Pom. Fruit	Texas Red Pom. Fruit	Texas Salavatski Pom. Fruit	Ready-to-Eat California Pom. Arils	Ready-to-Eat Texas Pom. Arils	Mixed Pom. Juice	Pineapple
	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)
Constant	-0.250	-0.104	-0.116	-0.029	-0.181	0.947**	0.715*
	(0.321)	(0.335)	(0.314)	(0.398)	(0.394)	(0.406)	(0.379)
Demographics/ Behaviors							
DAGE2	0.121	0.065	0.061	0.102	0.135	0.171	0.302
	(0.199)	(0.208)	(0.195)	(0.247)	(0.245)	(0.255)	(0.237)
DAGE3	0.137	0.030	0.061	-0.021	0.097	-0.051	-0.170
	(0.187)	(0.196)	(0.183)	(0.234)	(0.231)	(0.243)	(0.226)
DEDU2	0.189	0.397*	0.260	0.404	0.522*	0.294	0.245
	(0.223)	(0.232)	(0.218)	(0.279)	(0.274)	(0.285)	(0.265)
DEDU3	0.237	0.088	0.182	0.350*	0.286	0.019	-0.063
	(0.162)	(0.170)	(0.159)	(0.202)	(0.200)	(0.209)	(0.195)
HOUSE	-0.124*	-0.136*	-0.141**	-0.208**	-0.179**	-0.194**	-0.219***
	(0.069)	(0.073)	(0.068)	(0.085)	(0.084)	(0.088)	(0.082)
FEMALE	0.274*	0.195	0.249	0.572***	0.465**	0.086	0.432**
	(0.159)	(0.165)	(0.156)	(0.197)	(0.195)	(0.201)	(0.188)
DMAR	-0.062	0.087	-0.032	0.134	0.227	0.155	0.266
	(0.185)	(0.193)	(0.182)	(0.227)	(0.225)	(0.237)	(0.219)
DINC2	0.114	0.017	0.114	0.092	0.171	0.342	0.230
	(0.178)	(0.185)	(0.174)	(0.221)	(0.218)	(0.229)	(0.212)
DINC3	0.327	0.125	0.190	0.568*	0.527*	0.059	0.498*
	(0.249)	(0.263)	(0.246)	(0.310)	(0.307)	(0.326)	(0.299)
SPENDFV	0.006	0.003	0.005	0.006	0.005	0.008	0.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
FPOH	0.014	0.022	0.022	0.004	0.008	0.007	-0.008
	(0.017)	(0.017)	(0.016)	(0.021)	(0.021)	(0.021)	(0.020)
POMFRUITP	0.942***	0.781***	0.789***	0.672***	0.654***	0.423**	0.217
	(0.157)	(0.164)	(0.154)	(0.196)	(0.194)	(0.204)	(0.191)
ILLNESS	-0.038	-0.056	-0.034	-0.028	-0.060	0.205	0.284
	(0.162)	(0.169)	(0.158)	(0.202)	(0.199)	(0.207)	(0.193)
TOBACCO	-0.081	0.019	0.020	0.078	0.151	0.049	0.126
	(0.220)	(0.229)	(0.215)	(0.272)	(0.269)	(0.278)	(0.258)
EXERCISE	0.084	-0.043	-0.052	0.184	0.176	-0.234	0.543**
	(0.228)	(0.238)	(0.223)	(0.283)	(0.279)	(0.290)	(0.271)
Price Information	0.456***	0.528***	0.481***	0.527***	0.630***	0.532***	0.707***
	(0.149)	(0.156)	(0.146)	(0.185)	(0.183)	(0.190)	(0.176)
σ	0.899***	0.938***	0.881***	1.134***	1.121***	1.187***	1.109***
	(0.055)	(0.058)	(0.054)	(0.066)	(0.066)	(0.066)	(0.059)
Log-Likelihood	-236.662	-241.988	-233.574	-282.182	-281.105	-303.102	-296.397

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are given in parentheses.

Table 49. Tobit Model Marginal Effects, Baseline Round

	Baseline Round						
	California Wonderful Pom. Fruit	Texas Red Pom. Fruit	Texas Salavatski Pom. Fruit	Ready-to-Eat California Pom. Arils	Ready-to-Eat Texas Pom. Arils	Mixed Pom. Juice	Pineapple
	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x
Demographics/ Behaviors							
DAGE2	0.068	0.036	0.034	0.061	0.082	0.122	0.243
	(0.113)	(0.113)	(0.110)	(0.149)	(0.150)	(0.184)	(0.192)
DAGE3	0.077	0.016	0.034	-0.013	0.059	-0.036	-0.135
	(0.107)	(0.106)	(0.103)	(0.139)	(0.141)	(0.172)	(0.178)
DEDU2	0.110	0.231	0.153	0.256	0.341*	0.216	0.200
	(0.134)	(0.145)	(0.134)	(0.187)	(0.192)	(0.216)	(0.221)
DEDU3	0.136	0.048	0.104	0.216*	0.177	0.013	-0.050
	(0.096)	(0.094)	(0.093)	(0.128)	(0.127)	(0.148)	(0.154)
HOUSE	-0.069*	-0.074*	-0.079**	-0.124**	-0.108**	-0.138**	-0.175***
	(0.039)	(0.039)	(0.038)	(0.051)	(0.051)	(0.062)	(0.065)
FEMALE	0.149*	0.103	0.135*	0.327***	0.272**	0.061	0.338**
	(0.084)	(0.086)	(0.082)	(0.108)	(0.110)	(0.141)	(0.143)
DMAR	-0.035	0.047	-0.018	0.080	0.137	0.109	0.212
	(0.104)	(0.104)	(0.102)	(0.135)	(0.135)	(0.168)	(0.173)
DINC2	0.064	0.009	0.064	0.055	0.104	0.247	0.185
	(0.101)	(0.100)	(0.099)	(0.133)	(0.135)	(0.167)	(0.172)
DINC3	0.195	0.069	0.110	0.369*	0.345	0.042	0.415
	(0.158)	(0.149)	(0.149)	(0.218)	(0.216)	(0.234)	(0.260)
SPENDFV	0.003	0.002	0.003	0.003	0.003	0.005	0.006
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
FPOH	0.008	0.012	0.012	0.002	0.005	0.005	-0.006
	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)	(0.015)	(0.016)
POMFRUITP	0.595***	0.466***	0.490***	0.429***	0.423***	0.310**	0.176
	(0.112)	(0.108)	(0.106)	(0.134)	(0.134)	(0.155)	(0.156)
ILLNESS	-0.021	-0.030	-0.019	-0.016	-0.036	0.148	0.230
	(0.090)	(0.090)	(0.088)	(0.120)	(0.119)	(0.151)	(0.159)
TOBACCO	-0.045	0.010	0.011	0.046	0.091	0.034	0.101
	(0.123)	(0.124)	(0.120)	(0.162)	(0.163)	(0.197)	(0.206)
EXERCISE	0.047	-0.023	-0.029	0.110	0.107	-0.166	0.433**
	(0.127)	(0.128)	(0.125)	(0.169)	(0.169)	(0.206)	(0.215)
Price Information	0.244***	0.270***	0.256***	0.303***	0.363***	0.366***	0.547***
	(0.077)	(0.077)	(0.075)	(0.103)	(0.102)	(0.127)	(0.132)

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are given in parentheses.

Table 50. Tobit Model Estimates, Tasting Information Round

	Tasting Information Treatment						
	California Wonderful Pom. Fruit	Texas Red Pom. Fruit	Texas Salavatski Pom. Fruit	Ready-to-Eat California Pom. Arils	Ready-to-Eat Texas Pom. Arils	Mixed Pom. Juice	Pineapple
	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)
Constant	-0.251	-0.254	-0.201	0.151	0.108	0.604	0.813**
	(0.382)	(0.399)	(0.389)	(0.429)	(0.447)	(0.408)	(0.383)
Demographics/ Behaviors							
DAGE2	0.356	0.267	0.203	0.169	0.067	0.106	0.478**
	(0.239)	(0.249)	(0.243)	(0.269)	(0.280)	(0.257)	(0.240)
DAGE3	0.285	-0.019	0.096	-0.013	-0.010	0.265	-0.138
	(0.227)	(0.236)	(0.230)	(0.256)	(0.266)	(0.243)	(0.228)
DEDU2	0.559**	0.671**	0.661**	0.430	0.595*	0.229	0.092
	(0.269)	(0.279)	(0.272)	(0.303)	(0.314)	(0.289)	(0.268)
DEDU3	0.461**	0.290	0.414**	0.509**	0.463**	0.174	-0.061
	(0.196)	(0.205)	(0.199)	(0.221)	(0.229)	(0.209)	(0.196)
HOUSE	-0.091	-0.112	-0.109	-0.139	-0.129	-0.216**	-0.237***
	(0.083)	(0.086)	(0.084)	(0.093)	(0.096)	(0.089)	(0.082)
FEMALE	0.231	0.127	0.019	0.379*	0.155	0.151	0.222
	(0.189)	(0.197)	(0.192)	(0.213)	(0.221)	(0.202)	(0.189)
DMAR	0.070	0.235	0.149	0.045	0.015	0.159	0.220
	(0.221)	(0.230)	(0.225)	(0.248)	(0.258)	(0.239)	(0.221)
DINC2	-0.011	0.075	0.010	-0.053	0.137	0.262	0.315
	(0.214)	(0.224)	(0.218)	(0.242)	(0.251)	(0.229)	(0.214)
DINC3	0.072	0.022	0.082	0.261	0.247	0.166	0.543*
	(0.306)	(0.316)	(0.309)	(0.341)	(0.354)	(0.326)	(0.303)
SPENDFV	0.004	0.005	0.004	0.004	0.005	0.004	0.007
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
FPOH	0.004	0.002	0.026	0.016	0.016	0.019	0.007
	(0.020)	(0.021)	(0.020)	(0.023)	(0.024)	(0.022)	(0.020)
POMFRUITP	0.819***	0.780***	0.610***	0.741***	0.658***	0.501**	0.435**
	(0.190)	(0.199)	(0.193)	(0.214)	(0.223)	(0.205)	(0.192)
ILLNESS	-0.162	0.143	-0.030	-0.287	-0.066	0.252	0.324*
	(0.196)	(0.204)	(0.198)	(0.222)	(0.229)	(0.208)	(0.195)
TOBACCO	0.491*	0.342	0.432	0.199	0.264	0.579**	0.346
	(0.261)	(0.273)	(0.265)	(0.294)	(0.306)	(0.279)	(0.261)
EXERCISE	-0.156	0.073	-0.095	-0.063	-0.083	-0.357	0.413
	(0.274)	(0.285)	(0.278)	(0.308)	(0.319)	(0.291)	(0.273)
Price Information	0.685***	0.839***	0.815***	0.604***	0.808***	0.484**	0.600***
	(0.179)	(0.188)	(0.183)	(0.202)	(0.211)	(0.190)	(0.177)
σ	1.099***	1.147***	1.117***	1.240***	1.288***	1.183***	1.120***
	(0.064)	(0.067)	(0.065)	(0.072)	(0.076)	(0.067)	(0.059)
Log-Likelihood	-276.998	-284.062	-278.999	-297.326	-302.877	-297.148	-298.652

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are given in parentheses.

Table 51. Tobit Model Marginal Effects, Tasting Information Round

	Tasting Information Treatment						
	California Wonderful Pom. Fruit	Texas Red Pom. Fruit	Texas Salavatski Pom. Fruit	Ready-to-Eat California Pom. Arils	Ready-to-Eat Texas Pom. Arils	Mixed Pom. Juice	Pineapple
	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x
Demographics/ Behaviors							
DAGE2	0.212	0.160	0.120	0.101	0.040	0.070	0.388**
	(0.146)	(0.152)	(0.145)	(0.163)	(0.169)	(0.170)	(0.197)
DAGE3	0.169	-0.011	0.056	-0.008	-0.006	0.176	-0.109
	(0.137)	(0.140)	(0.135)	(0.152)	(0.159)	(0.163)	(0.181)
DEDU2	0.356*	0.437**	0.426**	0.271	0.385*	0.155	0.074
	(0.186)	(0.199)	(0.192)	(0.202)	(0.218)	(0.201)	(0.218)
DEDU3	0.282**	0.176	0.251**	0.315**	0.288*	0.116	-0.048
	(0.125)	(0.128)	(0.125)	(0.143)	(0.148)	(0.141)	(0.156)
HOUSE	-0.053	-0.066	-0.064	-0.082	-0.077	-0.142**	-0.189***
	(0.048)	(0.051)	(0.049)	(0.055)	(0.058)	(0.059)	(0.066)
FEMALE	0.133	0.074	0.011	0.219*	0.092	0.098	0.175
	(0.107)	(0.115)	(0.112)	(0.120)	(0.130)	(0.130)	(0.148)
DMAR	0.041	0.139	0.087	0.027	0.009	0.104	0.176
	(0.129)	(0.135)	(0.131)	(0.147)	(0.154)	(0.156)	(0.175)
DINC2	-0.006	0.044	0.006	-0.031	0.083	0.175	0.254
	(0.125)	(0.134)	(0.127)	(0.143)	(0.153)	(0.155)	(0.174)
DINC3	0.043	0.013	0.049	0.161	0.153	0.111	0.455*
	(0.183)	(0.188)	(0.185)	(0.218)	(0.226)	(0.224)	(0.264)
SPENDFV	0.002	0.003	0.002	0.002	0.003	0.003	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
FPOH	0.002	0.001	0.015	0.009	0.009	0.012	0.005
	(0.012)	(0.012)	(0.012)	(0.013)	(0.014)	(0.014)	(0.016)
POMFRUITP	0.521***	0.498***	0.379***	0.471***	0.418***	0.344**	0.358**
	(0.131)	(0.137)	(0.128)	(0.146)	(0.150)	(0.147)	(0.162)
ILLNESS	-0.093	0.086	-0.017	-0.166	-0.039	0.169	0.263
	(0.111)	(0.124)	(0.115)	(0.126)	(0.136)	(0.142)	(0.161)
TOBACCO	0.287*	0.203	0.252	0.118	0.158	0.381**	0.276
	(0.153)	(0.161)	(0.155)	(0.175)	(0.183)	(0.183)	(0.208)
EXERCISE	-0.091	0.043	-0.055	-0.037	-0.050	-0.235	0.330
	(0.160)	(0.169)	(0.162)	(0.183)	(0.191)	(0.191)	(0.218)
Price Information	0.379***	0.465***	0.445***	0.343***	0.000	0.308***	0.467***
	(0.095)	(0.099)	(0.095)	(0.111)	(0.000)	(0.118)	(0.134)

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are given in parentheses.

Table 52. Tobit Model Estimates of WTP, Health and Nutrition Information

	Health and Nutrition Information						
	California Wonderful Pom. Fruit	Texas Red Pom. Fruit	Texas Salavatski Pom. Fruit	Ready-to-Eat California Pom. Arils	Ready-to-Eat Texas Pom. Arils	Mixed Pom. Juice	Pineapple
	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)
Constant	-0.652*	-0.500	-0.617	0.006	0.158	0.701	0.723*
	(0.372)	(0.396)	(0.422)	(0.419)	(0.422)	(0.430)	(0.384)
Demographics/ Behaviors							
DAGE2	0.405*	0.392	0.209	0.215	0.175	0.052	0.410*
	(0.232)	(0.246)	(0.262)	(0.263)	(0.264)	(0.269)	(0.241)
DAGE3	0.293	0.217	0.154	0.062	0.094	0.207	-0.049
	(0.220)	(0.233)	(0.248)	(0.249)	(0.250)	(0.254)	(0.229)
DEDU2	0.571**	0.569**	0.430	0.429	0.393	0.353	0.297
	(0.261)	(0.276)	(0.295)	(0.294)	(0.296)	(0.301)	(0.269)
DEDU3	0.470**	0.318	0.471**	0.392*	0.221	0.009	0.051
	(0.190)	(0.201)	(0.214)	(0.214)	(0.216)	(0.220)	(0.197)
HOUSE	-0.081	-0.110	-0.037	-0.186**	-0.169*	-0.182*	-0.217***
	(0.081)	(0.085)	(0.091)	(0.092)	(0.091)	(0.093)	(0.083)
FEMALE	0.353*	0.166	0.263	0.348*	0.127	0.058	0.224
	(0.186)	(0.195)	(0.209)	(0.207)	(0.208)	(0.213)	(0.190)
DMAR	0.093	0.058	-0.058	0.238	0.092	0.188	0.173
	(0.217)	(0.228)	(0.244)	(0.244)	(0.244)	(0.250)	(0.222)
DINC2	-0.006	0.091	0.115	0.054	0.118	0.232	0.304
	(0.209)	(0.220)	(0.235)	(0.235)	(0.236)	(0.240)	(0.216)
DINC3	0.217	0.070	0.433	0.406	0.285	0.048	0.534*
	(0.294)	(0.313)	(0.332)	(0.331)	(0.335)	(0.344)	(0.305)
SPENDFV	0.006	0.007	0.010*	0.005	0.004	0.002	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
FPOH	0.003	0.008	0.009	0.011	0.032	0.033	0.010
	(0.020)	(0.021)	(0.022)	(0.022)	(0.022)	(0.023)	(0.020)
POMFRUITP	0.792***	0.689***	0.861***	0.709***	0.633***	0.572***	0.485**
	(0.185)	(0.196)	(0.209)	(0.208)	(0.210)	(0.214)	(0.193)
ILLNESS	-0.042	0.058	-0.049	-0.259	-0.236	0.240	0.310
	(0.190)	(0.200)	(0.214)	(0.215)	(0.216)	(0.218)	(0.196)
TOBACCO	0.493*	0.341	0.341	0.282	0.364	0.515*	0.353
	(0.255)	(0.270)	(0.288)	(0.287)	(0.288)	(0.292)	(0.263)
EXERCISE	0.034	0.017	0.017	0.029	-0.149	-0.362	0.266
	(0.266)	(0.281)	(0.300)	(0.299)	(0.300)	(0.305)	(0.275)
Price Information	0.738***	0.883***	0.635***	0.627***	0.804***	0.433**	0.753***
	(0.175)	(0.186)	(0.198)	(0.196)	(0.198)	(0.200)	(0.178)
σ	1.064***	1.124***	1.197***	1.200***	1.210***	1.240***	1.127***
	(0.063)	(0.067)	(0.072)	(0.071)	(0.071)	(0.071)	(0.059)
Log-Likelihood	-268.083	-276.321	-282.848	-290.315	-292.987	-303.983	-301.094

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are given in parentheses.

Table 53. Tobit Model Marginal Effects on WTP, Health and Nutrition Information

	Health and Nutrition Information						
	California Wonderful Pom. Fruit	Texas Red Pom. Fruit	Texas Salavatski Pom. Fruit	Ready-to-Eat California Pom. Arils	Ready-to-Eat Texas Pom. Arils	Mixed Pom. Juice	Pineapple
	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x
Demographics/ Behaviors							
DAGE2	0.239*	0.229	0.115	0.129	0.107	0.034	0.334*
	(0.141)	(0.147)	(0.147)	(0.160)	(0.163)	(0.176)	(0.198)
DAGE3	0.171	0.125	0.085	0.037	0.057	0.135	-0.039
	(0.131)	(0.136)	(0.137)	(0.149)	(0.153)	(0.168)	(0.184)
DEDU2	0.360**	0.354*	0.251	0.271	0.251	0.240	0.245
	(0.179)	(0.186)	(0.183)	(0.197)	(0.200)	(0.213)	(0.227)
DEDU3	0.284**	0.187	0.268**	0.241*	0.137	0.006	0.041
	(0.120)	(0.122)	(0.128)	(0.136)	(0.136)	(0.143)	(0.159)
HOUSE	-0.047	-0.063	-0.020	-0.111**	-0.102*	-0.118*	-0.174***
	(0.046)	(0.049)	(0.049)	(0.055)	(0.056)	(0.061)	(0.066)
FEMALE	0.198**	0.094	0.141	0.202*	0.076	0.037	0.178
	(0.101)	(0.108)	(0.110)	(0.117)	(0.124)	(0.137)	(0.150)
DMAR	0.054	0.033	-0.032	0.141	0.056	0.121	0.139
	(0.125)	(0.130)	(0.134)	(0.144)	(0.147)	(0.161)	(0.178)
DINC2	-0.004	0.052	0.063	0.032	0.072	0.152	0.247
	(0.120)	(0.127)	(0.130)	(0.141)	(0.145)	(0.159)	(0.176)
DINC3	0.129	0.040	0.252	0.256	0.180	0.032	0.450*
	(0.182)	(0.182)	(0.207)	(0.221)	(0.220)	(0.226)	(0.266)
SPENDFV	0.003	0.004	0.005*	0.003	0.002	0.001	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
FPOH	0.002	0.005	0.005	0.007	0.020	0.021	0.008
	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)	(0.016)
POMFRUITP	0.496***	0.422***	0.512***	0.451***	0.407***	0.390**	0.402**
	(0.126)	(0.128)	(0.135)	(0.141)	(0.143)	(0.153)	(0.165)
ILLNESS	-0.024	0.033	-0.026	-0.150	-0.140	0.159	0.254
	(0.108)	(0.116)	(0.116)	(0.122)	(0.126)	(0.147)	(0.163)
TOBACCO	0.284*	0.194	0.186	0.167	0.221	0.334*	0.284
	(0.147)	(0.154)	(0.157)	(0.171)	(0.175)	(0.190)	(0.211)
EXERCISE	0.020	0.010	0.009	0.017	-0.090	-0.235	0.214
	(0.153)	(0.160)	(0.164)	(0.178)	(0.182)	(0.198)	(0.221)
Price Information	0.399***	0.468***	0.330***	0.356***	0.460***	0.274**	0.587***
	(0.090)	(0.093)	(0.099)	(0.107)	(0.108)	(0.123)	(0.135)

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are given in parentheses.

Table 54. Tobit Model Estimates of WTP, Anti-Cancer Information Treatment

	Anti-Cancer Information Treatment						
	California Wonderful Pom. Fruit	Texas Red Pom. Fruit	Texas Salavatski Pom. Fruit	Ready-to-Eat California Pom. Arils	Ready-to-Eat Texas Pom. Arils	Mixed Pom. Juice	Pineapple
	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)	Parameter (Std. Error)
Constant	-0.193	-0.053	-0.091	-0.046	0.051	0.523	0.848**
	(0.367)	(0.396)	(0.380)	(0.438)	(0.409)	(0.394)	(0.377)
Demographics/ Behaviors							
DAGE2	0.058	-0.011	-0.077	0.198	0.255	0.235	0.402*
	(0.228)	(0.246)	(0.236)	(0.274)	(0.256)	(0.248)	(0.236)
DAGE3	0.104	0.085	0.042	-0.016	-0.032	0.247	-0.028
	(0.215)	(0.232)	(0.222)	(0.261)	(0.243)	(0.235)	(0.225)
DEDU2	0.470*	0.647**	0.559**	0.424	0.535*	0.304	0.541**
	(0.256)	(0.274)	(0.264)	(0.309)	(0.286)	(0.277)	(0.264)
DEDU3	0.409**	0.307	0.333*	0.441*	0.246	0.094	0.071
	(0.187)	(0.202)	(0.194)	(0.225)	(0.210)	(0.202)	(0.194)
HOUSE	-0.059	-0.083	-0.070	-0.120	-0.127	-0.182**	-0.215***
	(0.078)	(0.085)	(0.081)	(0.094)	(0.088)	(0.085)	(0.081)
FEMALE	0.204	0.135	0.118	0.344	0.262	0.011	0.229
	(0.182)	(0.196)	(0.189)	(0.218)	(0.203)	(0.195)	(0.187)
DMAR	-0.085	-0.052	-0.019	0.020	0.055	0.041	0.162
	(0.212)	(0.228)	(0.219)	(0.254)	(0.236)	(0.230)	(0.218)
DINC2	0.010	-0.082	-0.050	0.153	0.217	0.316	0.292
	(0.205)	(0.221)	(0.212)	(0.246)	(0.229)	(0.222)	(0.212)
DINC3	0.128	-0.096	-0.041	0.396	0.241	0.296	0.592**
	(0.291)	(0.313)	(0.301)	(0.348)	(0.324)	(0.315)	(0.299)
SPENDFV	0.006	0.005	0.005	0.007	0.004	0.006	0.006
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
FPOH	0.021	0.022	0.029	0.023	0.043**	0.020	0.015
	(0.019)	(0.021)	(0.020)	(0.023)	(0.022)	(0.021)	(0.020)
POMFRUITP	0.885***	0.733***	0.706***	0.628***	0.498**	0.415**	0.225
	(0.181)	(0.196)	(0.188)	(0.219)	(0.204)	(0.198)	(0.190)
ILLNESS	-0.152	-0.018	-0.128	-0.161	-0.053	0.209	0.136
	(0.187)	(0.200)	(0.193)	(0.225)	(0.209)	(0.201)	(0.193)
TOBACCO	0.280	0.157	0.178	0.359	0.338	0.507*	0.410
	(0.251)	(0.271)	(0.259)	(0.300)	(0.280)	(0.269)	(0.258)
EXERCISE	-0.509*	-0.339	-0.378	-0.204	-0.328	-0.157	0.200
	(0.264)	(0.283)	(0.272)	(0.315)	(0.292)	(0.281)	(0.270)
Price Information	0.702***	0.750***	0.796***	0.710***	0.789***	0.788***	0.545***
	(0.173)	(0.186)	(0.179)	(0.206)	(0.192)	(0.184)	(0.175)
σ	1.039***	1.121***	1.077***	1.266***	1.181***	1.149***	1.105***
	(0.063)	(0.068)	(0.066)	(0.073)	(0.068)	(0.063)	(0.059)
Log-Likelihood	-259.394	-271.376	-265.412	-301.357	-292.980	-297.238	-296.252

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are given in parentheses.

Table 55. Tobit Model Marginal Effects on WTP, Anti-Cancer Information

	Anti-Cancer Information Treatment						
	California Wonderful Pom. Fruit	Texas Red Pom. Fruit	Texas Salavatski Pom. Fruit	Ready-to-Eat California Pom. Arils	Ready-to-Eat Texas Pom. Arils	Mixed Pom. Juice	Pineapple
	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x	∂y/∂x
Demographics/ Behaviors							
DAGE2	0.033	-0.006	-0.043	0.120	0.120	0.168	0.325*
	(0.128)	(0.136)	(0.131)	(0.167)	(0.167)	(0.179)	(0.193)
DAGE3	0.059	0.047	0.024	-0.010	-0.010	0.177	-0.023
	(0.122)	(0.129)	(0.125)	(0.156)	(0.156)	(0.170)	(0.179)
DEDU2	0.284*	0.396**	0.343*	0.269	0.269	0.224	0.454**
	(0.166)	(0.184)	(0.176)	(0.207)	(0.207)	(0.211)	(0.231)
DEDU3	0.238**	0.175	0.193*	0.274*	0.274*	0.067	0.057
	(0.114)	(0.118)	(0.116)	(0.145)	(0.145)	(0.146)	(0.156)
HOUSE	-0.033	-0.046	-0.039	-0.072	-0.072	-0.130**	-0.172***
	(0.044)	(0.047)	(0.046)	(0.057)	(0.057)	(0.061)	(0.065)
FEMALE	0.112	0.074	0.065	0.201	0.201	0.008	0.181
	(0.099)	(0.106)	(0.104)	(0.124)	(0.124)	(0.139)	(0.146)
DMAR	-0.047	-0.029	-0.011	0.012	0.012	0.029	0.129
	(0.119)	(0.126)	(0.123)	(0.152)	(0.152)	(0.163)	(0.173)
DINC2	0.005	-0.045	-0.028	0.092	0.092	0.228	0.236
	(0.115)	(0.121)	(0.118)	(0.150)	(0.150)	(0.162)	(0.172)
DINC3	0.073	-0.052	-0.023	0.250	0.250	0.218	0.498*
	(0.170)	(0.168)	(0.167)	(0.232)	(0.232)	(0.240)	(0.263)
SPENDFV	0.003	0.003	0.003	0.004	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
FPOH	0.012	0.012	0.016	0.014	0.014	0.014	0.012
	(0.011)	(0.011)	(0.011)	(0.014)	(0.014)	(0.015)	(0.016)
POMFRUITP	0.547***	0.437***	0.427***	0.398***	0.398***	0.305**	0.182
	(0.123)	(0.126)	(0.122)	(0.146)	(0.146)	(0.150)	(0.156)
ILLNESS	-0.084	-0.010	-0.071	-0.095	-0.095	0.150	0.109
	(0.102)	(0.110)	(0.106)	(0.131)	(0.131)	(0.147)	(0.156)
TOBACCO	0.157	0.087	0.100	0.215	0.215	0.360*	0.327
	(0.141)	(0.150)	(0.145)	(0.180)	(0.180)	(0.191)	(0.205)
EXERCISE	-0.285*	-0.187	-0.212	-0.122	-0.122	-0.111	0.160
	(0.148)	(0.156)	(0.153)	(0.188)	(0.188)	(0.199)	(0.215)
Price Information	0.369***	0.388***	0.416***	0.405***	0.405***	0.534***	0.425***
	(0.087)	(0.092)	(0.089)	(0.113)	(0.113)	(0.120)	(0.133)

Note: Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are given in parentheses.

APPENDIX H

COMPARISON OF ONE VERSUS TWO VARIABLES FOR TEXAS VARIETIES

Table 56. Comparison of Random Effects Tobit Model Parameter Estimates for WTP for Fruit Products by Engaged Bidders, One Texas Variety vs. Two Texas Varieties

	Two Texas Variety Variables with Bidders Who Are Unengaged for *Any* Product Excluded [b] [c]		"Any Texas Variety" Variable with Bidders Who Are Unengaged for *Any* Product Excluded [b] [c]	
	Parameter	Standard Error	Parameter	Standard Error
Constant	0.419 [a]	0.272	0.419	0.272
Variety				
1: Texas Red	0.056	0.036	---	---
2: Texas Salavatski	0.057**	0.027	---	---
Any Texas Variety	---	---	0.057**	0.025
Product Form				
Ready-To-Eat (RTE)	0.320***	0.027	0.320***	0.025
Juice	0.567***	0.036	0.567***	0.035
Pineapple	0.948***	0.036	0.948***	0.035
Price Information	0.723***	0.134	0.723***	0.134
Additional Information				
Tasting	0.172***	0.029	0.172***	0.029
Health and Nutrition	0.137***	0.029	0.137***	0.029
Anti-Cancer	0.145***	0.029	0.145***	0.029
Demographics/ Behaviors				
DAGE2	0.038	0.171	0.038	0.171
DAGE3	-0.062	0.161	-0.062	0.161
DEDU2	0.281	0.192	0.281	0.192
DEDU3	0.219	0.141	0.219	0.141
HOUSE	-0.120**	0.059	-0.120**	0.059
FEMALE	0.115	0.138	0.115	0.138
DMAR	0.016	0.162	0.016	0.162
DINC2	-0.047	0.155	-0.047	0.155
DINC3	0.469**	0.231	0.469**	0.231
SPENDFV	0.001	0.003	0.001	0.003
FPOH	0.002	0.014	0.002	0.014
POMFRUITP	0.376***	0.133	0.376***	0.133
ILLNESS	0.094	0.142	0.094	0.142
TOBACCO	0.058	0.183	0.058	0.183
EXERCISE	-0.015	0.198	-0.015	0.198
$\sigma(u)$ [d]	0.706***	0.042	0.706***	0.042
$\sigma(e)$ [e]	0.670***	0.008	0.670***	0.008
ρ	0.526***	0.030	0.526***	0.030
Log-Likelihood	-4681.491		-4681.491	
Likelihood ratio test [f]	2652.20***		2652.20***	
N (individuals)	154		154	

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

[b] Unengaged bidders are those who submitted bids of $0.00 for all rounds for the specified fruit product.

[c] "Any product" refers to bidders who were unengaged for *any* one of the seven included fruit products.

[d] Standard deviation of individual-specific error.

[e] Standard deviation of overall error.

[f] Likelihood ratio test that $\sigma(u) = 0$.

Table 57. Comparison of Random Effects Tobit Model Marginal Effects Estimates for WTP for Fruit Products by Engaged Bidders, One Texas Variety vs. Two Texas Varieties

	Two Texas Variety Variables with Bidders Who Are Unengaged for *Any* Product Excluded [b] [c]		"Any Texas Variety" Variable with Bidders Who Are Unengaged for *Any* Product Excluded [b] [c]	
	∂y/∂x	Standard Error	∂y/∂x	Standard Error
Variety				
1: Texas Red	0.043[a]	0.027	---	---
2: Texas Salavatski	0.043**	0.021	---	---
Any Texas Variety	---	---	0.043**	0.019
Product Form				
Ready-To-Eat (RTE)	0.243***	0.021	0.243***	0.020
Juice	0.431***	0.029	0.431***	0.029
Pineapple	0.720***	0.032	0.720***	0.031
Price Information	0.525***	0.093	0.525***	0.093
Additional Information				
Tasting	0.130***	0.022	0.130***	0.022
Health and Nutrition	0.103***	0.022	0.103***	0.022
Anti-Cancer	0.109***	0.022	0.109***	0.022
Demographics/ Behaviors				
DAGE2	0.029	0.130	0.029	0.130
DAGE3	-0.047	0.122	-0.047	0.122
DEDU2	0.221	0.155	0.221	0.155
DEDU3	0.169	0.110	0.169	0.110
HOUSE	-0.091**	0.045	-0.091**	0.045
FEMALE	0.087	0.103	0.087	0.103
DMAR	0.012	0.123	0.012	0.123
DINC2	-0.036	0.118	-0.036	0.118
DINC3	0.378*	0.195	0.378*	0.195
SPENDFV	0.001	0.003	0.001	0.003
FPOH	0.001	0.011	0.001	0.011
POMFRUITP	0.294***	0.106	0.294***	0.106
ILLNESS	0.072	0.109	0.072	0.109
TOBACCO	0.044	0.139	0.044	0.139
EXERCISE	-0.011	0.150	-0.011	0.150

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

[b] Unengaged bidders are those who submitted bids of $0.00 for all rounds for the specified fruit product.

[c] "Any product" refers to bidders who were unengaged for *any* one of the seven included fruit products.

Table 58. Comparison of Mixed Linear Model Parameter Estimates for WTP for Fruit Products by Engaged Bidders, One Texas Variety vs. Two Texas Varieties

	Two Texas Variety Variables with Bidders Who Are Unengaged for *Any* Product Excluded [(b) (c)]		"Any Texas Variety" Variable with Bidders Who Are Unengaged for *Any* Product Excluded [(b) (c)]	
	Parameter	Standard Error	Parameter	Standard Error
Constant	0.438[(a)]	0.268	0.438	0.268
Variety				
1: Texas Red	0.053	0.035	---	---
2: Texas Salavatski	0.054**	0.026	---	---
Any Texas Variety	---	---	0.054**	0.024
Product Form				
Ready-To-Eat (RTE)	0.308***	0.026	0.308***	0.024
Juice	0.555***	0.035	0.555***	0.034
Pineapple	0.930***	0.035	0.930***	0.034
Price Information	0.725***	0.132	0.725***	0.132
Additional Information	0.000	0.000		
Tasting	0.158***	0.028	0.158***	0.028
Health and Nutrition	0.128***	0.028	0.128***	0.028
Anti-Cancer	0.136***	0.028	0.136***	0.028
Demographics/ Behaviors				
DAGE2	0.057	0.168	0.057	0.168
DAGE3	-0.057	0.159	-0.057	0.159
DEDU2	0.278	0.189	0.278	0.189
DEDU3	0.210	0.139	0.210	0.139
HOUSE	-0.116**	0.059	-0.116**	0.059
FEMALE	0.104	0.136	0.104	0.136
DMAR	0.015	0.159	0.015	0.159
DINC2	-0.038	0.153	-0.038	0.153
DINC3	0.469**	0.227	0.469**	0.227
SPENDFV	0.001	0.003	0.001	0.003
FPOH	0.002	0.014	0.002	0.014
POMFRUITP	0.367***	0.131	0.367***	0.131
ILLNESS	0.106	0.140	0.106	0.140
TOBACCO	0.067	0.180	0.067	0.180
EXERCISE	-0.015	0.195	-0.015	0.195
$\hat{\sigma}_u^2$ [(d)]	0.483***	0.057	0.483***	0.057
Log-Likelihood	-4523.360		-4523.360	
LR Test [(e)]	2756.57***		2756.57***	
N (individuals)	154		154	

[(a)] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and

[(b)] Unengaged bidders are those who submitted bids of $0.00 for all rounds for the specified fruit product.

[(c)] "Any product" refers to bidders who were unengaged for *any* one of the seven included fruit products.

[(d)] Estimated standard deviation for the random effects specified at the individual level.

[(e)] Likelihood Ratio Test of Mixed Linear Model versus Linear Regression.

APPENDIX I

PROBABILITY THAT A PARTICULAR PRODUCT WILL BE RANKED FIRST

Table 59. Likelihood of a Fruit Product Option Being Ranked First, Fully-Ranked Preferences

	Fully-Ranked Preference Rankings				
	Baseline	Tasting Information	Health and Nutrition Information	Anti-Cancer Information	Full Information
California Wonderful Pomegranate Fruit	0.074	0.090	0.090	0.085	0.092
Texas Red Pomegranate Fruit	0.077	0.140	0.111	0.113	0.132
Texas Salavatski Pomegranate Fruit	0.083	0.119	0.104	0.111	0.119
Ready-to-Eat Pomegranate Arils - California Wonderful	0.124	0.111	0.135	0.137	0.126
Ready-to-Eat Pomegranate Arils - Texas Salavatski	0.140	0.148	0.157	0.178	0.163
Mixed Pomegranate Juice	0.156	0.080	0.091	0.125	0.072
Pineapple	0.309	0.293	0.282	0.221	0.272
No Product	0.037	0.019	0.030	0.030	0.022

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 60. Likelihood of a Fruit Product Option Being Ranked First, Partially-Ranked Preferences

	Partially-Ranked Preference Rankings				
	Baseline	Tasting Information	Health and Nutrition Information	Anti-Cancer Information	Full Information
California Wonderful Pomegranate Fruit	0.053	0.075	0.065	0.062	0.071
Texas Red Pomegranate Fruit	0.048	0.114	0.084	0.091	0.103
Texas Salavatski Pomegranate Fruit	0.060	0.102	0.078	0.080	0.093
Ready-to-Eat Pomegranate Arils - California Wonderful	0.105	0.090	0.117	0.123	0.105
Ready-to-Eat Pomegranate Arils - Texas Salavatski	0.119	0.123	0.141	0.159	0.138
Mixed Pomegranate Juice	0.178	0.099	0.109	0.158	0.090
Pineapple	0.374	0.363	0.363	0.283	0.361
No Product	0.063	0.033	0.044	0.044	0.039

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 61. Likelihood of a Fruit Product Option Being Ranked First, Fully-Ranked Implied Ordered Bids

	Fully-Ranked Implied Ordered Bids				
	Baseline	Tasting Information	Health and Nutrition Information	Anti-Cancer Information	Full Information
California Wonderful Pomegranate Fruit	0.054	0.075	0.068	0.065	0.069
Texas Red Pomegranate Fruit	0.048	0.089	0.070	0.071	0.086
Texas Salavatski Pomegranate Fruit	0.055	0.089	0.076	0.074	0.079
Ready-to-Eat Pomegranate Arils - California Wonderful	0.113	0.114	0.116	0.136	0.110
Ready-to-Eat Pomegranate Arils - Texas Salavatski	0.116	0.136	0.129	0.154	0.125
Mixed Pomegranate Juice	0.203	0.123	0.128	0.181	0.104
Pineapple	0.397	0.358	0.397	0.303	0.410
No Product	0.014	0.016	0.016	0.017	0.016

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 62 . Likelihood of a Fruit Product Option Being Ranked First, Partially-Ranked Implied Ordered Bids

	Partially Ranked Implied Ordered Bids				
	Baseline	Tasting Information	Health and Nutrition Information	Anti-Cancer Information	Full Information
California Wonderful Pomegranate Fruit	0.043	0.059	0.057	0.051	0.058
Texas Red Pomegranate Fruit	0.037	0.076	0.062	0.063	0.074
Texas Salavatski Pomegranate Fruit	0.045	0.075	0.063	0.060	0.069
Ready-to-Eat Pomegranate Arils - California Wonderful	0.106	0.105	0.113	0.127	0.103
Ready-to-Eat Pomegranate Arils - Texas Salavatski	0.110	0.133	0.125	0.149	0.122
Mixed Pomegranate Juice	0.212	0.130	0.133	0.197	0.117
Pineapple	0.428	0.403	0.428	0.333	0.438
No Product	0.019	0.019	0.020	0.020	0.019

[a] Single (*), double (**), and triple (***) asterisks are used to denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

APPENDIX J

STATA CODE

```
*DOFILE 0STARTUP:
cd E:\
*Start log file and append to the end of previous file
log using E:\THESIS\DATA\STATALONGOUT1All.log, append name(OUT1ALL)
*Start command log and append to the end of previous command log file
cmdlog using E:\THESIS\DATA\STATALONGOUT2CMD.log, append
*============================================================
*=============================================DATE = ________
*============================================================
*Increase Memory Space to use
set memory 100M
*============================================================
*Use the specified data
use "E:\Thesis\Data\STATAIn9AllLongFormMissingDropped.dta"
*#####################################################################
*============================================================
*============================================================
*============================================================
*#####################################################################


*DOFILE 1BLOCALS:
di ”MODEL TYPE Ai- No interactions, no demographic variables, no info,
no price”
local typeAi var1txr var2txs formrte formjuice productpine
*
di "MODEL TYPE Aii- No interactions, no demographic variables, no info,
with price"
local typeAii var1txr var2txs formrte formjuice productpine i.price
*
di “MODEL TYPE B- No interactions, no demographic variables, info
included, with price”
local typeB var1txr var2txs formrte formjuice productpine i.price
i.info
*
di “MODEL TYPE C- No interactions, with  demographic variables, info
included, with price”
local typeC var1txr var2txs formrte formjuice productpine i.agefew2sta
i.agefew3sta i.edufew2sta i.edufew3sta house i.female i.dmarfewsta
i.incfew2sta i.incfew3sta c.spendfvavgstat c.fpohstat i.pomfruitp
i.hissue c.tobacavgstat c.exeravgstat i.price i.info
*
di "MODEL TYPE H- No interactions, with  demographic variables, info
NOT included, with price"
local typeH var1txr var2txs formrte formjuice productpine i.agefew2sta
i.agefew3sta i.edufew2sta i.edufew3sta house i.female i.dmarfewsta
i.incfew2sta i.incfew3sta c.spendfvavgstat c.fpohstat i.pomfruitp
```

```
i.hissue c.tobacavgstat c.exeravgstat i.price
*
di "MODEL TYPE I- No interactions, with  demographic variables, info
NOT included, NO price"
local typeI var1txr var2txs formrte formjuice productpine i.agefew2sta
i.agefew3sta i.edufew2sta i.edufew3sta house i.female i.dmarfewsta
i.incfew2sta i.incfew3sta c.spendfvavgstat c.fpohstat i.pomfruitp
i.hissue c.tobacavgstat c.exeravgstat
*
di"MODEL TYPE J- No interactions, NO Product Characteristics, with
demographic variables, info NOT included, with price"
local typeJ  i.agefew2sta i.agefew3sta i.edufew2sta i.edufew3sta house
i.female i.dmarfewsta i.incfew2sta i.incfew3sta c.spendfvavgstat
c.fpohstat i.pomfruitp i.hissue c.tobacavgstat c.exeravgstat i.price
*
di “MODEL TYPE K- One Texas Variable, No interactions, with
demographic variables, info included, with price”
local typeK vartexas formrte formjuice productpine i.agefew2sta
i.agefew3sta i.edufew2sta i.edufew3sta house i.female i.dmarfewsta
i.incfew2sta i.incfew3sta c.spendfvavgstat c.fpohstat i.pomfruitp
i.hissue c.tobacavgstat c.exeravgstat i.price i.info”
*
di “MODEL TYPE L- SAME AS TYPE C BUT FOR DELTAS- Forces all Information
to be kept”
local typeL var1txr var2txs formrte formjuice productpine i.agefew2sta
i.agefew3sta i.edufew2sta i.edufew3sta house i.female i.dmarfewsta
i.incfew2sta i.incfew3sta c.spendfvavgstat c.fpohstat i.pomfruitp
i.hissue c.tobacavgstat c.exeravgstat i.price inform2 inform3 inform4
*
di “Variables to force all information treatments to be kept”
local forceinfo inform2 inform3 inform4
di"Variables for random effects"
local infodemo agefew2sta agefew3sta edufew2sta edufew3sta house female
dmarfewsta incfew2sta incfew3sta spendfvavgstat fpohstat pomfruitp
hissue tobacavgstat exeravgstat price inform2 inform3 inform4
*
di"=========================================================="
di"RANKINGS LOCAL VARIABLES"
di"MODEL TYPE RAi- FOR RANKINGS- No interactions, no demographic
variables, no info , no price, (with no product included)"
local typeRAi var1txr var2txs formrte formjuice productpine
productnoprod
*
di"MODEL TYPE RI- RANKINGS LOCAL VARIABLES and interactions"
di"MODEL TYPE RI- FOR RANKINGS- info#prod chars. interactions, no
demographic , no info , no price, (with no product included)"
local typeRI `typeRAi' i.info#i.(formrte )
*
di “Create list of ranks to be dropped for calculations based on
rankings”
local dropforrank id!=108 & id!=204 & id!=208 & id!=209 & id!=220 &
id!=313 & id!=412 & id!=420 & id!=422 & id!=810 & id!=833
*#####################################################################
*==========================================================
```

```
*==========================================================
*==========================================================
*#################################################################


*DOFILE 1CSUMMARY:
display "Start log file and append to the end of previous file"
log using ".\THESIS\DATA\STATALONGOUT1cSummary.log", append
name(OUT1CSUMMARY)
display "Start log file and replace previous file"
log using ".\THESIS\DATA\STATALONGOUT1cSummaryrep.log", replace
name(OUT1CSUMMARYrep)
*
*===================================================================
*==============Summary Statistics, As Needed=========================
*=== (Data are balanced, so values will be correct for all data======
*===================================================================
di”Summary Statistics for included variables”
summarize `typeC’ if key==”naivecali”
*
di"Summary Statistics for previous experience with Pomegranates"
summarize pomsee-pomflavn if key=="naivecali"
di"Detailed summary statistics for previous experience with
pomegranates"
summarize pomsee-pomflavn if key=="naivecali", detail
di “Count of individuals with any pomegranates on hand”
count if key=="naivecali" & pomhand!=1
*
di"Summarize vairables by session"
forvalues i= 1(1)8{
summarize `typeC' if info!=5&prodkey!="noprod"&s`i's==1
}
*
di "Count of individuals in each session"
forvalues i=100(100)800{
list id if key=="naivecali" & `i'<=id & id<=(`i'+99)
count if key=="naivecali" & `i'<=id & id<=(`i'+99)
}
*
di"Count of total bidders included"
count if key=="naivecali"
log close OUT1CSUMMARY
log close OUT1CSUMMARYrep
*#################################################################
*==========================================================
*==========================================================
*==========================================================
*#################################################################


*DOFILE 2TOBITS:
log using E:\THESIS\DATA\STATALONGOUT2TOBITS.log, append
name(OUT2TOBITS)
*===================================================================
```

```
*=====================================================================
*===================TOBIT MODELS, WTP================================
*======== WTP= f(WTP= f(product characteristics, info, demographics)=
*======== 1 model for all WTP bids for all products==================
*=====================================================================
*=====================================================================
di"TOBIT MODEL"
di"MODEL TYPE Ai- No interactions, no demographic variables, no info ,
no price"
tobit bids `typeAi'  if info!=5&prodkey!="noprod", ll(0) log
margins, dydx(*) predict(e(0,.))
estimates store tobitAi
*
di"TOBIT MODEL"
di"MODEL TYPE Aii- No interactions, no demographic variables, no info ,
with price"
tobit bids `typeAii' if info!=5&prodkey!="noprod", ll(0) log
margins, dydx(*) predict(e(0,.))
estimates store tobitAii
*
di"TOBIT MODEL"
di"MODEL TYPE B- No interactions, no demographic variables, info
included, with price"
tobit bids `typeB' if info!=5&prodkey!="noprod"&i, ll(0) log
margins, dydx(*) predict(e(0,.))
estimates store tobitB
*
di"TOBIT MODEL"
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
tobit bids `typeC' if info!=5&prodkey!="noprod", ll(0) log
margins, dydx(*) predict(e(0,.))
estimates store tobitC
*
di"TOBIT MODEL"
di"MODEL TYPE H- No interactions, with  demographic variables, info NOT
included, with price"
tobit bids `typeH' if info!=5&prodkey!="noprod", ll(0) log
margins, dydx(*) predict(e(0,.))
estimates store tobitH
*
di"Do a likelihood ratio test on the model specifications and obtain
AIC and BIC values"
lrtest tobitH tobitAi, stats
lrtest tobitH tobitAii, stats
lrtest tobitH tobitB, stats
lrtest tobitH tobitC, stats
*
log close OUT2TOBITS
*
*#####################################################################
*==========================================================
*==========================================================
*==========================================================
```

```
*#####################################################################


*DOFILE 3ROLOGITS:
log using E:\THESIS\DATA\STATALONGOUT3rologits.log, append
name(OUT3ROLOGITS)
log using E:\THESIS\DATA\STATALONGOUT3rologitsRE.log, replace
name(OUT3ROLOGITSRE)
di"Generate variables to be used in saving estimates of rank-ordereled
logit models"
foreach ranking of varlist pref prefpart brprefer brprefpart{
forvalues i =1(1)5{
generate pRAi`ranking'info`i' =0
}
}
*
di"Create nested loops to run rank-ordered logit models for:
di"Outside Loop: fully and partially ranked explicit rankings and
implied rankings"
di"Inside Loop: Each information treatment (identified 1-5)"
foreach ranking of varlist pref prefpart brprefer brprefpart{
forvalues i =1(1)5{
di"====================================================================="
di"============RANK-ORDERED LOGIT MODELS, Rankings====================="
di"=================== Rank= f(product characteristics)================"
di"===== 5 models (BASELINE, TASTING, HEALTH, ANTI-CANCER, FULL)======"
di"====================================================================="
di"===========rologit, Baseline Treatment (info=`i')==================="
di"================`ranking'========================================="
rologit `ranking' `typeRAi' if info==`i' & `dropforrank' , group (id)
reverse
di"-------Probability of ranking a specific product as first----------"
drop pRAi`ranking'info`i'
predict pRAi`ranking'info`i' if e(sample)
sort id `ranking' pRAi`ranking'info`i'
gsort - pRAi`ranking'info`i'
list pRAi`ranking'info`i' prodkey `typeRAi' if id==101 & info==`i',
noobs
estimates store e`ranking'`i'
di"-------------------------------------------------------------"
di"-------------------------------------------------------------"
}
*
}
*
di"Make table of all estimated values based on rank-ordered logits"
estimates table epref1 epref2 epref3 epref4 epref5 eprefpart1
eprefpart2 eprefpart3 eprefpart4 eprefpart5 ebrprefer1 ebrprefer2
ebrprefer3 ebrprefer4 ebrprefer5 ebrprefpart1 ebrprefpart2 ebrprefpart3
ebrprefpart4 ebrprefpart5
*
log close OUT3ROLOGITS
log close OUT3ROLOGITSRE
*
```

```
*#####################################################################
*==============================================================
*==============================================================
*==============================================================
*#####################################################################


*DOFILE 4DELTAS:
log using E:\THESIS\DATA\STATALONGOUT4DELTAS.log, append
name(OUT4DELTAS)
log using E:\THESIS\DATA\STATALONGOUT4DELTASrep.log, replace
name(OUT4DELTASrep)
di"log using E:\THESIS\DATA\STATALONGOUT4DELTAS.log, append
name(OUT4DELTAS)"
di"log using E:\THESIS\DATA\STATALONGOUT4DELTASrep.log, replace
name(OUT4DELTASrep)"
*
di"Summary Statistics of Deltas"
summarize deltabid* if key=="naivecali", detail
summarize deltafbid* if key=="naivecali", detail
graph box deltabidtastecali deltabidtastetxr deltabidtastetxs
deltabidtastertec deltabidtastertet deltabidtastejuice
deltabidtastepine deltabidhealthcali deltabidhealthtxr
deltabidhealthtxs deltabidhealthrtec deltabidhealthrtet
deltabidhealthjuice deltabidhealthpine deltabidcancercali
deltabidcancertxr deltabidcancertxs deltabidcancerrtec
deltabidcancerrtet deltabidcancerjuice deltabidcancerpine if
key=="naivecali"
*graph save "E:\Thesis\Data\STATAOUT4boxplot.gph", replace
graph use "E:\Thesis\Data\STATAOUT4boxplot.gph"
*==============================================================
di"Count of total bids marked unengaged"
count if unengall2==1
di"Count of unique unengaged bids (taste, health, cancer)"
count if unengall2==1 & info!=5
*
di"Loop to calculate counts for each unengaged category"
forvalues i= 2(1)5{
di"========Counts for Each Category=================="
di"=======================info = `i'==================="
di""
di"..................Unengaged Bids..................."
count if unengall2==1 & info==`i'
di"..............Total Bid Count....................."
count if info==`i'
}
*
foreach prod in cali txr txs rtec rtet juice pine{
forvalues i= 2(1)5{
di"========Counts for Each product in each category=================="
di"=======================info = `i'========================="
di"=======================Product = `prod'==================="
di""
di"............Unengaged Bids info=`i' and prod
```

```
=`prod'..................."
count if unengall2==1 & info==`i' & prodkey=="`prod'"
di".....Number of total bids for info=`i' and prod
=`prod'................"
count if info==`i' & prodkey=="`prod'"
}
}
*
*=====================================================================
*==============DELTA BIDS ============================================
*==============MIXED LINEAR MODELS, DELTA BIDS WTP===================
*========== WTP= f(product characteristics, demographics)============
*========================== 1 model===================================
*=====================================================================
di"DELTA'S refer to the changes in bids that an individual has for a
single product across information treatments"
di"Removes full bids, naive bids, noproduct bids, and unengaged bids"
di"unengall2 identifies any individual that was a case four unengaged
bid for that particular product and round"
*
di"MIXED LINEAR MODEL- DELTAS"
di"MODEL TYPE Ai- No interactions, no demographic variables, no info ,
no price"
xtmixed deltabids `typeAi' if info!=5 & info!=1 & prodkey!="noprod" &
unengall2!=1, noconstant|| id: ,  mle
*xtmixed deltabids `typeAi' if info!=5 & info!=1 & prodkey!="noprod" &
unengall2!=1, noconstant|| id: , variance  mle
estimates store randdeltAi
*
di"MIXED LINEAR MODEL- DELTAS"
di"MODEL TYPE Aii- No interactions, no demographic variables, no info ,
with price"
xtmixed deltabids `typeAii' if info!=5 & info!=1 & prodkey!="noprod" &
unengall2!=1, noconstant|| id: ,  mle
*xtmixed deltabids `typeAii' if info!=5 & info!=1 & prodkey!="noprod" &
unengall2!=1, noconstant|| id: , variance mle
estimates store randdeltAii
*
di"MIXED LINEAR MODEL- DELTAS"
di"MODEL TYPE B- No interactions, no demographic variables, info
included, with price"
xtmixed deltabids `typeAii' `forceinfo' if info!=5 & info!=1 &
prodkey!="noprod" & unengall2!=1, noconstant|| id: ,  mle
xtmixed deltabids `typeAii' `forceinfo' if info!=5 & info!=1 &
prodkey!="noprod" & unengall2!=1, noconstant|| id: ,   variance mle
estimates store randdeltB
*
di"MIXED LINEAR MODEL- DELTAS"
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
xtmixed deltabids `typeH' `forceinfo' if info!=5 & info!=1 &
prodkey!="noprod" & unengall2!=1, noconstant|| id: ,  mle
xtmixed deltabids `typeH' `forceinfo' if info!=5 & info!=1 &
prodkey!="noprod" & unengall2!=1, noconstant|| id: ,  variance mle
```

```
estimates store randdeltC
*
di"MIXED LINEAR MODEL- DELTAS"
di"MODEL TYPE H- No interactions, with  demographic variables, info NOT
included, with price"
xtmixed deltabids `typeH' if info!=5 & info!=1 & prodkey!="noprod" &
unengall2!=1, noconstant|| id: ,  mle
*xtmixed deltabids `typeH' if info!=5 & info!=1 & prodkey!="noprod" &
unengall2!=1, noconstant|| id: ,  variance mle
estimates store randdeltH
*
di"Show statistics for each set of estimates"
estimates stats randdeltAi randdeltAii randdeltB randdeltC randdeltH
di"*****NOTE THAT THIS PREFERS THE MODELS WITH THE LOWEST AIC, BIC"
di"see stata reference[R] XTMIXED on page 334-335"
*=====================================================================
*
*=====================================================================
*==============DELTA BIDS, BASELINE TO FULL INFO=====================
*==============MIXED LINEAR MODELS, DELTA BIDS WTP===================
*========== WTP= f(product characteristics, demographics)============
*========================== 1 model==================================
*=====================================================================
di"Removes full bids, naive bids, noproduct bids, and unengaged bids"
di"unengall2 identifies any individual that was a case four unengaged
for that particular product and round"
*
di"MIXED LINEAR MODEL- DELTAS"
di"MODEL TYPE Ai- No interactions, no demographic variables, no info ,
no price"
xtmixed deltabids `typeAi' if info==5 & prodkey!="noprod" &
unengall2!=1|| id: ,  mle
*xtmixed deltabids `typeAi' if info==5 & prodkey!="noprod" &
unengall2!=1|| id: ,  variance mle
estimates store randdeltFAi
*
di"MIXED LINEAR MODEL- DELTAS"
di"MODEL TYPE Aii- No interactions, no demographic variables, no info ,
with price"
xtmixed deltabids `typeAii' if info==5 & prodkey!="noprod" &
unengall2!=1|| id: ,  mle
*xtmixed deltabids `typeAii' if info==5 & prodkey!="noprod" &
unengall2!=1|| id: ,  variance mle
estimates store randdeltFAii
*
di"MIXED LINEAR MODEL- DELTAS"
di"MODEL TYPE H- No interactions, with  demographic variables, info NOT
included, with price"
xtmixed deltabids `typeH' if info==5 & prodkey!="noprod" &
unengall2!=1|| id: ,  mle
*xtmixed deltabids `typeH' if info==5 & prodkey!="noprod" &
unengall2!=1|| id: ,  variance mle
estimates store randdeltFH
*
```

```
di"Display all stored estimates for full bids"
estimates stats randdeltFAi randdeltFAii randdeltFH
di"NOTE THAT THIS PREFERS THE MODELS WITH THE LOWEST AIC, BIC"
di"see stata reference[R] XTMIXED on page 334-335"
*=========================================================
*
log close OUT4DELTAS
log close OUT4DELTASrep
*
*#####################################################################
*==========================================================
*==========================================================
*==========================================================
*#####################################################################


DOFILE 5MIXEDLINEAR:
log using E:\THESIS\DATA\STATALONGOUT5MIXED.log, append name(OUT5MIXED)
*=====================================================================
*==============MIXED LINEAR MODELS, FULL BIDS WTP====================
*========== WTP= f(product characteristics, demographics)============
*========================== 1 model==================================
*=====================================================================
di"MIXED LINEAR MODEL"
di"MODEL TYPE Ai- No interactions, no demographic variables, no info ,
no price"
xtmixed bids `typeAi' if info!=5&prodkey!="noprod"|| id: , variance mle
estimates store randAi
*
di"MIXED LINEAR MODEL"
di"MODEL TYPE Aii- No interactions, no demographic variables, no info ,
with price"
xtmixed bids `typeAii' if info!=5&prodkey!="noprod"|| id: , variance
mle
estimates store randAii
*
di"MIXED LINEAR MODEL"
di"MODEL TYPE B- No interactions, no demographic variables, info
included, with price"
xtmixed bids `typeB' if info!=5&prodkey!="noprod"|| id: , variance mle
estimates store randB
*
di"MIXED LINEAR MODEL"
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
xtmixed bids `typeC' if info!=5&prodkey!="noprod"|| id: , variance mle
estimates store randC
*
di"MIXED LINEAR MODEL"
di"MODEL TYPE H- No interactions, with  demographic variables, info NOT
included, with price"
xtmixed bids `typeH' if info!=5&prodkey!="noprod"|| id: , variance mle
estimates store randH
*
```

```
di"MIXED LINEAR MODEL"
di"MODEL TYPE G- No interactions, with  demographic variables, info
included, with price, nested effects"
xtmixed bids `typeC' if info!=5&prodkey!="noprod"|| id: R.info,
variance mle
estimates store randG
*
estimates stats randAi randAii randB randC randH randG
di"NOTE THAT THIS PREFERS THE MODELS WITH THE LOWEST AIC,BIC"
di"see stata reference[R] XTMIXED on page 334-335"
log close OUT5MIXED
*
*#####################################################################
###
*==============================================================
*==============================================================
*==============================================================
*#####################################################################


*DOFILE 6RANDOMEFFECTSTOBITS:
*====================================================================
*==============RANDOM EFFECTS TOBIT, FULL BIDS WTP===================
*========== WTP= f(product characteristics, demographics)============
*========================== 1 model==================================
*====================================================================
di"XTTOBIT- RANDOM EFFECTS TOBIT MODEL"
di"MODEL TYPE Ai- No interactions, no demographic variables, no info ,
no price"
xtset id
xttobit bids `typeAi'  if info!=5&prodkey!="noprod", ll(0) log tobit
margins, dydx(*) predict(e(0,.))
estimates store xttobitAi
xtset, clear
*
di"XTTOBIT- RANDOM EFFECTS TOBIT MODEL"
di"MODEL TYPE Aii- No interactions, no demographic variables, no info ,
with price"
xtset id
xttobit bids `typeAii' if info!=5&prodkey!="noprod", ll(0) log tobit
margins, dydx(*) predict(e(0,.))
estimates store xttobitAii
xtset, clear
*
di"XTTOBIT- RANDOM EFFECTS TOBIT MODEL"
di"MODEL TYPE B- No interactions, no demographic variables, info
included, with price"
xtset id
xttobit bids `typeB' if info!=5&prodkey!="noprod", ll(0) log tobit
margins, dydx(*) predict(e(0,.))
estimates store xttobitB
xtset, clear
*
di"XTTOBIT- RANDOM EFFECTS TOBIT MODEL"
```

```
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
xtset id
xttobit bids `typeC' if info!=5&prodkey!="noprod", ll(0) log tobit
margins, dydx(*) predict(e(0,.))
estimates store xttobitC
xtset, clear
*
di"XTTOBIT- RANDOM EFFECTS TOBIT MODEL"
di"MODEL TYPE H- No interactions, with  demographic variables, info NOT
included, with price"
xtset id
xttobit bids `typeH' if info!=5&prodkey!="noprod", ll(0) log tobit
margins, dydx(*) predict(e(0,.))
estimates store xttobitH
xtset, clear
*
di"Do a likelihood ratio test on the model specifications and obtain
AIC and BIC values"
lrtest xttobitH xttobitAi, stats
lrtest xttobitH xttobitAii, stats
lrtest xttobitH xttobitB, stats
lrtest xttobitH xttobitC, stats
*
*#####################################################################
*==========================================================
*==========================================================
*==========================================================
*#####################################################################


DOFILE 8OLS:
*=====================================================================
*==============ORDINARY LEAST SQUARES, FULL BIDS WTP=================
*========== WTP= f(product characteristics, info, demographics)======
*========================== 1 model==================================
*===================(28 obsevations/ individual)=====================
*=====================================================================
*
di"Ordinary Least Squares Regression"
di"MODEL TYPE Ai- No interactions, no demographic variables, no info ,
no price"
regress bids var1txr var2txs formrte formjuice productpine  if
info!=5&prodkey!="noprod"
*
di"Ordinary Least Squares Regression"
di"MODEL TYPE Aii- No interactions, no demographic variables, no info ,
with price"
regress bids var1txr var2txs formrte formjuice productpine i.price if
info!=5&prodkey!="noprod"
*
di"Ordinary Least Squares Regression"
di"MODEL TYPE B- No interactions, no demographic variables, info
```

```
included, with price"
regress bids var1txr var2txs formrte formjuice productpine i.price
i.info if info!=5&prodkey!="noprod"
*
di"Ordinary Least Squares Regression"
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
regress bids var1txr var2txs formrte formjuice productpine i.agefew2sta
i.agefew3sta i.edufew2sta i.edufew3sta house i.female i.dmarfewsta
i.incfew2sta i.incfew3sta c.spendfvavgstat c.fpohstat i.pomfruitp
i.hissue c.tobacavgstat c.exeravgstat i.price i.info if
info!=5&prodkey!="noprod"
*
di"Ordinary Least Squares Regression"
di"MODEL TYPE H- No interactions, with  demographic variables, info NOT
included, with price"
regress bids var1txr var2txs formrte formjuice productpine i.agefew2sta
i.agefew3sta i.edufew2sta i.edufew3sta house i.female i.dmarfewsta
i.incfew2sta i.incfew3sta c.spendfvavgstat c.fpohstat i.pomfruitp
i.hissue c.tobacavgstat c.exeravgstat i.price if
info!=5&prodkey!="noprod"
*
*#####################################################################
*==========================================================
*==========================================================
*==========================================================
*#####################################################################



*DOFILE 9PRODUCTTOBITS:
log using E:\THESIS\DATA\STATALONGOUT9PRODTOBITS.log, append
name(OUT9PROD)
di "==35 Tobit Models for Each Product and Each information
Treatment=="
di"====================================================================="
di"===========SEPARATE TOBIT MODELS, FULL BIDS WTP====================="
di"========== Bids= f(product characteristics, demographics)==========="
di"===5 info trtmts:(BASELINE, TASTING, HEALTH, ANTI-CANCER, FULL)===="
di"==========7 products:(cali txr txs rtec rtet juice pine)==========="
di"====================================================================="
di"====================================================================="
*
di"Create Nested Loops to Do Individual Tobit Models by Product and
Information Treatment"
forvalues i = 1(1)5{
foreach prod in cali txr txs rtec rtet juice pine{
di"====================================================================="
di"============TOBIT MODEL, INFO = `i',  PRODUCT = `prod'============="
di"====================================================================="
di"MODEL TYPE H- No interactions, with  demographic variables, info NOT
included, with price"
tobit bids `typeJ' if info==`i'&prodkey== "`prod'", ll(0) log
margins, dydx(*) predict(e(0,.))
```

```
}
}
*
log close OUT9PROD
*#####################################################################
*==========================================================
*==========================================================
*==========================================================
*#####################################################################



*DOFILE 10UNENGAGED:
di"Start log file and append to the end of previous file"
log using E:\THESIS\DATA\STATALONGOUTT10UNENGAGED.log, append
name(OUT10UNENGAGED)
log using E:\THESIS\DATA\STATALONGOUTT10UNENGAGEDrep.log, replace
name(OUT10UNENGAGEDrep)
di" log using E:\THESIS\DATA\STATALONGOUTT10UNENGAGED.log, append
name(OUT10UNENGAGED)"
di" log using E:\THESIS\DATA\STATALONGOUTT10UNENGAGEDrep.log, append
name(OUT10UNENGAGEDrep)"
*====================================================================
*==============ANALYSIS OF UNENGAGED BIDDERS, FULL BIDS WTP==========
*====================================================================
*====Random effects tobits, mixed linear, and separate product tobits
*====================================================================
*
*********************************************************************
*==========NO BIDDERS WHO ARE UNENGAGED FOR ANY PRODUCT==============
*********************************************************************
di"Bidders are identified as unengaged in the overall models if there
was any product for which they were unengaged"
di"Further described as 'case 4' in the text"
*
*From DOFILE 6RANDOMEFFECTSTOBITS
*====================================================================
*==============RANDOM EFFECTS TOBIT, FULL BIDS WTP====================
*========== WTP= f(product characteristics, demographics)============
*========================== 1 model==================================
*==========NO BIDDERS WHO ARE UNENGAGED FOR ANY PRODUCT==============
*====================================================================
*
di"XTTOBIT- RANDOM EFFECTS TOBIT MODEL"
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
xtset id
*random effects tobit model with information treatment and demographic
variables
xttobit bids `typeC' if info!=5&prodkey!="noprod"&casefourany!=1, ll(0)
log tobit
margins, dydx(*) predict(e(0,.))
xtset, clear
*
```

```
di"From DOFILE 5MIXEDLINEAR"
*=====================================================================
*==============MIXED LINEAR MODELS, FULL BIDS WTP====================
*========== WTP= f(product characteristics, demographics)============
*========================== 1 model==================================
*==========NO BIDDERS WHO ARE UNENGAGED FOR ANY PRODUCT==============
*=====================================================================
di"MIXED LINEAR MODEL"
di"REMOVE ALL UNENGAGED BIDDERS, Removes anyone unengaged for any
product"
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
xtmixed bids `typeC' if info!=5&prodkey!="noprod"& casefourany!=1|| id:
, variance mle
estimates store randcaseC
*
*********************************************************************
*==========NO BIDDERS WHO ARE UNENGAGED FOR ALL PRODUCTS=============
*********************************************************************
di"Bidders are identified as unengaged for all products in the overall
models if they were unengaged for all of the included products"
di"Further described as 'case 4' in the text"
*
*From DOFILE 6RANDOMEFFECTSTOBITS
*=====================================================================
*==============RANDOM EFFECTS TOBIT, FULL BIDS WTP====================
*========== WTP= f(product characteristics, demographics)============
*========================== 1 model==================================
*==========NO BIDDERS WHO ARE UNENGAGED FOR ALL PRODUCTS=============
*=====================================================================
di"XTTOBIT- RANDOM EFFECTS TOBIT MODEL"
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
xtset id
di"random effects tobit model with information treatment and
demographic variables"
xttobit bids `typeC' if info!=5&prodkey!="noprod"&casefourall!=1, ll(0)
log tobit
margins, dydx(*) predict(e(0,.))
xtset, clear
*
di"From DOFILE 5MIXEDLINEAR"
*=====================================================================
*==============MIXED LINEAR MODELS, FULL BIDS WTP====================
*========== WTP= f(product characteristics, demographics)============
*========================== 1 model==================================
*==========NO BIDDERS WHO ARE UNENGAGED FOR ALL PRODUCTS=============
*=====================================================================
di"MIXED LINEAR MODEL"
di"REMOVE ALL UNENGAGED BIDDERS, Removes anyone unengaged for any
product"
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
xtmixed bids `typeC' if info!=5&prodkey!="noprod"& casefourall!=1|| id:
```

```
, variance mle
estimates store randcaseC
*
*******************************************************************
*====NO BIDDERS WHO WERE UNENGAGED FOR THAT PARTICULAR PRODUCT=======
*******************************************************************
di"Bidders are identified as unengaged in the individual product and
information models"
di"if for that particular product they were unengaged"
di"Further described as 'case 4' in the text"
*
*From STATADoLong9ProdTobits
di"=35 Tobit Models, 1 for Each Product and Each information
Treatment=="
di"======================================================================"
di"===========SEPARATE TOBIT MODELS, FULL BIDS WTP====================="
di"======== Bids= f(product characteristics, demographics)============"
di"===5 info trtmts:(BASELINE, TASTING, HEALTH, ANTI-CANCER, FULL)====="
di"============7 products:(cali txr txs rtec rtet juice pine)=========="
di"======================================================================"
di"====NO BIDDERS WHO WERE UNENGAGED FOR THAT PARTICULAR PRODUCT======="
di"======================================================================"

forvalues i = 1(1)5{
foreach prod in cali txr txs rtec rtec juice pine{
di"======================================================================"
di"==============TOBIT MODEL, INFO = `i',  PRODUCT = `prod'==========="
di"======================================================================"
di"MODEL TYPE H- No interactions, with  demographic variables, info NOT
included, with price"
di"tobit bids `typeJ' if info==`i'&prodkey==
"`prod'"&casefour`prod'!=1, ll(0) log"
di" margins, dydx(*) predict(e(0,.))"
tobit bids `typeJ' if info==`i'&prodkey== "`prod'"&casefour`prod'!=1,
ll(0) log
margins, dydx(*) predict(e(0,.))
di ""
di ""
di
"======================================================================"
di ""
}
}
*
*******************************************************************
*====NO BIDDERS WHO WERE UNENGAGED FOR THAT PARTICULAR PRODUCT ======
*---------IN THAT PARTICULAR ROUND-----------------------------------
*******************************************************************
di"Bidders are identified as unengaged in the individual product and
information models"
di"if for that particular product in that particular round they were
unengaged"
di"(Participants could be unengaged for a product in one round and not
in another"
```

```
di"Further described as 'case 4' in the text"
*=====================================================================
*==============RANDOM EFFECTS TOBIT, FULL BIDS WTP===================
*========== WTP= f(product characteristics, demographics)============
*========================== 1 model==================================
*==========Only particular unengaged bids are removed================
*=====================================================================
di"XTTOBIT- RANDOM EFFECTS TOBIT MODEL- UNENGALL Bids Removed"
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
xtset id
di"random effects tobit model with information treatment and
demographic variables"
xttobit bids `typeC' if info!=5&prodkey!="noprod"&unengall!=1, ll(0)
log tobit
margins, dydx(*) predict(e(0,.))
xtset, clear
*
**=====================================================================
*==============MIXED LINEAR MODELS, FULL BIDS WTP====================
*========== WTP= f(product characteristics, demographics)============
*========================== 1 model==================================
*==========Only particular unengaged bids are removed================
*=====================================================================
di"MIXED LINEAR MODEL"
di"REMOVE ALL UNENGAGED BIDDERS, Removes anyone unengaged for any
product"
di"MODEL TYPE C- No interactions, with  demographic variables, info
included, with price"
xtmixed bids `typeC' if info!=5&prodkey!="noprod"& unengall!=1|| id: ,
variance mle
estimates store randunengC
*
log close OUT10UNENGAGED
log close OUT10UNENGAGEDrep
*
*#####################################################################
*==========================================================
*==========================================================
*==========================================================
*#####################################################################


*DOFILE 11ROMixedLogit:
cd E:\
*Start log file and append to the end of previous file
log using E:\THESIS\DATA\STATALONGOUT1All.log, append name(OUT1ALL)
*Start command log and append to the end of previous command log file
cmdlog using E:\THESIS\DATA\STATALONGOUT2CMD.log , append
*=====================================================================
* ==================================================DATE = _________
*=====================================================================
*Increase Memory Space to use
set memory 500M
```

```
*=================================================================
*
di"Create Mixed Rank-Ordered Logit Log"
log using .\THESIS\DATA\STATALONGOUT11ROMixed, append
name(OUT11MIXEDROLOGIT)
*
di"=================================================================
"
di"===================MIXED RANK-ORDERED LOGIT========================"
di"==================PREFERENCE RANKINGS, FULLY RANKED MODELS=========="
di"=================================================================="
di"Use the specified data"
use "E:\Thesis\Data\STATAIn11MissDropGLLAMM.dta", replace
di"EXPLODE DATA"
di"Based on Rabe-Hesketh, Pickles, and Skrondal (2001)
egen maxr=max(pref), by (idinfo)
gen chosen=1
gen idx=_n
stset pref, fail(chosen) id(idx)
stsplit, at(failures) strata (idinfo) riskset (stage)
replace chosen=0 if chosen==.
drop if pref==maxr
bysort stage: generate groupcount=sum(chosen)
*
di"=================================================================="
di"=================================================================="
di"==================MIXED RANK-ORDERED LOGIT========================="
di"==================PREFERENCE RANKINGS, FULLY RANKED MODELS=========="
di"==================NO INTERACTION TERMS============================="
di"=================================================================="
di"=================================================================="
di"=================================================================="
mixlogit chosen  if info!=5 & `dropforrank' & stage!=. &groupcount==1 ,
group(stage) rand(`typeRAi') id(id) nrep(100)
mixlpred pRPLfull if e(sample) & info!=5 & `dropforrank' & stage!=.
&groupcount==1, nrep(100)
sort id prodkey
log using .\THESIS\DATA\STATALONGOUT11ROMixedProbs, append
name(OUT11MIXEDROLOGITprobs)
log using .\THESIS\DATA\STATALONGOUT11ROMixedProbsRep, replace
name(OUT11MIXEDROLOGITprobsRep)
list pRPLfull1 prodkey id if pref==1& info==1, noobs
list pRPLfull1 prodkey id if pref==1& info==2, noobs
list pRPLfull1 prodkey id if pref==1& info==3, noobs
list pRPLfull1 prodkey id if pref==1& info==4, noobs
log close OUT11MIXEDROLOGITprobs
log close OUT11MIXEDROLOGITprobsRep
mixlbeta `typeRAi' if info!=5 & `dropforrank' & stage!=. &groupcount==1
, saving (E:\THESIS\DATA\STATAOUT11Betas100I1) replace
save "E:\Thesis\Data\STATAIn11MissDropGLLAMMmixlogit2011_03_21.dta",
replace
*
di"=================================================================="
di"===================MIXED RANK-ORDERED LOGIT========================"
```

```
di"==================PREFERENCE RANKINGS, FULLY RANKED MODELS=========="
di"===========WITH INTERACTION TERMS=================================="
di"====================================================================="
di"====================================================================="
*
forvalues i=2(1)4{
di"====================================================================="
di"===================MIXED RANK-ORDERED LOGIT========================="
di"==================PREFERENCE RANKINGS, FULLY RANKED MODELS=========="
di"=============WITH INTERACTION TERMS================================"
di"====================================================================="
di"====================================================================="
di"=========info= `i' INTERACTION TERMS==============================="
mixlogit chosen  if info!=5 & `dropforrank' & stage!=. &groupcount==1 ,
group(stage) rand(`typeRAi' interact*`i') id(id) nrep(100)
mixlpred pRPLfullI`i' if e(sample) & info!=5 & `dropforrank' & stage!=.
&groupcount==1, nrep(100)
sort id prodkey
log using .\THESIS\DATA\STATALONGOUT11ROMixedProbsI`i', append
name(OUT11MIXEDROLOGITprobsI`i')
log using .\THESIS\DATA\STATALONGOUT11ROMixedProbsI`i'Rep, replace
name(OUT11MIXEDROLOGITprobsI`i'Rep)
forvalues k=1(1)4{
di"=====================Probabilities if info= `k'==================="
list pRPLfullI`i' prodkey id if pref==1& info==`k', noobs
}
log close OUT11MIXEDROLOGITprobsI`i'
log close OUT11MIXEDROLOGITprobsI`i'Rep
mixlbeta `typeRAi' interact*`i' if info!=5 & `dropforrank' & stage!=.
&groupcount==1 , saving (E:\THESIS\DATA\STATAOUT11Betas100I`i') replace
save E:\Thesis\Data\STATAIn11MissDropGLLAMMmixlogit2011_03_21.dta,
replace
}
*
di"====================================================================="
di"===================MIXED RANK-ORDERED LOGIT========================="
di"==================PREFERENCE RANKINGS, FULLY RANKED MODELS=========="
di"===========WITH INTERACTION TERMS=================================="
di"====================================================================="
di"====================================================================="
di"=========FULL INFORMATION INTERACTION TERMS========================="
mixlogit chosen  if info!=2 & info!=3&info!=4 & `dropforrank' &
stage!=. &groupcount==1 , group(stage) rand(`typeRAi' interact*5)
id(id) nrep(100)
mixlpred pRPLfullI5 if e(sample) & info!=2 & info!=3&info!=4 &
`dropforrank' & stage!=. &groupcount==1, nrep(100)
sort id prodkey
log using .\THESIS\DATA\STATALONGOUT11ROMixedProbsI5, append
name(OUT11MIXEDROLOGITprobsI5)
log using .\THESIS\DATA\STATALONGOUT11ROMixedProbsI5Rep, replace
name(OUT11MIXEDROLOGITprobsI5Rep)
list pRPLfullI5 prodkey id if pref==1& info==1, noobs
list pRPLfullI5 prodkey id if pref==1& info==5, noobs
log close OUT11MIXEDROLOGITprobsI5
```

```
log close OUT11MIXEDROLOGITprobsI5Rep
mixlbeta `typeRAi' interact*5 if info!=2 & info!=3&info!=4  &
`dropforrank' & stage!=. &groupcount==1 , saving
(E:\THESIS\DATA\STATAOUT11Betas100I5) replace
save E:\Thesis\Data\STATAIn11MissDropGLLAMMmixlogit2011_03_21.dta,
replace
*
di"=================================================================="
di"=================================================================="
di"===========ESTIMATED BETA PARAMETERS============================="
di"=================================================================="
di"=================================================================="
di"Do these at the end to copy and paste data"
use "E:\Thesis\Data\STATAOUT11Betas100I1.dta",
browse
pause on
pause "copy data and save and then type --pause off--"
*pause off
use "E:\Thesis\Data\STATAOUT11Betas100I2.dta",
browse
pause on
pause "copy data and save and then type --pause off--"
*pause off
use "E:\Thesis\Data\STATAOUT11Betas100I3.dta",
browse
pause on
pause "copy data and save and then type --pause off--"
*pause off
use "E:\Thesis\Data\STATAOUT11Betas100I4.dta",
browse
pause on
pause "copy data and save and then type --pause off--"
*pause off
use "E:\Thesis\Data\STATAOUT11Betas100I5.dta",
browse
pause on
pause "copy data and save and then type --pause off--"
*pause off
*################################################################
di"=================================================================="
di"===================MIXED RANK-ORDERED LOGIT========================"
di"==============ORDERED BIDS, FULLY-RANKED MODELS=================="
di"=================================================================="
di"=================================================================="
di"=================================================================="
*
destring brpref, generate (brprefsta)
di"Use the specified data"
use "E:\Thesis\Data\STATAIn11MissDropGLLAMM.dta", replace
di"EXPLODE DATA"
egen maxr=max(brprefsta), by (idinfo)
gen chosen=1
gen idx=_n
stset brprefsta, fail(chosen) id(idx)
```

```
stsplit, at(failures) strata (idinfo) riskset (stage)
replace chosen=0 if chosen==.
drop if brprefsta==maxr
bysort stage: generate groupcount=sum(chosen)
di"==================MIXED RANK-ORDERED LOGIT========================="
di"==================ORDERED BIDS, FULLY RANKED MODELS================"
di"==================WITH INTERACTION TERMS==========================="
di"====================================================================="
*
mixlogit chosen  if info!=5 & `dropforrank' & stage!=. &groupcount==1 ,
group(stage) rand(`typeRAi') id(id) nrep(100)
mixlpred pRPLfullBRI1 if e(sample) & info!=5 & `dropforrank' & stage!=.
&groupcount==1, nrep(100)
sort id prodkey
log using .\THESIS\DATA\STATALONGOUT11ROMixedBRProbs, append
name(OUT11MIXEDROLOGITBRprobs)
log using .\THESIS\DATA\STATALONGOUT11ROMixedBRProbsRep, replace
name(OUT11MIXEDROLOGITBRprobsRep)
forvalues k=1(1)4{
di"======Probabilities if info=`k'======================"
list pRPLfullBRI1 prodkey id if pref==1& info==`k', noobs
}
log close OUT11MIXEDROLOGITBRprobs
log close OUT11MIXEDROLOGITBRprobsRep
mixlbeta `typeRAi' if info!=5 & `dropforrank' & stage!=. &groupcount==1
, saving (E:\THESIS\DATA\STATAOUT11Betas100BRI1) replace
save "E:\Thesis\Data\STATAIn11MissDropORDEREDBIDS.dta", replace
*
di"====================================================================="
di"===================MIXED RANK-ORDERED LOGIT========================="
di"==================Ordered Bids, FULLY RANKED MODELS================"
di"===========WITH INTERACTION TERMS================================="
di"====================================================================="
di"====================================================================="
*
forvalues i=2(1)4{
di"====================================================================="
di"===================MIXED RANK-ORDERED LOGIT========================="
di"==================ORDERED BIDS, FULLY RANKED MODELS================"
di"===========WITH INTERACTION TERMS================================="
di"====================================================================="
di"====================================================================="
di"=========info= `i' INTERACTION TERMS==============================="
mixlogit chosen  if info!=5 & `dropforrank' & stage!=. &groupcount==1 ,
group(stage) rand(`typeRAi' interact*`i') id(id) nrep(100)
mixlpred pRPLfullBRI`i' if e(sample) & info!=5 & `dropforrank' &
stage!=. &groupcount==1, nrep(100)
sort id prodkey
log using .\THESIS\DATA\STATALONGOUT11ROMixedProbsBRI`i', append
name(OUT11MIXEDROLOGITprobsBRI`i')
log using .\THESIS\DATA\STATALONGOUT11ROMixedProbsBRI`i'Rep, replace
name(OUT11MIXEDROLOGITprobsBRI`i'Rep)
forvalues k=1(1)4{
di"=====================Probabilities if info= `k'==================="
```

```
list pRPLfullBRI`i' prodkey id if pref==1& info==`k', noobs
}
log close OUT11MIXEDROLOGITprobsBRI`i'
log close OUT11MIXEDROLOGITprobsBRI`i'Rep
mixlbeta `typeRAi' interact*`i' if info!=5 & `dropforrank' & stage!=.
&groupcount==1 , saving (E:\THESIS\DATA\STATAOUT11Betas100BRI`i')
replace
save "E:\Thesis\Data\STATAIn11MissDropORDEREDBIDS.dta", replace
}
*
di"======================================================================"
di"=====================MIXED RANK-ORDERED LOGIT======================="
di"==================PREFERENCE RANKINGS, FULLY RANKED MODELS=========="
di"=============WITH INTERACTION TERMS================================"
di"=====================================================================”
di"====================================================================="
di"===========FULL INFORMATION INTERACTION TERMS======================="
mixlogit chosen  if info!=2 & info!=3&info!=4 & `dropforrank' &
stage!=. &groupcount==1 , group(stage) rand(`typeRAi' interact*5)
id(id) nrep(100)
mixlpred pRPLfullBRI5 if e(sample) & info!=2 & info!=3&info!=4 &
`dropforrank' & stage!=. &groupcount==1, nrep(100)
sort id prodkey
log using .\THESIS\DATA\STATALONGOUT11ROMixedProbsBRI5, append
name(OUT11MIXEDROLOGITprobsBRI5)
log using .\THESIS\DATA\STATALONGOUT11ROMixedProbsBRI5Rep, replace
name(OUT11MIXEDROLOGITprobsBRI5Rep)
list pRPLfullBRI5 prodkey id if pref==1& info==1, noobs
list pRPLfullBRI5 prodkey id if pref==1& info==5, noobs
log close OUT11MIXEDROLOGITprobsBRI5
log close OUT11MIXEDROLOGITprobsBRI5Rep
mixlbeta `typeRAi' interact*5 if info!=2 & info!=3&info!=4  &
`dropforrank' & stage!=. &groupcount==1 , saving
(E:\THESIS\DATA\STATAOUT11Betas100BRI5) replace
save "E:\Thesis\Data\STATAIn11MissDropORDEREDBIDS.dta", replace
*
di"======================================================================"
di"======================================================================"
di"=========ESTIMATED BETA PARAMETERS=================================="
di"======================================================================"
di"======================================================================"
di"Do these at the end to copy and paste data"
use "E:\Thesis\Data\STATAOUT11Betas100BRI1.dta",
browse
pause on
pause "copy data and save and then type --pause off--"
*pause off
use "E:\Thesis\Data\STATAOUT11Betas100BRI2.dta",
browse
pause on
pause "copy data and save and then type --pause off--"
*pause off
use "E:\Thesis\Data\STATAOUT11Betas100BRI3.dta",
browse
```

```
pause on
pause "copy data and save and then type --pause off--"
*pause off
use "E:\Thesis\Data\STATAOUT11Betas100BRI4.dta",
browse
pause on
pause "copy data and save and then type --pause off--"
*pause off
use "E:\Thesis\Data\STATAOUT11Betas100BRI5.dta",
browse
pause on
pause "copy data and save and then type --pause off--"
*pause off
*#####################################################################
*==============================================================
*==============================================================
*==============================================================
*#####################################################################



*DOFILE 12KSTestWilcoxonTest:
log using ".\data\KSTESTandSignedRankTest.log", append (OUT12TESTS)
codebook
di"Do a test for normality using skewness and kurtosis and correcting
for sample size"
di"Similar in design to the Jarque-Bera Tests for normality"
sktest deltabidtastecali deltabidtastetxr deltabidtastetxs
deltabidtastertec deltabidtastertet deltabidtastejuice
deltabidtastepine deltabidhealthcali deltabidhealthtxr
deltabidhealthtxs deltabidhealthrtec deltabidhealthrtet
deltabidhealthjuice deltabidhealthpine deltabidcancercali
deltabidcancertxr deltabidcancertxs deltabidcancerrtec
deltabidcancerrtet deltabidcancerjuice deltabidcancerpine deltafbidcali
deltafbidtxr deltafbidtxs deltafbidrtec deltafbidrtet deltafbidjuice
deltafbidpine
*
di"Do a Wilcoxon Signed Rank Test for differences across information
treatments"
foreach DELTAWTP in deltabidtastecali deltabidtastetxr deltabidtastetxs
deltabidtastertec deltabidtastertet deltabidtastejuice
deltabidtastepine deltabidhealthcali deltabidhealthtxr
deltabidhealthtxs deltabidhealthrtec deltabidhealthrtet
deltabidhealthjuice deltabidhealthpine deltabidcancercali
deltabidcancertxr deltabidcancertxs deltabidcancerrtec
deltabidcancerrtet deltabidcancerjuice deltabidcancerpine deltafbidcali
deltafbidtxr deltafbidtxs deltafbidrtec deltafbidrtet deltafbidjuice
deltafbidpine {
display "`DELTAWTP'"
signrank `DELTAWTP' = 0
}
*
log close OUT12TESTS
```

```
*#################################################################
*=============================================================
*=============================================================
*=============================================================
*#################################################################
```

VITA

Callie Pauline McAdams was raised in Efland, North Carolina as one of the fifth-generation to work on her family's crop and livestock farm. She attended Orange High School and graduated in May 2005. She then enrolled in North Carolina State University. She was active in several agricultural organizations during her time there, taking on leadership roles and receiving scholarships from many of them. While enrolled, she held various positions with the university including work as a tobacco Extension intern, work for the diversified agriculture program, and work in an animal science nutrition lab. She received her Bachelor of Science degree from North Carolina State University with majors in Agricultural Business Management and Animal Science and a minor in Economics in May 2009. Her research interests include agricultural policy, experimental economics, and horticultural marketing. She intends to pursue a career in the agricultural field when she completes her formal education.

Ms. McAdams' contact information is available through the Department of Agricultural Economics, 600 John Kimbrough Blvd., TAMU M.S. 2124, College Station, TX 77843-2124. Her email is callie.mcadams99@gmail.com.