EVALUATING THE EXTERNAL VALIDITY OF EXPERIMENTAL AUCTIONS: THE CASE OF HYDROPONIC LETTUCE

A Thesis

by

MEGHAN LEIGH NESS

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

MASTER OF SCIENCE

Chair of Committee,	David P. Anderson
Co-Chair of Committee,	Marco A. Palma
Committee Members,	Daniel I. Leskovar
	Luis A. Ribera
Head of Department,	C. Parr Rosson

December 2014

Major Subject: Agricultural Economics

ABSTRACT

Agribusinesses have been investigating alternative methods for food and agriculture production as a way to differentiate their product to consumers. Although experimental auctions have increasingly become a popular tool for gathering information about consumers and their valuations of differentiated products, little is known about their valuations for vegetables that are grown using different methods and few studies have simultaneously studied external validity and the influence of outside prices. This study investigates consumers' valuations of different agricultural production methods and provides a unique method for studying whether consumers' purchasing behavior reflects their willingness to pay. Additionally, it provides insight into the relationships between consumers' valuations and their prestige-seeking behavior and health-consciousness.

A Vickrey 2nd price auction was conducted and immediately followed by the introduction of an on-site secondary market that used induced value theory and the retail prices of the auction products in surrounding stores in the Bryan-College Station area of Texas. Several econometric models were thereafter estimated using data collected from the experiment; however a random parameters tobit model proved to be most appropriate due to the heterogeneous nature of the data. Results indicate that consumers express deep discounts for red colored lettuce. While tasting the products did not have an impact on valuations, consumers did express significant premiums for organic lettuce after they learned about hydroponic lettuce production and the growing methods of the products

were revealed. The same can be said for valuations of mixed lettuce, which was hydroponically grown.

Consumers were also categorized using three applications of Latent Class Analysis and responses to scale-style questions about health-consciousness and prestige-seeking buying behavior. The willingness to pay for lettuce was estimated using a random parameters tobit model for each latent class in each application.

In addition to advancing the understanding of consumers' valuations of horticultural production methods, this study contributed to the external validity of experimental auctions. By using an on-site secondary market, it was discovered that consumer surplus and the relative importance of the compensation fee affect an individual's behavior in the experiment setting.

DEDICATION

I would like to dedicate this work to my beautiful, strong mother who instilled in me a positive outlook on life and the courage to ask questions. Thanks for giving that last push, Mom.

ACKNOWLEDGEMENTS

First, I would like to thank Dr. Anderson and Dr. Palma, for their guidance and support during this research and my graduate program. I would also like to thank the rest of my committee, Dr. Leskovar and Dr. Ribera, for their support and encouragement over the past year.

I would also like to extend my appreciation to the faculty and staff of the Department of Agricultural Economics for the knowledge and advice they have given me during my tenure at Texas A&M University. Special thanks go to my fellow Aggies in the graduate program for the memories we have shared during my time in College Station.

My deepest gratitude and appreciation go to my father and mother who taught me a strong work ethic and how to love, to my sister who reminds me to live a spirited life, and to James for his constant love and patience.

TABLE OF CONTENTS

Page

ABSTRACT ii

DEDICATION iv

ACKNOWLEDGEMENTS v

LIST OF TABLES ix

LIST OF FIGURES xii

CHAPTER I INTRODUCTION 1

CHAPTER II LITERATURE REVIEW 10

- Eliciting Consumers' Values 10
- The Evolution of Consumer Theory According to McFadden 11
- Value Elicitation Methods 13
  - Stated Preference Methods 14
  - Revealed Preference Methods 15
  - Advantages, Disadvantages, and Biases 16
  - Experimental Economics 20
    - History of Field Experiments 20
    - Experimental Auctions 22
    - Continuous Auctions, Sealed-Bid Auctions, Endowed, and NonEndowed 23
    - Types of Auctions 24
    - Comparisons of Auction Mechanisms 26
    - Incentive Compatibility 30
    - Induced Value Theory 31
    - Homegrown Values 34
    - Secondary Markets 35
    - Issues Associated with Experimental Auctions 36
    - Reference Prices and Outside Substitutes 37
    - Affiliated Beliefs 39
    - Internal Validity 40
    - External Validity 41
    - Experimental Auction Applications 46
- Consumers' WTP for Novel Products 47
- Consumers' WTP for Production Attributes 49

CHAPTER III HYDROPONIC LETTUCE REVIEW 53

Economics of Lettuce Industry 53
Hydroponic Fruit and Vegetable Production 54
Types of Hydroponic Systems 55
Production Advantages of Hydroponics 56
Production Disadvantages of Hydroponics 57
Quality Comparisons 58
Hydroponics and Consumers 61
Hydroponics and Food Safety 66

CHAPTER IV METHODOLOGY 69

Theoretical Foundation 69
Willingness to Pay 69
Random Utility Theory 70
Vickrey Second Price Auction 72
Induce Value Theory 76
Combined Approach 77
Health and Prestige Scales 82
Auction Procedures and Details 84
WTP Data Organization 91
Ordinary Least Squares Model 95
Tobit Model 96
Random Effects Tobit Model 100
Random Parameters Linear Model 103
Random Parameters Tobit Model 104
Implied Differences Model 106
Latent Class Analysis 108
Secondary Market Data Analysis 112
Probit Model 115
Random Effects Probit Model 117
Heteroskedastic Probit Model 118

CHAPTER V RESULTS AND DISCUSSION 121

Demographic and Behavioral Characteristics 121
Willingness to Pay Models with Experimental Auction Bids 124
Bid Censoring 136
Ordinary Least Squares Model 138
Tobit Model 140
Random Effects Tobit Model 143
Random Parameter Linear Model 147
Random Parameters Tobit Model 150

Comparison of Estimated WTP Models....153
Implied Differences in Bids for Lettuce Products....155
Differences in Bids between Treatments....155
Implied Differences in WTP: Blind Tasting Treatment....160
Implied Differences in WTP: Production Information Treatment....162
Latent Class Analysis....164
Health & Prestige Scales Combined....164
Health Consciousness Scale....178
Prestige-Seeking Scale....189
Latent Class Analyses Conclusion....198
Secondary Market Results....201
Probit Model....204
Random Effects Probit Model....207
Heteroskedastic Probit Model....209

CHAPTER VI SUMMARY AND CONCLUSIONS....212

Summary and Conclusions....212
Economic and Marketing Implications....220
Limitations and Suggestions for Future Research....222

REFERENCES....224

APPENDIX A NEWSPAPER ADVERTISEMENT....244

APPENDIX B EXPERIMENTAL AUCTION QUESTIONNAIRE....245

APPENDIX C BIDDING SHEETS & ORDER FORM....279

APPENDIX D HYDROPONIC PRODUCTION INFORMATION....284

LIST OF TABLES

Page

Table 1. Demographic and Behavioral Variables 93

Table 2. Description of Variables used in Secondary Market Behavior Analysis 114

Table 3. Demographic and Behavioral Characteristics of Experiment Participants 122

Table 4. Rated Relative Importance of Factors in Lettuce Purchases [a] 124

Table 5. Descriptive Statistics for Willingness to Pay (WTP) Bids 126

Table 6. Mean Willingness to Pay (WTP) Bids by Production Method and Treatment 128

Table 7. Kolmogorov-Smirnov Test for Normality P-values 129

Table 8. Percentage of Bids Censored at $0.00 by Round and Product 137

Table 9. Ordinary Least Squares Estimates for Willingness to Pay (WTP) for Lettuce Products 139

Table 10. Constant Parameters Tobit Model Estimates of Willingness to Pay (WTP) for Lettuce Products 142

Table 11. Random Effects Tobit Model of Willingness to Pay (WTP) for Lettuce Products 146

Table 12. Random Parameter Linear Model Estimates of Willingness to Pay (WTP) for Lettuce Products 149

Table 13. Random Parameter Tobit Estimates of Willingness to Pay (WTP) for Lettuce Products 153

Table 14. Results from Wilcoxon Signed Rank Tests [a] 156

Table 15. Proportions of Positive, Negative, and Zero Changes in Willingness to Pay (WTP) from Baseline Round, Summed for All Products 158

Table 16. Summary Statistics for Implied Differences of Bids 159

Table 17. Random Parameter Linear Model Estimates of Implied Differences in Willingness to Pay (WTP) for Lettuce Products, Blind Tasting Treatment....161

Table 18. Random Parameter Linear Model Estimates of Implied Differences in Willingness to Pay (WTP) for Lettuce Products, Production Information Treatment....163

Table 19. Comparison of Latent Class Models: Combination of Health-Consciousness and Prestige-Seeking Scales....166

Table 20. Latent Class Parameter Estimates for Four-Class Model: Combination of Health and Prestige Scales....170

Table 21. Demographic and Behavioral Characteristics of Participants by Latent Class: Combination of Health and Prestige Scales....173

Table 22. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products by Latent Class: Combination of Health and Prestige Scales....176

Table 23. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products: Class 3 as Baseline, Combination of Health and Prestige Scales....177

Table 24. Comparison of Latent Class Models: Defined by Health-Consciousness Scale....179

Table 25. Latent Class Parameter Estimates for Four-Class Model: Health Scale Only....181

Table 26. Demographic and Behavioral Characteristics of Participants by Latent Class: Health Scale Only....183

Table 27. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products by Latent Class: Health Scale Only....187

Table 28. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products: Class 3 as Baseline, Health Scale Only....188

Table 29. Comparison of Latent Class Models: Defined by Prestige-Seeking Scale....190

Table 30. Latent Class Parameter Estimates for Four-Class Model: Prestige Scale Only 193

Table 31. Demographic and Behavioral Characteristics of Participants by Latent Class: Prestige Scale Only 195

Table 32. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products by Latent Class: Prestige Scale Only 199

Table 33. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products: Class 3 as Baseline, Prestige Scale Only 200

Table 34. Secondary Market Behavior: Gender Statistics 202

Table 35. Secondary Market Behavior: Income Statistics 203

Table 36. Tabulation of Individuals' Expected Behavior versus Actual Behavior 204

Table 37. Probit Model: Full Set 205

Table 38. Probit Model: Condensed Set 206

Table 39. Random Effects Probit by Individual: Full Set 207

Table 40. Random Effects Probit by Individual: Condensed Set 208

Table 41. Random Effects Probit by Sessions: Full Set 208

Table 42. Random Effects Probit by Sessions: Condensed Set 209

Table 43. Heteroskedastic Probit: Full Set 210

Table 44. Heteroskedastic Probit: Condensed Set 211

LIST OF FIGURES

Page

Figure 1. Mean Bids for Lettuce Products by Treatment 127

Figure 2. Gaussian Kernel Density Distribution of Baseline Round Bids for Vegetable Products 130

Figure 3. Gaussian Kernel Density Distribution of Blind Tasting Round Bids for Vegetable Products 131

Figure 4. Gaussian Kernel Density Distribution of Information Round Bids for Vegetable Products 132

Figure 5. Gaussian Kernel Density Distribution for Conventionally Grown Lettuce Products by Round 133

Figure 6. Gaussian Kernel Density Distribution for Organically Grown Lettuce Products by Round 134

Figure 7. Gaussian Kernel Density Distribution for Hydroponically Grown Lettuce Products by Round 135

CHAPTER I

INTRODUCTION

Over the last three decades, experimental economic methods have allowed researchers to gather primary data about consumers and their purchasing behavior. Experimental auctions represent a subset of research tools within this field that have been thoroughly used over the past twenty years to elicit consumers' willingness-to-pay (WTP) values for new products and differentiating attributes. These auctions operate off of the institutions of incentive-compatibility and utility theory – that is, real money is used and real economic consequences are enforced to incentivize consumers, through utility maximizing behavior, to reveal their truest valuations. Additionally, the ability to induce real markets in a laboratory setting affords economists the opportunity to amplify control, which is not normally found in markets. Overall, the elements of incentive compatibility and increased control are the principle differences between experimental methods and more orthodox value elicitation techniques, such as stated preference and observational methods. Aside from these appealing attributes, experimental auctions have the advantage of allowing researchers to fit the auction mechanism to the scope and objectives of the experiment and directly interpret participants' valuations of the auction goods.

From the beginning, the advantage of heightened control is utilized. If the researcher is interested in testing a theory, she may induce a stylized market by assigning prices and roles to participants. However, if the researcher wants to know how much consumers would be willing to pay for a new product using an auction mechanism to elicit the raw values consumers bring in to the experiment, also called homegrown values, may be a more appropriate route. Another customizable feature of experimental auctions allows researchers to endow participants with the good and infer participants' WTP values from the value they would be willing to forfeit to exchange the good for something else. The mechanisms themselves vary in information feedback and market prices, from being open out-cry auctions in which the last standing offer is the market price, such as the familiar English auction, to sealed bid auctions in which the second highest bid is the market price, such as Vickrey auctions.

Regardless of the type of auction mechanism used, consumers' homegrown WTP values can be directly inferred from their bid values. The effortless interpretation of consumers' WTP values is appealing to researchers who are investigating the market potential for new products or specific differentiating attributes. Agribusinesses that gather market information and consumer demand data may find the application of experimental auctions valuable during the research and development stage of bringing a new product to the market (Lusk and Shogren, 2007; Lusk and Hudson, 2004; Hoffman et al., 1993; Urban and Hauser, 1993; Pride and Ferrell, 2014).

Although experimental auctions have an attractive way of combining the advantages of stated preference and revealed preference methods to test theory and collect valuable marketing information, several issues must not be neglected when using these mechanisms. These issues include external validity and the influence of outside prices and substitutes on participants' behavior in the laboratory experiment.

While a handful of studies have used post-auction outside secondary markets to account for outside influences' effects laboratory behavior, others have addressed external validity separately by comparing data from field experiments and laboratory experiments. External validity refers to how well the results from the experiment mirror actual behavior outside of the experiment, in the real marketplace. The debate of whether or not experimental economics in general produce externally valid results has been a heated one, with input from behavior economists and psychologists (Loewenstein, 1999; Schram, 2005; Guala and Mittone, 2005; Brookshire, Coursey, and Shulze, 1987; Chang, Lusk and Norwood, 2009; List and Shogren, 1998). Secondary markets outside of the auction experiment have been used to investigate the influence of time in experimental auctions and the influence of outside options on participants' bidding behavior (Haile, 2001; Corrigan, 2005; Cherry et al., 2004). One study worth mentioning used induced value theory and a secondary market to analyze how outside substitutes affected consumers' behavior in the laboratory (Cherry et al., 2004). The paramount faults of induced value studies are that the good being auctioned is not disclosed and participants are asked to assign value to unknown products in studies that use induced values to provoke homegrown values.

Although the experimental economic literature attempts to address each of these issues separately, there has not been an attempt to combine secondary markets, induced value theory, and experimental auctions with real, identifiable products in such a way to simultaneously address both external validity issues and the effects of outside influences. Furthermore, although studies have used experimental auctions to elicit consumer preferences and valuations for novel food products, little is known in general about consumers' willingness to pay (WTP) for hydroponically grown leafy greens (Huang et al., 2002; Batt and Lim, 1999; Huang, Kan, and Fu, 1999). Additionally, the random utility framework developed by McFadden (1974), upon which many experimental economic studies have relied on, only assumes that the individual derives utility from the product and its attributes. Of course, the individuals' idiosyncrasies and other unobserved factors are capture in a random error term, but what if a participant derives utility not only from the product and its attributes, but also from the fee they collect for their participation in the experiment? What if the participant derives more utility from maximizing the compensation fee than from the auction products and adjusts their behavior accordingly? These questions prompt a deeper look into random utility theory as it relates to incentive compatible, compensation fee bearing auction mechanisms.

The more practical objectives of this research relate to consumers' vegetable purchasing behaviors. In spite of the fact that obesity arguably remains as one of America's "heaviest" problems, several pieces of evidence point toward a trend of Americans making more informed, healthier food choices. A proliferation of programs have emerged in the last decade that aim to help people make healthier choices, such as First Lady Michelle Obama's Let's Move campaign, and popular television shows that promote health education. Menus of fast-food chains are starkly different now than they were even ten years ago, as they now showcase a bevy of healthy options and often provide the calorie count beside each item (Food and Drug Administration, 2010). In addition to changes at the food service level, Americans have been ditching carbonated beverages and preservative-laden snack foods and reaching for more natural options such as water and fruit (Hellmich, 2013). Conventionally produced fruits and vegetables now compete with organic and local produce for shelf space in farmers markets and supermarkets alike (Martin, 2009). Research has shown that consumer preferences for certain quality and credence attributes such as traceability, source information, and production methods are on the rise and have significant and imminent policy implications (Abidoye et al., 2011; Fatka, 2014).

Likely recognizing this consumer trend, Texas agribusinesses and producers are investigating alternative methods for food and agriculture production as a way to differentiate their product. The temperate climates of the Texas Winter Garden Region and the Lower Rio Grande Valley provide ideal growing conditions for the almost year-round production of most fruits and vegetables. In the past ten years, Texas has fallen from being ranked third top producing state in U.S. vegetable production to seventh due to the devastating impacts of consecutive periods of drought (Leskovar, et al., 2013).

Although Texas remains in the top tier of national vegetable production, covering over 100,000 acres and generating over $360 million from vegetable production alone, producers have recently identified water supply and environmental stress as factors hindering the progress of the industry and have thus expressed interest in non-conventional, water efficient technologies (Leskovar et al., 2013). The 2010-2014 droughts and a lack of irrigation water in reserves have profoundly impacted Texas' agriculture industry – estimations of specialty crop production losses from drought range from $100 million to north of $200 million (Santa Ana, 2013; Ribera and McCorkle, 2012). Foreseeing a water crisis and in a combined effort to conserve water and stall negative economic impacts from future water shortages, the Uvalde County Underground Water Conservation District and the Texas A&M AgriLife Research and Extension Center at Uvalde, Texas, have jointly expressed interest in assessing the market potential of hydroponic fruits and vegetables (Leskovar et al., 2013).

Although scattered in use throughout history, commercial farms began successfully using hydroponics in the U.S., Europe, Africa, and Asia by the mid-1900s (Shrestha and Dunn, 2013). This unique production method is usually categorized based on whether or not a medium is used and even further specified by how the plant receives its nutrients. A greenhouse structure allows producers to choose from several techniques: floating hydroponics, the nutrient film technique (NFT), aeroponics, the wick system, water culture system, the ebb and flow system, drip systems, and rockwool culture systems (Shrestha and Dunn, 2013).

Over the past decade, hydroponic fruit and vegetable production has attracted more attention and provides an interesting area for market research (Huang et al., 2002; Haggerty, 2013). Hydroponics is a highly controlled method for growing vegetables, ornamental plants, and foliage plants in which soil is either entirely absent or replaced with a medium, such as brick shards, sand, or wood fiber (Coolong and Foran, 2012). This soil-less production method provides an alternative method for producing fresh fruits and vegetables in extreme, typically infertile climates. From a potential producer's perspective the hydroponic structure usually requires a greenhouse and the delicate nutrient balance demands more attention and maintenance than conventional production. However, the highly controlled environment provides a spectrum of advantages, from water conservation and reduced weather risk to faster growth time and the diminished presence of soil-related pests, fungi, and bacteria (Shrestha and Dunn, 2013; Coolong and Foran, 2012). Consumers may associate the soilless production method with an increase in food safety or certain health benefits and may find hydroponic fruits and vegetables appealing (Huang, Kan, and Fu, 1999; Haggerty, 2013). In contrast to these many advantages and the potential profits form a hydroponic venture, a hefty upfront investment, demanding nutrient management, and largely unknown market potential often discourage producers from investing (Shrestha and Dunn, 2013).

Although the initial investments for the required infrastructure and marketing costs may be higher than conventional production, an increase in demand across America for leafy greens has been driven by the aforementioned trend in consumers making more informed, healthier choices and thus may provide significant returns to the producer. Potential markets have been identified as specific grocers, specialty food retailers, restaurant chefs, caterers, wholesalers, and schools, but little is known about how consumers view and value hydroponic lettuce (Cooligan and Foran, 2012; Huang et al., 2002). Many studies discover consumers' WTP and preferences for food products, but few actually use experimental economics to focus on fresh fruits and vegetables that differ in production methods and varieties (McAdams et. al, 2013; Jaeger and Harker, 2005). Furthermore, little is known about consumers' views and valuations of hydroponic products.

The overall objective of this research is to advance understanding and external validity of experimental auction valuations. Secondly, this research will provide the fresh fruit and vegetable industry with valuable marketing information about hydroponic lettuce. External validity and random utility theory will be combined through an on-site secondary market that will also incorporate the essence of induced value theory in such a way that to this author's knowledge has not been done before. In a combined effort to address the previously mentioned shortcomings of the current literature and aid in this market research, this study has multiple objectives: (1) evaluate the external validity of a Vickrey 2nd price auction by entwining the essence of induced value theory, real market prices, and a post-auction secondary market; (2) elicit consumers' WTP values and compare preferences for differentiating attributes of lettuce such as production method and color; (3) compare results from sensory evaluations of hydroponic, organic, and conventional lettuces through a blind tasting treatment; and (4) investigate how consumers' behavior related to health and prestige influences their valuations of hydroponic and organic vegetables.

In conclusion, this study aims to utilize induced value theory and secondary markets to investigate the external validity of Vickrey 2nd price auctions and assess consumers' WTP for hydroponic lettuce, in a unique way to fill a gap in the current literature. Ultimately, this research may provide insight into consumers' decision-making processes and bring up questions for future research involving random utility theory as it relates to experimental auctions. Added benefits include providing marketers of hydroponic fruits and vegetables with evidence of consumers' valuations of hydroponic lettuce and possibly uncovering a connection between higher WTP values from the auction and health conscious and prestige conscious grocery shoppers. Also, this study may have serious implications for policymakers, theorists, and future developments in experimental auction research. Any results will be used in any publications that come from this study and communicated to Texas Department of Agriculture, the Uvalde County Underground Water Conservation District, and Texas A&M AgriLife Research and Extension Center.

This study is structured as follows. First a literature review is warranted to provide the reader with knowledge of value elicitation methods, experimental auctions, the issues that come to light in the literature, and previous applications of experimental methods to elicit consumers' WTP values for food products. Included in the literature review is a robust narration of the debate on external validity, as well as a description of induced value theory and secondary markets. Next will be a review of the lettuce industry and the evolution of hydroponics, as well as a more detailed description of hydroponic systems. Special attention is paid to studies that have analyzed the differences of food products produced under organic, hydroponic, and conventional production methods. An explanation of the methodologies used and the procedures follows, with a subsequent discussion of the results. Finally, a conclusion will provide the reader with any implications of this research and suggest possible extensions for future research.

CHAPTER II

LITERATURE REVIEW

Eliciting Consumers' Values

One might describe the modern-day economist as a scientist, a storyteller, and a problem-solver, fueled by copious amounts of coffee and a perpetual curiosity to observe, describe what is, and predict what will be. One of the more recent developments of this occupation, specifically in the area of consumer research, is discovering individuals' true valuations in an effort to estimate the demand of a specific product. Determining these valuations for goods and services has traditionally been a challenge for economists because consumers' truest, most pure valuations are difficult to uncover.

The most widely accepted terms of value measurement are willingness-to-pay (WTP) and willingness-to-accept (WTA) values. Whereas WTP values are most commonly known as the maximum amount of income an individual would give up to obtain a good, WTA values are usually thought of as the minimum amount of compensation individuals would be willing to accept to give up a good. These concepts can be easily visualized in a market setting by thinking of WTP as the price at which consumers would be willing to purchase a specific good and WTA as the price at which producers would be willing to sell the good. Because this study primarily concerns consumers, we will say adieu to WTA and proceed with WTP value elicitation methods.

Revealing shoppers' WTP values may be especially valuable to agribusinesses that are contemplating introducing a novel food product to the market. Several value elicitation methods and theories exist in the experimental economic literature. This review of literature aims to salute the evolution of consumer theory and provide the reader with a brief description of the most widely used value elicitation methods, an introduction to experimental economics and a robust discussion of experimental auctions and design issues, and concludes by suggesting the application of a harmonious blend of existing valuation methods that may advance the paradigm through which economists study consumer theory.

The Evolution of Consumer Theory According to McFadden

In an effort to predict the future of experimental economics, McFadden (2013) asserted that the history of consumer theory began over two hundred years ago with Jeremy Bentham's (1789) idea of self-interest and increasing pleasure and reducing pain as the motivational forces for the choices consumers make. Bentham's (1789) description of what we now call "utility" was attached to the process of increasing pleasure or reducing pain, not necessarily with the consequences of these actions as neoclassical theory suggests later. According to Bentham, intensity, duration, certainty (or uncertainty), and propinquity (or remoteness) were the four criteria that determine utility. Famous economists such as Adam Smith (1753) and Francis Edgeworth (1881) shared Bentham's call for the inclusion of altruism and reciprocity as crucial components of utility. Unfortunately, it became difficult to recover utility from observed behavior under this definition. In the mid 1800s, Jules Dupuit (1844) and Hermann Gossen (1854) introduced the concept of using the marginal utility of money as a means for calculating maximized utility. Dupuit's concept of relative utility (which later became known as consumer surplus) and William Stanley Jevons (1871), Edgeworth (1881), Alfred Marshall (1895), and Vilfredo Pareto's (1906) development of the inverse problem (using demand to recover utility) forever changed economists' relationship with utility.

As McFadden's (2013) narration moves into the mid 20th century, he explained that utility moved away from Bentham's idea of pleasure, pain, reciprocity, and altruism and quickly drifted toward a more narrow definition. The new, neoclassical concept of utility was solely measured through revealed demand behavior and left no room for introspective explanations. Irving Fisher (1892), John Hicks (1939), and Paul Samuelson (1947) further developed the relatively new framework and established it as the go-to method for measuring utility. Eugen Slutsky (1915), Hicks (1939), and Samuelson (1947) developed the formal economic framework and Rene Roy (1942), Rudolph Auspitz and Richard Lieben (1889), Harold Hotelling (1935), Lionel McKenzie (1957), and Hirofumi Uzawa (1971) made significant contributions to the theory. Utility became a function of the good; attributes of the goods and the consumer's experience, social and environmental cues, and information; and unobserved primitive characteristics of the individual such as heterogeneous tastes. McFadden (2013) claims that although the attributes of the good and the consumer's surroundings and unobserved characteristics were implicit in the framework, and although the former variables affected pleasure and pain, neoclassical theory failed to account for any influence on market demand behavior or the consumer's well being.

McFadden (2013) described the impact of technology on theory as the 1960s ushered in a new age of econometric data analysis and the advancement of technology that allowed variables such as attributes of the good and characteristics of the consumers' surroundings to be accounted for in demand analysis. Richard Stone (1954) and Erwin Diewert (1971), among others, became the pioneers of consumer demand analysis through econometric demand systems. A new question was brought to the economics table regarding the effect of changes in a "consumers' economic environment" on indirect utility. Dupuit, Marshall, and Hicks' concept of consumer surplus was dusted off and revisited to help explain compensating variation or WTP. However, even with all of the theoretical advancements over the last century, the neoclassical framework still falls short in accounting for non-market attributes' impact on observable consumer behavior.

Value Elicitation Methods

Throughout the last forty years, economists have tweaked the tools through which they study how consumers value certain goods and services (Lusk and Shogren, 2007). The advancement of value elicitation methods can largely be attributed to environmental economists and their efforts in assessing damages or benefits of public goods. Tietenberg and Lewis (2009) claim the question of valuation methods rose to the surface in the aftermath of the Exxon Valdez oil spill off the coast of Alaska on March 24, 1989. Economists were called on throughout the litigation process to calculate the value of the short-term and long-term damage done to the environment, the people, and the community, in an effort to determine the appropriate compensation due to the victims of the oil spill. This famous court case ignited a movement of value elicitation methods in the economic literature. What are consumers' true values for public goods not observed in the market place, such as wildlife habitats and parks, and for private goods that are observed in the market place, such as a pint of strawberries or a coffee mug? The multitude of methods that have been developed in the past forty years to answer these questions can be grouped into two broad categories, stated preference methods and revealed preference methods.

Stated Preference Methods

Stated preference methods involve asking individuals to state their value for the good or issue at hand, usually in a survey format. One of the most fervently discussed methods is the contingent valuation method (CVM) in which subjects are directly asked to state the value they place on the good. A more complex version of CVM might establish upper and lower bounds by providing subjects with specific conditions and asking if they are willing to pay $X for the good (Tietenberg and Lewis, 2009). Individuals' values can also be inferred indirectly through hypothetical, attribute-based models such as the contingent ranking method and discrete choice experiments (DCE). The contingent ranking method takes the form of a survey, in which subjects are asked to rank-order different goods or bundles or attributes. If one of the goods or attributes is expressed in monetary terms, the individuals' value regarding tradeoffs can then be inferred. Similar to CVM, a discrete choice experiment is a survey-based design, but instead of asking participants to state their value for the good, they are asked to choose between alternative scenarios or bundles of attributes. If the bundles or scenarios are associated with a specific price, marginal WTP values can be indirectly inferred from a participant's response.

Revealed Preference Methods

If stated preference methods are at one end of the value elicitation method spectrum, revealed preference methods occupy the opposite end. Revealed preference methods are based on actual observable choices and values can be directly obtained through market prices and real transactions, such as scanner data, or indirectly obtained through the travel cost method, hedonic pricing method, and hedonic wage method. Scanner data records the price an individual pays at the point of purchase and is collected from most retail stores. The travel cost method and hedonic property values method have been particularly useful for environmental economists assessing the value of goods that are not usually traded in the marketplace. The travel cost method involves analyzing how much an individual spent, in terms of expenditures and opportunity cost, to travel to a recreational resource, such as the Grand Canyon National Park, whereas the hedonic property value model involves using existing market data and property values in the surrounding area to extract marginal WTP for components of a house, such as an extra bathroom. In a similar style, the hedonic wage method involves using wage data to assess the WTP to avoid working under certain conditions.

Advantages, Disadvantages, and Biases

Revealed preference methods and stated preference methods have advantages and disadvantages. For example, Lusk and Shogren (2007) clarify that although stated preference methods provide the researcher with the freedom and flexibility to create hypothetical scenarios and goods, and therefore more control over the stimuli subjects are asked to act on, a major drawback is that subjects respond to the hypothetical questions by giving hypothetical answers – meaning that subjects may overstate or understate their true values, perhaps even unknowingly, because the entire situation is hypothetical and inconsequential in nature. Revealed preferences, alternatively, also have advantages and disadvantages. Lusk and Shogren (2007) briefly mention that one of the most attractive characteristics of revealed preference methods is their ability to observe actual behavior and real values in the market place. Although nonhypothetical behavior and choices are studied, they are observed after the transaction and still rely on inference and empirical patterns to implicitly derive consumers' valuations for a certain good. Furthermore, the post-transaction nature of the data limits the amount of control researchers have compared to stated preference methods, in that they cannot instantly observe how consumers' behavior changes when specific conditions change.

One of the most widely published concerns with stated preference methods is the issue of biases. Economists have fervently debated CVM's hypothetical structure and whether it is able to elicit consumers' truest valuations. Tietenberg and Lewis (2009) identified five types of bias that may arise with stated preference methods: (1) strategic bias; (2) information bias; (3) starting-point bias; (4) WTP does not equal willingness-to-accept (WTA) bias; and (5) hypothetical bias. Strategic bias refers to the subject stating a value that will influence a particular outcome, while information bias occurs when subjects are required to value attributes for which they have little or no experience with. Starting-point bias may exist as a result of the spread and magnitude of a predefined answer range. Another crucial consideration in designing the plan for eliciting consumers' values is choosing whether to elicit WTP or WTA values. List and Gallet (2001) conducted a meta-analysis of 29 experimental studies and, among other findings, discovered that WTP studies showed less overstatement of preferences compared to WTA studies. Hypothetical bias arises when subjects respond differently to hypothetical questions than to questions that have real consequences, and can generally be thought of as the difference between stated preference values and revealed preference values (Lusk and Hudson, 2004; Murphy et al., 2005).

Whether or not hypothetical bias compromises the validity of stated preference methods, specifically CVM, has been hotly debated amongst economists for well over twenty years. Igniting this debate was Bohm's (1972) study that compared hypothetical and real values. Among those who have found that hypothetical values eclipse actual values are Bishop and Heberlein (1979, 1986), Cummings, Harrison, and Rutström (1995), and List and Shogren (1998). Alternatively, studies that disagree with the existence of hypothetical bias include Dickie, Fisher, and Gerking (1987), Johannesson, Lilijas, and O'Conor (1997), Sinden (1988), and Smith and Mansfield (1998). Although the factors that cause hypothetical bias are largely unspecified due to a lack of theory and empirical shortcomings, several studies have conducted meta-analyses in an attempt to identify the experimental design factors that can lead to bias (Carson et al., 1996; List and Gallet, 2001; Murphy et al. 2005; Little and Berrens, 2004; and Harrison and Rutström, 2008).

List and Gallet (2001) used a calibration factor (mean hypothetical WTP divided by mean actual value) and regression analysis with the natural logarithm of the calibration factor as the dependent variable in their meta-analysis to investigate the experimental design characteristics that encourage a disparity between stated values in and actual values. The wide range of design characteristics included the setting, type of good used, type of comparison, and the elicitation method enlisted. Their results indicated that on average subjects who responded to hypothetical questions in the studies of interest overstated their responses by a factor of three. Additionally, List and Gallet (2001) established several factors to consider when designing an experiment: (1) hypothetical WTP studies yield results that are more in line with subjects' actual WTP values compared to WTA studies; (2) the disparity between hypothetical stated values and actual values is smaller when private goods instead of public goods; and (3) elicitation methods matter, as a first price sealed bid auction reduces bias between hypothetical values and real values.

Little and Berrens (2004) revisited List and Gallet's (2001) meta-analysis and expanded it to include more observations to analyze additional factors of experimental design, such as the impact of referenda, cheap talk scripts, and certainty corrections. Little and Berrens' (2004) results supported List and Gallet's (2001) conclusions that elicitation mechanisms matter, but were unable to confirm that private goods lessen hypothetical bias relative to public goods. Their results from a calibration factor model and probit model suggest that certainty corrections and referenda seem to diminish the disparity between hypothetical stated values and actual values.

Murphy et al. (2005) continued the trend of meta-analysis by analyzing twenty-eight stated preference studies. All of these studies had similar themes in that they reported WTP values in monetary terms and used the same value elicitation mechanism to elicit hypothetical and real values. They claimed choice-based elicitation mechanisms, specifically “dichotomous and polychotomous choice, referendum, payment card and conjoint,” were effective in narrowing the gap between hypothetical stated values and actual values. Additionally, they introduced the idea that using students in the sample may cause hypothetical bias and they find weak evidence to support List and Gallet’s (2001) claim that the use of public goods increases hypothetical bias.

After investigating the existence of hypothetical bias in studies that use CVM and private goods, CVM and public goods, open-ended elicitation in the laboratory, dichotomous choice elicitation in the laboratory, social elicitation in the laboratory, Harrison and Rutström (2008) echo the sentiments of List and Gallet (2001) and Murphy et al. (2005) in that they agree that hypothetical bias undoubtedly exists and that the use of a private, deliverable good instead of a public good, such as a policy or environmental scenario, helps to reduce the amount of bias that may arise. Furthermore, they identify one of the causes of hypothetical bias to be “lack of real economic commitment” in the hypothetical settings.

Experimental Economics

History of Field Experiments

Levitt and List (2009) provided economists with a historical timeline of experiments in science, from Galileo to Rutherford, and identified three distinct time periods in experimental economics. The first is dubbed the dawn of field experimentation, in which experiments were conducted in the field to answer questions about agricultural productivity in the 1920s and 1930s. As previously mentioned by McFadden (2013), the 1960s changed the way data was analyzed. This change allowed for analysis of large-scale social experiments that evaluated government social programs. The third period related to the development of experimental economics, which emphasized control and blended characteristics of conventional lab experiments, social experiments, randomization and realism.

The groundwork for experimental economic markets in the laboratory was largely the work of Vernon Smith's (1976) seminal paper titled "Experimental Economics: Induced Value Theory." He proposed that economics in the laboratory can be a vehicle to test theories before applying them to the outside world, where ceteris paribus is not easy to find. Furthermore, laboratory exercises help prevent researchers from tweaking and fitting the model to a random body of field data. Smith (1976) claimed that an increased level of control in the laboratory setting allows researchers to observe changes in participants' behavior through fabricated reward structures, the application of different treatments, and as specific values induced on participants. By using the theory of neoclassical demand, nonsatiation, and the utility for money and by inducing supply and demand on participants, Smith (1976) successfully created a functional market and observed competitive equilibria emerge in the laboratory.

Later, in 1982, Smith formally established the theoretical underpinnings and structure for experimental economics in the laboratory. Smith (1982) extended beyond his earlier framework to define the components of an experiment and stressed the importance of incentivizing participants to reveal their true market behavior. Smith (1982) reemphasized that control and replicability were the primary differences between experimental economics and other methods of studying economics. He provided five necessary conditions for microeconomic experiments: nonsatiation, saliency, dominance, privacy and parallelism. Nonsatiation refers to the theoretical concept that our utility for money is an increasing monotonic function – in other words, we prefer more money to less at all times. The second condition, saliency, implies that an individual's reward in the experiment is an indirect result of their actions in the experiment. Dominance, the third condition, suggests that the reward structure in the experiment should offset any subjective costs of participating in the experiment. The fourth condition, privacy, says that each subject in the experiment is provided with information regarding only his or her own payoffs. The final condition, parallelism, refers to propositions about how the observations in the experiment relate to non-laboratory environments where similar ceteris paribus conditions hold. These five conditions support control in experiments, which allows results of experiments to be replicated follow-up experiments – a characteristic not found in other methods of studying economics.

Additionally, Smith (1982) makes a strong case for microeconomic experiments by separating a laboratory experiment into two main components, the environment and the institution. While the environment describes physical characteristics of the experiment such as information about the participants' utility functions and the types of goods being used, the institution establishes the language and rules that are meant to guide the participants' decisions in the experimental marketplace. A participants' behavior is a function of the institution and the environment and together, the institution, the environment, and the behavior form the microeconomic system in the laboratory. Smith extends beyond this framework to define two crucial components of an institution – a mechanism, which is a formal theory that encourages equilibrium behavior among subjects, and incentive compatibility, which he defined as the ability of an institution's rules to produce Pareto optimal results (1982).

Experimental Auctions

Smith (1976, 1982) blazed the trail for a new theoretically sound, value elicitation method to emerge. Lusk and Shogren (2007) propose that perhaps the most effective tool for eliciting consumers' truest values would combine the advantages of revealed preference methods and stated preference methods in an entirely novel method, experimental auctions. Experimental auctions were formally introduced as a viable value elicitation method in Smith's (1976, 1982) studies and have become a popular tool for market research over the last twenty years, being used in more than 100 studies (Lusk and Shogren, 2007; Lusk, Alexander, and Rousu, 2007). Although auctions tend to lack context and create an unfamiliar environment for participants, they offer a plethora of advantages – including increased control and straightforward interpretations of the participants' valuations (Hoffman et al., 1993; Loewenstein, 1999; Lusk and Shogren, 2007). This subsection addresses the broad groups experimental auctions can be divided into, the types of auction mechanisms, the incentive compatibility of auctions, salutes studies that have compared differing auction mechanisms with each other and with other methods, and explains homegrown values and induced values.

Continuous Auctions, Sealed-Bid Auctions, Endowed, and NonEndowed

Smith (1982) established two broad groups of auctions – continuous auctions and sealed-bid auctions. Continuous auctions can be thought of as a traditional English auction, in which a participant can change their bid in response to other participants' bids (Smith, 1982). The rules of the institution, also known as the auction mechanism, allow for individuals (bidders) to change their WTP values (bids) based off of the messages that are exchanged between individuals and the auctioneer and also among other participating individuals in the auction setting (Smith, 1982). The second type of auctions, sealed-bid auctions, establish rules and a setting in which participants privately write down and discreetly submit their bid to a center or the auctioneer. No information is exchanged about valuations between the auctioneer and the individuals or between the individuals themselves. The bids are organized according to the auction mechanism and the buyer and the price is announced. Smith (1982) noted that the most significant difference between these two styles is the amount of information available to the bidders and recognized the continuous auction provides "a message history between successive contracts."

Additionally, Lusk and Hudson (2004) established that participants in experimental auctions can either be endowed with a good and subsequently asked to bid to be able to exchange the good for a new good, or not endowed with an existing good, and asked to directly bid on a selection of competing goods. In the latter case, one of the goods is randomly drawn to be binding and, according to theory, demand can be elicited for the binding good (Lusk and Hudson, 2004).

Types of Auctions

Smith (1982) identified several types of common auction mechanisms: English, Dutch, first price, and second price. Lusk and Shogren (2007) added in other incentive-compatible mechanisms for consideration such as the Becker-DeGroot-Marschak (BDM) mechanism, Vickrey *n*th price auctions, and the random *n*th price auction. English auctions are continuous in nature and begin with the auctioneer announcing a relatively low price, believed to be lower than the participants' maximum WTP for the good. The auctioneer calls for bids as he or she ascends in price and once a participant bids at a specific price that bid stands until it is displaced by another participants' bid, which must be higher. The bidding ends when the auctioneer recognizes no higher bids are being elicited (Smith, 1982). The standing bid's owner becomes the buyer and pays the associated price. The Dutch auction is continuous in nature and is similar to the English auction, except that instead of starting at a low price and ascending, the auctioneer begins at a high price, believed to be higher than the participants' maximum WTP for the good. The auctioneer proceeds to lower the price in increments and goes bids until a participant is willing to accept the auctioneer's price or a pre-determined price floor level.

Sealed-bid auctions include first price auctions and the incentive compatible mechanisms of Vickrey second-price auctions, random *n*th price auctions and BDM auctions. First price auctions are relatively simple – participants privately submit bids to a center, the bids are organized, and the person who bid the highest price for the good becomes the buyer and pays a price equal to their bid. Vickrey second-price auctions, random *n*th price auctions, and BDM auctions are incentive compatible by enforcing tangible monetary transactions and separating participants' stated values in their bids from what they actually pay for the good. Additionally, they absorb some of the benefits of stated preference methods and revealed preference methods by directly observing stated values in the form of submitted bids and they avoid hypothetical bias through the incentive compatibility characteristic.

William Vickrey (1961) introduced the concept of a 2^{nd} price auction through the illustration of a marketing (brokerage firm) agency's problem with determining the equilibrium price and quantity that will sustain a competitive environment between buyers and sellers. In a 2^{nd} price auction, the award will be delivered to the highest bidder, who will pay the second-highest bid, which becomes the market price in the auction. Note that unless two or more participants bid the same price and that price ended up being the highest price, the second-highest bid indicates usually only one buyer. Vickrey (1961) points out that although the second-price auction is more sophisticated in nature and less self-policing than more simple auctions, such as the

English and Dutch auctions, the advantages of the Pareto-optimal properties of a second-price auction are quite attractive to market researchers. Theoretically, any level of bids can be the designated indicator of the market price and also indicate the buyer(s) (i.e. fifth-highest bid, third-highest bid, etc.). For example, in a Vickrey style fifth-price auction, participants submit sealed bids and the four bidders who submitted bids higher than the fifth price become buyers and pay a market price equal to the fifth-highest bid (Lusk, Alexander, Rousu, 2007; Hoffman et al., 1993). The BDM mechanism is comparable to Vickrey auctions, but incorporates more of a random component. In a BDM mechanism, participants bid against a randomly established price and those participants who bid higher than the random price become buyers and purchase the good. A random *n*th price auction entices subjects to submit bids for the good being auctioned and randomly draws one of the bids to be the market price. Individuals whose bids exceed the randomly drawn price pay the market price for the good. The random *n*th price auction embodies characteristics of both the *n*th-price auction (as in the second-price auction) and the BDM mechanism (Lusk, Alexander, and Rousu, 2007; Lusk and Shogren, 2007).

Comparisons of Auction Mechanisms

In the quest to improve value elicitation mechanisms, many studies have made comparisons between the theoretical properties and practical aspects of stated preference methods, revealed preference methods, and experimental auction mechanisms (Shogren et al., 2001; Lusk and Hudson, 2004; Noussair et al., 2004, Lusk and Rousu, 2006). Wertenbroch and Skiera (2002) used a unique combination of stated preference methods, auction mechanisms, and field experiments to compare elicited WTP values across settings, methods, and goods to examine the feasibility, reliability, and validity of the BDM mechanism. First they used the BDM mechanism and "price matching" in the form of open-ended contingent valuation to elicit consumers' WTP values for a can of Coca-Cola on a beach in Kiel, Germany. In a second application, they employed the same methods but changed the good and the setting to be a piece of pound cake on a commuter ferry in Kiel. A third group's WTP values were elicited for three pens using a hypothetical contingent valuation method in which they were asked whether they would buy or not buy at certain price points. A between subjects design was used and mean WTP values elicited in the first two applications were compared to measure the reliability of the BDM mechanism. To evaluate the internal validity of the BDM mechanism, researchers used a discrete choice logit analysis of the purchase probabilities. Researchers also investigated the effect of using candy as compensation relative to no compensation. Between the BDM subsamples, no difference seemed to exist, but the price matching subsamples were not equivalent. The authors concluded that WTP values elicited through a BDM mechanism are unfazed by the level of compensation participants receive. Although this was a profound step in analyzing the incentive compatibility, reliability, and internal validity of BDM mechanism relative to CVM, compensation were bags of candy, not money. Money can be exchanged for something of value post-auction whereas the candy cannot, and thus may influence a different outcome. Regardless, Wertenbroch and Skiera (2002) concluded that the BDM mechanism is a feasible, reliable, and valid tool for eliciting consumers' WTP values in point-of-purchase situations.

Lusk, Alexander, and Rousu (2007) compared the theoretical properties, payoff functions, and cost of deviation of three popular incentive compatible value elicitation auction mechanisms: Becker, DeGroot, Marschak (BDM) mechanism, Vickrey *n*th price auctions, and the random *n*th price auction. They define on-margin bidding and off-margin bidding and show that the mechanisms differ with regard to the expected cost of misbehaving (deviating from true values, or over and underbidding). They also illustrate that incentive compatibility relies on the distribution of other participants' bids and their true values. In addition to this broader topic, Lusk, Alexander, and Rousu shed light onto the induced value second price Vickrey auction conducted by Shogren et al. (2001).

Offering a more applied approach, Lusk, Feldkamp, and Schroeder (2004) used steaks to investigate how WTP values elicited from experimental auctions were influenced by certain factors, specifically auction mechanism, reference-dependency of preferences, and the presence of multiple goods influenced. Consumers submitted valuations for five different types of rib-eye steaks: generic, guaranteed tender, natural, USDA Choice, and Certified Angus Beef. The first treatment used an endowment approach and captured consumers' WTP bids through four commonly used auction mechanisms: English, Becker-DeGroot-Marschak (BDM), Vickrey second-price, and random nth price. The second treatment measured the endowment effect by repeating the first treatment sans endowment. In an effort to measure the influence of multiple goods the final treatment consisted of no endowment, and only used the second price auction mechanism to elicit values for only the generic and guaranteed tenderness steaks. Results indicated that the type of auction mechanism significantly influenced WTP values (bids) of the steaks. Bids became significantly higher following the first round of the second price auction relative to bids from the other three mechanisms. Lusk, Feldkamp, and Schroeder (2004) suggested the posting of prices, bidder affiliation, and competitiveness among bidder personalities could have caused this inflation in bids. When an endowment was provided, bids were significantly lower in all rounds of the random *n*th price auction than in the BDM and English auction mechanisms. Although divergent in terms of market feedback and price determination, BDM and English mechanisms generated statistically equivalent bids. The endowment effect significantly influenced prices in the second price and random *n*th price auctions, but not in the BDM and English. This could be due to the single round nature of the English and BDM mechanisms.

Not only have comparisons been made between experimental auctions and other value elicitation methods, and between auction mechanisms themselves, researchers have juxtaposed econometric methods for analyzing different auction mechanisms. For example, Chang, Lusk, and Norwood (2009) compared the predictive performance of three popular value elicitation methods (hypothetical choice, non-hypothetical choice, and non-hypothetical ranking) and three econometric models (multinomial logit (MNL), independent availability logit (IAL), and random parameter logit (RPL)) by exploring whether consumers' actual buying behavior in a grocery store mirrored their preferences elicited in a laboratory setting. Chang, Lusk, and Norwood (2009) concluded that the non-hypothetical choice and ranking methods were better methods for predicting consumers' behavior, while the RPL model was the best performing econometric model due to its flexibility and compatibility with the heterogeneity within the data.

Incentive Compatibility

Perhaps the most notable advantage of experimental auctions relative to other methods of value elicitation, such as stated preference, is the application of real money consequence and reward mechanisms. When an individual is asked to state how much they would be willing to pay per month to support a local park or how much they would be willing to pay for a rare bottle of Scotch whisky, their answer is not tied to any consequences or payment – the person will not have to shell out the money and thus is inclined to not give their most truthful valuation.

One of the most attractive characteristics of experimental auctions is that they are incentive compatible, meaning they facilitate a live market with real money at stake and enforce payment and reward mechanisms and "a person has a dominant strategy to submit a bid exactly equal to his or her value for the good" (Lusk and Shogren, 2007). Real monetary rewards and consequences incentivize participants to submit their truest values and discourage any deviating behavior from their truest valuations. As evidenced from List and Gallet's (2001) previously mentioned meta-analysis, several studies have confirmed that people often state their WTP values when there is no incentive to answer truthfully or exert the energy to give their truest valuations, compared to when a monetary reward or cost is linked to their answer. For example, in a Vickrey second-price auction, the market price is equal to the second highest bid. The participant who bid the highest amount for the binding good becomes the buyer and must pay the second highest bid (market price) for the good. Participants are unaware of where their bid falls in the distribution of bids for the binding good; therefore it is in their best interest to bid a value that is exactly equal to their maximum WTP. A mathematical proof is shown in Chapter IV.

Induced Value Theory

As previously mentioned, Smith (1976) established induced value theory to explain the theory behind market experiments in the laboratory. After defining the assumption of nonsatiation and a foundation of utility theory, Smith hypothesized that "if an individual is faced with a costless choice between two possibilities that are identical except that one yields a higher reward than the other, the alternative with the higher reward payoff is always preferred." Generally, induced value experiments insure incentive compatibility by implementing reward mechanisms. For example, participants gain value, or profits, by selling a good back to the researcher for the market price and a participant's profit is equal to the difference between the market price and the individual's induced value (Lusk and Shogren, 2007).

Smith proved his theory through a stylized trade experiment in which subjects were assigned (induced with) specific values for an abstract, nondescript good and assumed the roles of buyers and sellers. Participants naturally converged to market equilibrium through the assigned values and assumed roles. Induced value theory essentially provided researchers with the element of control in a market experiment and maintained incentive compatibility by enforcing real market consequences.

Traditionally, this customized characteristic of design has been useful for directly observing bidding behavior and can be used to explicitly test the demand-revealing tendencies of different auction mechanisms. Although several studies have used induced value theory to test the internal validity of auction mechanisms, including Coppinger et al. (1980), Kagel, Harstad, and Levin (1987), Shogren et al. (2001), and Lusk and Rousu (2006), fewer studies have used induced values to address the impact of goods outside of the laboratory on bidding behavior in the laboratory experiment.

One of the studies that inspired this research's methodology involved applying induced value theory in a unique way to assess the impact of outside substitutes on bidding behavior in the laboratory. The researchers investigated incentive compatibility as it relates to outside options and auction behavior – specifically, they looked at any effect private goods' outside substitutes have on bidding behavior (Cherry et al., 2004). This paper used an induced valuation experiment to detect any bid shaving behavior when an outside option is present. Bid shaving behavior occurs when a participant adjusts his or her bidding behavior to account for outside substitutes and thus shave (move) his or her bid toward the price of the outside option. Auction goods with known substitutes outside of the laboratory may undermine the controlled setting.

Cherry et al. (2004) used a second-highest bid Vickrey auction and treatments consisted of real and hypothetical payments, three outside option prices ($2, $4, $6), with a no outside option as the baseline measurement. The participants were assigned induced values that were considered "resale" or "redemption" prices at which participants could sell the good back to experimenter after the auction and incur either a profit or a loss.

These assigned, induced values were unique and, as a set, formed a complete induced demand curve for the private good. After the individuals were assigned a random induced value (also considered their resale value), they bid on the product up for auction. The highest bidder became the buyer and paid the second-highest bid, which was in line with the rules of a Vickrey second-price auction. The buyer could then keep the product and potentially sell it outside of the auction at the outside option price or sell it back to the monitor in the auction at their assigned resale value (also induced value) for a potential profit or loss. Cherry et al. (2004) stressed that, theoretically, the participants have an incentive to make their bid price equal to their induced value if the price of the outside option is greater than or equal to the induced value. Conversely, the bid price will be equal to the price of the outside option when the induced value exceeds the price of the outside option. Results indicated the availability of an outside option value significantly decreased bid levels in the auction compared to the baseline of no outside option. The authors suggested participants might have encountered fatigue in repeated hypothetical rounds, which could have affected the results. To further explain individual bidding behavior, a random effects tobit model was used. Once they controlled for hypothetical bias, bid shaving was not statistically different to bid shaving between the hypothetical rounds and actual rounds.

Cherry et al. (2004) concluded that people incorporate outside options into their bidding behavior and move their bids toward the outside option prices. Although this experiment used induced value theory in a unique way to address the impact of external forces, which is often forgotten by experimental economists, the experiment did not specify what the auction good was! The benefit of using an abstract good is often highlighted in studies using induced value theory because it allows researchers to focus solely on the demand-revealing properties of the mechanism being used. However, for value elicitation purposes, the good being auctioned and its substitutes are extremely important, especially if participants are familiar with the value of the good in the outside world, for example food products. Incentive compatibility and the influence of outside option values could vary greatly between food and non-food products.

Homegrown Values

Traditionally, induced value theory gave researchers the theoretical structure to conduct experiments in the laboratory that compared the demand-revealing abilities of auction mechanisms. However, consumers' direct valuations of private goods were not necessarily the objective of induced value studies. One of the benefits of experimental auctions is the flexibility it provides to researchers, meaning the experiment can be designed to directly elicit participants' true valuations for the good at hand. Lusk and Shogren (2007) and Harrison, Harstad, and Rutström (2004) define homegrown values as values that are the values participants bring into the experiment, unknown to the researcher, can be directly elicited, and are not induced values. Whereas induced values are used in auctions where the good is abstract and indefinable, homegrown values are elicited in auctions that use real, identifiable products.

Secondary Markets

In addition to experimental auctions being used to test theories and elicit consumers' WTP values for goods, economists have also incorporated secondary markets to analyze the effect outside options or subsequent market opportunities have on behavior in auctions. Corrigan (2005) investigated how participants' perceptions about the relative difficulty of post-auction transactions affected their WTP values in a random *n*th price auction. A group of students were asked to bid on an Iowa State University-logo coffee mug in a random *n*th price auction and answer follow-up questions regarding how difficult they thought it would be to delay (buy later, outside of the auction) or reverse (resell later, outside of the auction) their transaction. Results from Corrigan's (2005) study suggested that a dynamic component exists in experimental auctions and concluded that participants' behavior in experimental auctions is influenced by a certain time component that is a function of the difference between option values of buying or selling the specific good in question. Furthermore, results indicated that participants who perceive buying the good later (delaying the transaction) outside of the auction to be relatively difficult, bid significantly higher than those who perceive buying the good outside of the auction to be relatively easy. Corrigan (2005) suggested that these results provide evidence that bidding behavior is affected by outside influences.

Haile (2001) looked at how the opportunity to buy or sell in resale markets affected valuations in the U.S. Forest Service's timber contract auctions. Haile (2001) developed a model that explained bidders' bidding and participation behavior as a function of increased competitors entering the auction and applied the model in the form of an English auction. Ultimately, Haile's (2001) model and empirical analysis proved that when a post-auction resale opportunity is available, bidders' valuations are endogenously affected by the value of this option. Haile (2001) concluded that bidders' valuations are higher when there is a high value associated with selling in the resale market and lower when there is a low value associated with buying in the resale market.

A third example of offering subsequent market opportunities to participants is the previously discussed study conducted by Cherry et al. (2004). When researchers provided participants with induced values that were to be considered "resale" or "redemption" prices at which participants could sell the good back to experimenter after the auction and incur either a profit or a loss, they essentially introduced another component in consumers' decision making process and bidding behavior. The opportunity for bidders who became buyers to buy or resell the good after the auction rounds were completed essentially introduced a secondary market into the experiment. Although these studies examine consumers' behavior when additional opportunities are present, none of them use actual private goods or use secondary markets to test the deeper issues of experimental auctions as a valid method.

Issues Associated with Experimental Auctions

Although experimental auctions are useful for testing theories and eliciting consumers' WTP values for goods, several issues have been discussed in the literature. Harrison, Harstad, and Rutström (2004) brought to light three concerns plaguing experimental methods that elicit homegrown WTP values: field price censoring, affiliated beliefs about field prices, and affiliated beliefs about the quality of the good being auctioned. The discussion of these matters will be a natural progression from Cherry et al.'s (2004) study. Additionally, internal validity and the debate on external validity will be visited.

Reference Prices and Outside Substitutes

When raw WTP values are being elicited for a common good that is available in the real market, outside of the laboratory, participants' bids are prone to being influenced by the value of that good. The outside value of the auction good have several names that can be used interchangeably, such as field prices, reference prices, outside substitute, or field substitutes. Research has shown that outside values can significantly influence bids in experimental auctions (Cherry et al. 2004; Harrison, Harstad, and Rutstöm, 2004; Alfnes, 2009; and Drichoutis, Lazaridis, and Nayga, 2008).

Alfnes (2009) took a theoretical look at auction design and constructed a model that illustrates how the value consumers place on a good in the auction and the price of the same good in the market place affect the surplus he or she receives. These components, in conjunction with consumers' true valuation for the auction good and the retail prices of auction good outside of the laboratory ultimately make up a consumer's bid. Using the theoretical model he constructed, Alfnes (2009) derived weakly dominant strategies in Vickrey auctions and conducted a sensitivity analysis to see how transaction costs, resale potential, the availability of auction products in the market, and auction products valued less than their field substitutes affect the model. Alfnes (2009) concluded that consumers are likely to have different outside substitutes for the same auction products and that these substitutes have a profound impact on the subjects' valuation of the good in the auction. He concluded that, with the presence of field substitutes, consumers' bids were lower and bounded by the market price.

Choosing a more applied route, Drichoutis, Lazaridis, and Nayga (2008) investigated if and how the presence of field price information (reference prices) affected experimental auctions through a multiproduct 2^{nd} price Vickrey auction with two information treatments – one informing the participants of the products' field prices and one not including the reference price information. A 6-inch sub sandwich, a wrapped pita sandwich, and a Mediterranean type of sandwich were the three products used in the bidding rounds. After the WTP data was collected, a random effects tobit model analyzed the values. Drichoutis, Lazaridis, and Nayga (2008) found evidence that the provision of reference prices had a statistically significant effect on consumers' bids – specifically, the bids tended to be higher after the participants were presented with the three products' actual field prices. This study provided empirical evidence of the effect of reference prices and suggested an awareness of the effects reference prices have on willingness to pay values in experimental settings.

Harrison, Harstad, and Rutstöm (2004) suggested that homegrown values elicited in the laboratory experiment are not actually raw in nature; rather they are influenced by prices of the good outside of the laboratory and will be censored at the "perceived extra-laboratory price of the good." Additionally, they stressed the danger of revealing values or market prices in between auction rounds, as they too could be considered reference prices and taint consumers' homegrown WTP values of the auction good. The revelation of values, such as announcing the market price in between rounds, would contaminate the subject's thought process of submitting their true valuations and he or she may either raise or lower their true value and shave it toward the revealed price. Harrison, Harstad, and Rutström (2004) claim this is likely because, "a rational subject will not agree to obtain the same commodity in an experiment at a price that he perceives can be beaten outside the lab with sufficiently high probability."

These studies stress the importance of accounting for reference prices, whether they are in laboratory, in between auction rounds or outside of the experiment, in nearby retail outlets, when designing an experimental auction that elicits homegrown WTP values from consumers. Additionally, these studies showcase the attention that must be paid to auction designs that use real goods, especially food products, to elicit consumers' WTP values, as consumers are often familiar with the retail value of close substitutes.

Affiliated Beliefs

Another issue brought up in experimental economics is that of belief affiliation. According to Harrison, Harstad, and Rutström (2004), beliefs among subjects about field prices can be affiliated, as well as beliefs about the actual characteristics of the auction good, can influence other subjects' bids. For example, Sally's WTP value for the auction good may be influenced by John's beliefs about the quality of the good being auctioned or their estimates of the good's field prices. Alternatively, Sally may adjust her bid after viewing John's bid for the auction good. If she does, her bid is now affiliated with John's and is not her truest homegrown valuation of the good. Harrison, Harstad, and Rutström (2004) suggest that experiment designs that reveal market prices in the previous round, before the next auction round, and repeated choices may increase the possibility of eliciting bids or preferences that have been influenced by other subjects' opinions and perceptions.

Internal Validity

Internal validity is a crucial component in any science project – it forces researchers to ask themselves, "Does the theoretical construct used measure what it is supposed to measure? Is the experiment structure sound and does it produce results that theory says it is supposed to produce?" In general terms, internal validity can be defined as a cause-and-effect relationship – all of the independent variables of the experiment cause and explain the dependent variable. According to Schram (2005), "An internally valid design will yield results that are robust and replicable." Lusk and Shogren (2007) describe an elicited individuals' WTP value as a function of their true value, and unknown variables like systematic error and random error. A method of measurement can be said to be internally valid if the systematic error and random error terms are equal, therefore the individual's elicited WTP value is equal to their true value (Lusk and Shogren, 2007). This means that the tool of measurement has accounted all of the things that could possibly influence a person's valuation, including unknown factors. Campbell and Stanley (1963) examined sixteen experimental designs in conjunction with several common threats to the validity of an experiment. The factors that affected internal validity are as follows: history, maturation, testing, instrumentation, statistical regression, selection bias, and selection-maturation interaction. Campbell and Stanley (1963) concluded that randomization is the key to avoid potential problems from these factors.

External Validity

Whereas internal validity refers to the design and theoretical structure of an experiment, external validity of experimental auctions and other value elicitation methods refers to a model's prediction abilities outside of the laboratory; that is how well the WTP values elicited from the experiment match the actual behavior of consumers in the real marketplace. As the issue of the external validity in any science project is paramount, for experimental economics it has been at the core of a fiery debate.

Loewenstein (1999) compared behavioral economics with experimental economics and questioned the external and internal validity of the latter field of study. He challenged the relevance of laboratory experiments by claiming that mechanisms used in the laboratory rarely occur in the participant's daily life and the lack of context makes economics in the laboratory an unrealistic measurement of human behavior. People rely on context, characteristics of the world around them, to make simple decisions and solve complex problems. Loewenstein (1999) argued that the laboratory environment of market experiments lack context and unfamiliar procedures confuse the participants. He suggested that experimental economists can achieve externally valid designs by striving to create "a context that is similar to the one in which economic agents will actually operate" in, instead of removing all of the environmental clues in favor of a more sterile setting. Loewenstein (1999) also made an interesting point when he suggested that monetary rewards are not necessarily the only forms of motivation in daily life.

Echoing Loewenstein's (1999) sentiments regarding poor environmental cues, Schram (2005) offered a blistering critique and claimed that market experiments in the laboratory failed to mirror the context and incentives present in the real marketplace, outside of the laboratory. This lack of context, he claimed, is crucial in the consumer's decision-making process when purchasing a good outside of the laboratory. Schram (2005) claimed that experimental economists are more focused on using market experiments in the laboratory to test existing theories and develop new ones and, as a result, tend to emphasize internal validity and empirical regularities more so than external validity. He calls for more robust discussion among experimental economists about methodological issues plaguing experiments in the laboratory.

Somewhat answering Schram's (2005) call for more discussion, Guala and Mittone (2005) defined and discussed external validity as it pertains to Alvin Roth's (1986, 1988, 1995) three reasons for experimental economics: (1) speaking to theorists; (2) searching for facts; and (3) whispering in the ears of princes. Guala and Mittone (2005) discussed one of Roth's (1986, 1988, 1995) three reasons, "Speaking to Theorists," through two common replies made by economists: 1) the generalizability of economic theories in application and 2) economic experiments should mirror the assumptions of the model. Guala and Mittone (2005) replied by citing Plott (1991) and responded that general models that do not apply to the simplest of cases are not general by definition and cannot be considered as such. Guala and Mittone (2005) suggested: 1) the assumptions and conditions which allow a fundamental economic theory to be general are not actually general in application; and 2) the economic models may not be "general in scope and application" but should be something to strive for. Guala and Mittone (2005) made an interesting counterpoint to Loewenstein (1999) and Scram (2005) by suggesting that if economic theories attempted to include all of the conditions and factors which validate their theories, then the field would rely more heavily on neuroscience and psychology, whose relationships with economics is fairly underdeveloped. Guala and Mittone (2005) suggest that market experiments help bridge the gap between theory and the buzzing, complex world. Guala and Mittone (2005) describe the gap between the theory and market experiments as the challenge of internal validity and the gap between the market experiment and the real, live world as gap of external validity, which is harder to close.

Several studies have investigated the external validity of hypothetical experimental methods, specifically CVM, by comparing elicited responses from a survey with actual referenda results (Johnston, 2006; Vossler and Kerkvliet, 2003; and Vossler et al., 2003). Depending on the coding technique used, results from these studies indicated that CVM was a relatively well indication of voting behavior. However, the participants in these studies were responding to public goods; the use of private goods may have yielded a different outcome (Chang, Lusk, and Norwood, 2009). Experimental economists have also compared results from nonhypothetical methods used in the laboratory setting, such as experimental auctions, with field behavior to assess external validity (Brookshire, Coursey, and Schulze, 1987; and Shogren et al. 1999).

Chang, Lusk, and Norwood (2009) chimed in on the external validity debate of experimental methods by exploring whether consumers' actual buying behavior in a grocery store mirrored preferences elicited in a laboratory experiment. They compared the external validity across methods, a hypothetical choice experiment, a nonhypothetical choice experiment, and a nonhypothetical ranking method, and compared the predictive performance of three popular econometric models used in experimental economic analysis, multinomial logit (MNL), independent availability logit (IAL), and random parameter logit (RPL). Researchers used the three methods to capture the preferences of random sample of Stillwater, OK residents for twelve products that were grouped into three categories: wheat flour, dishwashing liquid, and ground beef. Each of these categories contained three incumbent brands and one new brand. Following the collection of the experimental data, researchers gathered retail sales data from a local grocery store that had agreed to stock the same twelve products as were in the experimental setting.

By comparing the predicted market shares from the experiment setting with the actual market shares at the retail level, researchers concluded that all elicitation methods showed a “reasonably high level of external validity.” Although each model at times performed better in one category than another, the nonhypothetical choice and ranking methods were better methods for predicting than the hypothetical choice method and the RPL model happened to be the best performing econometric model due to its flexibility and compatibility with panel data.

In Germany, the external validity of hypothetical methods were examined when Grebitus et al. (2010) compared field purchasing behavior with responses from a hypothetical survey that questioned 700 pork consumers about the importance of different pork attributes and their knowledge about the attributes of their actual pork purchases. They found a strong correspondence between the hypothetical survey responses and participants' actual purchasing behavior.

Following the trend of comparing experimental results with actual retail behavior, Shogren et al. (1999) tested the external validity of a hypothetical method in the form of a mail survey, and a nonhypothetical method in the form of a laboratory market experiment, against consumers' behavior in a grocery store. Shogren et al. (1999) analyzed consumers' acceptability and purchasing decisions regarding irradiated chicken and nonirradiated chicken in all three settings under different pricing scenarios. Results were mixed regarding external validity and design issues created concerns (Chang, Lusk, and Norwood, 2009).

Shogren et al. (1999) and Chang, Lusk, and Norwood (2009) contributed to the existing literature by using grocery products and food products to investigate the issue external validity, but failed to incorporate experimental auctions. In an effort to address the external validity of experimental auctions, List and Shogren (1998) compared the market price of sports cards from a second-price Vickrey auction with the actual market book value of the cards to address the issue of and external validity in experimental auctions. List and Shogren's (1998) concluded that the second-price Vickrey auction generated results that were highly externally valid.

Specifically pertaining to experimental auction mechanisms, of the studies that compared laboratory results with field data to measure the external validity, few have used food products as the good of interest. Brookshire, Coursey, and Schulze (2007) filled this gap in the literature by comparing the WTP values for strawberries elicited from a Vickrey auction in a laboratory setting to WTP values from door-to-door sales of the strawberries. Both sets of participants represented the 1980 Census block data for Laramie, Wyoming. Researchers failed to reject the hypothesis that the WTP valuations from the field sales data and from the laboratory auction were the same and concluded that the auction mechanism was externally valid. One of the largest concerns associated with this study was that the data sets from the field and from the laboratory were different because of the vector of bids obtained for several different pints of strawberries in the lab provided a different data set than the field data. This incongruity in data construction made direct comparison difficult.

Experimental Auction Applications

From the value of new food products to the value of information, economists have used experimental auctions to measure a variety of things. Knowing consumers' values for a novel variety or new production method of a specific food product can be extremely valuable to agribusinesses in the research and development stage of introducing a new good to the market and can provide priceless information to marketers.

Lusk and Hudson (2004) discuss why WTP values are important to agribusinesses and provide methods for incorporating cross-price effects into value elicitation methods. Lusk and Hudson (2004) suggest that many agribusinesses and producer cooperatives are becoming increasingly interested in making their products more attractive to consumers by introducing generic agricultural products with differentiating qualities to the supermarket shelves. In a combined contribution to the marketing efforts of agribusinesses and the field of experimental economic research, Lusk and Hudson (2004) discussed the advantages, disadvantages, theoretical background, and practical application several hypothetical and nonhypothetical value elicitation methods, including choice-based-conjoint analysis, dichotomous and double-bounded choice experiments, and experimental auctions. The study asserted that investigating consumers' WTP values for food products has the potential to help agribusinesses estimate market demand for a good or a specific attribute and calculate own-price elasticity and price sensitivity of a product, and advised that consumer heterogeneity is mentioned as something agribusinesses should be aware of.

Consumers' WTP for Novel Products

Alfnes (2007) formally introduced a theoretical model for analyzing how consumers' uncertainty about a novel product affects bidding behavior in Vickrey auctions. Hoffman et al. (1993) asserted the importance of market measurement for businesses and suggested experimental auctions as a viable means for this assessing consumers' WTP for new products. This article is one of the first to make the connection between experimental auctions and marketing research and its objective was to describe the theoretical advantages and disadvantages of using experimental auctions in "a pretest market research program for a new product." The advantages and disadvantages reflected the statements of other researchers in the field of experimental economics, for example benefits include the ability of the auction mechanism to endogenously indicate the consumers' valuations for the product through their submitted bids and the structural design provides a disadvantage, due to the lack of context in the laboratory setting. Hoffman et al. (1993) demonstrated an application of a fifth-price Vickrey auction for market research with new vacuum-packaged beef.

Jaegar and Harker (2005) investigated consumers' WTP and preferences for a traditional variety of kiwifruit, Hayward, and a novel variety of kiwifruit, Hongyang. Researchers also investigated consumers' concerns and associations about foods and genetic modification. The endowment method was used in a fifth-price Vickrey auction with four treatments, as well as a variety-seeking tendency mechanism, and questionnaires. On average, consumers were willing to pay a premium to exchange the traditional variety for the novel variety. The WTP data indicated a preference for the novel variety and consumers were willing to pay 191% more for the fruit. Results suggested that before the information treatment, consumers showed uneasiness toward the novel fruit because of they made an association with it and genetic modification. This changed after they were informed that the new fruit is in fact not genetically modified.

McAdams et al. (2013) used an eleventh-priced sealed bid modified Vickrey auction and a nonhypothetical ranking method to elicit consumers' preferences and WTP values for pomegranate products that differed in variety, growing location, and form and processing. The products were defined as novel due to the fact that most participants had scant experience with the fruit and they were not available at retail markets. Three randomized information treatments were used that involved a blind tasting, health and nutrition information, and anticancer information. A random parameters model was used to analyze the WTP information gathered from the auction part of the experiment and a rank-ordered mixed logit model was applied to the preference information provided by the ranking procedure. Results indicated that the two methods of value-elicitation did not yield identical results. The authors suggested this incongruity might be a result of the cognitive complexity of the ranking procedure. Results indicated on average increases in WTP values for several of the novel products over the predominant pomegranate variety.

Consumers' WTP for Production Attributes

Researchers have become increasingly interested in consumers' preferences for different production methods and quality differentiating attributes of food products. Hypothetical experimental methods, such as choice experiments and surveys, have been used to estimate consumers' WTP values for quality differentiating attributes in salmon and credence attributes of beef products (Abidoye et al., 2011; Alfnes et al., 2006). Alternatively, and more aligned with the objectives of this thesis, experimental auctions have proven very useful for eliciting consumers' WTP for quality differentiating attributes for a range of food products (Kanter, Messer, Kaiser, 2009; Lusk, Feldkamp, Schroeder, 2004; Rousu et al., 2007).

Kanter, Messer, and Kaiser (2009) analyzed consumer preferences and WTP for conventional milk (unlabeled milk and the majority of milk available on the market, which may or may not have been produced with recombinant bovine somatotrophin (rBST)), relative to rBST-free milk and organic milk. Researchers investigated whether a stigma existed among consumers against conventional milk, as a repercussion of rBST-free and organic labels. Consumers' WTP was elicited through a BDM bidding mechanism and a within-subject design. A total of nine combinations through three flights of conventional, organic, and rBST-free milk, varying in fat levels and order presentation, were presented to participants. During each flight, participants were provided with production and nutritional information about the types of milk, similar to the actual labels consumers would see in the market. Although initially difficult to detect, results revealed that conventional milk was stigmatized by the presence of rBST-free and organic milk in the market. After participants were informed about the properties of rBST-free milk, they showed a 33 percent decrease in WTP values for conventional milk. When subjects were provided with information regarding organic milk, they exhibited a 45 percent reduction in WTP values for conventional milk. From a revealed demand curve, researchers suggested the presence of organic and rBST-free milk not only stigmatized conventional milk, but also had a negative effect on all milk in general. Further research is warranted to determine how long this stigma lasts. This study is an example of consumers expressing preference for specific production attributes in food products. Also, a noteworthy result of this experiment shows that differentiation may have negative effects on whole industries and not just competing goods.

As discussed previously, Brookshire, Coursey, and Schulze (2007) used Vickrey auctions to generate consumers' WTP values for strawberries. Buhr et al. (1993) used a technique that combined the endowment approach and repeated trials, Vickrey auctions, and a split valuation method to elicit consumers' WTP and pros and cons of a good of ambiguous quality – a lean pork product produced with growth enhancers. Buhr et al. (1993) found that their sample of students were willing to pay a premium for the leaner product, even after they were informed of the growth enhancers.

In addition to using experimental auctions as a vehicle to extract consumers' WTP values for quality differentiating attributes of food products, Rousu et al. (2007) proved that auctions can be used to elicit consumers' valuations of verifiable production information of food products. Several countries have adopted policies that mandate specific labeling for foods that are agriculturally bioengineered. Currently, the U.S. employs a voluntary policy with regard to labeling genetically modified (GM) foods. Consumers are constantly receiving asymmetric information from biotech industries and environmental groups. Rousu et al. (2007) was curious whether verifiable information that is provided to consumers by an unbiased third party could be of value in a such a controversial market. This study used a random *n*th price auction design with six randomly assigned information treatments made up of one or a combination of perspectives from the industry (probiotech), environmental groups (antibiotech), and a third-party (verifiable information) and randomly sequenced products: "GM-labeled vegetable oil, plain-labeled vegetable oil, GM-labeled tortilla chips, plain-labeled tortilla chips, GM-labeled Russet potatoes, and plain-labeled Russet potatoes. Rousu et al. (2007) analyzed consumers' responses to the introduction of verifiable information to a market that already circulates biased information from interested parties. Results indicated the potential public good value of verifiable information to be approximately $2.6 billion annually and diminish over time.

It is apparent from the aforementioned review of literature that the use of food products in experimental auctions has become a popular way to investigate consumers' valuations of differentiating attributes such as production methods and novel varieties. Despite the proliferation of these studies, or perhaps because of it, several criticize the external validity of experimental auctions and claim that the laboratory-environment does not yield realistic results. Thus, a second-price sealed bid Vickrey auction will be used to investigate consumers' valuations of differentiating attributes of vegetable products, specifically production method and color, and followed by a secondary market mechanism infused with elements of induced value theory and a distribution of the auction products' actual retail prices in an attempt to address the external validity of experimental auctions.

CHAPTER III

HYDROPONIC LETTUCE REVIEW

Lettuce (*Lactuca sativa*) is believed to have been cultivated in the Mediterranean region and later transported to the Americas by Christopher Columbus (Jensen, 1997; Boriss and Brunke, 2005). The four forms that lettuce largely takes in the U.S. include head lettuce, such as iceberg, cos or romaine, leaf lettuce, and butterhead (Davis et al., 1997). The different forms, textures, and tastes allow for lettuce to be incorporated in a variety of ways into Americans' diets, from salads and on sandwiches to being used as wraps or even grilled. Leaf lettuce and romaine have become especially popular for their richer hues of green and benefits of vitamins A and C, compared to their butterhead and crisphead counterparts (Davis et al., 1997). Traditionally, this popular vegetable has been grown in the field, under direct sunlight and is vulnerable to pests and diseases.

Economics of Lettuce Industry

Lettuce is one of the most valuable fresh vegetable crops in the U.S. (USDA NASS, 2014). Head lettuce represented 44.5% of the total value of production of lettuce in 2013, while romaine and leaf cultivars shared the remainder (USDA NASS, 2014). Leaf lettuce is primarily grown in Arizona and California and in 2013, over 50,000 acres were harvested domestically, with the value of production exceeding $450 million (USDA NASS, 2014). On average, Americans consumed 18.6 pounds of lettuce annually from 2000 to 2010 and although head lettuce continues to rule production, leaf lettuce and romaine have seen growth in demand in recent years (USDA ERS, 2014; Boriss and Brunke, 2005). Although China was the world's largest lettuce producer in 2010, the U.S. was a net exporter sending the majority of its lettuce exports to Canada, Taiwan, and Mexico (Boriss and Brunke, 2005).

Hydroponic Fruit and Vegetable Production

Covered food production was first recorded around the first century, when Roman Emperors had off-season produce grown under "transparent stone" (Jensen, 1997). Although the production method offered an innovative way of protecting plants from frigid temperature, it was abandoned until around the seventeenth century, when various materials such as glass materials, bell jars, hot beds covered with glass, and oiled translucent paper were tested as suitable covers for food production (Jensen, 1997). In the eighteenth century, France and England were using glasshouses to grow melons, grapes, and strawberries (Dalrymple, 1973).

Greenhouse food production really kicked off around the mid-1900s when polyethylene was discovered to be a less expensive and just as effective cover material (Jensen, 1997). Although scattered in use throughout history, the formal transition of hydroponics from the laboratory to the field for commercial production occurred in the late 1920s (Shrestha and Dunn, 2013). The term hydroponics was derived from two Greek words – 'hydro' translates into water and 'ponos' translates into labor (Shrestha and Dunn, 2013). Throughout the twentieth century, scientists at experiment stations in New Jersey, California, and Indiana further developed hydroponics as the answer to fertilizer and soil problems (Jensen, 1997). This new method replaced soil with nutrient solution-based methods that used aeration techniques or artificial forms of soil (Withrow and Withrow, 1948). During World War II, the U.S. Army used this unique production method to provide troops with fresh foods on infertile islands and by mid-Century commercial farms were successfully using hydroponics in the U.S., Europe, Africa, and Asia. The skyrocketing oil prices in the early 1970s increased energy costs for many producers who used greenhouses and hydroponic production methods and, as a result, overall greenhouse production slowed. However, the widespread use of plastics renewed interest in controlled environment agriculture systems, as well as hydroponics (Jensen 1997). By 1995, Asia shared over 50% of the total hectares occupied by plastic greenhouses in the world (Jensen, 1997).

Types of Hydroponic Systems

Since the 1920s, hydroponics as a viable commercial operation has been further defined into different types of operating systems. Hydroponics can be initially categorized based on the use of a medium liquid (non-aggregate) systems and aggregate systems. Liquid systems involve the most popular methods of deep flow hydroponics, nutrient film technique (NFT), and aeroponics. Deep flow systems were independently developed by Jensen and Massantini (Jensen and Collins, 1985; Massantini, 1976) and are good for lettuce and other leafy vegetables because the plants grow on a floating raft and “are spread in a single horizontal plane” over nutrient pools in large rectangularshaped tanks. NFT was further defined by Graves (Winsor, Hurd, and Price, 1979; Graves, 1983) and involves a thin film of nutrient solution traveling through plastic lined conduits to the exposed roots, whereas aeroponics uses closed misting boxes over the roots to provide the plants with the necessary nutrient solution.

Aggregate hydroponic systems involve a solid, inert medium that is soilless by design and provides support to the plants. Similar to how the materials used in the construction of a greenhouse vary in durability, costs, and popularity among producers, so do the materials used for a soilless medium. Several materials, such as peat moss, sawdust, perlite, rockwool, and coconut coir, can be used for the medium, but many producers rely on what is most cost effective in their location (Jensen, 1997). Both aggregate systems and liquid systems have the potential to be open systems (solution is recovered, but not used on the plants) or closed systems (nutrient solution is recovered, replenished to the correct balance, and recycled through the plants).

Production Advantages of Hydroponics

Many advantages are associated with hydroponic food production, including the ability to conserve water, faster growth time, higher yield, and more control of the growing environment compared to conventional field methods, as well as an alternative production method in extreme climates or areas where ground is infertile (Shrethsa and Dunn, 2013). Conventional methods often involve continuously growing plants without rotation or interruption in open fields can lead to a decline in soil quality and lead to soil-borne pathogens that have the ability to make their way into the food chain via the plants, therefore the reduced soil-related variables in hydroponics prevent soil-borne insects, fungi, and bacteria from entering the food chain or damaging yield (Jensen, 1997; Shrethsa and Dunn, 2013). Additionally, the controlled environment minimizes pesticide use compared to conventional production method (Coolong and Foran, 2012). Kimura and Rodriguez-Amaya (2003) stated several advantages of hydroponic production, which ranged from a smaller production area that yields higher productivity and decreased water and fertilizer usage to a decreased chance of contamination from soil-borne microorganisms. The controlled environment of hydroponic production systems in greenhouses allows producers to achieve a higher quality crop. Tomatoes, cucumbers, and specialty lettuce respond especially well to the hydroponic system and, as a result, are the primary food crops grown hydroponically in the U.S. (Jensen, 1997). Europe and Japan have had commercial success in hydroponic food production through the aforementioned vegetables, as well as eggplant, peppers, melons, and herbs (Jensen, 1997).

Production Disadvantages of Hydroponics

While hydroponic food production offers producers many advantages, it does come with its drawbacks. One of the most noticeable disadvantages of hydroponic food production is the hefty upfront capital required to establish the infrastructure. Jensen (1997) notes that although higher yields and longer production cycles can be achieved through hydroponics, gross returns must be high enough to make up for the extensive capital investment. A second disadvantage of managing a hydroponic operation is finding and maintaining the optimal balance between major elements and micronutrients in the nutrient solution. Although computers can help to automate the production process and provide valuable feedback about the efficiency of the system, technical skills and knowledge of the optima nutrient content is necessary in a hydroponic operation (Jensen, 1997; Shrestha and Dunn, 2013). Each commercial grower has a unique recipe and this recipe is critical for the success of the plants and the operation (Shrestha and Dunn, 2013). Heating and cooling a hydroponic system in a greenhouse can be costly, especially if oil prices spike as they did in the early 1970s. Although operating costs can be higher than conventional production, Jensen (1997) mentioned that solar energy and waste heat from nearby factories have been explored as options to mitigate energy costs of managing a greenhouse (Shrestha and Dunn, 2013).

Quality Comparisons

Bourn and Prescott (2002) conducted a thorough review of studies that compared organically grown foods to conventionally grown foods. They discovered four trends among the studies that compared the nutritional value of organic and conventional foods: (1) comparisons regarding chemical makeup; (2) how nutritional quality was affected by different fertilizer treatments; (3) analysis at the farm level; and (4) how human and animal health were affected by organic productions relative to conventional productions (Bourn and Prescott, 2002). Results from studies within these four themes proved difficult to compare due to differences in design. Given the large amount of mixed findings and issues with the study designs, the only conclusion Bourn and Prescott (2002) could confidently make was that some studies within the fertilizer theme showed evidence lower nitrate levels in the crops that were produced organically compared to crops that were grown under conventional methods, in which mineral fertilizer was applied.

In 2013, Ibrahim and Zuki investigated how using hydroponics, aquaponics, and conventional, soil based methods affected the quality of lettuce. Results indicated that hydroponics produced higher yield and better postharvest quality compared to the other two methods. Ibrahim and Zuki (2013) conducted a sensory evaluation in which lettuce produced hydroponically proved superior in terms of appearance, taste, texture, odor, and overall acceptability attributes. Regarding lettuce produced using conventional and aquaponic methods, results from the sensory evaluation showed no statistical significant differences ($p>0.05$) between the two products. Given the initial results and the findings from the sensory evaluation, Ibrahim and Zuki (2013) concluded that the hydroponic method produces higher yield and better quality lettuce compared to conventional and aquaponic methods.

Antioxidant properties of organic versus conventional foods have also been addressed in the literature. More specifically, and of particular importance to this review, Durazzo et al. (2014) compared the antioxidant properties of organic lettuce and conventional lettuce grown by conducting greenhouse experiments in the Bergamo province of Italy. Antioxidants, also known as phytochemicals, are compounds produced by plants that contribute to human health (American Cancer Society, 2013). The American Cancer Society (2013) suggests that consuming a diet that is rich in fruits and vegetables that contain health-promoting phytochemical compounds, like vitamin C, carotenoids, such as vitamin A, beta-carotene, and lutein, and vitamin E, may reduce the risk of chronic diseases and cancer. Blasco et al. (2008) suggest that antioxidants have been shown to combat oxidative stress and prevent cardiovascular arteriosclerosis (hardening of the arteries), cancer, degenerative eye disorders, as well as Alzheimer's and Parkinson's diseases. Several studies had previously identified several factors that have the ability to affect the phytochemical properties of crops, including "climate, soil type, light intensity, irrigation, nutrient supply, pest control, weather, growing location, cultivation methods and time of harvest" (Amarowicz et al., 2009; Fallovo et al., 2009; Lima and Vianello, 2011). Durazzo et al. (2014) contributed to this area of literature by finding evidence of organic lettuces having significantly higher levels of beta-carotene and vitamin C levels compared to lettuces produced under conventional conditions in a greenhouse.

Although a multitude of studies have addressed the health-boosting phytochemical properties of lettuce, including Du Pont et al. (2000), Rattler et al. (2005), and Llorach et al. (2008), very few studies have compared the health benefits of hydroponic lettuce with conventionally grown lettuce. In the case of carotenoid composition, Kimura and Rodriguez-Amaya (2003) found that the conventional lettuce had significantly higher levels of carotenoids, specifically in the forms of beta-carotene, lutein, violaxanthin, than the hydroponic lettuce. One of the reasons, the authors suspect, for this difference is that the greenhouse covering led to less exposure to sunlight and lower temperatures could have affected the carotenogensis process (Kimura and Rodriguez-Amaya, 2003).

Despite Kimura and Rodriguez-Amaya's (2003) findings that hydroponic lettuce came second to conventional lettuce in terms of carotenoid content, hydroponics have been used as a means to successfully increase the amount of other chemical characteristics in lettuce. For example, Neeser, Savidov, and Driedger (2005) showed that hydroponic systems could be used to produce calcium-fortified lettuce. In a similar manner, Blasco et al. (2008) proved that iodine application to hydroponic lettuce significantly increased the antioxidant profile, including the vitamin C and flavonoid content, in lettuce in Spain.

Hydroponics and Consumers

Although extensive data on the hydroponic crop industry is obscure, the value of the industry in sales in 2007 was estimated to be more than $553 million (Haggerty, 2013). A small group of studies investigate consumers' preferences and WTP values for hydroponic crops, thus warranting more research on this innovative production method. With a focus on consumer demand and marketing issues, Yiridoe, Bonti-Ankomah, and Martin (2005) provided a comprehensive review of the literature that compared organic and conventional products. Among the topics investigated, the magnitude of the premium consumers were willing to pay compared to conventional foods was investigated (Yiridoe, Bonti-Ankomah, and Martin, 2005). Unlike Bourn and Prescott's (2002) inconclusive findings due to mixed results and designs, Yiridoe, Bonti-Ankomah, and Martin (2005) were able to make several conclusions from studies about consumers'

WTP for organic foods relative to conventional foods: (1) consumers showed an increased WTP value for organic fruits and vegetables, compared to cereals; (2) consumers were sensitive to the magnitude of the premium on organic foods; and (3) although the compared studies varied in design and methods, premiums ranged from 10-100% across several countries, but most consumers were not willing to pay a premium more than 10-20%. Despite this resolution, Yiridoe, Bonti-Ankomah, and Martin (2005) were not able to come to a conclusion about whether organic foods were perceived by frequent consumers to be a normal good or a luxury good.

In the case of lettuce products, Wolf et al. (2002) surveyed head-lettuce (lettuce sold by the head) consumers in three different regions of California about their preferences for organic lettuce using a five-point desirability scale. Results revealed that 29% of the sample indicated an intention to purchase organic head lettuce in the near future. Although hydroponic lettuce was not included in the study, one point worth noticing from this study is that results from the desirability scale indicated that consumers value "environmentally friendly" characteristics more than "organically grown and certified" (Wolf et al., 2002).

As Bourn and Prescott (2002) noted in their comparison of studies comparing the sensory qualities of organic and conventional foods, several postharvest factors may be responsible for consumers' preferences toward a particular food produced either organically or conventionally that may not be a result of the production method, such as transportation and distribution factors. Zhao et al. (2007) used this statement as a springboard for a consumer sensory analysis of organic and conventional vegetables that were produced in replicated side-by-side plots. Consumers were asked about their overall liking and perceptions of flavor and bitterness intensity of organic and conventional versions of red leaf lettuce, spinach, arugula, and mustard greens. A second consumer test was conducted using organically and conventionally produced tomatoes, cucumbers, and onions. Results from the overall liking analysis and consumer-perceived sensory evaluation indicated that, overall, no statistical difference existed between the two production methods, with the exception of tomatoes. Zhao et al. (2007) found that consumers associated a statistically significant stronger flavor with the conventionally grown tomato, relative to the organically grown tomato. This study also found that the over 70% of the consumers in the study perceived organic produce to be healthier; 51% perceived organically produced food to be more environmentally friendly compared to conventional production methods; and 28% of the sample perceived organic produce to taste better than conventional produce.

In the case of hydroponic lettuce, aside from Ibrahim and Zuki (2013), a trivial amount of research has been done on consumers' preferences and willingness to pay studies for hydroponic lettuce. Murphy et al. (2011) attempted to gauge consumers' taste preferences for hydroponically grown lettuce by comparing it to its organic and conventional counterparts in a sensory evaluation. Echoing Amarowicz et al. (2009), Fallovo et al. (2009), Lima and Vianello, (2011), and Durazzo et al. (2014) findings, this study suggested that changes in environmental conditions can affect the nutritional quality of fruits and vegetables. Although limited in design, Murphy et al. (2011) discovered valuable information about consumer preferences for five different varieties of lettuce grown in hydroponic methods, conventional lettuce, and organic lettuce. Murphy et al. (2011) found no differences among the lettuces and production methods tested.

As one of the few studies that investigated consumer demand for hydroponic vegetables, Huang, Kan, and Fu (1999) elicited Tawainese female homemakers' WTP for hydroponically grown vegetables through a consumer survey and analyzed the survey data using a binary-ordinal probit model. The survey collected demographic information, perceptions of pesticide residue as a health risk, and information about previous hydroponically grown vegetable purchases. Respondents in the study were first asked to indicate whether or not they would pay a premium for hydroponic vegetables and then, conditional upon them answering yes, they were asked to indicate how much more they would be willing to pay. Huang, Kan, and Fu (1999) referred to the binary-ordinal probit model as a joint estimation of a probit and ordered probit model. This analysis revealed that socioeconomic variables drive how much more consumers were willing to pay for hydroponic vegetables. Results indicated that a respondent who had a family member suffering from a chronic disease in the household would be willing to pay 16% or more for hydroponic vegetables. Although this study is one of the select few that investigate consumers' WTP values for hydroponic vegetables, it was a hypothetical survey and only displays consumers' intentions instead of their incentive-based actual values. Regardless, this is the closest study to determining consumers' willingness to pay for hydroponic lettuce.

Across the Indian Ocean, Batt and Lim (1999) investigated consumer demand for hydroponic lettuce by asking Australian shoppers to complete a survey that included questions about their perceptions of hydroponically grown produce. More specifically, consumers were asked about their likes, dislikes, the perceived advantages and disadvantages, and how they were able to differentiate hydroponically grown produce from conventionally grown produce. Batt and Lim (1999) used Scheffe's Test to analyze the data collected and results indicated that most consumers perceived a decrease in the use of pesticides in hydroponically grown produce and those who had a preference for hydroponic produce, superior taste was identified as the primary differentiating factor. Again, as with Huang, Kan, and Fu's (1999) study, more research is warranted because a hypothetical method was used and the values elicited were potentially susceptible to hypothetical bias.

In the early 2000s, Huang et al. (2002) investigated the demand for hydroponic lettuce and other hydroponically grown vegetables from local restaurants and wholesalers in the Nashville, Tennessee area. With regards to hydroponic lettuce, Huang et al. (2002) identified and evaluated the sources of supply and the economic feasibility of a hydroponic farm selling to a wholesaler. Researchers distributed a survey to restaurants and fruit and vegetable wholesalers. Responses revealed that wholesalers and restaurateurs viewed the major advantages of growing hydroponic lettuce as more consistent product attributes, such as appearance and taste, a shorter growing period (about 35 days) compared to conventional field production, and year-round availability as a product of the controllable environment greenhouses offer. Huang et al. (2002) concluded that a relationship is feasible between hydroponic producers and wholesalers, but not necessarily between hydroponic producers and restaurants. Furthermore, Huang et al. (2002) concluded that limited opportunities exist in the Nashville area due to a lack of demand at the wholesaler level, however they did establish that opportunities exist for hydroponic tomatoes and cucumbers in the market. Similar to previous studies that have investigated consumer demand for hydroponic vegetables, Huang et al. (2002) used a hypothetical value elicitation method and not an incentive compatible one.

Although Coolong and Foran (2012) failed to reveal their method, they identified potential markets for hydroponic lettuce as chefs, schools, local grocers, specialty food retailers, restaurant chefs, caterers, and wholesalers. Coolong and Foran (2012) claimed that hydroponic lettuce is of particular interest to chefs and schools because it is uniquely harvested and sold with its roots intact, which offers an extended shelf life compared to conventional and organic lettuce. Additionally, Coolong and Foran (2012) suggested that another attribute consumers who are concerned with food safety and sanitation may find attractive is the fact that the absence of soil in the production process prevents the transmission of any soil-borne pathogens that cause food illnesses.

Hydroponics and Food Safety

As mentioned throughout this chapter, one of the most significant differences between hydroponic, organic, and conventional production methods is the absence of soil in the growing environment. Continuously growing plants without rotation or interruption in open fields can lead to a decline in soil quality and lead to soil-borne pathogens that have the ability to make their way into the food chain via the plants (Jensen, 1997). Because hydroponic production relies on a liquid, water-based solution to nourish the plants instead of soil, pathogens and microorganisms in the soil that cause illnesses are virtually absent, thus creating a more hygienic product (Kimura and Rodriguez-Amaya, 2003).

The CDC investigated a decade's worth of data, from 1998 to 2008, that documented over 125,000 illnesses, hospitalizations, and deaths caused by nearly 4,900 food-borne illness outbreaks (Hallock, 2013). Leafy greens were identified as the primary vehicle for most food-borne illnesses, causing 23% of the food-related illnesses and 14% of the hospitalizations (Hallock, 2013). Hoffmann and Anekwe (2013) compared two recent estimates of the cost of foodborne illnesses that estimated the total costs of food-borne illnesses to be between $14.1 billion and $152 billion. Hoffmann and Anekwe (2013) analyzed the comparable pathogens used in the two estimates and recalculated the average costs of recent foodborne illnesses to be between $14.1 billion and $16.3 billion.

The costs associated with a food-illness outbreak also have lingering effects on consumption. For example, Arnade, Calvin, and Kuchler (2009) analyzed the consumption effects of the Food and Drug Administration's 2006 warning against consuming fresh spinach due to concerns of an E. coli outbreak in bagged spinach. Arnade, Calvin, and Kuchler (2009) used pre-FDA-announcement revealed preference, scanner retail data for six leafy greens and post-outbreak they used an AIDS model with shock variables and simulated expenditures to estimate changes in consumer demand.

From the simulation, spinach expenditures seemed sharply decline immediately following the FDA's announcement. Results indicated that expenditures on other leafy greens decreased as well. These expenditures seemed to return to near their normal levels about four months after the outbreak, with the exception of bagged spinach consumption. Arnade and company (2009) concluded that although spinach expenditures were depressed, expenditures on other leafy greens recovered quickly enough in expenditures to nearly cancel out the negative effects the outbreak had on bagged spinach expenditures.

In addition to the damage control and the mounting costs that need to be addressed after a food-borne illness outbreak, farmers who produce foods that are the root of a food-borne illness outbreak may face legal prosecution, as in the Jensen Farms cantaloupe outbreak that left 33 people dead (Danovich, 2014). Consumers have expressed value for safer food in the laboratory, as well as in the market place. Fox et al. (1995) proved that consumers placed value on safer food by using experimental auctions to elicit consumers' WTP for food safety. Outside of the laboratory, food illness outbreaks such as E.coli and salmonella in spinach, scallions, chiles, cantaloupes, and other fresh fruits and vegetables and an increased demand for local lettuce during the off-season inspired hydroponic lettuce operations in Northeastern Pennsylvania (Haggerty, 2013). Although hydroponic lettuce and other vegetables may not provide a difference in the phytochemical health attributes relative to conventional and organic production methods, consumers may find value in food safety attributes of the former.

CHAPTER IV

METHODOLOGY

Theoretical Foundation

Thus far, a review of the associated literature has been conducted and, from it, a new method that intertwines a selection of theories and mechanisms has been proposed. Moving forward, this chapter will use the literature review as a springboard to delve deeper into the theoretical underpinnings of consumer utility theory, induced value theory, and Vickrey second-price auctions and discuss their contribution to the theoretical foundation of this study. Additionally, a detailed explanation of the experimental procedures and the econometric models used for analysis will be provided for the reader's understanding.

Willingness to Pay

As mentioned previously in the literature review, a modern way of measuring a consumer's value for a good is through WTP values – that is, how much money an individual would be willing to pay to obtain a specific good or service. The magnitude of an individual's maximum WTP for a good can be derived from an indirect utility function, which was born from a marriage of traditional Marshallian demand curves and the individual's original utility function. An indirect utility function reveals the maximum utility that can be attained given the market prices, income, and quantity (Lusk and Shogren, 2007). In other words, an individual's maximum WTP, in theory, is largely a function of the maximum amount of satisfaction she derives from the good or service in question.

Random Utility Theory

Consumers are presented with a vast array of goods and services to choose from upon entering the marketplace. How and why do they choose which goods and services to buy? Historically, economists have based their study of consumer behavior on the aforementioned idea of utility. This concept of measuring satisfaction and calling it "utility" may appear as a vague concept, but it has allowed economists to formally place a measurement on what motivates individuals' tradeoff and purchasing decisions. While utility plays a role in consumers' decision-making process, it is not the only component.

Among modern economists, it is a widely accepted notion that people face certain constraints, such as budget constraints, which restrict their available choice set. Maximizing utility while satisfying a given budget constraint is at the core of consumer theory and provides the theoretical foundation for most experimental economic studies. Although economists have attempted to identify every microscopic detail of the inner workings of consumers, several motivating factors remain random in nature and are largely a mystery. McFadden (1974) attempted to better incorporate this random component of consumer behavior when he established Random Utility Theory (RUT), which was specifically formulated for analyzing consumers' utility in discrete choice experiments. Consider the following RUT framework that describes the utility individual i derives from a specific product, product j in this case:

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

Where V_{ij} are all of the deterministic factors that are visible to the economist's eye and ε_{ij} represents everything else – that is, all of the independently and identically distributed (iid) factors that are random and known to the individual (i), but largely unobserved from the economist. The factors that are obvious (V_{ij}) to the researcher and those factors that are unobserved (ε_{ij}) jointly form individual i's utility for product j (U_{ij}). The economist's goal is then to shrink the incomplete information gap by specifying all of the known factors (V_{ij}) and minimizing the unobserved factors (ε_{ij}). In other words, by identifying more of the variables that are contained within the random component and including them into the deterministic component, economists may reveal more of the factors at play in a consumer's thought process and empirically inch closer to answering the question of why do consumers do the things they do.

In an incentive compatible experimental auction setting, like the one in this study, participants assign value to the products available to them in the form of bids and at the end of the experiment, subjects gain compensation in the form of U.S. dollars less any purchases made. Essentially, any market actions or purchasing decisions affect the level of compensation the participants receive at the end of the experiment, which tees up the question of how does the participation fee of the experiment affect consumers' utility-based behavior during the experiment? What if individuals participated in this study and derived more utility from the participation fee than from the product attributes of the lettuce products? Furthermore, can the RUT model be further specified to account for the fee and potentially explain more of the randomness in participants' behavior?

Vickrey Second Price Auction

As mentioned previously in the literature review, Vickrey (1961) introduced second-price auctions in an effort to gather more information about the consumers' willingness to pay for a specific, indivisible good. The designs of simple auctions were described and thoroughly developed before arriving at the article's more interesting part, "the sale or purchase of a single lot by sealed bids." First, three assumptions were made: (1) each individual has their own independent private value; (2) there is one divisible unit for sale; and (3) bidders have a smooth, differentiable utility function that is supported by expected utility theory. Upon these pillars, Vickrey designed an auction in which the award will be delivered to the highest bidder, who becomes the buyer and pays the second-highest price in the auction. Because bids are sealed upon submission and delivery, each bidder has an incentive to make his or her individual bid equal to nothing more or less than their true valuation of the good being auctioned. This auction design is not guaranteed to elicit bidders' truest homegrown values; rather it provides an environment that is conducive to individuals bidding their truest values for the good.

Lusk and Shogren (2007) showed the theoretical framework that ensures incentive compatibility in a Vickrey second price auction. Let v_i be the value that individual i places on the good being auctioned, b_i denote individual i's bid for the good, and p denotes the market price of the good. Therefore, individual i derives utility U_i from the difference in value between their true value, v_i, and the market price of the good, p such that:

$$(2) \qquad U_i(v_i - p)$$

As a result of uncertainty – that is, not knowing others' bids, who the highest bidder will be, or how high the market price will be – Lusk and Shogren (2007) suggest that a bidder's optimal strategy is to submit a bid b_i that will maximize her expected utility. To construct her utility, an individual may use her expectations of the market price distribution $[\underline{p_i}, \overline{p_i}]$, represented by their cumulative distribution function and probability density function, $G_i\,(p)$ and $g_i(p)$, respectively. Lusk and Shogren (2007) illustrate the expected utility function for individual i as:

$$(3) \qquad E[U_i] = \int_{\underline{p_i}}^{b_i} U_i(v_i - p)dG_i(p) + \int_{b_i}^{\overline{p_i}} U_i(0)$$

$$= \int_{\underline{p_i}}^{b_i} U_i(v_i - p)g_i(p)dp + \int_{b_i}^{\overline{p_i}} U_i(0)$$

Lusk and Shogren (2007) first point out that U is a function increasing in income. The first integral is taken over all prices less than the individual's bid (the individual bids the highest, becomes the buyer, and wins the auction) and the second is taken over all the prices greater than the individual's bid (in which case the individual does not bid the highest, does not become the buyer, and derives zero utility from the good). An individual's optimal bid can then be determined by taking the derivative of expected utility (equation 3) with respect to individual i's bid, b_i, and setting it equal to zero:

(4)

$$\frac{\partial E[U_i]}{\partial b_i} = U_i(v_i - b_i)g_i(b_i) = 0$$

Individual i's optimal bid is the value at which his or her expected utility is maximized, which in turn is when $b_i = v_i$. In other words, it is in individual i's best interest to submit a bid that is exactly equal to their value for the good, because this is when his or her expected satisfaction from that good will be maximized. Lusk and Shogren clarify that "the optimal strategy of 'bidding one's value' does not depend on the bidder's risk preferences, the number of rival bidders, initial wealth levels, or any of the other bidders' bidding strategies" (see Milgrom and Weber (1982) for more information). The highest bidder becomes the buyer and pays the market price for the good, which is equal to the second-highest bid that was submitted. If two participants bid an identical amount that ended up being the highest bids, both of the subjects would become the buyers and pay the second-highest bid for the good being auctioned.

Lusk and Shogren (2007) provide several possible payoff scenarios in which individual i under-bids (she bids less than her true value, i.e. $b_i < v_i$), over-bids (she submits a bid for more than her true value, i.e. $b_i > v_i$), and truthful bidding (she submits a bid exactly equal to her true value for the good being auctioned, i.e. $b_i = v_i$). Lusk, Alexander, and Rousu (2007) describe the expected payoff structure of a risk-neutral individual in the following form:

(5) $\mathrm{E}[\pi_i] = (v_i - \mathrm{E}[\text{Price}|(\text{winning}|\ b_i)])(\text{Probability of winning}|\ b_i)$

where $\mathrm{E}[\pi_i]$ reflects the expected profits or level of payoff, v_i is equal to the individual i's value for the auction good, $\mathrm{E}[\text{Price}|(\text{winning}|\ b_i)]$ represents the expected price individual i would have to pay given that they won the auction with their bid, b_i, and $(\text{Probability of winning}|\ b_i)$ is the probability of individual i winning the auction, given that they submitted a bid value equal to b_i. That is to say, the expected payoff an individual would receive is equal to the difference between their true value and any price they would have to pay if they win the auction multiplied by the chance of them winning the auction, given their bid value. Lusk, Alexander, and Rousu (2007) stress that in most auction mechanisms, it is an individual's weakly-dominant strategy to submit a bid equal to their true value for the good ($b_i = v_i$) because it yields a payoff that is at least as great as the expected payoffs from all other strategies and, given that the individual does not know the distribution of other bids, it does not depend on other rivals' bids.

Vickrey (1961) affirmed that although the second-price auction is more sophisticated and less self-policing than the more simple auctions, such as the English and Dutch auctions, the advantages of the Pareto-optimal properties of the second-price auction are quite attractive to market researchers. For example, the structural separation between what individuals bid and what they pay helps to reinforce incentive compatibility. For comparison purposes, participants in a first-price auction may deal with conflicting factors of increasing their bid and essentially decreasing their utility from an increased potential payout because an individual's bid value is directly coupled to what they potentially have to pay upon becoming the buyer.

Induce Value Theory

As described earlier in the literature review, induced value theory was formally introduced by Smith (1976) and used as a method of controlling the participants' behavior to induce market equilibrium through assigned roles and prices. Although Smith's (1976) induced value experiment was a stylized market and not a completely free market atmosphere, it provided a useful method for testing the external validity of economic theories. Vickrey (1961) suggested that an individual's dominant strategy is to bid exactly their induced value when an outside option is not present. Several studies have addressed field-price censoring and the influence of outside options on subjects' bids and, including Alfnes (2009) and Harrison, Harstad, and Rutström (2004).

However, as there is rarely a product for which no substitute exists, Cherry et al. (2004) used induced value theory to describe the expected behavior when outside options are present as:

$$b_i = \begin{cases} v_i & \text{if} \quad p_{oo} \geq v_i \\ p_{oo} & \text{if} \quad p_{oo} < v_i \end{cases} \tag{6}$$

where a bidder's optimal bid is represented by b_i, which will equal either the induced value, v_i, or the price of the outside option, p_{oo}. Profit (Π) is equal to the induced value less the price paid ($\Pi = v_i - \textit{price paid}$). In the case of a second-price Vickrey auction, the highest bidder becomes the buyer of the auction and pays the market price for the good, which is the second highest bid. Cherry et al. (2004) identified profit as the motivating factor for bidding. It can also be thought of as consumer surplus. If the price of the outside option is greater than or equal to the induced value ($p_{oo} \geq v_i$), the individual's bid will be equal to the induced value ($b_i = v_i$). Alternatively, if the price of the outside option is less than the induced value ($p_{oo} < v_i$), it will be in individual *i*'s best interest to set their bid equal to the price of the outside option ($b_i = p_{oo}$).

For example, if Susan is participating in a second-price Vickrey auction and has an induced value of \$6 (v_i = \$6) and knows she can get the product outside of the auction for \$5 (p_{oo}), she will set her bid equal to the price of the product outside the laboratory ($b_i = p_{oo}$). If she followed the framework and bid \$5 and became the buyer, she would gain \$1 in consumer surplus ($\Pi = v_i - price\ paid$). According to theory, pay if the good was offered outside of the experiment for less than the individual's induced value inside the experiment, the individual would gain by setting their bid equal to the lower of the two prices, which would be the outside price. From a researcher's perspective, one of the most attractive qualities of using induced value theory lies in the amount of control it gives the researcher. The ability to easily assign values to each bidder and then directly observe bidding behavior allows researchers to test whether an auction mechanism is demand revealing in nature.

Combined Approach

A sealed-bid second-price Vickrey auction will be this study's auction design of choice, largely because of its incentive compatibility properties and relatively simple-to-explain procedures. Additionally, it provides the most information given the objectives and budget of this study. The induced value theory framework mentioned previously is usually applied in experiments that are testing whether or not a specific auction mechanism is demand revealing. However, this study will use elements of induced value theory to connect the individual's valuations of the products to their actual behavior in an on-site, post-auction secondary market.

The essence of induced value theory will be used in conjunction with a uniform distribution of prices that reflect the current retail prices of the auction products (organically grown, hydroponically grown, and conventionally grown red and green lettuces and spinach as a control product). This combination will act as the primary catalyst that will shed light on whether or not the subjects generate utility in equation 1 from the participation fee. More explicitly stated, following the sealed-bid second-price auction rounds, participants were offered the opportunity to purchase the binding lettuce product at a "market" at the back of the room. Participants were instructed to treat this stand at the back of the room like they would a farmer's market stand. It is worth noting that this on-site, post auction secondary market was not made available to participants until after the auction rounds had concluded. Each participant had a unique "assigned price" that was offered to him or her for one head of lettuce – a price that fell within the distribution of outside option prices at the time of the experiment.

Participants' were induced by an assigned price to either forego or make a transaction in the secondary market. The combination of the pseudo induced value framework and the prices of lettuce outside of the experiment in conjunction with a secondary market that had zero transaction costs aimed to test the laboratory WTP utility specifications. Theoretically, an individual should make a purchase if their WTP value, or their bid, is greater than the price they are offered in the secondary market, also known as their assigned values, v_i. More specifically:

$$(7) \qquad \begin{gathered} Make\ Transaction \text{ if } b_i \geq v_i \\ Abstain\ from\ Transaction \text{ if } b_i < v_i \end{gathered}$$

Participants who's maximum WTP value (bid, b_i) is greater or equal to the price they would have to pay in the secondary market (assigned value, v_i), they would be incentivized to make a purchase because the product is being offered to them at a lower price than they were originally willing to pay. However, if an individual's WTP (bid, b_i) is less than her individual price in the secondary market (assigned value, v_i), it does not make sense for her to make a transaction in the secondary market. In this case, the individual would have to pay more than her maximum WTP and could suffer from a consumer deficit, as opposed to a consumer surplus.

What if individuals who were theoretically supposed to make transactions in the secondary market, based off of the aforementioned framework, did not? What if those who were induced to behave a certain way in the secondary market had other motivations for behaving unexpectedly? If Lusk and Shogren (2007) stressed that the utility function that Vickrey second-price auctions rely on, equation 3, is a function increasing in income, should McFadden's (1974) utility framework that explains choice behavior reflect some sort of utility for money? More simply asked, what if subjects who were theoretically supposed to make transactions in the secondary market did not because they valued the utility gained from the compensation fee at the end of the experiment more relative to the utility they would have gained from purchasing the lettuce in the secondary market? Perhaps McFadden's (1974) random utility theory for choice behavior needs to be further specified to include the participation fee in the laboratory. Incorporating utility gained from the fee would reduce the unobserved factors in the error term and provide analysts with greater insight into why individuals may deviate from utility maximizing behavior. Adding a fee component to equation 1 would result in the following:

(8) $$U_{ij} = U_i(product) + U_i(fee) + \varepsilon_{ij}$$

Where U_{ij} is jointly composed of the utility individual i gained from the product, $U_i(product)$, and the utility gained from the participation fee, $U_i(fee)$. All random factors that are unobserved by the analyst are still represented by ε_{ij}. The primary difference between equation 1 and equation 8 is the inclusion of a variable that represents individual i's utility gained from the fee. This framework introduces the question of whether the individual's actions in the experiment are more a result of the utility for the product or the utility for the fee. Fortunately, the previously discussed secondary market and induced value theory may act as the first step for determining which utility function individual i operates off of.

Transactional behavior in the secondary market as described in equation 7 can now be further explained to incorporate equation 8:

(9) $$Make\ Transaction \text{ if } b_i \geq\ v_i \text{ and } U(lettuce) > U(fee)$$

$$Abstain\ from\ Transaction \text{ if } b_i < v_i \text{ or } U(lettuce) <\ U(fee)$$

Theoretically, if individual i's utility for the product, in this study's case lettuce, is greater than the utility gained from the fee *and* if her WTP value (bid, b_i) is greater than or equal to the price being offered in the secondary market (induced value, v_i), then she should make a transaction in the secondary market. It can then be inferred that all other participants who did not make a transaction in the secondary market either valued the lettuce products less than the price that was being offered to them, v_i, or they gained more utility from the participation fee than they did from the lettuce[1].

Because each individual's assigned price in the secondary market (coded as *psm*) and WTP value in the last round (either post-tasting treatment or post-information handout treatment) are both known, a measure of consumer surplus can be established.

(10) $$csurplus\ =\ wtp_{ij}(treatment) - psm$$

[1] Theoretically, transaction costs of participating in the secondary market were equal to zero, because the market was located on-site. However, in reality, some participants may have had other reasons that increased their transaction costs, which influenced their decision to participate in the secondary market (i.e. they were not going home after the experiment and purchasing the lettuce meant an increase in the transaction cost of delivering it home).

where *csurplus* represents the difference between what individual *i* was willing to pay for product *j* after a specific *treatment* (either the blind tasting or the information) and the price they could have purchased product *j* for in the secondary market, *psm*. If *csurplus* is positive, theoretically, the consumer should have made a purchase in the secondary market because they were offered product *j* at a lower price than what they were willing to pay after learning about the product. On the other hand, if *csurplus* is negative, theoretically the individual should not have made a purchase in the secondary market because the price being offered to them was more than what they were willing to pay after learning about the product. This variable, *csurplus*, will help identify which transaction the individual should theoretically make.

Health and Prestige Scales

Organic food represents a multi-billion dollar industry that grew 11.5% in 2013 alone (Stampler, 2014). Historically, more affluent households have been the main consumer segment of organic foods, but increased availability and a narrowing price differential between organic and conventional foods have made organics more accessible (Watson, 2014). Another market that has seen recent growth is the packaged produce industry, which is projected to increase in value from $4.8 billion in 2012 to $5.7 billion by 2017 (Brezosky, 2014). Although this growth primarily stems from consumers' desires for convenient fruits and vegetables, analysts also suggest healthier eating habits as one of the driving forces for the growth (Brezosky, 2014).

Hydroponic lettuce is currently differentiated at the retail level not only by its production method, but also by its appearance on the shelves. It is sold in plastic clamshell containers, similar to strawberries. If hydroponic lettuce continues to be sold in this product form, its producers and marketers could benefit from the forecasted growth in the packaged produce industry.

As these industries gain media attention and become more popular among consumers, it is worth investigating if there is a health-consciousness motivation or, equally as interesting, a prestige-sensitivity motivation behind consumers' purchasing decisions. Are consumers are conveying status through their food purchases, as Dubois, Rucker, and Galinsky (2012) suggest? Investigating these issues may have profound implications for the marketing efforts of the fresh produce industry.

One tool that is commonly used by market researchers to gain market feedback and classify consumers is a Likert scale. Developed in the early 1930s, this popular research tool takes the form of carefully constructed questions, known as Likert items, and a provision of 5-point or sometimes 7-point possible responses that vary in degrees from least to most (Allen and Seaman, 2007). Consumers indicate the degree to which they agree or disagree, or approve or disapprove with each Likert item. Bearden, Netemeyer, and Haws (2011) provided a thick compilation of the many scales that have been developed over the past eighty years.

With an exploratory spirit, this research will take a step toward discovering if lifestyle factors play into consumers' WTP for hydroponic lettuce. To accomplish this, subjects provided answers to two sets of Likert-scale questions that occurred at the end of the questionnaire in APPENDIX B. Out of all the motivating factors one might have for purchasing hydroponic lettuce, the uniqueness, novelty, and marketed food safety attributes of said lettuce products may spur a particular interest in two motivating forces in shoppers, health-consciousness and prestige-sensitivity.

Several constructs have been developed that describe how people respond to price cues, however this investigation will be using the prestige-sensitivity scale, which is a subscale within the price perception scale, developed and validated by Lichtenstein, Ridgway, and Netemeyer (1993) and also documented in Bearden, Netemeyer, and Haws (2011). In an effort to better understand consumers' buying behavior for health reasons, a health-consciousness scale that was developed by Gould (1988) will be used in the survey. The prestige-sensitivity scale will help identify the individual's proneness to purchase goods for the "feelings of prominence and status" from others (Lichtenstein, Ridgway, and Netemeyer, 1993), while the health-consciousness scale will help identify how aware and conscious an individual is of their own health. Responses to these two sets of questions will be used in a Latent Class Analysis to identify and characterize subgroups of different types of consumers within the sample. The prestige-sensitivity scale and health-consciousness scale can be found at the back of the questionnaire in APPENDIX C.

Auction Procedures and Details

A total of 201 members of the Bryan-College Station, Texas community participated in this study (n=201), which took place over three days at the Horticulture Gardens on the campus of Texas A&M University in late February 2014. The study was designed for a total of 200 participants over eight sessions, with an average of 25 subjects in each session. The budget permitted a last-minute ninth session to take place during the afternoon on the last day, which allowed individuals who had previous time conflicts to participate. Actual attendance averaged 22 subjects per session, with a range of n=21 to n=25. While recruiting a sample chock full of college students may have been convenient and albeit less expensive, one of the objectives during the recruitment process was to attract a sample that is representative of Bryan-College Station grocery shoppers. Toward this end, a series of advertisements were issued in a local newspaper, The Eagle, prior to the experiments. Additionally, email correspondence was established with interested parties. A copy of the advertisement used can be found in APPENDIX A.

Upon arrival, participants were checked in using a database that contained the participant's details, such as their name, age, whether or not they were the primary shopper in the household, and their email address under the appropriate session time. After check-in, participants were asked to read and sign a consent form that was required by the Texas A&M University Institutional Review Board (IRB). Contingent on the individual signing the consent form, they were next seated and provided with a participant identification number which secured anonymity, a participation packet which included a questionnaire and a description of the auction procedures, and a smaller packet that contained blank bid sheets and an order form to be used after the auction rounds in the secondary market.

A within-subjects and between-subjects design was used for the experiment. The experiment was largely a between-subjects design, which means that all individuals did not receive the same treatment – half of the subjects participated in a blind tasting as the treatment and the other half of the sample learned about hydroponic production and received labeling information. The within-subject design of each treatment group permits comparisons to be made between bids submitted during the baseline round and the specified treatment round, but bids from the blind tasting treatment and those from the production information treatment must not be compared because all individuals were not exposed to the same stimuli. Several reasons are behind this experimental design and chief among them is simplicity. It was straightforward to explain consumers' behavior in the secondary market as a function of their WTP in the only treatment round.

Following a script, the monitor explained how a second-price Vickrey auction worked and provided two simple examples on the white board. It was stressed to the subjects that it is their weakly dominant strategy to set their bid exactly equal to the maximum amount they would be willing to pay for each item on the auction table. After explaining the procedures and answering any initial questions, two practice rounds of auctions were completed. The first practice round consisted of bidding on three pen products (Paper Mate, Pilot B2P, and BIC pen) and filling out a short quiz that tested the subjects' knowledge of the recently explained procedures. One of the pen products was randomly chosen to be binding and the bids for the binding product were sorted from highest to lowest to determine the hypothetical buyer and market price, per the rules of the Vickrey second-price auction. During this time, the monitor reviewed the quiz with the participants and provided explanations for the correct answers. The monitor then revealed the binding product, the hypothetical buyer, and market price of the practice round and answered any questions the participants had.

Next, participants completed a second practice round in which they submitted bids on four glue products (Instant Krazy, Elmer's Glue, 3M Scotch Gel, and Elmer's Clear). The monitor once again revealed the binding product, the hypothetical buyer, and market price. Any questions the participants had were answered promptly before the real auction rounds.

In the first round of real auctions, participants in all sessions bid on eight vegetable products: organically produced green lettuce; organically produced red lettuce; conventionally produced green lettuce; conventionally produced red lettuce; hydroponically produced red lettuce; hydroponically produced green lettuce; hydroponically produced red and green mixed lettuce; and spinach. The seven heads of lettuce and one bunch of spinach were laid out on a table at the back of the room and randomly given an identification number. The organic and conventional varieties were purchased at the same time at a local Kroger grocery store, while the hydroponic varieties were grown by Texas A&M AgriLife Research and Extension Center at Uvalde, Texas. Researchers grew Progreen and Kremlin varieties of lettuce using hydroponic methods, which were the respective green and red varieties used in the experiments. The hydroponic mixed lettuce was a red and green variety that had been planted together and grew intertwined with one another to form one head of lettuce. Spinach was used as the control product, as it is often considered a substitute for lettuce.

During the first round of vegetable auctions, the baseline round, all of the products were displayed on the auction table at the back of the room and participants were able to pick up and examine each product before submitting their bid sheet. Participants did not know the name of the product or how it was produced and they were asked to submit their bid such that it is exactly equal to their maximum WTP value for each vegetable product. Bids from this first vegetable auction round were considered the baseline level of bids, against which all subsequent bids were compared. To minimize order effects, participants in all sessions only participated in a total of four rounds – 2 practice rounds and 2 vegetable auction rounds (a baseline and a treatment round).

Up to this point in the experiments, all participants in all sessions have been exposed to the same explanation of auction procedures and the baseline round. Participants in Group A (sessions 1, 2, 3, 4, and 9) participated in a blind tasting as the treatment. During the blind tasting, participants were provided with bite-size samples of each lettuce product in a numbered plastic cup, unsalted crackers to cleanse the palate, and a cup of water. Numbers on the sample cups corresponded to representative heads of lettuce on the auction table. For each sample they tasted, participants were asked to evaluate six sensory characteristics (appearance, color, smell, taste, freshness, and overall acceptance) on a 9-point scale that ranged from "extremely dislike" to "extremely like" in a tasting report in the participation packet. Following the completion of the tasting report, participants were asked to examine the auction products once again and submit bids for the vegetable products for a second time. A copy of the tasting report and questionnaire Group A received can be found in APPENDIX B.

Instead of participating in a blind tasting as the treatment, the second half of the sample, Group B (subjects in sessions 5, 6, 7, and 8), received a production information treatment in which each participant was given a sheet of paper with bullet points about hydroponic production of vegetables. This information was provided to the monitor by the Texas A&M AgriLife Research and Extension Center at Uvalde, Texas. While the subjects read the handout, labels that identified the products were placed in front of each of the eight vegetable products on the auction table. Now, participants knew the production method (organic, conventional, or hydroponic production) and color of each lettuce product (red, green, and mixed). After reading the hydroponic production information handout, participants were asked to examine the auction table as they did in the baseline round and submit bids once again for all eight products. Group B received the same participation packet as the one in APPENDIX B, only without the tasting reports. All consumers received a packet of blank bid sheets and order form, which have been provided in APPENDIX C. The hydroponic information handout Group B received can be found in APPENDIX D.

Following each group's treatment, one of the two vegetable auction rounds in each session was randomly chosen to be binding and the bids for the binding product in that round were sorted from highest to lowest. The hydroponic red lettuce was chosen as the binding product based on availability and remained as such throughout the entire study. Complying with the second-price Vickrey auction framework, the highest bidder became the buyer and paid the market price (which was the second highest bid) for the product. Participants were made aware that the vegetable auction rounds were real and if they became a buyer, an amount equivalent to the market price would be deducted from their compensation fee and they would receive the binding product to take home.

The auction portion of the experiment concluded after participants submitted their second round of bids. At this point, all subjects in all sessions filled out a questionnaire that collected information about demographics (age, income, employment, marital status, race, etc.) and vegetable-buying behavior (purchase outlet, frequency, importance of factors when purchasing lettuce, etc.). In addition, participants answered the aforementioned scale-style questions that related to perceptions of their individual health awareness and prestige-sensitivity behavior. Following the completion of the questionnaire, the buyer(s), the market price, and the binding product and round were unveiled.

Next, the experiment transitioned into studying external validity using induced values and an on-site secondary market. The monitor acknowledged the completion of the auctions and offered the participants a chance to purchase the binding product at a "market" at the back of the room. Previously hidden from participants, this market now displayed several units of the binding product (hydroponic red lettuce). Participants were instructed to look at their individual order form in what used to be the packet that contained blank bid sheets and observe the written price listed on the order form. Each individual had received a unique value within a distribution of actual retail prices $[\underline{\$0.5}, \overline{\$3.5}]$. This distribution represented the retail prices of hydroponic, conventional, and organic lettuce in local grocery stores such as Kroger, Wal-Mart, and HEB. Values were pre-assigned to the participation packets prior to the experiments in $0.25 increments, such that i=101 received an induced value (also referred to in this research as the *price in secondary market* or *psm*) equal to the first number in the distribution, psm_{101} = $0.5, individual i=102 was assigned the next highest price in the distribution, psm_{102} = $0.75. If need be, the distribution was repeated. An individual's *psm* value represented the unique price at which she may purchase any of the heads of lettuce from the secondary market at the back of the room. Theoretically, all transaction costs were essentially lowered to zero because the secondary market was on-site. This allows an easier comparison between the final WTP values with the individual-specific induced values.

Participants were instructed to treat the secondary market at the back of the room as they would a Farmer's Market stand. They were then told to indicate on their individual order form how many products they wished to purchase in the secondary market (keep in mind that zero was an acceptable answer). Compensation fees were $30 per person, less any purchases made including those from the secondary market. To collect the compensation fee, participants were told to fill out the order form and exchange it for the compensation fee with the cashier before exiting the study.

WTP Data Organization

After all of the data had been collected, before running any sort of econometric analysis, a step must be taken back to visualize the study's objectives and properly organize the data. The overall objective of this study is to identify the significant factors that affect consumers' willingness to pay for the focal products and estimate their impact. This being said, WTP was the dependent variable (on the left hand side) in the estimations. Generally, willingness-to-pay models in experimental economics stem from the previously described random utility framework developed by McFadden (1974) and it can be inferred that a rational individual will consume product *j* if the utility gained from product *j* is greater than or equal to the utility accrued without product *j* (Collart, 2013). Segovia (2014) provides a useful illustration of what an individual's WTP function may look like:

(11)

$$wtp = f(sociodemographic\ factors, behavioral\ characteristics,$$
$$product\ characteristics, treatments)$$

Socio-demographic factors relate to variables such as age, income, household size, race, employment, education, marital status, and sex. Behavioral characteristics reflect all of the factors that provide insight into the consumer's fruit and vegetable consumption patterns, such as weekly food expenditures, fresh fruit and vegetable expenditures, outlet of fruit and vegetable purchases, how often fruit and vegetables are purchased, and the amount of fresh vegetables on hand. Product characteristics describe any characteristics of the product, such as its color and its method of production.

Finally, depending on the session, WTP estimates may be affected by either the blind tasting treatment or the production information treatment. All subjects participated in a baseline round which acted as the control, then half of the subjects received a blind tasting as a treatment and the other half received information about hydroponic vegetable production as a treatment. Therefore, any effects from the treatment will be seen in the full bids. Table 1 provides a description of the demographic and behavioral variables used for econometric analysis.

Table 1. Demographic and Behavioral Variables

Type	Variable Name	Description
Continuous	AGE	Age (years)
Dummy	DEDU1[a]	Dummy for education of high school degree or less
Dummy	DEDU2	Dummy for education x, where: some college< $x\leq$ 4-year/ Bachelor's Degree
Dummy	DEDU3	Dummy for education for some graduate school or more
Dummy	DINC1[a]	Dummy for annual income of $49,999 or less
Dummy	DINC2	Dummy for annual income x, where \$50,000< x ≤ \$79,999
Dummy	DINC3	Dummy for annual income greater than $80,000
Dummy	DRACE1[a]	Dummy for Caucasian individuals
Dummy	DRACE2	Dummy for Hispanic individuals
Dummy	DRACE3	Dummy for Asian/ Pacific Islander, African American, Native American, or other races
Dummy	FEMALE	Dummy for female individuals
Dummy	MARRIED	Dummy for married individuals
Continuous	HHSIZE	Household size (number of individuals)
Continuous	AWFV	Weekly expenditures on fruits and vegetables ($)

[a] Indicates dummy variable base levels

Dummy variables were used to further specify the raw quantitative and qualitative information that was collected. For example, the variable *MARRIED* is a dummy variable that represents an individual's marital status and will take a value of 1 if the individual is married and 0 otherwise. Another binary variable, *FEMALE*, will take the value of 1 if the individual is a female and 0 if the individual is a male. Additionally, several dummy variables were generated to represent categorical information. Due to the nature of the data, the demographic variable representing race was further defined into three mutually exclusive dummy variables: *DRACE1*, *DRACE2*, and *DRACE3*. If the individual is white/Caucasian, the dummy variable *DRACE1* will take a value of 1 and 0 if the individual is not white. If the individual is Hispanic, the dummy variable *DRACE2* will take the value of 1 and 0 otherwise. Alternatively, if individual is any other race (Asian/Pacific Islander, African American, Native American/ Indigenous, or other), the dummy variable *DRACE3* will take the value of 1 and 0 otherwise. Education and income information were also represented by three dummy variables each: *DEDU1*, *DEDU2*, *DEDU3*; and *DINC1*, *DINC2*, *DINC3*. Individuals were asked to indicate the highest level of education they had completed. If the individual had obtained some high school or a high school diploma, *DEDU1* will take the value of 1 and 0 otherwise, whereas if the individual had completed some college, a 2-year/ Associates Degree, or a 4-year/ Bachelor's Degree, the dummy variable *DEDU2* will take the value of 1 and 0 otherwise. Alternatively, if the individual completed some graduate school or a Graduate Degree, the dummy variable *DEDU3* will take the value of 1 and 0 otherwise. The income dummy variables of *DINC1*, *DINC2*, *DINC3* were coded in a similar manner and represented annual incomes of less than $49,999, incomes between $50,000 and $79,999, and incomes greater than $80,000, respectively.

Quantitative data points are represented by the numerous continuous variables. These were coded to represent the corresponding question in the survey. Examples of these continuous variables can be found in *WFV* and *HHSIZE*, which respectively represent the weekly average amount spent on fruits and vegetables and the number of individuals in the household.

In addition to providing valuable demographic and behavior information, each participant also submitted WTP information in the form of bids. Each session contained two vegetable auction rounds, which garnered a total of 16 bids on vegetable products (8 from the baseline round and 8 from the treatment round) from most individuals. The treatment rounds in the experiment are designated by indicator variables: Baseline (*Base*), Blind Tasting (*Tasting*), and Production Information (*Info*). According to theory, these bids can be directly interpreted as the individual's homegrown, WTP value for each product (Lusk and Shogren, 2007). The product attributes that were analyzed included the color and production method of the lettuce products: red color (Red), green color (Green), mixed color (Mixed), organic production (Org), and conventional production (Conven). These variables took a value of 1 if the attribute was found in the product and 0 otherwise.

Although there are several ways to analyze the mounds of data collected from the experiments, this study will initially apply the more simplistic estimations such as Ordinary Least Squares (OLS) and tobit models for pedagogical purposes, but will eventually ramp up to the more precise, complex econometric models by explaining the random parameters linear and random parameters tobit models.

Ordinary Least Squares Model

After cleaning and organizing the data, the first step in data analysis is often OLS estimation. An OLS model is considered a fundamental way to obtain estimates for the true value of the parameters, also known as the coefficients of the exogenous variables. Estimation of the intercept and slope values in a simple OLS regression can be done by minimizing the sum of squared residuals. Although an OLS model can be applied to a variety of data sets, it is not recommended for data with several observations censored at zero in the dependent variable and does not account for the potential correlation that may occur when individuals submit multiple bids for various products in several rounds. As a result of informing the participants that they could submit any value for their bids, several WTP observations were zero.

Tobit Model

Actual data, especially primary data collected from experiments, often resembles real life in that it is unorganized, messy, and complicated. Just as one would not fit a frame to a picture before measuring the picture, one would not impose an econometric model on to a dataset before becoming acquainted with the data. As previously mentioned, OLS estimation could not accurately represent a data set with a large portion of the observations taking the value of zero and after getting to know the data, several observations of the dependent variable, WTP bids, revealed themselves to be zero. Through a household expenditure application, Tobin (1958) introduced an econometric model that properly and statistically accounted for these values. Appropriately named the tobit model, this econometric model recognized the importance of observations that defy conventional limits and has the ability to account for observations in the dependent variable at zero.

Greene (2003) provides a more current explanation of the tobit method by addressing the differences between truncation and censoring. Often used interchangeably, these two terms represent the two primary methods of dealing with observations that take on zero values. Truncation is defined by drawing a sample from a population's subset that may leave out crucial observations that, upon inclusion, could better represent the whole population, whereas censoring refers to including all data points but modifying or transforming those that are outside of a certain range to take on a single value (Greene, 2003).

Greene (2003) describes the distribution of the tobit model, also known as the censored regression model, as a fusion of discrete and continuous distributions. First, a new variable, y_i, must be developed that will represent all observations, including the transformed, censored observations. The original observations, including the zero values, are represented by the hidden, latent variable y_i*. An illustration of this can be seen by

$$y = 0 \qquad if\ y^* \leq 0$$
$$y = y^* \qquad if\ y^* > 0 \tag{12}$$

That is, if y*, the original observation, is less than or equal to zero, it takes on a value of 0. If y* is greater than 0, the observation remains as is. Greene (2013) points out that if y* is normally distributed with a mean of μ and a variance of σ^2 ($y^* \sim N\ [\mu, \sigma^2]$), the following distribution is assumed

$$\text{Prob}(y = 0) = \text{Prob}(y^* \leq 0) = \phi\left(-\frac{\mu}{\sigma}\right) = 1 - \phi\left(\frac{\mu}{\sigma}\right) \tag{13}$$

Otherwise, if y*>0, y takes on the density of y*. The standard normal cumulative density function (cdf) is represented by $\phi(\cdot)$. Discrete and continuous components still contribute to a total probability equal to one – only the full probability in the censored region is assigned to the censoring point, which is zero in this case (Greene, 2003).

If the distribution described above has been censored at zero (a = 0), the mean is shown as:

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

where λ is further simplified to

(15) $$\lambda = \frac{\varphi\,(\frac{\mu}{\sigma})}{\phi(\frac{\mu}{\sigma})}$$

Where λ is a ratio of the population density function (pdf), represented by $\varphi(\cdot)$, and the cdf, once again represented by $\phi(\cdot)$. As Greene (2003) and Tobin (1958) note, the tobit regression is secured by making the mean correspond with the mean of a classical regression model. By doing so, the following equations are produced:

(16) $$y_i^* = x_i'\beta + \varepsilon_i$$

$$\begin{array}{ll} y_i = 0 & if\ y_i^* \leq 0 \\ y_i = y_i^* & if\ y_i^* > 0 \end{array}$$

where x_i' represents a vector of behavioral and demographic variables for individual i, that are hypothesized to explain an individual's bid, y_i. A vector of coefficients is represented by β, and any unexplained effects are represented by the error term, ε_i. If the data has been censored, the expected value of the latent variable, y^*, can be thought of as

$$\text{(17)} \qquad \mathrm{E}[y_i^* \mid x_i] \text{ is } x_i'\beta$$

However, if an observation is randomly drawn from the population and it is unknown whether the data has been censored, Greene (2003) suggested the expected value of *y* provides a more useful description.

$$\text{(18)} \qquad \mathrm{E}[y_i | \, x_i] = \, \phi\left(\frac{x_i'\beta}{\sigma}\right)(x_i'\beta + \sigma\lambda_i)$$

where λ_i is simplified into

$$\text{(19)} \qquad \lambda_i = \frac{\varphi[(0-x_i'\beta)/\sigma]}{1-\,\phi[(0-x_i'\beta)/\sigma]} = \frac{\varphi(x_i'\beta/\sigma)}{\phi(x_i'\beta)/\sigma}$$

Greene (2003) structured the marginal effects of x_i on y_i as

$$\text{(20)} \qquad \frac{\partial \mathrm{E}[y_i | \, x_i]}{\partial x_i} = \, \beta\phi\left(\frac{\beta' x_i}{\sigma}\right)$$

However, McDonald and Moffitt (1980) decomposed the marginal effects equation above, such that the slope vector was broken down into two parts

$$\text{(21)} \qquad \frac{\partial \mathrm{E}[y_i | \, x_i]}{\partial x_i} = \mathrm{Prob}[y_i > 0] \frac{\partial \mathrm{E}[y_i | \, x_i, y_i > 0]}{\partial x_i} + \mathrm{E}[y_i \mid x_i, y_i > 0] \, \frac{\partial \mathrm{Prob}[y_i > 0]}{\partial x_i}$$

The forefront of this decomposition shows x_i's marginal effect on the conditional mean of y_i* in the uncensored, positive section of the distribution and the remaining component shows that effects due to a change in x_i will be felt in the probability that the observation will reside in that area of the distribution.

The likelihood function from which the model can be estimated is specified by Greene (2003) to be

$$(22) \qquad \text{LF} = \prod_{i=1}^{N} \left(\frac{1}{\sigma}\phi\left(\frac{y_i - \beta\prime x_i}{\sigma}\right)\right)^{Uncensored_i} \left(\phi\left(\frac{-\beta\prime x_i}{\sigma}\right)\right)^{Censored_i}$$

The aforementioned tobit model in all of its estimation provides analysts with a finer tool that has the statistical power to account for observations that might have previously been abandoned. This type of estimation is more sophisticated in nature and is one step closer to properly representing all of the data's complexities.

Participants in this study were instructed to bid their true value for the products, whether it was positive, zero, or negative. Although participants were allowed to bid negative values in the auction, no one did. Therefore, the results from the tobit regression will be discussed in the following chapter.

Random Effects Tobit Model

This study's data set, like similar WTP studies, is multidimensional with more than one observation from each individual and has been organized in a panel structure to make the individual's bids the dependent variable the data (Greene, 2003; Lusk and Shogreen, 2007). Experimental economic literature provides evidence of different econometric models that have been used for analyzing WTP data. The random parameters linear, random effects model, and the random parameters model have recently been used with panel data (Corrigan and Rousu, 2006; Lusk, Feldkamp, and Shroeder, 2004; Segovia, 2014). What makes these models special and highly useful for this study is that they specialize in accounting for potential correlation and heterogeneity that is likely to occur in experimental auctions with multiple products and multiple rounds of bidding. Furthermore, a random effects tobit model will account for bids censored at zero and any unobserved randomness that occurs with each random effect (sessions; individuals).

Unlike a fixed effects model, a random effects model accounts for randomness by assuming a zero correlation between the unobserved individual effects and the explanatory variables by implementing a specific random element for each individual. This new element is tied to the constant such that it absorbs randomness and any differences between individuals will be observed as parametric shifts of the function (Wooldridge 2009). Greene (2003) specified the following random effects model by reformulating a fixed effects model to account for the unobserved heterogeneity:

$$y_{isj} = x'_{isj}\beta + (\alpha + \eta_i) + \varepsilon_{isj} \tag{23}$$

where α is considered a constant term and η_i the added constant random element that accounts for the individual-specific unobserved heterogeneity for individual i, product j, and treatment s. What is needed is a hybrid of equation 23 and the tobit model that accounts for the bids censored at zero and the unobserved randomness in the data. Segovia (2014) offers a unique solution to this problem by combining the random element from the random effects model (equation 24), $(\alpha + \eta_i)$, with the tobit model (equation 17). The following is a specified random effects tobit model:

(24)
$$y^*_{isj} = x'_{isj}\beta + (\alpha + \eta_i) + \varepsilon_{isj}$$

$$y_{isj} = 0 \qquad if\ y^*_{isj} \leq 0$$
$$y_{isj} = y^*_{isj} \qquad if\ y^*_{isj} > 0$$

where y^*_{isj} is the uncensored latent variable that represents individual i's bid value for product j in round s and unobserved randomness is accounted for by $(\alpha + \eta_i)$.
While the random effects tobit model explains unobserved randomness that may affect an individual's WTP values, it does not take into account any unobserved randomness that is associated with the treatment effects or product attributes. That is to say, the random effects tobit model only adds a random constant term to the regression, when much more could be done to account for the dynamic nature of the data. Greene (2003) suggested expanding the general random effects model to, in addition to making the intercept random, allow coefficients to vary randomly across individuals. Segovia (2014)

supported this notion by pointing out the random effects model assumes treatments have the same effect on each individual, but in reality this is likely to not be the case. Thus, a model that is further specified to account for the unobserved differences between rounds, within each individual will be estimated next.

Random Parameters Linear Model

A random parameters linear model, also known as a random coefficients model, accounts for individual differences that are a product of treatments or changes in preferences for certain product attributes. Willingness-to-pay experiments often contain multiple rounds, in which a single individual submits sequential bids that are most likely correlated (Segovia, 2014). The analyst cannot possibly observe all of the factors that are affecting an individual's WTP values across rounds. One solution to account for these unobserved effects is to allow the individual parameters to vary randomly in the econometric analysis. By implementing an element that would allow coefficients to vary randomly over a specified distribution, a random parameters linear model accounts for any unobserved differences in preferences within each individual between rounds, that stem from the treatment or the product attributes (McAdams, et al., 2013). Toward this end, a random parameters linear model is specified to be:

$$y_{isj} = x_{isj}\theta + (\alpha + \eta_i) + \beta_i x_{isj} + \varepsilon_{isj} \quad (25)$$

where y_{isj} represents individual i's bid (WTP valuation) in round s for product j, θ denotes a set of constant coefficients for all bids, the intercept for all bidders is represented by α and η_i describes the variation in α for each individual, whereas βx_{isj} captures the variation in the set of explanatory variables for each individual, and, finally, ε_{isj} represents the normally distributed error terms with a mean equal to zero and variance of σ^2 (Segovia, 2014). The parameters follow a pre-specified distribution, with the normal distribution being the most widely used, and βx_{isj} considers individual-randomness for the parameters, which relaxes the assumption of independence of irrelevant alternatives of RUT (McAdams, 2011). Note that the error introduced by η_i and βx_{isj} are independently distributed of and not correlated with the general error term, ε_{isj} (McAdams, 2013). Although more of the unobserved randomness has been explained through this model, bid values censored at zero must still be accounted for, thus a tobit form of this model is warranted.

Random Parameters Tobit Model

An appropriate model for this study's data would take into account the heterogeneity that may arise between and within individuals across rounds, and the censored bid values at zero. These features are found in the following random parameters tobit specification:

(26)
$$y^*_{isj} = x_{isj}\theta + (\alpha + \eta_i) + \beta_i x_{isj} + \varepsilon_{isj}$$

$$y_{isj} = 0 \qquad if\ y^*_{isj} \leq 0$$
$$y_{isj} = y^*_{isj} \qquad if\ y^*_{isj} > 0$$

The above model is simply equation 25 with a latent variable, $y*_{isj}$, which allows for treatments and product features to have different effects on individuals, and also allows for censored WTP values.

The random parameters tobit model is described in detail by Collart and Palma (2013) as

(27) $$y^*_{isj} = \alpha\eta_i + x_{1,i}\beta_i + x_{2,i}\theta + \varepsilon_i$$

$$\eta_i = \bar{\eta} + \mu_i \text{ and } \beta_i = \bar{\beta} + \alpha_i$$

$$E(\varepsilon_i) = 0, \quad E(\varepsilon_i\varepsilon_i') = \sigma_e^2 I_{SXJ} \quad \text{if} \quad i = j \quad \text{or} \quad E(\varepsilon_i\varepsilon_i') = 0 \quad \text{if } i \neq j$$

$$E(\alpha_i) = 0, \quad E(\alpha_i\alpha_i') = \Delta = \begin{bmatrix} \sigma_{1,1}^2 & \cdots & \sigma_{1,k} \\ \vdots & \ddots & \vdots \\ \sigma_{k,1} & \cdots & \sigma_{k,k}^2 \end{bmatrix} \quad \text{if } i = j \ \text{ or } \ E(\alpha_i\alpha_i') = 0 \quad \text{if} \quad i \neq j$$

$$E(\mu_i) = 0, \quad E(\mu_i) = \sigma_\mu^2 \quad \text{if} \quad i = j \qquad \text{or} \qquad E(\mu_i) = 0 \quad \text{if} \quad i \neq j$$

where $y*_{isj}$ is an $(S \times J) \times 1$ column vector of latent values associated with each observation, α represents an $(S \times J) \times 1$ column vector of 1s, η_i denotes the mean intercept for the pool of observations submitted by individual i, $\bar{\eta}$ takes the form of a scalar that represents the grand mean of observations from all individuals, and μ_i captures the variation or deviation of the mean intercept for individual i from the grand mean, $\bar{\eta}$. Segovia (2014) notes that these random intercepts are distributed with a mean of zero and variance σ_μ^2. The variable $x_{1,i}\beta_i$ consists of a $(S \times J) \times K$ matrix with K random covariates and the coefficients vector, β_i, which is made up of $\bar{\beta}$, the sum of the grand mean coefficients from all individuals, and α_i, the associated individual-specific deviations of the mean coefficients from the grand mean coefficients. As it applies to each individual, it is assumed that these deviations are distributed with a mean of zero and variance-covariance matrix of Δ (Segovia, 2014). It is worth noting that the random elements of β_i and μ_i follow a multivariate normal and normal distribution such that $\beta_i \sim mvn(\bar{\beta}, \Delta)$ and $\mu_i \sim N\left(0, \sigma_\mu^2\right)$ if $i = j$. Finally, $x_{2,i}$ consists of a $(S \times J) \times L$ matrix of L set covariates and θ represents a vector of coefficients that are constant across all individuals. Finally, the error term, ε_i, is normally distributed with a mean of zero and common variance matrix of σ_e^2. Additionally, Segovia (2014) and others assume that the random effects of $\alpha, \mu, e,$ and x are uncorrelated (Moeltner and Layton, 2002; Swamy, 1970).

Implied Differences Model

Several analyses have focused on differences in an individual's bids before and after treatments or across like goods (Alfnes, 2009; Kanter, Messer, and Kaiser, 2009; McAdams, 2011; Segovia, 2014). Lusk, Feldkamp, and Schroeder (2004) named these differences "implied differences" and defined the differences in WTP with regard to individual *i* for product *j* for treatment *s* as

(28) $$Delta\ WTP_{isj} = WTP_{isj} - WTP_{i(Base)j}$$

where $s \neq Base$, maintaining that the treatment and the control baseline round are separate. The above equation for the implied difference in WTP can also be thought of as

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

where C acts as a constant and X is defined as a vector of product features, demographic and behavioral characteristics, and any treatments providing information to the bidders (McAdams, 2011). The variables C_s and C_{Base} can be condensed and re-specified, while the explanatory vector of X can be factored out to reveal

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

The framework above describes the magnitude of change in WTP bids between the baseline and the treatment, thus censorship is not necessary and all bids can be included, even negative values. The treatment (either the blind tasting or production information) provided the participant with information and could have influenced their bids either positively or negatively after the baseline round of bids was submitted. As an example, a participant in sessions 1,2,3,4 or 9 submitted bids during the baseline round (control), and once again after the blind tasting (treatment). If individuals disliked the taste or any other sensory factor of one of the lettuce samples, their WTP was expected to diminish and expected to translate into lower bids for that product relative to the previous baseline round bid. Hence, the treatment negatively affected the individual's bid. In this example, the opposite is expected to be true for those who had a positive experience during the blind tasting treatment.

The other half of the sample received a treatment in which they learned about vegetable production methods. Similar to the blind tasting treatment effects, participants may have negatively viewed the use of hydroponic techniques for vegetable production and reflected this sentiment in their WTP values. Thus, because implied differences simply address the magnitude and direction of change, and are not restricted to data that is positive or negative, the previously discussed random parameters linear (mixed linear) model will be sufficient to be used in the implied differences analysis.

Latent Class Analysis

Another method for studying consumer behavior is through Latent Class Analysis (LCA), where n consumers are classified into a number of S latent classes. By identifying potential underlying themes among certain groups of participants and sorting participants into latent groups, the analyst can add clarity to the data and even extract common characteristics among members in each class.

LCA operates off the premise that a population can be categorized into two or more subgroups. It uses a combination of classical regression and Bayesian analysis to estimate the probability of an individual belonging to one of those subgroups, also called a latent class, based on similar observed variables (Lanza, Tan, and Bray, 2013; Greene, 2003). This style of analysis will be necessary in categorizing participants based on their responses to the health-consciousness and prestige-sensitivity scale questions. Beyond identifying different types of consumers and participants in experimental studies, LCA has also been used to identify the mixture of observed variables that have the potential to predict which class the individual merits membership to (Lanza, Tan, and Bray, 2013; Collart, 2013).

Consider the latent class model specified by Segovia (2014), in which c = 1,…, k,… C latent classes defined from a number of j = 1,…, J observed variables, also known as the indicators. The number of possible outcomes associated with the variable j is denoted by R_j for individuals i = 1,…, n. The observable data, the individual i's observed responses to the J indicators, is represented by vector $X_i = (X_{i1},\dots, X_{ij})$, where the possible outcomes of X_{ij} are known as r and r = 1,…, R_j. Let $I(x_{ij} = r)$ act as an indicator function that is equal to 1 if the response to indicator $j = r$, and 0 if not. The probability density function of an individual demonstrating a specific membership profile is given as

(31)
$$X_i \sim f_i(x_i;\ \varphi) = \textstyle\sum_{c=1}^{C} \pi_c f_{i|c}\,(x_i; \theta_c)$$
$$= \sum_{c=1}^{C} \pi_c \prod_{j=1}^{J} \prod_{r=1}^{R_j} (\theta_{jr|c})^{I(x_{ij}=r)}$$

where the distribution and parameters of the indicator variables, X_i, is equal to the probability of individual i qualifying for membership in class c ($\sum_{c=1}^{C} \pi_c$), multiplied by the associated conditional probability density function ($f_{i|c}\,(x_i; \theta_c)$) for all classes. The density function is further defined as the product of the indicator (J) and possible outcome (R_j) vectors. Segovia (2014) clarifies that the parameters of the density function, ($\theta_{jr|c}$), represents the indicator-response probabilities of a specific response, r_j to the indicator variable j, given the individual's membership in class *c*. Therefore, if the observed indicators, *X*, and the number of latent classes, *C*, are known, then the idea is to solve for the parameters $\varphi = (\pi, \theta)$. This can be done through the following likelihood function for φ:

(32) $$\mathcal{L}(\varphi|X) = \prod_{i=1}^{n} f_i(x_i; \varphi).$$

The parameters φ can be estimated through the Expectation-Maximization (EM) algorithm because the individual's class membership is uncertain and thus may be regarded as missing data (Dempster, Laird, and Rubin, 1977; Collart, 2013). The log-likelihood application is specified as:

(33) $$ln\mathcal{L}(\varphi) = \sum_{i=1}^{n} \ln\left[\sum_{s=1}^{S} \pi_s f_{i|s}(y_i; \theta_s)\right]$$

From this equation, the EM algorithm can be used on $ln\mathcal{L}(\varphi)$ after imprinting random initial estimates of π_s and $f_{i|s}(y_i; \theta_s)$ on a Bayesian calculation of the posterior probability, all in an effort to determine the class membership parameters, φ (Collart, 2013). The following describes this process. The first equation describes the Bayesian approach to determining the class membership probability that individual *i* belongs to *s* class, given the observed *k* indicators:

(34) $$P(s = k|Y_i = y_i) = \alpha_{ik} = \frac{\pi_k \prod_{j=1}^{J} f_{ij|k}(y_{ij};\theta_k)}{\sum_{s=1}^{S} \pi_s f_{ij|s}(y_{ij};\theta_s)}$$

Next, applying the random initial estimates yields an estimated value, $\hat{\alpha}_{ik}^{(0)}$, for the unknown class membership probabilities

(35) $$P(s = k\big|Y = y_i, \varphi^{(0)}\big) = \hat{\alpha}_{ik}^{(0)}$$

Following this estimation, Collart (2013) proceeds to describe the second part of the EM algorithm as the maximization of the $E[ln\mathcal{L}\big(\varphi^{(0)}\big)]$ with respect to φ, subject to:

(36) $$\sum_{s=1}^{S} \pi_s = 1, \qquad \pi_s > 0, \qquad s = 1, \dots, S$$

This maximization yields maximum likelihood estimates of π_s and θ_s for s = 1,…*S*. Collart (2013) suggests these estimates are useful for recalculating the posterior probabilities in equation 35.

Because the actual number of existing subgroups, also referred to as *S* or latent classes, is unknown, certain criterion tests are used to gain a more accurate estimation of *S*. In general, Akaike's Information Criterion (AIC; Akaike, 1973) favors larger models, the Bayesian Information Criterion (BIC; Schwarz, 1978) accounts for sample size and favors more parsimonious models, and the Adjusted BIC (Sclove, 1987) are the primary methods for estimating which level of S is most appropriate. Collart (2013) suggests using the final posterior probability estimates, $\hat{\alpha}_{is}$, to sort individuals into the S latent classes by comparing the highest individual-specific posterior probabilities. For example, individual i has membership to class k if $\hat{\alpha}_{ik} > \hat{\alpha}_{is}$ for all $s \neq k$.

Secondary Market Data Analysis

As previously discussed, external validity of the experimental auction mechanism used in this study was tested with an on-site secondary market that immediately followed the conclusion of the vegetable auction rounds. In this test of external validity, inspired by farmers markets and Cherry et al.'s (2004) application of induced value theory, participants were assigned an individual price from a uniform distribution of outside prices of lettuce and then asked whether or not they would like to purchase the binding lettuce product at their unique price from the "market" at the back of the room.

A measurement of consumer surplus, explained in Equations 7 and 10, indicates the expected behavior of participants' in secondary market. It simultaneously accounts for the individual's WTP value after all information has been distributed and the individual's assigned price in the secondary market. In an effort to identify the factors that motivate people to purchase in the secondary market and thus move closer to answering the question of whether or not the Vickrey 2nd price auction is an externally valid value elicitation mechanism, the probability that an individual would make a purchase in the secondary market is described as

(37) $$purchase = f(importance\ of\ fee\ relative\ to\ income,\ behavioral\ characteristics, consumer\ surplus,\ sociodemographic\ factors)$$

A ratio of the study's compensation and an individual's hourly income shows the relative importance of the fee. If an individual's has a high income, then the fee becomes relatively unimportant, whereas if an individual's has a low income, then the fee becomes relatively more important. Therefore, if an individual places relatively high importance on gaining the full fee, they are hypothesized to be less likely to purchase in the secondary market because any purchases made will decrease the amount of the fee they receive at the end of the study. Due to this reasoning, the fee-to-income factor is hypothesized to negatively impact the probability of an individual making a purchase in the secondary market. Behavioral characteristics, such as the last time an individual purchased produce is expected to impact whether an individual decides to purchase the binding lettuce product after the auction rounds. Consumer surplus, as mentioned before, provides the theoretical foundation behind whether or not people make a purchase in the secondary market. Finally, sociodemographic characteristics refer to age, gender, and form of employment. Table 2 provides the name and description of the variables used to estimate the probability of an individual making a purchase in the market.

Table 2. Description of Variables used in Secondary Market Behavior Analysis

Type	Variable Name	Description
Continuous	*feetoinc*	fee to income ratio= total compensation/hourly income
Dummy	*dlast1*	Dummy for last purchase of fruit and vegetables was 4 days ago or less
Continuous	*csurplus*	consumer surplus = (WTP value in full information round for binding product – assigned price)
Dummy	*age*	Age (years)
Dummy	*female*	Dummy for female individuals
Dummy	*hhsize*	Household size (number of individuals)
Dummy	*student*	Dummy for student as form of employment

The factors take dummy and continuous forms and illustrate the primary factors that were hypothesized to affect an individual's purchase in the market. The variable *feetoinc* takes the form of a ratio of the total compensation an individual received and their average hourly income. Recent fruit and vegetable purchases were described by a dummy variable, *dlast1*, that takes the value of 1 if the last time an individual bought fruits and vegetables within four days prior to the experiment, and 0 if they have not. The variable *csurplus* is continuous and is the difference between the individual's bid in treatment round (which was also the full information bid) and the individual's assigned price. Sociodemographic factors were represented by continuous and dummy variables: *age* which is measured in years, *female* which is a dummy variable equal to 1 if the participant is a female and 0 if the participant is a male, *hhsize* which indicates the number of individuals in the household, and *student* which is a dummy variable that takes the value of 1 if the individual is a student and 0 if they are not. Students were of particular interest, as they were hypothesized to participate in the experiment primarily for the fee and thus expected to be less likely to make a purchase in the market.

These variables were used in a probit model, a random effects probit model, and a heteroskedastic probit model to estimate their impact on the probability of a participant making a purchase in the secondary market. These models were also estimated using a condensed set of the variables in Table 2, which included *feetoinc*, *dlast1*, *csurplus*, and *student*. Likelihood ratio tests will be performed to assess which version of each model, either the full or condensed version, is most appropriate.

Probit Model

Random Utility Theory (RUT) is also useful in accounting for the unobservable factors that influence individuals' choice behavior. RUT allows for researchers to specify utility as a function of observed factors, such as the attributes of the alternatives and attributes of the decision maker, and unobservable factors that known to the decision maker but not to the researcher. Discrete models are particularly useful for estimating the probability on a scale of 0 to 1 of an individual making a decision of "yes or no." The probability that an individual decides to choose one option over another can be defined by the advantages offered by the unobservable and observable factors associated with each option. Train (2009) illustrates choice probability as

$$P_{ni} = \mathrm{Prob}\left(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \; \forall j \neq i\right). \tag{37}$$

Equation 37 states that the probability that person *n* chooses alternative *i* depends on the advantage that alternative *j* has over alternative *i* in unobservable factors is not better than the advantage alternative *i* has over alternative *j* in factors that are observed by the researcher, given that the two alternatives are mutually exclusive. The models used for analyzing consumers' choice behavior differ in how the density of the unobservable factors is specified. Among the most common models used is the probit model, which assumes that the unobserved factors are normally distributed. By assuming ε_n is distributed normally with the covariance matrix of Ω and the mean vector equal to zero, Train (2009) specifies the probit model by first illustrating the density of ε_n as

(38) $$\phi(\varepsilon_n) = \frac{1}{(2\pi)^{J/2}|\Omega|^{1/2}} e^{-1/2\varepsilon_n'\Omega^{-1}\varepsilon_n},$$

then the choice probability is

(39) $$P_{ni} = \text{Prob}(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}\ \forall j \neq i)$$

$$= \int I(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}\ \forall j \neq i)\phi(\varepsilon_n)d\varepsilon_n.$$

The statement inside the parentheses provides the theoretical justification for an individual's decision to choose to buy in the secondary market or not. The variable *I* acts as an indicator and takes the value of either 1 or 0, with 1 being that the statement inside the parentheses holds and 0 if it does not. Given that the statement holds, the integral is taken over all values of $\varepsilon_n$using simulation (Train, 2009).

Random Effects Probit Model

By estimating a random effects probit model, one can determine if random effects in different groups (sessions) explain the variance in the model. In the random effects probit framework, developed by Heckman (1981), the error term is decomposed into two components:

(40) $$v_n = \mu_n + \varepsilon_n.$$

Guilkey and Murphy (1993) explain that $v_i$indicates all of the unobservable factors, of which there are those that do not vary within the sampling unit (μ_i) and those that do vary within and across the sampling units. If v_i is normally distributed, StataCorp (2013) specifies the choice probability as

(41)

$$\Pr(y_{i1}, \ldots, y_{in_i} | x_{i1}, \ldots, x_{in_i}) = \int_{-\infty}^{\infty} \frac{e^{-v_i^2/2\sigma_v^2}}{\sqrt{2\pi}\sigma_v} \left\{\prod_{t=1}^{n_i} F(y_{it}, x_{it}\beta + v_i\right\} dv_i$$

where

(42) $$F(y, z) = \begin{cases} \phi(z) & \text{if } y \neq 0 \\ 1 - \phi(z) & \text{otherwise} \end{cases}$$

where ϕ is the cumulative normal distribution.

The panel level likelihood and integrals are estimated using Gauss-Hermite quadrature methods, which approximates a weighted sum of the function's values at specific points and is useful when there are no more than four or five available alternatives (Train, 2009). Interested readers are referred to Guilkey and Murphy (1993), Geweke (1996), and StataCorp (2013) for a more detailed explanation.

Heteroskedastic Probit Model

In estimating the probability that an individual chooses one option over another, the variance of the unobservable factors (error term) may be different for different groups of individuals. This difference in the variance of the error term is often referred to as heteroskedasticity. To adjust for heteroskedastic errors and allow the comparison of choice probabilities for two sets of individuals for the same set of alternatives, a researcher may adjust overall scale of utility by "normalizing" the variance of one group and then estimating the variance for the other group relative to the first group. Train (2009) provides a good explanation of this index approach by using commuters from Chicago and Boston. The original utility functions for person *n*'s mode of transportation j are specified as

$$U_{nj} = \alpha T_{nj} + \beta M_{nj} + \varepsilon_{nj}^{B} \ \forall n \text{ in Boston} \tag{43}$$

$$U_{nj} = \alpha T_{nj} + \beta M_{nj} + \varepsilon_{nj}^{C} \ \forall n \text{ in Chicago.}$$

That is, for a traveler in Boston, the utility they gain from mode of transportation j is a function of time, T_{nj}, cost (money), M_{nj}, and unobservable factors that are specific to

Boston travelers, ε_{nj}^{B}. The same can be said for travelers in Chicago, only the unobservable factors influencing their decision, ε_{nj}^{C}, are specific to Chicago and the variances of ε_{nj}^{B} and ε_{nj}^{C} are not equal. To adequately compare these two utilities, they are scaled by a ratio of the variances such that the variance of the error term for travelers in Chicago is set relative to the variance of the error term for those in Boston. The ratio is as follows:

$$k = \frac{\mathrm{Var}(\varepsilon_{nj}^{C})}{\mathrm{Var}(\varepsilon_{nj}^{B})} \tag{44}$$

The variable *k* now provides a scale measurement of variances and the parameters of the utility function of travelers in Chicago can be divided by $\sqrt{k}$. By doing so, the variance of the unobservable factors becomes equivalent in both cities. Train (2009) specifies the newly adjusted utility functions as

$$U_{nj} = \alpha T_{nj} + \beta M_{nj} + \varepsilon_{nj}\ \forall n \text{ in Boston} \tag{45}$$

$$U_{nj} = (\alpha/\sqrt{k})T_{nj} + (\beta/\sqrt{k})M_{nj} + \varepsilon_{nj}\ \forall n \text{ in Chicago.}$$

This scale of utility through normalization of heteroskedastic errors now allows the comparison of error terms between the two cities. The variance of the unobserved factors in the two cities can now be explained in relative terms.

In an effort to compare the two groups of individuals in the secondary market, those who should have purchased and those who actually did make a purchase, the scale of utility will be set by normalizing the heteroskedasticity in one of the group's unobserved variables and estimating the variance of the other group relative to the first group. The scale-adjusted utilities might take the form of

(45) $$U_{nj} = \beta X_{nj} + \varepsilon_{nj} \ \forall n \text{ Who Actually Purchased}$$

$$U_{nj} = \left(\frac{\beta}{\sqrt{k}}\right) X_{nj} + \varepsilon_{nj} \ \forall n \text{ Who Should Have Purchased.}$$

where

(46) $$k = \frac{\mathrm{Var}(\varepsilon_{nj}^{Should})}{\mathrm{Var}(\varepsilon_{nj}^{Purchased})}.$$

CHAPTER V

RESULTS AND DISCUSSION

This chapter will provide results from the proposed analyses. The demographic and behavioral characteristics of the sample will be visited, followed by a description of the bid values. Next, findings from the aforementioned models will be provided and discussed. Lastly, this chapter will be rounded out through a juxtaposition of the various models and estimation techniques.

Demographic and Behavioral Characteristics

The experiment produced a total of 201 responses. Although a typographical error resulted in a loss of observations, several pieces of information were recovered and proved useful in the analysis. One of the goals of this experiment was to elicit consumers' willingness to pay for lettuce, thus the type of consumer targeted by the experiment's advertisement was a household's primary grocery shopper. Table 3 provides a description of the demographic and behavioral characteristics of the participants. It can be seen that roughly 84% of the participants were the primary grocery shopper for their household and over 57% of the sample was female. Nearly 44% identified with being married. Caucasians (73%) and Hispanic individuals (12%) largely made up the sample. Generally speaking, individuals were highly educated. The highest level of educational attainment was at least some college or a Bachelor's degree for over 58% of the sample and over 34% had at least taken some graduate course. The average participant was approximately 41 years old, earned around $51,599 per year, and lived in a household of 2.54 individuals. On average, participants spent $126 on food per week, of which around $29 was spent on fruits and vegetables. Moreover, fresh vegetables composed of more than a third of the average participant's full stock of food.

Table 3. Demographic and Behavioral Characteristics of Experiment Participants

Variable	Category	Sample		U.S. Population(a)		Texas Population(a)	
		Mean	Percent	Mean	Percent	Mean	Percent
Age (years)		40.94		37.40		33.90	
Household Size (individuals)		2.54		2.64		2.84	
Education	High School Diploma or Less		6.74		41.70		43.80
	Bachelor's Degree or at least some college		58.43		47.50		47.20
	Graduate Courses or More		34.83		10.90		9.00
Gender	Female		57.59		50.80		50.30
	Male		42.41		49.20		49.70
Marital Status	Married		43.72		48.00		49.40
	Not Married		56.28		51.90		50.50
Yearly Household Income ($)		51,599		71,317		70,730	
Race	Asian/ Pacific Islander		4.05		5.17		4.11
	African American		4.62		12.52		11.74
	Caucasian/ White		72.83		64.20		44.99
	Native American/ Indigenous		1.16		0.68		0.24
	Hispanic		12.14		17.24		38.79
	Other		5.20		0.20		0.12
Primary Shopper	Primary Shopper		84.08				
	Secondary Shopper		15.92				
Household Weekly Expenditures on Food ($/week)		125.87					
Household Weekly Expenditures on Fruits and Vegetables ($/week)		29.29					
Fresh Vegetables on Hand (out of full stock)			35.51				

(a)Source: U.S. Census Bureau 2012 American Community Survey 1-year Estimates

In addition to questions about basic demographic information and vegetable purchasing habits, subjects were asked to rate the relative importance of nine attributes that play a part in decisions when buying lettuce. This was included as a means of gaining information about the different factors that may contribute to an individual buying a specific lettuce product in the grocery store. Factors represented physical characteristics (i.e. size, visual appearance, and freshness), and product information (i.e. nutrition, growing location, and certified production practices), as well as marketing attributes (i.e. price and convenience) and experience features (taste). The scale of importance ranged from 1 to 4, with 1 representing "Not Important at all" and 4 being "Very Important." Table 4 displays a list of all factors, as well as their mean rating and an interpretation of each factor's importance.

Participants rated freshness (3.871) as the most important factor, followed by taste (3.706) and visual appearance (3.677). Relative to the other factors, participants, on average, cared least about where or how lettuce is grown, as they rated growing location (2.226) and certified production practices (2.585) as the least important factors when buying lettuce. An interesting result can be found when taking a closer look at the factor of convenience. With this being said, it is worth noting that participants had very distinct views regarding certified production practices, as a large amount of variability can be seen in responses. Although a more in-depth analysis is warranted, knowing which factors consumers view as most important when buying lettuce presents significant value to the lettuce industry.

Table 4. Rated Relative Importance of Factors in Lettuce Purchases [a]

Factor	Mean	Std. Dev.	Interpreted Level of Importance
Freshness	3.871	0.365	Very Important
Taste	3.706	0.488	Very Important
Visual Appearance	3.677	0.538	Very Important
Nutrition	3.452	0.686	Somewhat Important
Price	3.313	0.637	Somewhat Important
Size	3.237	0.705	Somwhat Important
Convenience	3.125	0.820	Somewhat Important
Certified Production Practices	2.585	0.958	Somewhat Important
Growing Location	2.226	0.813	Not Very Important

[a] Subjects were asked to rate the factors on a scale of 1 to 4; 1 = Not Important at all, 2 = Not Very Important, 3 = Somewhat Important, 4 = Very Important

Willingness to Pay Models with Experimental Auction Bids

Participants' bids from the auction rounds were pooled for all treatments and resulted in a total of 3,193 WTP observations. As specified in the methodology chapter, the eight products used were heads of lettuces that varied in color and production method: organic green lettuce, organic red lettuce, hydroponic red lettuce, hydroponic green lettuce, hydroponic mixed lettuce (red and green), conventional red lettuce, and conventional green lettuce. The conventional and organic heads of lettuce, as well as one bunch of spinach were purchased simultaneously at a local Kroger grocery store, while the hydroponic heads of lettuce were grown by Texas A&M AgriLife Research and Extension Center in Uvalde, Texas. Spinach was included in the product mix as a control.

Recall from the methodology chapter that the experiment was a between-subjects design. Nine sessions of participants were split up into two groups. Group A (Sessions 1, 2, 3, 4, and 9) participated in a baseline auction round and received a blind tasting as the treatment, whereas Group B (Sessions 5, 6, 7, and 8) submitted bids in a baseline round and received hydroponic production information as the treatment. Participants' baseline bids for each product are described in Table 4, as well as the bids for each treatment group. The experiment produced bids that ranged in value from \$0.00 to \$5.50. Organic green lettuce received the highest average bid of \$1.58 in the baseline round across all participants and hydroponic mixed lettuce was valued second highest at \$1.55.
Group A signaled a preference for organic green lettuce after the blind tasting treatment and gave it the highest average bid of \$1.66. Additionally, subjects exhibited relatively high WTP for conventional green lettuce and hydroponic mixed lettuce in the blind tasting round. In Group B's information round, hydroponic mixed lettuce and organic green tied for the highest valued product, as they both received the highest average WTP of \$1.90.

Table 5. Descriptive Statistics for Willingness to Pay (WTP) Bids

Product	Obs	Mean Bid	Std. Dev.	Minimum	Median	Maximum
A.WTP Bids - Baseline For All Participants						
Conventional Green	201	1.44	0.79	0.00	1.25	4.50
Conventional Red	201	1.13	0.71	0.00	1.00	3.50
Organic Green	200	1.58	0.80	0.00	1.50	5.00
Organic Red	201	1.32	0.89	0.00	1.25	3.75
Hydroponic Green	201	1.40	0.86	0.00	1.25	4.00
Hydroponic Red	201	1.32	0.79	0.00	1.25	4.00
Hydroponic Mixed	201	1.55	0.86	0.00	1.50	5.00
B. WTP Bids - Tasting Round (Group A)						
Conventional Green	111	1.56	0.79	0.00	1.50	4.00
Conventional Red	111	1.32	0.76	0.00	1.25	3.95
Organic Green	111	1.66	0.90	0.00	1.50	5.50
Organic Red	111	1.23	0.83	0.00	1.00	3.75
Hydroponic Green	111	1.46	0.88	0.00	1.50	3.79
Hydroponic Red	111	1.37	0.88	0.00	1.25	4.00
Hydroponic Mixed	111	1.54	0.77	0.00	1.50	3.75
C. WTP Bids - Information Round Group B)						
Conventional Green	90	1.36	0.81	0.00	1.23	3.75
Conventional Red	90	1.17	0.86	0.00	1.00	4.00
Organic Green	90	1.90	0.93	0.00	2.00	5.00
Organic Red	90	1.58	0.96	0.00	1.50	4.25
Hydroponic Green	90	1.46	0.93	0.00	1.28	4.50
Hydroponic Red	90	1.61	0.96	0.00	1.75	4.99
Hydroponic Mixed	90	1.90	1.01	0.00	1.75	5.00

A graphical representation of the mean bids for each product by treatments is provided in Figure 1. In viewing the graph, the blind tasting treatment increased mean WTP for most products, but decreased mean WTP for organic red lettuce. This indicates that some participants disliked the taste of the organic red leaf lettuce. From the baseline to the blind tasting, Figure 1 shows the largest jumps in average WTP among conventional varieties. Alternatively, organic varieties, as well as hydroponic red and hydroponic mixed lettuces showed visible increases in WTP from the baseline to the information treatment. It is unclear as to why the hydroponic green lettuce did not follow suit.

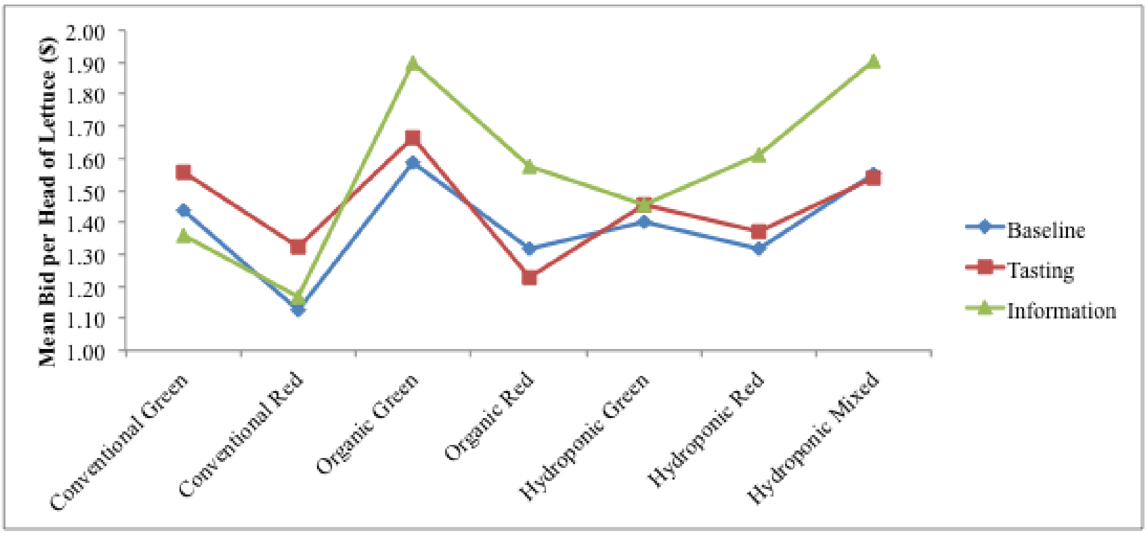


Figure 1. Mean Bids for Lettuce Products by Treatment

As previously mentioned, one of the goals of this analysis is to investigate whether production method is valued by consumers. Table 6 shows the mean WTP by production method and treatment for the lettuce products. It is clear that on average, over the course of the experiment, participants valued organic products highest, followed by hydroponics, and lastly conventional products. Overall, average bids for conventional varieties ($1.33) were in line with the average local retail price for conventional leafy lettuce at the time of the experiment ($1.38). However, mean bids for organic ($1.55) and hydroponic ($1.51) varieties were well below the average retail prices of $2.29 and $3.00, respectively.

Table 6. Mean Willingness to Pay (WTP) Bids by Production Method and Treatment

	Baseline	Tasting	Information	Total Average
Conventional	1.28	1.44 ***	1.26	1.33
Organic	1.45	1.45	1.74 **	1.55
Hydroponic	1.42	1.46	1.66	1.51

Null Hypothesis: $WTP_{baseline} = WTP_{treatment}$

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

On average, participants expressed a premium for conventionally produced products after the blind tasting, while average bids for organic and hydroponic varieties either remained steady or only slightly increased after the blind tasting treatment. In the information treatment, participants learned about hydroponic production and, prior to bidding, also learned the production method and color of each auction product; therefore, it was expected that average bids during the information round would not be equal to average bids during baseline round. Relative to the baseline, conventional products minimally decreased in average WTP and, as expected, large increases in average WTP for organic and hydroponic varieties were detected after learning about hydroponic production.

In addition to summary statistics for the bids and treatments, distributions of the bids were also constructed for comparison purposes. Figures 2-7 display the distribution of bids for each product by treatment, as well as the average bids for each method of production by treatment. Before any of the distributions were estimated, a Kolmogorov-Smirnov (K-S) test was used to test whether the bids for each product were normally distributed. A null hypothesis that the bids are normally distributed was tested and the p-values are organized in Table 7. The null hypothesis was rejected (P < 0.05) for the bids of all products in the baseline round, which means that they are not normally distributed. However, the null hypothesis was not rejected for the bids of four products in the production information round (hydroponic mixed lettuce, conventional red lettuce, conventional green lettuce, and hydroponic green lettuce) and four products in the blind tasting round (organic red lettuce, hydroponic red lettuce, conventional red lettuce, and hydroponic green lettuce), which indicates that these products have normal distributions in the respective rounds.

Table 7. Kolmogorov-Smirnov Test for Normality P-values[2]

	Treatment		
Product Type	Baseline	Tasting	Information
Organic Green	0.001	0.022	0.032
Organic Red	0.000	0.034	**0.076**
Hydroponic Red	0.046	0.002	**0.307**
Hydroponic Mixed	0.004	**0.201**	0.047
Conventional Red	0.000	**0.444**	**0.066**
Conventional Green	0.003	**0.274**	0.010
Hydroponic Green	0.036	**0.292**	**0.063**

$\alpha = 0.05$

After the K-S test was applied, distributions for the bids were estimated using the Gaussian kernel density form in Simetar©. Kernel density estimation is a procedure that assigns each observation a unique distribution and the accumulation of these smaller

[2] Boldface values indicate the null hypothesis was not rejected, which reveal the respective products and rounds that produced normally distributed bids.

distributions ultimately builds up the familiar normal probability distribution. Essentially, this function acts as a smoothing technique so that the distributions appear as a fluid form. Although not all of the bid distributions are normally distributed, for comparison purposes and simplicity's sake all distributions take the form of normal distributions.

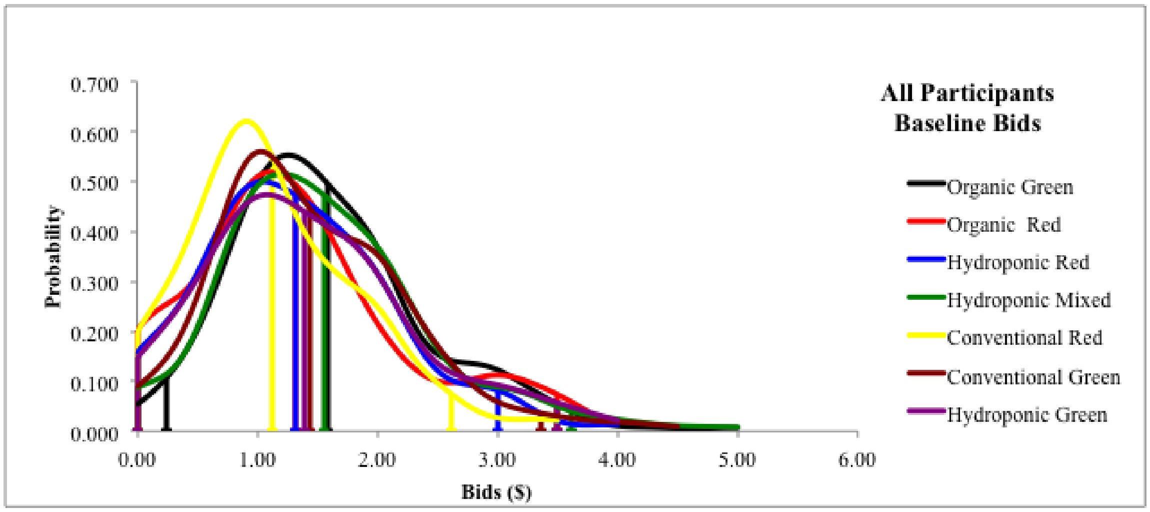


Figure 2. Gaussian Kernel Density Distribution of Baseline Round Bids for Vegetable Products

It is evident in Figure 2 that conventionally and organically grown red lettuce products appear to have the highest degree of bids censored at zero. A clustering of hydroponic red lettuce and hydroponic green lettuce secures the second-highest degree of censored bids, and organic green lettuce appears to have the least amount of bids censored. The mean bid for conventional red lettuce is shown farthest to the left, which means participants clearly valued it the least in the baseline round compared to all the other products. The mean bids of hydroponic mixed lettuce and organic green lettuce were farthest to the right, which implies they were the highest valued products in the baseline round.

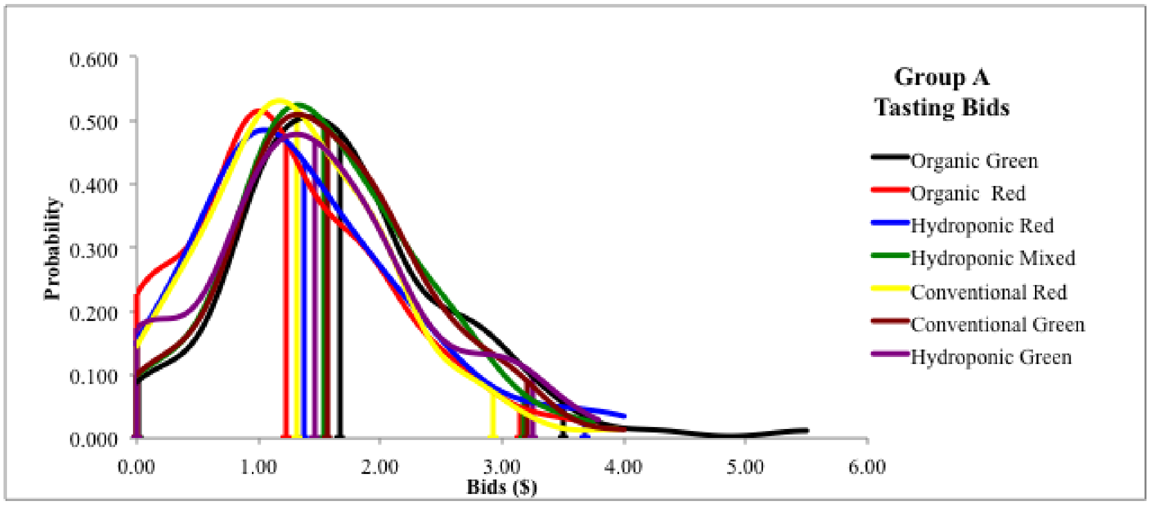


Figure 3. Gaussian Kernel Density Distribution of Blind Tasting Round Bids for Vegetable Products

During the blind tasting treatment, bid distributions show organic red as single-handedly receiving the largest degree of bids censored at zero, followed by a clustering of hydroponic and conventional varieties of red lettuce. Bids for conventional green lettuce, organic green lettuce, and hydroponic mixed lettuce had the lowest degree of censoring and follow similar distributions. This implies that, compared to red lettuce, participants were more familiar with the taste of green lettuce and awarded it fewer negative or bids that equaled zero. It is also evident that regardless of the production method, red lettuce received the lowest mean bids, whereas organic green remained among the highest valued products.

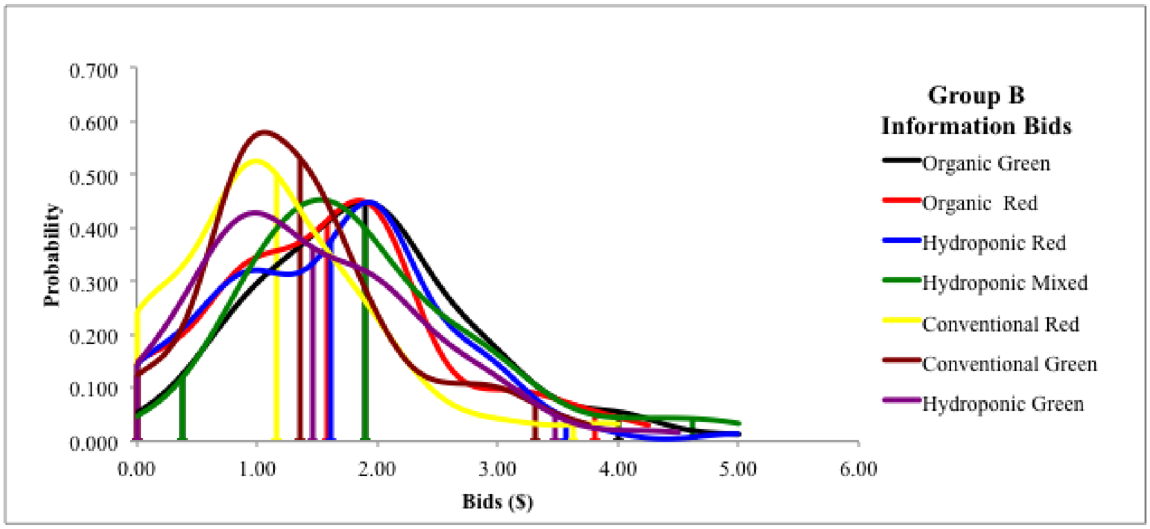


Figure 4. Gaussian Kernel Density Distribution of Information Round Bids for Vegetable Products

After participants learned about hydroponic production, as well as the production method and color of each product, three large clusters of censorship can be seen in Figure 4. It is most obvious that conventional red had highest degree of censored bids, followed by hydroponic green lettuce, hydroponic red lettuce, conventional green lettuce, and organic red lettuce, and lastly organic green lettuce and hydroponic mixed lettuce with the lowest degree of bid censoring at zero. As mentioned in the discussion of the bids' descriptive statistics, hydroponic mixed lettuce and organic green lettuce were valued the highest after consumers learned about them, with both nearly receiving an average of $2.00 in WTP. When comparing bids in the information round to the baseline, the rollercoaster-like distributions of the former show more variation and distinction across products. Perhaps participants took into account the knowledge accrued from the information round and exercised more discretion when submitting their bids. Bids for products of each production method were compiled and their distributions can be seen in Figures 5-7.

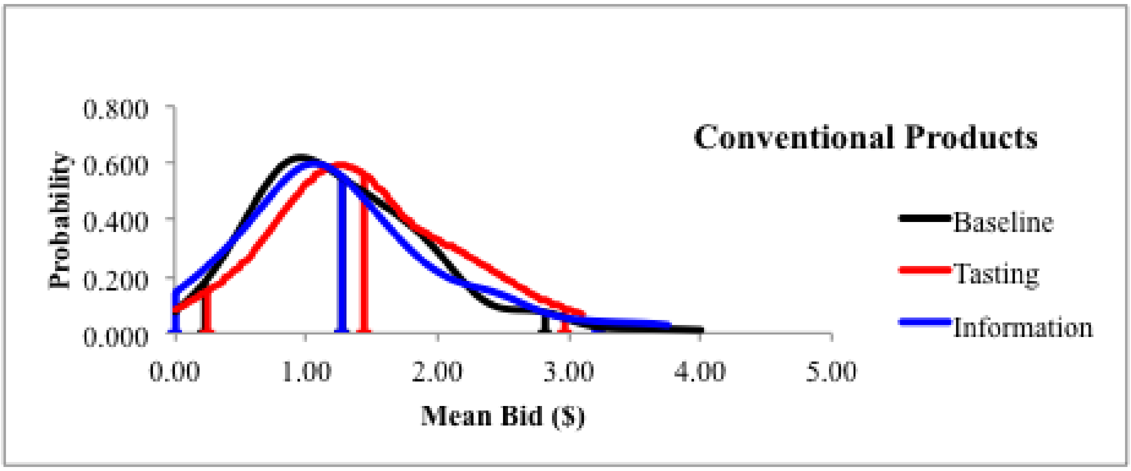


Figure 5. Gaussian Kernel Density Distribution for Conventionally Grown Lettuce Products by Round

In Figure 5 bids for conventional products in the information round exhibited the highest degree of censoring while the baseline and blind tasting rounds clustered at a lower degree. Despite the cluster effect, the mean WTP in the blind tasting treatment exceeded the mean bids of the other rounds. This implies that participants on average liked the taste of conventional products and placed higher values on conventional products.

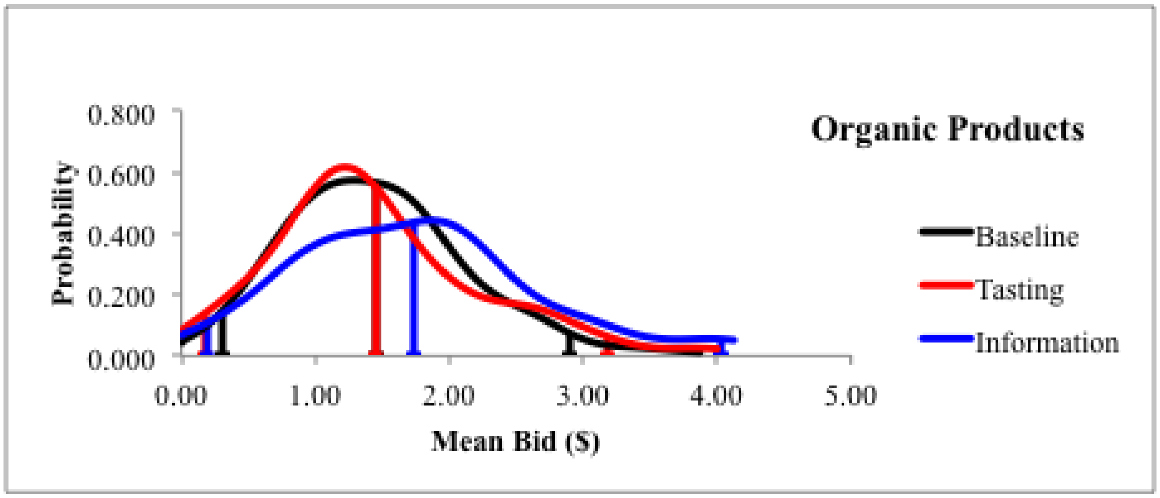


Figure 6. Gaussian Kernel Density Distribution for Organically Grown Lettuce Products by Round

Unlike the distributions in Figure 5, bids for organic products changed the most after the information treatment, which can be seen in the rightward movement of the mean bid in the information round from the baseline. No wide disparities in the degree of bid censoring across the rounds can be seen in Figure 6. Organic products saw little change in mean WTP after the blind tasting from the baseline, but the average bid value in the production information round was clearly greater than the other two rounds. Compared to the conventional product bid distributions in Figure 5, the flatter, wider distribution of bids from the information round in Figure 6 indicates greater variance among the bids for organic products after the dissemination of production information.

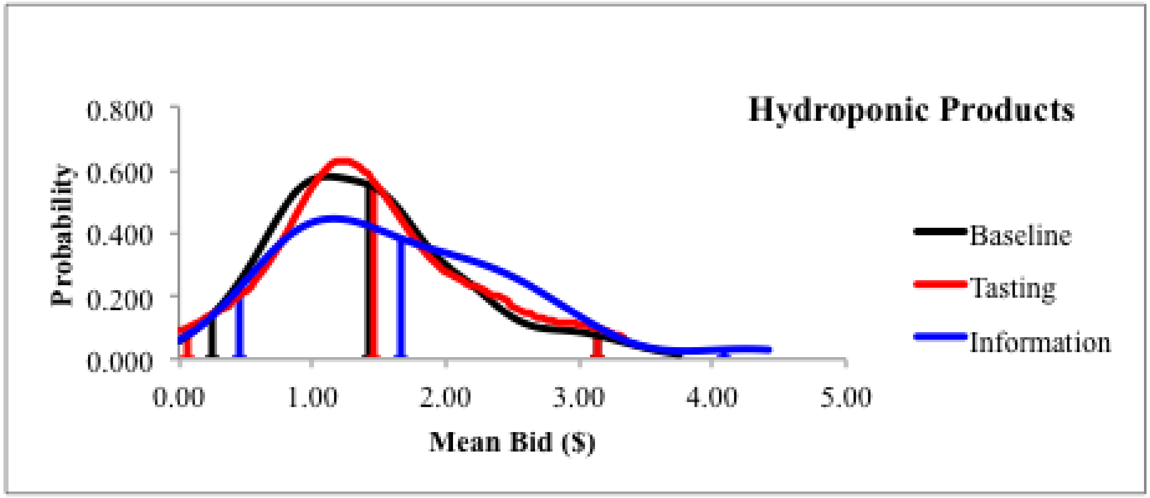


Figure 7. Gaussian Kernel Density Distribution for Hydroponically Grown Lettuce Products by Round

Several similarities can be drawn from Figures 6 and 7. First, organic products in Figure 6 and the hydroponic products in Figure 7 both saw increases in mean WTP in the information round. Additionally, for both types of products, there was minimal change in bids from the baseline round to the blind tasting round. In comparing the distribution of bids across all production methods, the blind tasting treatment changed mean WTP more for the conventional lettuce than the information treatment and the information treatment moved average WTP for organic lettuce and hydroponic lettuce more than the blind tasting treatment did. This implies that consumers were willing to pay more for conventional lettuce after tasting it, but seemed unaffected by the taste of the hydroponically and organically grown products. However, the hydroponic production information and the disclosure of the products' color and production methods proved to be impactful when consumers bid for organic and hydroponic products, but not so much for the conventional products.

Although mean values and censorship can be extracted from Figures 2-7, caution should be taken when making further assumptions and implications. To analyze which factors affect consumers' WTP for the vegetable products, a more sophisticated analysis of the bids is necessary.

First, an OLS model of the WTP bids will next be estimated, followed by a tobit model to account for any negative bid values and the zero-valued bids. Then, a random effects tobit model, random parameters model, and finally a random parameters tobit model will be estimated to account for any unobserved randomness. Following the estimations using full bids, this chapter will take a look at the implied differences in WTP. Afterwards, the prestige-sensitivity scale and health-consciousness scale questions will be used in a Latent Class Analysis (LCA) to identify the subgroups of consumers. Indicator variables will be formed that will characterize each individual's prestige and health tendencies and will be included in the econometric models. Finally, a random parameters model will be estimated using information from the LCA.

Bid Censoring

As mentioned in the methodology chapter, participants were allowed to bid any value for the auction products, even negative and zero values. Negative bids for a good can be interpreted in one of two ways – either the individual would be willing to pay to not consume the good or the negative bid is the amount of money they would have to get paid to consume the good. Generally, negative bidding behavior is found in valuation studies in which the focal products have controversial or undesirable attributes, such as genetically modified foods and irradiated meat (Parkhurst, Shogren, and Dickinson, 2004). This study produced no negative WTP observations, however several bids took the value of zero. Table 8 shows the percentage of bids equal to zero for each product by treatment. The amount of zero bids ranged 1% to nearly 13.5% for the products. Table 8 also reflects the censorship observed in the probability distributions of Figures 2-4.

Table 8. Percentage of Bids Censored at $0.00 by Round and Product

	Treatment		
Product Type	Baseline	Tasting	Information
Organic Green	1.00	2.68	2.25
Organic Red	8.46	8.93	8.99
Hydroponic Red	6.97	4.46	7.87
Hydroponic Mixed	3.98	3.57	2.25
Conventional Red	6.97	4.46	13.48
Conventional Green	2.99	3.57	6.74
Hydroponic Green	5.97	8.93	7.87
All Bids	5.29	5.49	7.44

Subjects' pooled WTP bids for the lettuce products were modeled as a function of product attributes (production method and color) and treatment variables (blind tasting and production information treatments), as well as demographic and behavior characteristics (age, education, income, race, gender, marital status, household size, and average weekly fruit and vegetable expenditures). Any interaction effects were detected through implied differences in bids for each model, which are discussed later. Conventionally grown green lettuce was used as the baseline for all econometric models. See Table 1 for definitions of the demographic and behavioral variables used in the WTP econometric models.

Ordinary Least Squares Model

Initially, the bids for the lettuce products were pooled and used in a rudimentary ordinary least squares (OLS) model. Although OLS estimation provides a good first step in analysis, it is just that. It fails to account for bid censoring and any unobserved correlation or heterogeneity that may affect bids. Therefore, any estimates obtained from the OLS model have the potential to be biased and unreliable. Regardless, output from OLS estimation is a first look at which factors may play a significant role in the more advanced models to come.

Results from the OLS estimation of WTP for the lettuce products can be seen in Table 9. Several factors are revealed as significant in consumers' WTP valuations. Compared to conventional green lettuce, consumers were generally willing to pay more for organically grown lettuce and less if the lettuce was red ($P<0.10$ and $P<0.01$, respectively). Evidently, hydroponic production seemed to have no significant effect on WTP. The same can be said for both of the treatments. However, mean bids for organically grown lettuce and mixed color lettuce increased significantly after individuals learned about hydroponic production and each of the lettuce products' production methods (conventional, organic, or hydroponic production) in the production information treatment. It is worth noting that only one product was mixed in color and it was hydroponically grown. Therefore, the variable "Mixed" also represents the impact of the hydroponically grown mixed lettuce product.

Table 9. Ordinary Least Squares Estimates for Willingness to Pay (WTP) for Lettuce Products

	Parameter		Standard Error
Constant	1.540	***	0.108
Organic	0.105	*	0.061
Hydroponic	-0.006		0.061
Red	-0.269	***	0.051
Mixed	0.047		0.084
Treatments			
Tasting	0.067		0.069
Production Information	0.020		0.079
Product/Treatment			
Tasting x Organic	-0.078		0.099
Tasting x Hydroponic	-0.016		0.099
Tasting x Red	0.018		0.083
Tasting x Mixed	-0.039		0.137
Info x Organic	0.192	*	0.115
Info x Hydroponic	0.057		0.115
Info x Red	0.103		0.097
Info x Mixed	0.303	*	0.160
Demographics/ Behaviors			
AGE	-0.004	***	0.001
DEDU2	-0.054		0.077
DEDU3	0.040		0.080
DINC2	0.277	***	0.056
DINC3	0.233	***	0.053
DRACE2	0.059		0.056
DRACE3	-0.015		0.048
FEMALE	0.094	***	0.036
MARRIED	-0.133	***	0.048
HHSIZE	0.026	**	0.013
AWFV	-0.001		0.001

Note: *, **, ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Regarding the demographic and behavior factors, the OLS estimation reveals several interesting points. In general, older individuals and subjects who are married express significant price discounts for the lettuce products ($P<0.01$). Individuals who earn more than $49,999 annually, larger households, and females are willing to pay significant premiums for the lettuce products. Plausible explanations for the direction of each significant factor will be included in discussions of the more advanced models.

Tobit Model

Using the same regressors that are in the OLS model, a constant parameters tobit model is estimated to account for the previously ignored censored bids. Table 10 presents the results from the tobit estimation, as well as the marginal effects of each variable, the standard deviation of residuals (σ), and the value for the maximized log-likelihood function.

When comparing output from the two estimations thus far, the OLS and tobit models, hardly any differences exist. Both models are similar in the sense that of the variables that were statistically significant in the OLS model continued to be significant in the tobit estimation ($P<0.05$). The signs of the significant variables' coefficients did not change across the two models, but minute differences in the magnitudes can easily be seen. Although being a female and married still significantly affect bids, the confidence interval decreases from 99% to 95%.

Unlike the OLS output, only the direction of change can be interpreted from the coefficients in the tobit output. Table 10 displays the magnitude of change as the factors' marginal effects on the dependent variable ($\partial y/\partial x$). Regarding production and color attributes, organically produced lettuce and mixed color lettuce had a positive marginal effect on consumers' bids. However, red-colored lettuce caused a negative marginal effect, which suggests consumers prefer the baseline color, green lettuce. This negative reaction may mean consumers are unfamiliar with red lettuce, compared to the common green color of lettuce, or it could imply that consumers view red lettuce as a complementary lettuce product to be used with green lettuce and not necessarily consumed alone. However, the blind tasting continued to have no significant effect on consumers' WTP. This could be for several reasons, one of which is that the lettuce samples were prepared without dressing, which may not be how the participants usually eat lettuce. Another reason may that the lettuce samples were not different enough to affect consumers WTP valuations. This hypothesis will later be addressed in the random parameters tobit model.

One structural difference between the OLS model and the tobit model is that the tobit estimation reveals a large amount of censored bids (165 bids censored at $0.00 out of 2,699 total observations), which confirms the hypothesis that the OLS model ignores several observations. Another attractive quality of the tobit model, relative to the OLS estimation, is that a calculation of the standard deviation of residuals is included, which indicates the tobit model's predictive ability. In this case, the standard deviation of residuals was estimated to be 0.900, which was statistically significant at the 99% confidence interval.

Table 10. Constant Parameters Tobit Model Estimates of Willingness to Pay (WTP) for Lettuce Products

	Parameter		Standard Error	∂y/∂x
Constant	1.498	***	0.113	
Organic	0.109	*	0.064	0.086
Hydroponic	-0.011		0.064	-0.009
Red	-0.283	***	0.054	-0.225
Mixed	0.052		0.089	0.041
Treatments				
Tasting	0.063		0.073	0.050
Production Information	0.003		0.084	0.002
Product/Treatment				
Tasting x Organic	-0.086		0.104	-0.086
Tasting x Hydroponic	-0.017		0.104	-0.017
Tasting x Red	0.028		0.087	0.028
Tasting x Mixed	-0.031		0.144	-0.031
Info x Organic	0.206	*	0.122	0.206
Info x Hydroponic	0.065		0.122	0.065
Info x Red	0.106		0.102	0.106
Info x Mixed	0.322	*	0.169	0.322
Demographics/ Behaviors				
AGE	-0.004	***	0.001	-0.004
DEDU2	-0.056		0.082	-0.056
DEDU3	0.044		0.085	0.044
DINC2	0.281	***	0.059	0.281
DINC3	0.239	***	0.056	0.239
DRACE2	0.073		0.059	0.073
DRACE3	0.004		0.051	0.004
FEMALE	0.093	**	0.038	0.093
MARRIED	-0.121	**	0.050	-0.121
HHSIZE	0.029	**	0.014	0.029
AWFV	-0.001		0.001	-0.001
σ	0.900	***	0.013	
Log-Likelihood	-3537.693			

Note: *, **, ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Random Effects Tobit Model

The constant parameters tobit model accounts for censored bids, but it is still a relatively low-powered analysis of the WTP data. Experimental auctions like the ones in this study usually produce bids for several similar products over multiple rounds, which result in panel data that is multilayered and complex in nature. Lusk, Feldkamp, and Schroeder (2004) advise that bids submitted by the same participant for repeated products across multiple rounds are most likely strongly associated. In an effort to remedy this correlation and to pay heed to any unobserved randomness that may affect individuals' bids, a modified version of the constant parameter tobit model was estimated. The resulting unrestricted model is a random effects tobit model, which accounts for random differences within individuals while continuing to recognize the censored bids. Results from the random effects tobit estimation are organized in Table 10.

Because this model takes the tobit form, it can easily be compared to the constant parameters tobit model. A likelihood ratio (LR) test was used to compare the fit of the two tobit models. This comparison test stems from Maximum Likelihood Estimation (MLE), which is a method that uses random sampling to measures whether all necessary variables are included. In other words, out of all of the possible values the parameters of the random sample can take, the value that has the highest probability of resembling the observed data should be chosen (Wooldridge, 2009).

In a LR test, one of the models is assumed to be a restricted version, while the other (in this case, the one incorporating random effects) is considered as the unrestricted model. The following LR test statistic is estimated as twice the amount of difference between the log-likelihood functions of the restricted and unrestricted models, L_R and L_U, respectively (Wooldridge, 2009).

(34) $$LR = -2\ln\left(\frac{L_R}{L_U}\right) = -2[\ln(L_R) - \ln(L_U)]$$

The LR test statistic is distributed as chi-squared with as many degrees of freedom as there are restrictions and with a null hypothesis that the omitted variables' coefficients are not statistically significant, which means that there is minimal difference between the two maximized likelihood functions and that the unrestricted model is statistically sufficient (Greene, 2003). In an LR test that compared the random effects tobit model to the constant parameters tobit model, the null hypothesis ($H_0\colon \sigma_u = 0$) was rejected, which implies that random effects exist in the data and the random effects tobit model is sufficient ($P<0.01$).

In addition to the standard deviation of the individual specific randomness, σ(u), and the standard deviation of the overall error term, σ(e), the percentage of total variance that stems from individual random effects, ρ, is included in Table 10. McAdams (2011) states that ρ takes a value between zero and one and is interpreted as the percentage of variance that is due to randomness. If ρ is equal to zero, none of the existing variance originates from individual random effects. On the other hand, if ρ takes a value of one, it can be implied that 100% of the variance in the data is due to randomness at the individual level. In this case, ρ is 0.537 and statistically significant at the 99%

confidence interval, which means that 53.7% of the variance in the data is caused by individual random effects.

With regard to the product characteristics, treatments, and interaction effects, several differences exist when comparing the standard tobit model and the random effects tobit model. In addition to slight adjustments in the magnitude of the significant variables' effects, organic production becomes more significant. Increases in significance are also detected in the interaction effects, which can be seen in the impact of the information treatment on consumers' bids for organically grown lettuce products and mixed color lettuce products.

Several differences can be seen between the two models when analyzing the effects of demographic and behavioral factors on WTP. Because the most recent analysis is performed at the individual level, the demographic and behavior characteristics that were significant in the standard tobit model (Table 10) are not detected in the random effects tobit model's output (Table 11).

Like the constant parameters tobit model, the marginal effects should be used to make inferences about the size of the variables' impacts on WTP. Table 11 shows that individuals were willing to pay \$0.09 more for organic lettuce compared to conventional lettuce. However, consumers were willing to pay \$0.23 less for red lettuce than they were for green lettuce. After learning about hydroponic vegetable production and following the revelation of the production method of each lettuce product, consumers are willing to pay \$0.17 more for organic lettuce products and \$0.25 more for the mixed product, which is hydroponically produced.

Table 11. Random Effects Tobit Model of Willingness to Pay (WTP) for Lettuce Products

	Parameter		Standard Error	∂y/∂x
Constant	0.314	***	0.314	
Organic	0.108	***	0.043	0.086
Hydroponic	-0.010		0.043	-0.008
Red	-0.282	***	0.036	-0.225
Mixed	0.052		0.060	0.042
Treatments				
Tasting	0.038		0.051	0.030
Production Information	0.055		0.060	0.044
Product/Treatment				
Tasting x Organic	-0.087		0.070	-0.070
Tasting x Hydroponic	-0.020		0.070	-0.016
Tasting x Red	0.027		0.059	0.022
Tasting x Mixed	-0.037		0.097	-0.030
Info x Organic	0.208	**	0.082	0.166
Info x Hydroponic	0.071		0.082	0.057
Info x Red	0.105		0.069	0.084
Info x Mixed	0.315	***	0.114	0.251
Demographics/ Behaviors				
AGE	-0.004		0.003	-0.003
DEDU2	-0.055		0.241	-0.044
DEDU3	0.033		0.250	0.026
DINC2	0.283		0.174	0.226
DINC3	0.238		0.167	0.190
DRACE2	0.066		0.173	0.053
DRACE3	0.015		0.149	0.012
FEMALE	0.101		0.112	0.081
MARRIED	-0.122		0.148	-0.097
HHSIZE	0.028		0.040	0.023
AWFV	-0.001		0.003	-0.001
σ(u)	0.652	***	0.037	
σ(e)	0.605	***	0.009	
ρ	0.537	***	0.029	
Log-Likelihood	-2768.934			
Likelihood Ratio Test	1537.520	*** [c]		

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively

[a] Standard deviation of individual-specific error

[b] Standard deviation of overall error

[c] Likelihood ratio test of Random Effects Tobit versus Constant Parameters Tobit

Random Parameter Linear Model

To account for randomness individual-specific heterogeneity in the coefficients, a random parameter linear model, also referred to as a random parameters linear model, was estimated using simulated maximum likelihood estimation methods in NLOGIT 5.0©. This estimation's results are shown in Table 12.

Unlike the previously discussed tobit models, this linear estimation allows for direct interpretation of the coefficients' magnitudes and signs. Participants expressed price premiums of $0.10 for organically grown lettuce and a deep price discount of $0.28 for red lettuce. Hydroponic production and the treatments continue to have an insignificant impact on consumers' WTP for lettuce. However, consumers' bids for organically grown lettuce significantly increased after they learned about hydroponic production. The significant increase of $0.18 suggests that the more consumers know about specific products, the more they are willing to spend on them. A similar result can also be seen in the significant price premium of $0.30 for mixed lettuce (which is hydroponically produced) following the information treatment.

Almost all demographic and behavior characteristics become statistically significant ($P<0.10$) in the random parameters linear estimation. Positive effects are found among females and individuals earning more $49,999 annually, as well as Hispanic consumers and those who have completed some graduate school ($P<0.05$). Furthermore, females are willing to pay $0.14 more than males in WTP and Hispanic individuals are willing to pay $0.10 more than Caucasian shoppers. In contrast, older consumers and those who are married expressed price discounts of for the lettuce products. An interesting result arises in married individuals, who are willing to pay \$0.24 less for the lettuce products than consumers who are not married.

Estimates of the standard deviations of the random effects at the individual level ($\hat{\sigma}_u^2$), which shows that not only are there significant random effects between individuals in general, but also individual-specific effects emanating from the treatment and specific product characteristics, are also reported in Table 12. Other measurements included in Table 12 are the standard deviations of the random variables, which measure the differences in the intercept and the coefficients between individuals, and otherwise recognize any unobserved individual heterogeneity (McAdams et al., 2013; Segovia, 2014). It is clearly seen that the product attributes and treatment variables, except for mixed color, as well the interaction effects of the blind tasting and information treatments on hydroponic and organic lettuces have statistically significant standard deviations, which means that the random effects of the product attributes and treatments varied from participant to participant and responses are, therefore, heterogeneous.
In comparing results from the random effects tobit model (intercept is random) to the random parameters linear estimation results, (intercept and coefficients are random) several differences must be addressed. Organic production and the information treatment become slightly less significant after coefficients are allowed to vary randomly in the random parameters linear model. Other changes emerge in analyzing the demographic characteristics; specifically age, income, post-graduate education, race, gender, marital status, and household size become significant (P<0.10). Now, being older and married have a significantly negative impact on WTP, while being Hispanic, a female, and

earning a higher income cause positive effects on WTP for lettuce (P<0.01). Married individuals may be willing to pay less for lettuce than their non-married counterparts as a result of the influence of the tastes and preferences of their spouses.

Table 12. Random Parameter Linear Model Estimates of Willingness to Pay (WTP) for Lettuce Products

	Parameter	Standard Error
Means of Random Parameters		
Constant	1.442 ***	0.072
Product		
Organic	0.100 **	0.047
Hydroponic	-0.011	0.045
Red	-0.281 ***	0.037
Mixed	0.048	0.048
Treatments		
Tasting	0.052	0.051
Production Information	0.055 **	0.064
Product/Treatment		
Tasting x Organic	-0.075	0.079
Tasting x Hydroponic	-0.027	0.075
Tasting x Red	-0.026	0.062
Tasting x Mixed	-0.036	0.109
Info x Organic	0.178 **	0.086
Info x Hydroponic	0.061	0.087
Info x Red	0.086	0.098
Info x Mixed	0.308 **	0.128
Demographics/ Behaviors		
AGE	-0.004 ***	0.001
DEDU2	-0.027	0.050
DEDU3	0.104 **	0.052
DINC2	0.407 ***	0.032
DINC3	0.262 ***	0.033
DRACE2	0.102 ***	0.035
DRACE3	-0.056 *	0.031
FEMALE	0.134 ***	0.022
MARRIED	-0.238 ***	0.030
HHSIZE	0.015 *	0.008
AWFV	0.000	0.001

	Parameter	Standard Error
Standard Deviations of Random Parameters		
Constant	0.597 ***	0.010
Organic	0.229 ***	0.019
Hydroponic	0.163 ***	0.017
Red	0.196 ***	0.018
Mixed	0.021	0.032
Tasting	0.171 ***	0.017
Production Information	0.110 ***	0.025
Tasting x Organic	0.148 ***	0.038
Tasting x Hydroponic	0.101	0.030
Tasting x Red	0.006	0.033
Tasting x Mixed	0.089	0.062
Info x Organic	0.194 ***	0.048
Info x Hydroponic	0.380 ***	0.035
Info x Red	0.027	0.046
Info x Mixed	0.096	0.071
$\hat{\sigma}^2_u$	0.529 ***	0.003
Log-Likelihood	-2526.506	

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Random Parameters Tobit Model

While the random parameters linear model accounts for heterogeneity in the intercept and the coefficients, it does not accommodate the censored nature of the WTP data like the tobit models do. Therefore, a random parameters tobit model is warranted. Such a model captures any unobserved individual random effects, while also satisfying any bid values that are negative or zero.

Several interesting results are found in the output from this paramount estimation, which is displayed in Table 13. In reference to the product attributes of production method and color, organic production and red colored lettuce remain significant across models, as do the interaction effects of the information treatment on bids for organically grown lettuce and mixed color lettuce. More specifically, consumers are willing to pay a premium of $0.12 for organic lettuce compared to conventional green lettuce, whose average retail price is $1.47. This increase in WTP can be explained by the proliferation of organic versions of conventional products, as well as a growing desire and consciousness among consumers to fill their diets with a variety of healthy foods. Despite inconclusive findings in literature that compares organic and conventional products, the results in Table 13 support Yiridoe, Bonti-Ankomah, and Martin's (2005) conclusions that most consumers were generally not willing to pay a premium more than 20% for organically produced foods.

Red colored lettuce receives deep price discounts of around $0.28 in WTP for lettuce, compared to conventional green lettuce. Because lettuce is known for its green color, this negative effect may be a result of consumers' unfamiliarity with the deep red hue of some of the products. This deep discount may be a result of individuals viewing red leaf lettuce as more of an ingredient salads or a complementary good to green leaf lettuce.

While the blind tasting treatment and its interaction effects continued to be insignificant, the opposite is true for the information treatment. The dissemination of hydroponic production information continued to affect bids for specific lettuce products. Regarding the information treatment's interaction effects, consumers are willing to pay \$0.22 more for organically grown lettuce and \$0.30 more for mixed color lettuce (which is a hydroponically grown product) after learning about hydroponic production and knowing each lettuce product's respective production method. Regarding production information Mabiso et al. (2005) found a similar result when consumers expressed price premiums of \$0.48 for tomatoes that were labeled "U.S. grown." Segovia (2014) found a similar result when consumers were willing to pay more for domestic tomatoes compared to imported tomatoes after they knew where the growing location of the tomato products. Overall, these findings suggest that consumers are becoming more interested and conscious in how fresh fruits and vegetables are grown, but express price premiums only after they are provided with differentiating production information.
The random parameters tobit estimation also provides interesting results regarding demographic and behavioral characteristics. Unlike previously estimated models, females now express a price discount of \$0.07 compared to males for the lettuce products. Consumers who are married, older, individuals who are neither Caucasian nor Hispanic (Asian/Pacific Islander, African American, Native American/Indigenous, or

other race), and those who spend more on average weekly fruits and vegetable also express price discounts for the lettuce products. Specifically, married consumers are willing to pay $0.14 less for the lettuce products compared to those who are not married. Perhaps this negative effect occurs as a result of married individuals' changed tastes and preferences and indicates an influence of their spouses' tastes. Because the auctions focused on minimally processed heads of lettuce, the negative effects seen in married and older consumers may be negative because they may be comparing it to bagged lettuce and they may not usually buy heads of lettuce. Perhaps due to busy work and family schedules, married and older individuals may not purchase a head of lettuce because it takes more time to prepare. Alternatively, perhaps a head of lettuce provides too much lettuce for those who are married or older; therefore they may be discounting it from a practical standpoint. In contrast, Hispanic consumers and higher income individuals are willing to pay increases of $0.12 and an average of $0.30, respectively. This may reflect the amount of lettuce in Hispanic consumers' diets, relative to other individuals. The level of formal education attainment and household size revealed no significant effect on consumers' WTP for the lettuce products. Segovia (2014) found similar results regarding the effects of income and weekly expenditures on consumers' WTP for tomato products.

Table 12 also provides estimations of the standard deviations of the random parameters. Consumers' valuations are homogeneous for organic lettuce, red lettuce, and mixed lettuce after the blind tasting treatment. Consumers also reacted in a similar manner toward red lettuce following the information treatment. Additionally, a LR test was performed to compare the random parameters tobit model with the standard tobit and random effects tobit models. Results from the test show that the random parameters model was more appropriate for the data than both of the tobit models (P<0.01).

Table 13. Random Parameter Tobit Estimates of Willingness to Pay (WTP) for Lettuce Products

	Parameter		Standard Error	$\partial y/\partial x$
Means of Random Parameters				
Constant	1.732	***	0.073	
Product				
Organic	0.116	**	0.049	0.115
Hydroponic	-0.005		0.048	-0.005
Red	-0.284	***	0.040	-0.283
Mixed	0.049		0.061	0.049
Treatments				
Tasting	0.052		0.056	0.052
Production Information	0.042		0.067	0.042
Product/Treatment				
Tasting x Organic	-0.083		0.079	-0.082
Tasting x Hydroponic	-0.036		0.078	-0.036
Tasting x Red	0.033		0.063	0.033
Tasting x Mixed	-0.036		0.111	-0.036
Info x Organic	0.212	**	0.093	0.211
Info x Hydroponic	0.086		0.092	0.085
Info x Red	0.090		0.101	0.089
Info x Mixed	0.298	**	0.136	0.297
Demographics/ Behaviors				
AGE	-0.004	***	0.001	-0.004
DEDU2	0.018		0.053	0.017
DEDU3	0.039		0.055	0.039
DINC2	0.240	***	0.038	0.239
DINC3	0.348	***	0.036	0.346
DRACE2	0.119	***	0.038	0.118
DRACE3	-0.188	***	0.033	-0.187
FEMALE	-0.071	***	0.024	-0.071
MARRIED	-0.136	***	0.032	-0.135
HHSIZE	-0.008		0.009	-0.008
AWFV	-0.003	***	0.001	-0.003

	Parameter		Standard Error	$\partial y/\partial x$
Standard Deviations of Random Parameters				
Constant	0.653	***	0.073	
Organic	0.266	***	0.049	0.115
Hydroponic	0.218	***	0.048	-0.005
Red	0.200	***	0.040	-0.283
Mixed	0.069	**	0.061	0.049
Tasting	0.234	***	0.056	0.052
Production Information	0.153	***	0.067	0.042
Tasting x Organic	0.023		0.079	-0.082
Tasting x Hydroponic	0.061	*	0.078	-0.036
Tasting x Red	0.003		0.063	0.033
Tasting x Mixed	0.061		0.111	-0.036
Info x Organic	0.242	***	0.093	0.211
Info x Hydroponic	0.415	***	0.092	0.085
Info x Red	0.061		0.101	0.089
Info x Mixed	0.178	**	0.136	0.297
σ(e)	0.552	*** [a]	0.004	
Log-Likelihood	-2715.002			
Likelihood Ratio Test	1645.380	*** [b]		
Likelihood Ratio Test	107.865	*** [c]		

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

[a] Standard deviation of individual-specific error

[b] Likelihood ratio test of Random Parameters Tobit versus Constant Parameters Tobit

[c] Likelihood ratio test of Random Parameters Tobit versus Random Effects Tobit

Comparison of Estimated WTP Models

A range of models was estimated in an effort to gain a better understanding of the factors that affect consumers' valuations of the lettuce products. The OLS model provides a good starting point, but ultimately cannot cope with the idiosyncrasies of the data and despite the random parameters linear model's attempts to account for unobserved correlation and heterogeneity; its ignorance of the censored nature of the bids proved the estimation was ill-suited for the job. The opposite is true for the constant parameters tobit model – it deliberately accounts for bid censoring, but comes up short in accounting for the randomness of the data. In the estimated random effects tobit model, censored bids are accounted for and unobserved randomness between individuals was absorbed by the intercept; however, this model does not pick up on any unobserved randomness from the treatments or product characteristics that could affect consumers' bids. Therefore, a random parameters tobit estimation seems to describe the data the best, because it recognizes the censored nature of the data and accounts for heterogeneity in both the intercept and coefficients.

In the journey to find the most appropriate model, several findings revealed themselves to be robust across models. Significant variables such as organic production, red colored lettuce, and the effect of the information treatment on bids for organic lettuce and mixed color lettuce were all fairly consistent throughout the analysis. The insignificant effect of the blind tasting treatment might imply that consumers simply did not detect a large enough sensory difference to affect their bids for the lettuce products. Additionally, the demographic and behavioral variables had mixed effects on WTP across the several models that were estimated.

Implied Differences in Bids for Lettuce Products

The econometric models estimated thus far used the full bids to estimate the different variables that affect WTP for the lettuce products. A narrower, refined approach that compares the differences in an individual's WTP between treatments may provide more information about lettuce buying behavior.

Differences in Bids between Treatments

In analyzing WTP data from experimental auctions, one might be curious as to whether participants' bid values changed after a specific treatment. To measure whether there was a difference in bids across rounds, Wilcoxon's Paired t-tests (also called Mann-Whitney-U tests) were used to compare differences in bids values for each product from the baseline round to the designated treatment round. Results from the comparison tests can be found in Table 14.

A null hypothesis that bids in each treatment round were statistically equal to bids submitted in the baseline round was tested. The resulting p-values in Table 14 reveal mixed findings for each of the products. In comparing bids after the blind tasting treatment to bids submitted in the baseline round, the only products that saw significant differences in WTP were conventional red lettuce, conventional green lettuce, and hydroponic green lettuce ($P < 0.05$).

One interesting point here is that consumers valued the conventionally produced lettuces differently after tasting them, but did not significantly adjust their bids for organically produced lettuces. Both sets of products were alike in color and were purchased from the same vendor simultaneously; therefore, theoretically, the only explanation for this difference appears to be the production method.

In reference to changes in bids from the baseline round to the information treatment, several differences should be noted. The WTP for both organic lettuces, as well as all hydroponic products were statistically different after receiving information about hydroponic production ($P < 0.001$). This result was expected as the hydroponic information made comparisons to conventional production. The information treatment also caused significant changes in bids for conventional green lettuce ($P < 0.10$). Recall that the production method and variety of each lettuce product were revealed after the participants reviewed the hydroponic production handout. Thus, these changes in the bids are also due to labeling information that would typically be available in any retail environment.

Table 14. Results from Wilcoxon Signed Rank Tests [(a)]

	Conventional Green Lettuce	Conventional Red Lettuce	Organic Green Lettuce	Organic Red Lettuce	Hydroponic Green Lettuce	Hydroponic Red Lettuce	Hydroponic Mixed Lettuce
	p-values	p-values	p-values	p-values	p-values	p-values	p-values
Tasting	0.0304	0.0036	0.2424	0.5880	0.0157	0.4043	0.8909
Information	0.0963	0.3063	0.0000	0.0000	0.0000	0.0001	0.0003

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

The p-values in Table 14 only reflect comparisons made between each treatment and the baseline; therefore the estimates should not be compared between treatment rounds, as all participants did not receive the same treatment. Additionally, Table 14 does not reveal which direction the treatments influenced WTP values – it simply shows whether or not they were significantly equivalent to the baseline.

One way of analyzing the direction and magnitude of change in average WTP after a treatment is to measure the difference between the bids submitted in the baseline and the bids submitted during the treatment round. This process is also known as calculating the implied differences of WTP. Table 15 shows how the differences in bids between the baseline and the each treatment were calculated, as well as the proportion of bids that changed positively and negatively, as well as the percentage of bids that saw no change following the specified treatment.

In the case of the blind tasting treatment, a large number of participants either increased or decreased their bids after tasting the lettuce products. This was expected, as individuals are assumed to be heterogeneous in their taste preferences and palates when it comes to lettuce. Table 15 also shows that a majority of bids increased after participants learned about how lettuce products were grown. About 25% of bidders' WTP values were unaffected by the production information. One surprising result was the percentage of negative differences in participants' WTP after the information treatment. This result reveals that a portion of the sample decreased their WTP after learning about hydroponic production and after labeling information was made available.

Table 15. Proportions of Positive, Negative, and Zero Changes in Willingness to Pay (WTP) from Baseline Round, Summed for All Products

Type of Bid Difference	Calculation	Percentage of Negative Differences	Percentage of Zero Differences	Percentage of Positive Differences
DeltaBidTaste	$WTP_{Tasting}$ - $WTP_{Baseline}$	37.07	20.85	42.08
DeltaBidInfo	$WTP_{Production\ Information}$ - $WTP_{Baseline}$	22.26	24.96	52.78

Summary statistics of the implied differences are provided in Table 16. Regarding the blind tasting treatment, median bids for all products reflect negative differences, which means that the median subject's bid for every product decreased after tasting the products. In contrast, the only products to not receive a median value of zero after the information round were the conventionally grown lettuce products, which received negative values.

Aside from median values, other factors in Table 16 provide insight into how the specified treatments affected participants' bids for each product. For example, the range of differences illustrates the severity of the impact each treatment had on individuals' baseline bids. Moreover, Table 16 points out how the mean bids in each round changed in relation to the baseline product, conventional green lettuce. In the blind tasting treatment, bid differences for all of the lettuce varieties except for the conventional red lettuce were negative. This implies that nearly all of the differences were either discounts or smaller premiums than the mean difference in bids for conventional green lettuce. Table 16 also shows all positive values for mean bid differences relative to the baseline product in the information round, which means that compared to conventional green lettuce, consumers experienced increases in WTP for all of the products after they received the production and labeling information.

Table 16. Summary Statistics for Implied Differences of Bids

Product Type	Mean Bid Difference	Std. Dev.	Minimum	Median	Maximum	Deviation from Mean Bid of Baseline Product within the Round, Based on Implied Differences [a]
A. Bids - Blind Tasting Treatment						
Conventional Green Lettuce	0.14	0.68	-2.50	-0.10	2.00	Baseline Product
Conventional Red Lettuce	0.18	0.65	-2.00	-0.10	2.25	+0.04
Organic Green Lettuce	0.07	0.65	-1.50	-0.24	3.50	-0.07
Organic Red Lettuce	-0.11	0.59	-2.50	-0.50	1.25	-0.25
Hydroponic Green Lettuce	-0.17	0.74	-2.00	-0.50	2.01	-0.31
Hydroponic Red Lettuce	0.05	0.65	-1.25	-0.25	2.00	-0.09
Hydroponic Mixed Lettuce	0.01	0.60	-1.50	-0.30	2.25	-0.13
B. Bids - Production Information Treatment						
Conventional Green Lettuce	-0.10	0.57	-2.15	-0.25	1.25	Baseline Product
Conventional Red Lettuce	0.06	0.52	-2.00	-0.10	2.50	+0.16
Organic Green Lettuce	0.33	0.64	-3.00	0.00	1.50	+0.43
Organic Red Lettuce	0.28	0.56	-1.50	0.00	1.75	+0.38
Hydroponic Green Lettuce	0.34	0.61	-1.31	0.00	2.05	+0.44
Hydroponic Red Lettuce	0.29	0.67	-1.75	0.00	3.00	+0.39
Hydroponic Mixed Lettuce	0.33	0.82	-2.00	0.00	3.01	+0.43

Two random parameter linear models, one for each treatment, were estimated using the implied differences in WTP as the dependent variable and maximum likelihood simulation methods in NLOGIT 5.0©. In these models, the explanatory variables indicate how each individual's bid changes depending on the treatment. In other words, these analyses will detect which product attributes and demographic characteristics significantly affect changes in WTP after each treatment. Results from the two estimations of bid differences are separately estimated and discussed by treatment in the following section.

Implied Differences in WTP: Blind Tasting Treatment

Based on whether subject like or dislike the taste of the lettuce products, their WTP may increase, decrease, or remain constant from the baseline bid value. A random parameter linear model allows the dependent variable, implied differences, to vary in these directions while accounting for the individual randomness of tastes and preferences. Results for the random parameter linear estimation of implied differences for the blind tasting treatment are described in Table 17.

As previously mentioned, the difference in bids between the blind tasting round and the baseline round is considered the dependent variable. As a result, the parameter estimates in Table 17 reflect the differences in the parameters between the blind tasting and the baseline. For instance, compared to the baseline product (conventional green lettuce), the difference in WTP that was due to organic varieties and hydroponic products decreased in value by \$0.19 and \$0.23, respectively, from the baseline to the blind tasting round ($P < 0.01$). Table 17 also points out several demographic and behavioral factors that played a significant role in the difference of WTP between the baseline and tasting rounds. Specifically, household size, average weekly expenditures on fruits and vegetables, and individuals who were neither Caucasian nor Hispanic had significantly positive effects on the change in WTP that resulted from the blind tasting treatment ($P < 0.05$).

Table 17. Random Parameter Linear Model Estimates of Implied Differences in Willingness to Pay (WTP) for Lettuce Products, Blind Tasting Treatment

	Parameter		Standard Error
Means of Random Parameters			
Constant	-0.324	**	0.153
Organic	-0.188	***	0.060
Hydroponic	-0.234	***	0.061
Red	0.026		0.047
Mixed	0.087		0.088
Demographics/ Behaviors			
AGE	0.001		0.002
DEDU2	0.238	*	0.124
DEDU3	0.239	*	0.127
DINC2	0.097		0.096
DINC3	-0.066		0.094
DRACE2	0.009		0.092
DRACE3	0.162	**	0.063
FEMALE	0.011		0.049
MARRIED	-0.058		0.088
HHSIZE	0.045	***	0.017
AWFV	0.003	**	0.001
Standard Deviations of Random Parameters			
Constant	0.235	***	0.020
Organic	0.055		0.042
Hydroponic	0.028		0.035
Red	0.021		0.035
Mixed	0.005		0.066
$\hat{\sigma}_u^2$	0.608	***	0.021
Log-Likelihood	-712.088		

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In addition to the parameter estimations and significance levels, it is clear that none of the random parameters' standard deviations were significant, which means that any changes seen in WTP as a result of the product attributes were homogeneous at the individual level.

Implied Differences in WTP: Production Information Treatment

Just like the blind tasting treatment, the hydroponic production handout and the products' label information could affect participants' WTP values positively, negatively, or not at all. Consequently, implied differences for the production information treatment were analyzed using a random parameter linear model. The information handout compares certain aspects of hydroponic production (i.e. water-use efficiency, cleanliness of final product, and reduced pesticide applications) to field production, and it was assumed that consumers might change the valuations positively, negatively, or not at all after reviewing this information. Results from the random parameter linear estimation, in Table 18, show that the product attributes of organic production and hydroponic production had a significantly positive effect on the change in WTP from the baseline round to the information treatment.

In reference to the demographic characteristics that affected the difference in WTP between the baseline and information treatment, older individuals, those with at least some graduate education, and individuals who did not identify as Hispanic or Caucasian negatively impacted the change in WTP after the information treatment. The remainder of the demographic and behavioral factors did not have a significant effect on bids following the information treatment. Unlike the blind tasting treatment results in Table 17, all of the estimated standard deviations of the random parameters were statistically significant, which implies that the effects of every product attribute varied for each individual.

Table 18. Random Parameter Linear Model Estimates of Implied Differences in Willingness to Pay (WTP) for Lettuce Products, Production Information Treatment

	Parameter		Standard Error
Means of Random Parameters			
Constant	0.307	*	0.159
Organic	0.293	***	0.061
Hydroponic	0.348	***	0.060
Red	0.030		0.035
Mixed	0.074		0.085
Demographics/ Behaviors			
AGE	-0.005	***	0.002
DEDU2	-0.171		0.114
DEDU3	-0.323	***	0.118
DINC2	-0.022		0.069
DINC3	0.102		0.068
DRACE2	0.113		0.071
DRACE3	-0.267	***	0.101
FEMALE	0.076		0.051
MARRIED	-0.080		0.061
HHSIZE	0.019		0.022
AWFV	0.002	*	0.001
Standard Deviations of Random Parameters			
Constant	0.211	***	0.022
Organic	0.411	***	0.042
Hydroponic	0.350	***	0.033
Red	0.145	***	0.035
Mixed	0.653	***	0.058
$\hat{\sigma}_u^2$	0.465	***	0.011
Log-Likelihood	-406.126		

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Latent Class Analysis

The random parameters models described thus far have revealed that unobserved heterogeneity does exist at the individual level for certain product attributes and treatments, but they are not equipped to describe the origins of heterogeneity. A latent class analysis (LCA) provides a useful tool to further describe the behavioral tendencies and lifestyle peculiarities of consumers. By using a set of observed indicators that provide insight into the prestige seeking and health-consciousness behavior of the sample, a LCA classifies participants into unobserved latent classes, or subgroups. This analysis can be particularly useful to help researchers visualize the potential sources of heterogeneity. Initially, a LCA was applied by using a combination of the health and prestige scale responses. Next, a LCA was estimated separately for the health scale responses and then for the prestige scale responses. Each LCA proceeded as follows: 1) identify the appropriate number of latent classes, 2) characterize the latent classes using the demographic and indicator variables, and 3) estimate each class's WTP for lettuce using the random parameters tobit model.

Health & Prestige Scales Combined

The first LCA that was performed used a combination of the most relevant questions from the prestige scale and the health scale. The two scales were combined to investigate consumers' views of health and prestige combined. That is, in the age of juicing trends and celebrities turning into clean-diet cookbook authors, what if now being aware and involved with one's health has become a fashionable and prestigious product? If this is true, perhaps consumers can be described by their responses to the health-consciousness questions and prestige-related questions. The first step was to estimate the appropriate number of latent classes (also known as subgroups) within the sample. A series of latent class models were estimated, with the number of latent classes ranging from 2 to 9. To choose the appropriate number of classes, several measurements were compared. Estimates for the log-likelihood values, AIC, BIC, and Adjusted BIC are specified for model in Table 19. In comparing the minimum Information Criteria (IC) for each number of latent classes, it can be seen that the minimum AIC and Adjusted BIC statistics favored a four-class model, while the minimum BIC favored a three-class model. When IC measurements differ, as they do in Table 19, a researcher is often uncertain as to which criterion is best to follow. Dziak et al. (2012) suggested that when ICs differ, AIC frequently tends to favor a large model (overfitting), whereas BIC presents risks because it often supports a smaller model (underfitting). However, if the sample size n is small, Dziak et al. (2012) stated that the error is usually underfitting and the preferred criterion is the one with lower rates of underfitting, in this case the AIC. Additionally, the estimated class-membership probabilities for the three-class model were 40.72%, 27.04%, and 32.23% for each class, while the probabilities for the four-class model were a were 37.38%, 24.16%, 32.60%, and 5.85%. Regarding the size of each class in the two models, Lanza et al. (2007) suggested that the probabilities of each class should be nontrivial and differentiable such that the division of classes can easily be seen. Therefore, based on the IC values, guidance from the LCA literature, and the class membership probabilities, a four-class model was chosen.

Table 19. Comparison of Latent Class Models: Combination of Health-Consciousness and Prestige-Seeking Scales

Number of latent classes (S)	Log Likelihood at convergence	AIC[a]	BIC[b]	Adjusted BIC
2	-1215.0	701.7	784.3	705.1
3	-1158.0	613.7	739.3	618.9
4	-1132.4	588.5	757.0	595.4
5	-1125.7	601.2	812.6	609.8
6	-1112.1	600.1	854.4	610.5
7	-1101.2	604.2	901.5	616.4
8	-1092.8	613.4	953.7	627.4
9	-1081.6	616.9	1000.1	632.6

Note: Boldface type indicates the selected model

[a] AIC (Akaike Information Criterion)

[b] BIC (Bayesian Information Criterion)

Following the process of identifying the most appropriate number of latent classes, the estimated class membership probability and indicator-response probabilities for each of the four classes were organized and can be seen in Table 20. The class-membership probabilities show that 37.38% of participants gained membership to Class 1, 24.16% of participants were members of Class 2, 32.60% of participants were members of Class 3, and 5.85% of participants were members of Class 4. The indicator-response probabilities reflect the probability of observing a specific indicator variable in each latent class. The purpose of using the relevant questions from both the health and prestige scales was to investigate whether the differences between consumers can be defined by their prestige-seeking and health-conscious lifestyle habits.

Regarding individuals in Class1, Table 20 shows there is a 49% probability that they exercised four times per week or more and there is a 21% probability that consumers in this class spent more than $50 per week on fruits and vegetables. Additionally, 96% of consumers in this class identified with being involved with their health and there is a 91% probability that the consumers in this class are very self-conscious about their health. Moreover, there was 100% probability that consumers in Class 1 were aware of their health. Class 1 was relatively not affected by prestige, as only 15% of the members in Class 1 thought people notice when they buy the most expensive brand of a product, only 5% of the class were likely to think other people make judgments about them by their purchases, and there was a 9% probability that Class 1 consumers thought buying high priced versions of products evoked an emotion in other people. Class 1's relatively low preference for prestige can be seen more clearly in the fact that there was zero chance of observing a consumer who enjoyed the prestige of buying a high priced product and thought buying costly versions of inexpensive goods was impressive. Due to this description, Class 1 was characterized as "High Health, Low Prestige."

Class 2 was relatively similar to Class 1 in terms of habits related to health, such as weekly exercise and fruit and vegetable expenditures, and the indicators relating to health consciousness and awareness. However, the most obvious difference between Class 1 and Class 2 can be seen in the indicator response probabilities for the prestige variables. There was a 72% probability that members of Class 2 think people notice when they buy the most expensive brand of a product, compared to a 15% chance that consumers in Class 1 agreed with this statement. A similar result is found when it comes to evoking emotion in others by purchasing the high priced version of a product, with a 72% probability of observing consumers who agreed with this notion in Class 2, compared to a paltry 9% in Class 1. Moreover, there was a 60% probability that consumers in Class 2 thought others make judgments about them by the products they buy, compared to just 5% in Class 1. Given these comparisons, Class 2 was named “High Health, High Prestige.”

Class 3 represented 32.60% of participants and the probabilities of observing strong preferences toward healthy, active lifestyles and prestige-seeking behavior were relatively low compared to the other classes. For example, Table 20 shows that 28% of the consumers in Class 3 were likely to exercise four or more times per week and there was only a 3% probability of observing consumers who spent more than $50 per week on fruits and vegetables. Preferences for prestige in Class 3 were similar to those of Class 1, as Class 3 mirrored Class1’s relatively low probability (15%) of consumers who thought people notice when they the most expensive brands. Single-digit probabilities were also observed in Class 3, as only 6% enjoyed the prestige of buying a high-priced product, 8% thought it says something to people when they buying the high-priced version of a product, and a mere 2% thought that it was impressive to buy the costly brand of a relatively inexpensive good. However, response probabilities to the health questions are not the same as those in the “High Health” groups (Class 1 and Class 2). For instance, there was only a 17% probability of consumers in Class 3 being very self-conscious about their health and only 2% agreed that they constantly examine their health, compared to respective 83% and 55% indicator-response probabilities seen in Class 2. In addition, there was only a 37% probability that consumers in Class 3 identified with being very involved with their health, which intuitively supports the relatively low probabilities of frequent exercise habits and larger expenditures on fruits and vegetables. For these reasons, Class 3 was named "Low Health, Low Prestige."

The final class in the four-class LCA possesses similar characteristics of Class 2 and Class 3. Class 4 is similar to Class 2 in the sense that relatively high probabilities are seen in the indicator variables relating to prestige-seeking behavior. For example, there is a 64% probability that consumers in Class 4 think that others make judgments about them by their purchases, compared to a 60% probability in Class 2. Consumers in both classes agreed with questions regarding what others thought of them by their high-priced purchases (i.e. people notice when they buy the most expensive brand of a product; it says something to people when you buy the high priced version of a product). However, Class 4 exhibited similar probabilities to Class 3 with regard to the health-awareness and fruit and vegetable purchases. For example, there was an 18% probability of consumers in Class 4 being very self-conscious about their health, compared to a 17% probability in Class 3. Additionally, there is a zero probability that consumers in Class 4 constantly examined their health, compared to a 2% probability in Class 3. However, in terms of being involved with their health and being aware of their health, consumers in Class 4 exhibited the lowest probabilities of all the classes. Given this description, Class 4 was characterized as "Low Health, High Prestige."

Table 20. Latent Class Parameter Estimates for Four-Class Model: Combination of Health and Prestige Scales

Variable	Definition	Class 1 *High Health, Low Prestige*	Class 2 *High Health, High Prestige*	Class 3 *Low Health, Low Prestige*	Class 4 *Low Health, High Prestige*
		Latent class membership probabilities (π)			
		37.38%	24.16%	32.60%	5.85%
		Indicator-response probabilities (θ)			
EXER	Exercised 4 times per week or more	0.49	0.36	0.28	0.45
WFVEX	Spend more than $50 per week on fruits and vegetables	0.21	0.17	0.03	0.09
Agree with or are neutral to the following statements:					
PNOTICE	"People notice when you buy the most expensive brand of a product"	0.15	0.72	0.15	0.82
PENJOY	"I enjoy the prestige of buying a high priced product"	0.00	0.47	0.06	0.73
PSAYS	"It says something to people when you buy the high priced version of a product"	0.09	0.72	0.08	0.91
PCHEAP	"Your friends will think you are cheap if you consistently buy the lowest priced version of a pr	0.06	0.43	0.09	0.64
PJUDGE	"I think others make judgements about me by the kinds of products and brands I buy"	0.05	0.60	0.15	0.64
PIMPRESS	"Even for a relatively inexpensive product, I think that buying a costly brand is impressive"	0.00	0.23	0.02	0.18
HSELF	"I'm very self-conscious about my health"	0.91	0.83	0.17	0.18
HCONST	"I'm constantly examining my health"	0.69	0.55	0.02	0.00
HAWARE	"I'm usually aware of my health"	1.00	0.91	0.69	0.09
HINVOLV	"I'm very involved with my health"	0.96	0.98	0.37	0.00

The demographic and behavioral characteristics of each class can be seen in Table 21. On average, individuals in Class 1, Class 2, Class 3, and Class 4 were around 44 years old, 33 years old, 44 years old, and 32 years old, respectively. In reference to gender and marital status, Class 1 was made up of mostly females who were not married, Class 2 was composed of mostly males who were not married, Class 3 primarily included females who were not married, and Class 4 was made up of equal parts male and female, most of whom were not married.

The four classes can be grouped into two trends when it comes to analyzing average household size and income. Meaning, these statistics for Class 1 and Class 2 are higher than the sample mean for household size and income, while Class 3 and Class 4 average household size and income are lower than the means of the sample. The households of Class 1 and Class 2 were 2.58 and 2.71, which are on average larger than the sample mean household size of 2.54. A similar trend can be seen in the average annual incomes of Class 1 and Class 2, which are $55,000 and $53,085 – higher than the sample mean income of $51,599. On the other hand, households in Class 3 and Class 4, 2.37 and 2.40 respectively, were on average smaller than the sample mean household size of 2.54. Following in a similar manner, average annual incomes of Class 3 and Class 4 were $48,281 and $41,363, respectively, which fall below the sample mean income of $51,599.

With regard to education attainment, Class 2 was the most educated class, as 100% of the individuals in Class 2 had an education level that was higher than just a high school diploma (64% had a Bachelor's degree or at least some college and 36% had a graduate education). Based on the percentage of individuals with a high school education only, Class 1 was also highly educated, followed by Class 4, and lastly Class 3. It is worth mentioning that although only 6% of participants belonged to Class 4, it held the highest percentage of post-graduate education as 50% of its members had a graduate education or some graduate school. Classes 1 and 2 were mainly comprised of Caucasian individuals (approximately 76% and 65%, respectively) and Asian/ Pacific Islander, African American, Native American or other races (about 15% and 23%, respectively). Classes 3 and 4 also mostly consisted of Caucasian consumers (75% and 70%, respectively) and Hispanic individuals (around 15% and 20%, respectively). Each class's indicator-response probabilities for weekly fruit and vegetable expenditures in Table 20 are echoed in each class's means for fresh produce on hand as a percentage of their full stock in Table 21. In other words, it was expected that Class 1 would have the highest percentage of fresh vegetables on hand as a percentage of full stock compared to the other classes, because Class 1 had the highest probability of consumers who spent more than \$50 weekly on fruits and vegetables in Table 20. Class 2 had the next highest percentage of fresh vegetables on hand, followed by Class 4 and finally Class 3.

After the demographics and behavioral characteristics of the latent classes were characterized, the WTP for lettuce was estimated for each class using a random parameters tobit model. Results from this analysis are presented in Table 22 for each class and juxtaposed by estimates for all participants. All participants valued organically grown lettuce ($P < 0.05$), especially after learning about production and labeling information. Marginal effects indicate that increases in WTP for organic lettuce reached nearly \$0.10. Participants' WTP values for the mixed and organically grown lettuce were positively affected ($P< 0.05$) after they learned about production and labeling information – WTP values for mixed and organic products increased by \$0.28 and \$0.21, respectively. Red colored lettuce evoked a significant discount in consumers' valuations – their WTP decreased \$0.29 due to the red hue.

Table 21. Demographic and Behavioral Characteristics of Participants by Latent Class: Combination of Health and Prestige Scales

Variable	Category	All Participants		Class 1 *High Health, Low Prestige*		Class 2 *High Health, High Prestige*		Class 3 *Low Health, Low Prestige*		Class 4 *Low Health, High Prestige*	
		Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent
Age (years)		40.9		43.96		33.38		44.31		31.70	
Household Size (Individuals)		2.54		2.58		2.71		2.37		2.40	
Education	High School Diploma or less		6.74		5.63		0.00		12.73		10.00
	Bachelor's Degree or at least some college		58.43		60.56		64.29		54.55		40.00
	Graduate Courses or more		34.83		33.80		35.71		32.73		50.00
Race	Caucasian		72.83		76.47		65.12		75.00		70.00
	Hispanic		12.14		8.82		11.63		15.38		20.00
	Asian/ Pacific Islander, African American, Native American, or Other		15.03		14.71		23.26		9.62		10.00
Gender	Female		57.59		70.67		40.00		55.74		50.00
	Male		42.41		29.33		60.00		44.26		50.00
Marital Status	Married		43.72		45.45		40.43		45.31		36.36
	Not Married		56.28		54.55		59.57		54.69		63.64
Annual Household Income ($)		51,599		55,000		53,085		48,281		41,363	
Primary Shopper	Primary Shopper		84.08		84.62		78.72		87.69		81.82
	Secondary Shopper		15.92		15.38		21.28		12.31		18.18
Fresh Vegetables on Hand (% of full stock)		35.51		42.51		34.06		28.73		31.59	

In addition to analyzing the parameter estimates for the whole sample, further insight may be gained by estimating WTP for each of the latent classes. As can be seen in Table 22, all classes expressed significant price discounts for red lettuce. The red color had the smallest negative effect on consumers in Class 1 (around 37% of the participants), who decreased WTP by $0.18. With a decrease in WTP of $0.74, Class 4 (around 6% of the participants) expressed the largest discounts in WTP for red lettuce. Neither the blind tasting treatment nor the production information had a significant effect on WTP, but Class 3 (around 33% of the participants) increased their WTP for organic lettuce by $0.34 ($P < 0.05$) after they learned about hydroponic production and what the products were. Class 3's (Low Health, High Prestige) relatively unhealthy classification coupled with significant premiums for organic lettuce after the production information treatment indicate their tendency to "redeem" their sedentary lifestyles by placing value on unconventionally produced lettuce and thus perhaps communicating a desire or intention to eat what they perceive to be healthier lettuce. This result echoes Segovia's (2014) findings that consumers are willing to pay a price to redeem themselves and make up for their unhealthy habits.

A positive relationship was found between household size and WTP for lettuce for all classes except for consumers in Class 4, who decreased WTP by $0.27. Recall that Class 4 was comprised of individuals who were not very aware of or involved with their health, but did indicate prestige-seeking behavior through their purchases. However, in comparing the mean WTP (E[y]) across all classes, Class 4 has the highest value, followed by Class 1, then Class 2, and finally Class 3.

Even more detailed information when the classes are compared against a baseline class. Table 23 organizes results from a random parameters tobit model in which Classes 1, 2, and 4 were compared to Class 3. Relative to Class 3 (Low Health, Low Prestige), significant differences in WTP for the lettuce products can be seen with Classes 1 and 2, but not Class 4. More specifically, marginal effects reveal that consumers of Class 2 and Class 1 (the more health-conscious groups compared to Classes 3 and 4) were willing to pay $0.32 and $0.09 more for the lettuce products, respectively, than Class 3. On the other hand, no statistical difference exist between the WTP values submitted by consumers in Class 4 (Low Health, High Prestige) and the values submitted by individuals in Class 3, which was considered the baseline group. Findings from Table 22 and Table 23 not only provide a look at the behavior of each class, but also offer valuable marketing insight into how the classes relate to each other.

Table 22. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products by Latent Class: Combination of Health and Prestige Scales

	Class 1			Class 2			Class 3			Class 4			All Participants		
	High Health, Low Prestige			*High Health, High Prestige*			*Low Health, Low Prestige*			*Low Health, High Prestige*					
E[y]	1.56			1.43			1.30			1.59			1.45		
	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x
Means of Random Parameters															
Constant	1.251 ***	0.066		1.406 ***	0.080		1.034 ***	0.074		2.425 ***	0.283		1.519 ***	0.038	
Organic	0.127	0.083	0.123	-0.012	0.121	-0.012	0.137 *	0.078	0.136	0.209	0.461	0.208	0.099 **	0.047	0.098
Hydroponic	-0.080	0.076	-0.080	-0.073	0.098	-0.073	0.078	0.081	0.077	0.250	0.455	0.249	-0.005	0.046	-0.005
Red	-0.181 ***	0.068	-0.180	-0.291 ***	0.083	-0.291	-0.335 ***	0.068	-0.334	-0.741 ***	0.201	-0.739	-0.292 ***	0.039	-0.290
Mixed	0.069	0.113	0.068	0.152	0.119	0.152	-0.046	0.103	-0.046	0.063	0.464	0.063	0.500	0.062	0.050
Tasting	0.072	0.096	0.071	-0.067	0.109	-0.067	0.126	0.102	0.125	-0.013	0.567	-0.013	0.036	0.052	0.036
Production Information	-0.018	0.126	-0.018	0.078	0.140	0.078	0.051	0.123	0.051	1.564	1.256	1.560	0.069	0.066	0.069
Tasting x Organic	0.018	0.137	0.018	-0.006	0.208	-0.006	-0.224	0.140	-0.223	-0.276	1.198	-0.276	-0.082	0.080	-0.081
Tasting x Hydroponic	0.029	0.130	0.029	-0.014	0.180	-0.014	-0.234	0.144	-0.233	0.072	0.736	0.072	-0.030	0.076	-0.030
Tasting x Red	-0.022	0.105	-0.022	0.076	0.202	0.075	0.055	0.126	0.055	0.219	0.273	0.219	0.034	0.064	0.034
Tasting x Mixed	-0.092	0.186	-0.092	-0.096	0.279	-0.096	0.089	0.186	0.088	-0.269	0.513	-0.269	-0.038	0.112	-0.038
Info x Organic	0.193	0.165	0.192	0.277	0.248	0.276	0.337 **	0.167	0.335	0.038	0.900	0.038	0.209 **	0.091	0.208
Info x Hydroponic	0.067	0.156	0.067	-0.017	0.223	-0.017	0.164	0.161	0.163	-0.125	1.265	-0.125	0.061	0.089	0.061
Info x Red	0.071	0.174	0.071	0.042	0.175	0.042	0.067	0.166	0.067	0.183	1.119	0.183	0.079	0.103	0.079
Info x Mixed	0.322	0.234	0.320	0.159	0.287	0.159	0.298	0.249	0.296	0.507	1.497	0.506	0.284 **	0.137	0.282
Demographics/ Behaviors															
HHSIZE	0.050 ***	0.011	0.501	0.067 ***	0.016	0.067	0.104 ***	0.014	0.103	-0.262 ***	0.077	-0.268	-0.014 *	0.008	-0.014
AWFV	0.002 **	0.001	0.002	-0.002 **	0.001	-0.002	0.000	0.001	0.000	-0.012 **	0.005	-0.012	-0.001 **	0.001	-0.001
Standard Deviations of Random Parameters															
Constant	0.657 ***	0.019		0.644 ***	0.025		0.587 ***	0.019		0.431 ***	0.099		0.642 ***	0.010	
Organic	0.248 ***	0.037		0.427 ***	0.046		0.013	0.039		0.060	0.186		0.221 ***	0.020	
Hydroponic	0.205 ***	0.028		0.110 ***	0.036		0.329 ***	0.029		0.182	0.117		0.187 ***	0.016	
Red	0.222 ***	0.030		0.134 ***	0.036		0.203 ***	0.034		0.231 **	0.116		0.191 ***	0.017	
Mixed	0.062	0.056		0.142 **	0.059		0.103 **	0.052		0.435 *	0.232		0.016	0.032	
Tasting	0.164 ***	0.031		0.237 ***	0.044		0.192 ***	0.029		0.460 ***	0.135		0.148 ***	0.016	
Production Information	0.122 ***	0.040		0.151 ***	0.047		0.090 *	0.047		1.083	0.777		0.001	0.025	
Tasting x Organic	0.246 ***	0.061		0.065	0.088		0.030	0.069		0.066	0.337		0.159 ***	0.038	
Tasting x Hydroponic	0.122 **	0.054		0.057	0.073		0.238 ***	0.046		0.318 *	0.187		0.127 ***	0.029	
Tasting x Red	0.069	0.057		.34153D-04	0.093		0.043	0.051		0.371 **	0.182		0.021	0.035	
Tasting x Mixed	0.037	0.111		0.036	0.141		0.008	0.116		0.025	0.255		0.040	0.064	
Info x Organic	0.295 ***	0.070		0.031	0.112		0.552 ***	0.109		2.197	1.527		0.279 ***	0.047	
Info x Hydroponic	0.538 ***	0.060		0.048	0.089		0.276 ***	0.082		0.894	0.977		0.424 ***	0.035	
Info x Red	0.119	0.077		0.242 ***	0.086		0.019	0.094		0.254	0.675		0.023	0.046	
Info x Mixed	0.451 ***	0.107		0.025	0.189		0.244 **	0.120		0.361	2.411		0.218 ***	0.068	
σ(e)	0.551 ***	0.006		0.515 ***	0.009		0.481 ***	0.007		0.562 ***	0.040		0.554 ***	0.004	
Log-Likelihood	-1142.664			-629.966			-766.270			-173.447			-2804.041		

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 23. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products: Class 3 as Baseline, Combination of Health and Prestige Scales

	Parameter		Standard Error	∂y/∂x
Means of Random Parameters				
Constant	1.406	***	0.040	
Organic	0.107	**	0.047	0.107
Hydroponic	-0.005		0.045	-0.005
Red	-0.284	***	0.038	-0.283
Mixed	0.046		0.060	0.046
Tasting	0.030		0.052	0.029
Production Information	0.054		0.066	0.054
Tasting x Organic	-0.082		0.077	-0.082
Tasting x Hydroponic	-0.046		0.074	-0.046
Tasting x Red	0.029		0.062	0.029
Tasting x Mixed	-0.036		0.109	-0.036
Info x Organic	0.202	**	0.089	0.202
Info x Hydroponic	0.060		0.090	0.060
Info x Red	0.082		0.098	0.082
Info x Mixed	0.267	**	0.134	0.266
Demographics, Behavioral Characteristics, and Classes				
HHSIZE	0.031	***	0.007	0.031
AWFV	-0.005	***	0.001	-0.005
CLASS1	0.325	***	0.026	0.324
CLASS2	0.093	***	0.030	0.093
CLASS4	-0.015		0.050	-0.014
Standard Deviations of Random Parameters				
Constant	0.635	***	0.011	
Organic	0.263	***	0.019	
Hydroponic	0.215	***	0.016	
Red	0.205	***	0.018	
Mixed	0.077	***	0.027	
Tasting	0.222	***	0.019	
Production Information	0.148	***	0.025	
Tasting x Organic	0.004		0.040	
Tasting x Hydroponic	0.025		0.034	
Tasting x Red	0.062	*	0.033	
Tasting x Mixed	0.029		0.065	
Info x Organic	0.295	***	0.043	
Info x Hydroponic	0.411	***	0.031	
Info x Red	0.022		0.043	
Info x Mixed	0.232	***	0.068	
σ(e)	0.544	***	0.003	
Log-Likelihood	-2790.341			

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Health Consciousness Scale

Although the first LCA classified consumers based on a combination of the health and prestige information elicited from scale-style questions, perhaps health-consciousness and prestige-seeking behaviors are mutually exclusive. Therefore, the second LCA that was performed only used responses to the full health-consciousness scale, as well as information about weekly exercise and fruits and vegetable spending habits. The same process as the combination LCA was used to determine the number of latent classes, characterize the classes, and to estimate each class's WTP for lettuce using a random parameters tobit model.

Similar to the previous analysis, a sequence of models ranging from 2 to 9 classes was estimated to determine the appropriate number of classes. The corresponding log-likelihood values and Information Criteria (IC) are listed in Table 24. It can be seen that the minimum AIC and Adjusted BIC both favored a four-class model, while the minimum BIC suggested a three-class model. Keeping consistent with the methods used in determining the best number of classes for the previous LCA, the model chosen for this LCA was a four-class model.

Table 24. Comparison of Latent Class Models: Defined by Health-Consciousness Scale

Number of latent classes (S)	Log Likelihood at convergence	AIC[a]	BIC[b]	Adjusted BIC
2	-1063.0	542.9	618.9	546.0
3	-1018.9	478.7	594.3	483.4
4	-988.7	442.3	597.6	448.7
5	-979.0	446.9	641.8	454.9
6	-967.9	448.8	683.3	458.4
7	-962.4	461.8	735.9	473.0
8	-954.6	470.1	784.0	483.0
9	-947.4	479.8	833.2	494.2

Note: Boldface type indicates the selected model

[a] AIC (Akaike Information Criterion)

[b] BIC (Bayesian Information Criterion)

Table 25 shows the approximate class membership probabilities and indicator-response probabilities for the four-class model. Based on their responses to questions regarding perceived health-consciousness, weekly exercise, and weekly fruit and vegetable spending habits, it can be seen that around 43% of the participants are members of Class 1, roughly 20% of the sample belongs to Class 2, another 20% are members of Class 3, and about 18% of subjects are members of Class 4. Compared to the other classes, consumers in Class 1 were likely to be highly active (48% probability that they exercised four times per week or more) and relatively healthy eaters (17% probability that they spend more than $50 per week on fruits and vegetables). In addition to being active in their health, consumers in Class 1 were most likely to be conscious and aware of their health on a daily basis. For these reasons, consumers in Class 1 were dubbed “Health Fanatics.”

Alternatively, consumers in Class 2 were the least active out of all the classes, within only a 15% probability that they regularly exercised. The same trend is observed in Class 2’s fruit and vegetable purchasing behavior, as there was only an 8% probability that consumers spent more than $50 per week on produce. Similar to Class 1, individuals in Class 2 were likely to be aware of their health and sensitive to changes in their health. However, consumers in Class 2 were less likely than Class 1 to constantly examine their health or be involved with their health. Given that they were highly likely to be aware of their health, but were relatively less likely to act on improving their health through exercise and a diet heavy in fruits and vegetables, consumers in Class 2 were named the “Health Ponderers.”

Consumers in Class 3 were fairly active, as they exhibited exercise habits similar to Class 1, but the 8% probability that individuals in Class 3 spent more than $50 per week on fruits and vegetables was the same as Class 2. Although 100% of Class 3 agreed that they constantly examined their health, they were the least likely out of all the classes to be involved with their health and be aware of their health, especially on a daily basis (8% probability, 31% probability, and 3% probability, respectively). Despite their tendency to exercise regularly, individuals in Class 3 do not entertain other habits becoming of a health-conscious lifestyle, such as consuming a diet largely based fruits and vegetables and being aware of, conscious of, or involved with their health. Given their interest in exercising but failure to incorporate other elements of a healthy lifestyle, consumers in Class 3 were named the "Vanity Seekers."

Class 4 is relatively similar to Class 1 in its exercise behavior and fruit and vegetable spending habits (41% and 16% probabilities were respectively observed for Class 4). Consumers in Class 4 also exhibited relatively high probabilities when it comes to their consciousness, awareness, and involvement with their health. Although there was an 86% probability that members of Class 4 were aware of their health, there was only a 3% probability that they were aware of it throughout their day. Class 4 is similar to Class 3 in that there is a 41% probability that consumers in the former notice how they feel physically as they go through the day, which reinforces the idea that consumers in Class 4 were aware of and paid attention to their health, but not necessarily throughout the day. Therefore, due to their activity level, healthy eating habits, and general consciousness and awareness of their health, Class 4 is labeled as "Health Conscious."

Table 25. Latent Class Parameter Estimates for Four-Class Model: Health Scale Only

		Class 1 *Health Fanatics*	**Class 2** *Health Ponderers*	**Class 3** *Vanity Seekers*	**Class 4** *Health Conscious*
		Latent class membership probabilities (π)			
		42.84%	19.63%	19.58%	17.95%
Variable	Definition	Indicator-response probabilities (θ)			
exer	Exercised 4 times per week or more	0.48	0.15	0.41	0.41
wfvex	Spend more than $50 per week on fruits and vegetables	0.17	0.08	0.08	0.16
Agree with the following statements:					
href	"I reflect about my health a lot"	0.99	0.46	0.21	0.86
hself	"I'm very self-conscious about my health"	0.93	0.23	0.15	0.78
hatten	"I'm generally attentive to my inner feelings about my health"	0.96	0.56	0.18	0.65
hconst	"I'm constantly examining my health"	0.77	0.05	1.00	0.35
halert	"I'm alert to changes in my health"	0.97	0.95	0.26	0.92
haware	"I'm usually aware of my health"	0.99	0.97	0.31	0.86
hstate	"I'm aware of the state of my health as I go through the day"	1.00	0.95	0.03	0.03
hnotice	"I notice how I feel physically as I go through the day"	1.00	0.97	0.44	0.41
hinvolv	"I'm very involved with my health"	0.99	0.72	0.03	0.84

Table 26 depicts the demographic and behavioral characteristics for each of the four latent classes, as well as for the sample. Demonstrating general consistency, the estimated average ages of Class 1, Class 2, Class 3, and Class 4 were 41 years old, 42 years old, 39 years old, and 42 years old, respectively. Classes 1, 2, and 3 were mostly consisted of females who were not married, while married females predominantly occupied Class 4.

Compared to the other classes, consumers in Class 4 had the largest households and income levels on average (2.7 individuals per household with an average of $58,750 annually), while Class 2 represented, relatively, the smallest households (2.4 individuals per household) and consumers in Class 3 had the lowest annual incomes ($41,923 on average) compared to the other classes. Individuals in Classes 2 and 3 were mostly Caucasian or Hispanic, while 93.51% of the individuals in Class 1 and 87.51% of consumers in Class 4 were either Caucasian, Asian/Pacific Islander, African American, Native American or of other races. The percentage of fresh vegetables that consumers in Class 1 and Class 4 had on hand, roughly 40% and 34% respectively, reflected the high weekly fruit and vegetable expenditures expressed by these consumers in Table 24.

Table 26. Demographic and Behavioral Characteristics of Participants by Latent Class: Health Scale Only

Variable	Category	All Participants		Class 1 *Health Fanatics*		Class 2 *Health Ponderers*		Class 3 *Vanity Seekers*		Class 4 *Health Conscious*	
		Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent
Age (years)		40.9		40.47		42.21		39.26		42.34	
Household Size (Individuals)		2.54		2.51		2.43		2.53		2.73	
Education	High School Diploma or less		6.74		3.90		5.41		22.58		0.00
	Bachelor's Degree or at least some college		58.43		66.23		67.57		35.48		51.52
	Graduate Courses or more		34.83		29.87		27.03		41.94		48.48
Race	Caucasian		72.83		80.52		68.57		72.41		59.38
	Hispanic		12.14		6.49		17.14		20.69		12.50
	Asian/ Pacific Islander, African American, Native American, or Other		15.03		12.99		14.29		6.90		28.13
Gender	Female		57.59		56.63		57.89		57.14		60.00
	Male		42.41		43.37		42.11		42.86		40.00
Marital Status	Married		43.72		42.35		36.84		43.59		54.05
	Not Married		56.28		57.65		63.16		56.41		45.95
Annual Household Income ($)		51,599		53,869			49,737		41,923		58,750
Primary Shopper	Primary Shopper		84.08		83.72		87.18		89.74		75.68
	Secondary Shopper		15.92		16.28		12.82		10.26		24.32
Fresh Vegetables on Hand (% of full stock)		35.51			40.42		27.03		32.70		35.93

Just as in the first LCA, the WTP for lettuce was estimated for each latent class following the characterization of each class. Results from the random parameters tobit model are organized in Table 27 by latent class. It is evident from the parameter estimates for the full sample model that all participants placed a premium on organic lettuce, but discounted red lettuce. Additionally, participants expressed increases in WTP for organic and mixed varieties of lettuce after learning about hydroponic production and the color and production method of each lettuce product. Bear in mind that the one product that was of mixed color was also hydroponically produced. As expected, average weekly fruit and vegetable expenditures had a slightly negative effect on all participants' WTP for lettuce.

In the case of Class 1 (Health Fanatics, 42.8% of participants), red lettuce garnered WTP discounts of $0.22. The only lettuce products that saw a change in WTP after consumers learned about production and labeling information were the organic varieties. Health Fanatics' WTP for organic lettuce increased by $0.33 following the information treatment, but their valuations for hydroponic and mixed color (hydroponic) varieties were unaffected by the information treatment.

Similar to Class 1 (Health Fanatics), consumers in Class 2 (Health Ponderers, around 20% of the participants) expressed deep discounts in WTP for red lettuce and increased their WTP for organic lettuce after learning about hydroponic growing methods, as well as the production method and color of each lettuce product. Compared to the other classes, consumers in Class 1 (Health Fanatics) and Class 2 (Health Ponderers) increased their WTP for organic lettuce by $0.33 and $0.46, respectively after the information treatment. In contrast, consumers' WTP in Class 3 (Vanity Seekers, around 20% of the participants) and Class 4 (Health Conscious, about 18% of the participants) did not significantly change after they learned about hydroponic production and the growing method of each lettuce product.

In addition to displaying the econometric output of each class, Table 27 shows the average amount each class was willing to pay for each lettuce product. Consumers in classes 2, 3, and 4 (Health Ponderers, Vanity Seekers, and Health Conscious, respectively) were all willing to pay similar amounts of around \$1.37 per head of lettuce, which is below average for all participants of \$1.45. Consumers in Class 1, on the other hand, were willing to pay an average of \$1.56 per head of lettuce. This is expected as they were classified as "Health Fanatics" due to their strong tendencies toward a health-motivated lifestyle compared to the other classes.

Table 28 displays the WTP estimates from a Random Parameter Tobit model in which Classes 1, 2, and 4 (Health Fanatics, Health Ponderers, and Health Conscious, respectively) were compared to Class 3 (Vanity Seekers acted as a baseline). Unlike the previous LCA (in which participants were classified by a combination of the health and prestige classes), all classes were significantly different from consumers in Class 3 in their WTP for lettuce. For example, the Health Fanatics in Class 1 were willing to pay \$0.11 more for lettuce, compared to the Vanity Seekers in Class 3. This result was expected as consumers in Class 1 (Health Fanatics) spent more on fruits and vegetables weekly, and overall indicated more health-centered lifestyles compared to Class 3 (Vanity Seekers). Alternatively, Class 2 (Health Ponderers) and Class 4 (Health

Conscious) were willing to pay less for lettuce ($0.19 and $0.12, respectively) compared to Class 3. Class 2, the Health Ponderers, had the same low probability of spending more than $50 per week on fruits and vegetables as the Vanity Seekers in Class 3, but the Health Ponderers of Class 2 did have a lower percentage of fresh vegetables relative to their full stock than the Vanity Seekers in Class 3. One peculiar result was Class 4's lower WTP compared to Class 3. Class 3 and Class 4 had similar ratios of fresh vegetables on hand relative to their full stock. However, the Health Conscious individuals in Class 4 had higher probabilities of overall more health-centered lifestyle compared to the Vanity Seekers in Class 3 (i.e. Class 4 had higher probabilities of spending more than $50 on fruits and vegetables per week and overall greater health consciousness and awareness).

Table 27. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products by Latent Class: Health Scale Only

	Class 1			Class 2			Class 3			Class 4			All Participants		
	Health Fanatics			*Health Ponderers*			*Vanity Seekers*			*Health Conscious*					
E[y]	1.56			1.37			1.37			1.37			1.45		
Class Membership	42.84%			19.63%			19.58%			17.95%			100%		
	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x
Means of Random Parameters															
Constant	1.513 ***	0.066		1.832 ***	0.071		1.781 ***	0.101		1.310 ***	0.121		1.519 ***	0.038	
Organic	0.072	0.080	0.071	0.155 *	0.081	0.155	0.048	0.161	0.048	0.188	0.161	0.187	0.099 **	0.047	0.098
Hydroponic	-0.024	0.086	-0.024	-0.040	0.078	-0.040	0.046	0.124	0.045	-0.016	0.160	-0.016	-0.005	0.046	-0.005
Red	-0.217 ***	0.067	-0.216	-0.268 ***	0.061	-0.268	-0.408 ***	0.101	-0.405	-0.262 **	0.132	-0.261	-0.292 ***	0.039	-0.290
Mixed	0.014	0.118	0.014	-0.004	0.096	-0.004	-0.014	0.148	-0.014	0.237	0.193	0.235	0.051	0.062	0.050
Tasting	0.057	0.091	0.056	0.115	0.105	0.115	-0.046	0.141	-0.045	0.012	0.129	0.012	0.036	0.052	0.036
Production Information	-0.014	0.124	-0.014	-0.023	0.122	-0.023	0.189	0.179	0.187	0.097	0.223	0.096	0.069	0.066	0.069
Tasting x Organic	-0.008	0.132	-0.008	-0.134	0.144	-0.134	-0.144	0.328	-0.143	-0.181	0.199	-0.180	-0.082	0.080	-0.081
Tasting x Hydroponic	-0.019	0.148	-0.019	-0.040	0.140	-0.040	-0.122	0.225	-0.121	-0.063	0.166	-0.062	-0.030	0.076	-0.030
Tasting x Red	-0.022	0.099	-0.022	-0.040	0.133	-0.040	0.083	0.150	0.082	0.152	0.226	0.151	0.034	0.064	0.034
Tasting x Mixed	-0.070	0.217	-0.070	0.014	0.194	0.014	-0.048	0.285	-0.048	-0.010	0.252	-0.010	-0.038	0.112	-0.038
Info x Organic	0.335 **	0.156	0.334	0.455 ***	0.173	0.455	-0.071	0.238	-0.071	0.107	0.361	0.107	0.209 **	0.091	0.208
Info x Hydroponic	0.203	0.157	0.202	0.100	0.179	0.100	-0.077	0.227	-0.076	0.098	0.306	0.098	0.061	0.089	0.061
Info x Red	0.078	0.161	0.778	0.088	0.139	0.088	0.177	0.329	0.176	0.106	0.355	0.105	0.079	0.103	0.079
Info x Mixed	0.357	0.238	0.356	0.441	0.340	0.441	0.046	0.467	0.046	0.168	0.443	0.167	0.284 **	0.137	0.282
Demographics/ Behaviors															
HHSIZE	0.065 ***	0.013	0.064	-0.020	0.016	-0.020	-0.140 ***	0.021	-0.139	-0.016	0.014	-0.016	-0.014 *	0.008	-0.014
AWFV	-0.003 ***	0.001	-0.003	-0.013 ***	0.001	-0.013	-0.001	0.002	-0.001	0.002 *	0.001	0.002	-0.001 **	0.001	-0.001
Standard Deviations of Random Parameters															
Constant	0.638 ***	0.017		0.529 ***	0.023		0.513 ***	0.030		0.605 ***	0.029		0.642 ***	0.010	
Organic	0.344 ***	0.033		0.242 ***	0.040		0.085	0.066		0.074	0.053		0.221 ***	0.020	
Hydroponic	0.032	0.029		0.412 ***	0.039		0.320 ***	0.049		0.097 **	0.044		0.187 ***	0.016	
Red	0.083 ***	0.029		0.284 ***	0.041		0.284 ***	0.052		0.253 ***	0.048		0.191 ***	0.017	
Mixed	0.039	0.059		0.211 ***	0.065		0.238 ***	0.077		0.280 ***	0.078		0.016	0.032	
Tasting	0.245 ***	0.036		0.178 ***	0.032		0.353 ***	0.047		0.050	0.045		0.148 ***	0.016	
Production Information	0.136 ***	0.046		0.321 ***	0.075		0.080	0.082		0.058	0.075		0.001	0.025	
Tasting x Organic	0.118 *	0.066		0.032	0.073		0.053	0.127		0.250 ***	0.092		0.159 ***	0.038	
Tasting x Hydroponic	0.056	0.055		0.072	0.055		0.206 ***	0.078		0.005	0.082		0.127 ***	0.029	
Tasting x Red	0.025	0.056		0.032	0.060		0.107	0.078		0.055	0.090		0.021	0.035	
Tasting x Mixed	0.005	0.118		0.056	0.130		0.053	0.176		0.035	0.142		0.040	0.064	
Info x Organic	0.303 ***	0.074		0.542 ***	0.148		0.166	0.162		0.028	0.210		0.279 ***	0.047	
Info x Hydroponic	0.514 ***	0.067		0.821 ***	0.143		0.179	0.130		0.338 ***	0.108		0.424 ***	0.035	
Info x Red	0.067	0.065		0.066	0.093		0.002	0.112		0.112	0.128		0.023	0.046	
Info x Mixed	0.148	0.111		0.081	0.176		0.091	0.247		0.069	0.206		0.218 ***	0.068	
σ(e)	0.578 ***	0.006		0.410 ***	0.008		0.534 ***	0.013		0.540 ***	0.011		0.554 ***	0.004	
Log-Likelihood	-1272.798			-462.465			-469.928			-505.943			-2804.042		

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 28. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products: Class 3 as Baseline, Health Scale Only

	Parameter		Standard Error	∂y/∂x
Means of Random Parameters				
Constant	1.624	***	0.046	
Organic	0.099	**	0.048	0.098
Hydroponic	0.013		0.046	0.013
Red	-0.275	***	0.038	-0.274
Mixed	0.051		0.060	0.051
Tasting	0.041		0.054	0.041
Production Information	0.054		0.067	0.054
Tasting x Organic	-0.085		0.078	-0.084
Tasting x Hydroponic	-0.046		0.075	-0.045
Tasting x Red	0.027		0.062	0.027
Tasting x Mixed	-0.039		0.110	-0.039
Info x Organic	0.196	**	0.091	0.196
Info x Hydroponic	0.050		0.090	0.050
Info x Red	0.087		0.098	0.086
Info x Mixed	0.304	**	0.130	0.303
Demographics, Behavioral Characteristics, and Classes				
HHSIZE	0.004		0.008	0.004
AWFV	-0.004	***	0.001	-0.004
CLASS1	0.111	***	0.030	0.110
CLASS2	-0.195	***	0.035	-0.194
CLASS4	-0.118	***	0.037	-0.117
Standard Deviations of Random Parameters				
Constant	0.691	***	0.012	
Organic	0.272	***	0.019	
Hydroponic	0.221	***	0.015	
Red	0.172	***	0.018	
Mixed	0.006		0.032	
Tasting	0.227	***	0.018	
Production Information	0.150	***	0.026	
Tasting x Organic	0.007		0.040	
Tasting x Hydroponic	0.043		0.032	
Tasting x Red	0.030		0.035	
Tasting x Mixed	0.045		0.064	
Info x Organic	0.173	***	0.046	
Info x Hydroponic	0.403	***	0.037	
Info x Red	0.086	*	0.045	
Info x Mixed	0.021		0.073	
σ(e)	0.550	***	0.003	
Log-Likelihood				

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Prestige-Seeking Scale

In an effort to investigate how consumers' prestige-seeking behavior and their WTP for lettuce grown a variety of ways, a third LCA was performed using the full set of questions in the prestige scale. How do consumers who are concerned about the prestige that their purchases bring them respond to lettuce that is produced using a novel method? In other words, is there a connection between individuals who buy goods to be fashionable in the eyes of others and their WTP for unconventionally produced lettuce?

To help answer these questions, the final LCA used the full prestige scale, weekly exercise behavior, and weekly fruit and vegetable expenditures to define several classes, ranging from 2 to 9. Values for the log-likelihood, AIC, BIC, and Adjusted BIC for each class are included in Table 29. In a similar manner as the previous LCAs, Table 29 shows that the Information Criteria (IC) produce contradictory results for the optimal number of classes – the minimum BIC suggested a two-class model, while the minimum Adjusted BIC and AIC proposed a four-class model. To be consistent in selecting the appropriate number of classes, the same methods that were used in the previous LCAs were used for this analysis as well and a four-class model was chosen to be most appropriate.

Table 29. Comparison of Latent Class Models: Defined by Prestige-Seeking Scale

Number of latent classes (S)	Log Likelihood at convergence	AIC[a]	BIC[b]	Adjusted BIC
2	-846.7	335.6	404.9	338.4
3	-826.2	316.6	422.3	320.9
4	-813.3	312.8	454.8	318.6
5	-809.8	327.6	506.0	334.9
6	-802.2	334.5	549.2	343.3
7	-800.0	352.1	603.1	362.3
8	-788.3	350.8	638.2	362.5
9	-785.5	367.1	690.9	788.9

Note: Boldface type indicates the selected model
[a] AIC (Akaike Information Criterion)
[b] BIC (Bayesian Information Criterion)

Table 30 shows the estimated class membership and indicator-response probabilities for the four-class model. Participants were categorized based on their responses to questions about their buying behavior as it pertains to feelings of prestige. Information about participants' weekly exercise and weekly fruit and vegetable spending habits was also used to define the latent classes. Table 30 indicates around 12% of the participants are members of Class 1, about 69% of the sample is represented by Class 2, 9% are members of Class 3, and another 9% are members of Class 4. Relative to the other classes, consumers in Class 1 were the most active, as they had the highest probability of exercising four times per week or more. However, they also demonstrated the lowest probability of spending more than $50 per week on fruits and vegetables. Consumers in this class largely agreed with statements regarding others' perceptions of them by the type, price, or brand of the products they buy, but low probabilities were observed in the indicators that asked about gaining personal satisfaction through their purchases. For example, there was a relatively high probability that individuals in Class 1 thought that people notice when they buy the most expensive brand of a product (91.30%), it says something to people when you buy the high priced version of a product (95.65%), and that others make judgments about them based on the kinds of products and brands they buy (78.26%). Although the demographics of each class will be explained later, the average income of consumers in Class 1, $38,043, was the lowest of all classes. Their relatively low income, but high regard toward what others thought of them through their materialistic purchases led to Class 1 being named "Ambitious Shoppers."

In contrast, consumers in Class 2 (69.48% of participants) were least likely to be concerned about prestige when they purchase goods. For instance, there is a 0% probability that individuals in this class were emotionally affected by buying higher priced brands. Additionally, only 1.37% of Class 2 agreed that they enjoy the prestige of buying a high priced product and only 2.74% agreed that even for a relatively inexpensive product, buying a costly brand was impressive. Compared to the other classes, members of Class 2 were least concerned about what others thought about them and their purchases. Their exercising habits were most similar to Class 1, while their fruit and vegetable buying behavior was most analogous to Class 3's habits. As a result of their disinterest in prestige, members of Class 2 were labeled as "Utilitarian Buyers."

Individuals in Class 3 (9.19% of participants) were relatively least likely to exercise four or more times per week, but compared to the other classes they were likely to spend more than $50 on fruits and vegetables each week. Compared to the other classes, consumers in Class 3 earned the most in average annual income, $57,307. They also exhibited relatively high prestige-seeking behavior, but only for expensive brands. For example, there was a 69.23% probability that expensive brands of a product make them feel good about themselves and there was a 46.15% chance that buying the most expensive brand of a product makes individuals in Class 3 feel classy. Given their relatively high incomes and preference toward expensive brands, Class 3 was named the "Affluent Elitists."

All individuals in Class 4 (9.26% of participants) were likely to feel an increase in self-esteem and enjoy the garnered prestige after buying high priced products. Additionally, there was an estimated 47% probability that consumers in this class agreed that even for a relatively inexpensive product, buying a costly brand was impressive. Compared to the other classes, consumers in Class 4 were most concerned that their friends would think they were cheap if they consistently bought the lowest priced version of a product. As a result of their high regard toward prestige-seeking consumption behavior, Class 4 was named the "Prestige Lovers."

Table 31 describes the demographics and behavioral characteristics of each latent class, as well as for all participants. The average age of Class 1, around 28 years old, was relatively low when compared to the average age of the other classes: 44 years old, 38 years old, and 35 years old. Consumers in Class 1 were primarily male who were not married, while females who were not married made up most of Classes 2, 3, and 4.

Table 30. Latent Class Parameter Estimates for Four-Class Model: Prestige Scale Only

		Class 1	Class 2	Class 3	Class 4
		Ambitious Shoppers	*Utilitarian Buyers*	*Affluent Elitists*	*Prestige Lovers*
		Latent class membership probabilities (π)			
		12.07%	69.48%	9.19%	9.26%
Variable	Definition	Indicator-response probabilities (θ)			
exer	Exercised 4 times per week or more	0.52	0.41	0.15	0.21
wfvex	Spend more than $50 per week on fruits and vegetables	0.04	0.14	0.15	0.16
Agree with the following statements:					
pnotice	"People notice when you buy the most expensive brand of a product"	0.91	0.18	0.54	0.58
pfeel	"Buying a high price brand makes me feel good about myself"	0.00	0.00	0.69	1.00
pclassy	"Buying the most expensive brand of a product makes me feel classy"	0.39	0.00	0.46	0.95
penjoy	"I enjoy the prestige of buying a high priced product"	0.35	0.01	0.38	1.00
psays	"It says something to people when you buy the high priced version of a product"	0.96	0.12	0.15	0.79
pcheap	"Your friends will think you are cheap if you consistently buy the lowest priced version of a product"	0.57	0.09	0.08	0.58
pjudge	"I think others make judgements about me by the kinds of products and brands I buy"	0.78	0.12	0.31	0.53
pimpress	"Even for a relatively inexpensive product, I think that buying a costly brand is impressive"	0.04	0.03	0.00	0.47

The smallest average households occurred in Class 3 (2.00 individuals), while households were largest on average in Class 4 (2.65 individuals). Average annual income for Class 1, Class 2, Class 3, and Class 4 were $38,043, $52,922, $57,307, and $54,210, respectively. The relatively high-income levels of Class 3 consumers rationalize the name "Affluent Elitists," while the relatively low-income levels of consumers in Class 1 provide context to the name "Ambitious Shoppers." Despite their relatively low average income level, Class 1 was the most educated group, as 100% of its members had at least some college education or a Bachelor's degree (61.90%), or had completed at least some graduate school or a Graduate degree (38.10%). Consumers in Class 4 were also highly educated compared to all participants, as nearly 95% had more than a high-school education. Although they were still fairly educated individuals, a greater proportion of Class 2 and Class 3 only had a high school education relative to all participants. Class 4 had the smallest share of fresh vegetables relative to their full stock (25.29%), which could be related to household size as individuals in this class had the largest households (2.65 individuals). This negative relationship between household size and fresh vegetables on hand is also seen with consumers in Class 3, who had the smallest household sizes (2.00 individuals) and highest amount of fresh vegetables on hand as a percentage of their full stock.

Table 31. Demographic and Behavioral Characteristics of Participants by Latent Class: Prestige Scale Only

Variable	Category	All Participants		Class 1 *Ambitious Shoppers*		Class 2 *Utilitarian Buyers*		Class 3 *Affluent Elitists*		Class 4 *Prestige Lovers*	
		Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent
Age (years)		40.90		27.68		44.14		37.58		34.67	
Household Size (Individuals)		2.54		2.43		2.58		2.00		2.65	
Education	High School Diploma or less		6.74		0.00		7.69		10.00		5.88
	Bachelor's Degree or at least some college		58.43		61.90		59.23		50.00		52.94
	Graduate Courses or more		34.83		38.10		33.08		40.00		41.18
Race	Caucasian		72.83		71.43		75.00		81.82		52.94
	Hispanic		12.14		9.52		12.10		9.09		17.65
	Asian/ Pacific Islander, African American, Native American, or Other		15.03		19.05		12.90		9.09		29.41
Gender	Female		57.59		22.73		63.31		58.33		55.56
	Male		42.41		77.27		36.69		41.67		44.44
Marital Status	Married		43.72		26.09		46.53		38.46		47.37
	Not Married		56.28		73.91		53.47		61.54		52.63
Annual Household Income ($)		51,599		38,043		52,922		57,307		54,210	
Primary Shopper	Primary Shopper		84.08		73.91		85.62		76.92		89.47
	Secondary Shopper		15.92		26.09		14.38		23.08		10.53
Fresh Vegetables on Hand (% of full stock)		35.51		36.72		35.46		39.08		25.29	

Similar to the previous LCA applications, the WTP for lettuce was estimated for each latent class after the classes were characterized. Output from the random parameters tobit model is organized in Table 32 by each latent class, as well as for all participants.

The coefficient estimates for the full sample in Table 32 indicate that all participants were willing to pay an average of $1.45 per head of lettuce and they place value on organic lettuce, especially after learning that it was organically grown and after learning about hydroponic lettuce production. All participants were willing to pay premiums for mixed (also hydroponic) lettuce after learning how it was grown. As seen in previous estimations, all participants express strong decreases in WTP for lettuce when it is red.

To gain more information about the participants, separate WTP estimations were calculated for each class. Relative to the other classes, consumers in Class 1, the *Ambitious Shoppers*, were willing to pay the highest in WTP, an average of $1.61 per head of lettuce. Class 1 (12.07% of participants) also expressed the highest discounts for red lettuce – they decreased WTP by $0.57. At first glance, the information treatment did not seem to have a significant effect on WTP. However, once the marginal effects were calculated, the information treatment had a positive significant effect at the 90% confidence level. As expected, larger households were willing to pay less for lettuce. Table 32 shows interesting results for consumers in Class 2. The *Utilitarian Buyers* (69.48% of participants) placed premiums on organic lettuce, especially after the production information treatment. Perhaps this result implies that even consumers who are more concerned about function than prestige find organically grown lettuce attractive. After learning about hydroponic production and learning the growing method of each product, consumers in Class 2 increased their WTP for organic lettuce and mixed lettuce (which was grown hydroponically) by around \$0.24 and \$0.31, respectively. The information treatment had a significant effect on WTP for hydroponic lettuce ($P < 0.10$) as well. Significant decreases of around \$0.22 in WTP for red lettuce were also observed in Class 2. These results may suggest that consumers who are not necessarily motivated by gaining prestige through their purchases find the attributes of hydroponic production and unconventional growing methods attractive and valuable. Unlike Classes 1, 3, and 4, average weekly expenditures on fruit and vegetables have a positive effect on consumers' WTP for lettuce in Class 2.

A small number of significant effects were found in Class 3 (9.19% of participants). Table 32 indicates that *Affluent Elitists* decrease their WTP for lettuce as their households grow larger and as they spend more on fruits and vegetables. Unlike the other classes, consumers' WTP values were not negatively affected by red colored lettuce. Effects from the product attributes and the treatments were homogeneous across participants, with the exception of the red color attribute.

Lastly, consumers in Class 4, the *Prestige Lovers*, exhibited significant increases in WTP for organic lettuce ($P < 0.10$). However, unlike Class 2 (*Utilitarian Buyers*), consumers' WTP values for organic lettuce and mixed lettuce in Class 4 (*Prestige Lovers*, 9.26% of participants) were not significantly affected by the information treatment. Also dissimilar to the other classes, larger households positively affected

Class 4's WTP for lettuce – WTP increased by nearly $0.49. Like Class 3, average weekly expenditures on fruits and vegetables had a negative effect on WTP for lettuce in Class 4 (*Prestige Lovers*).

Table 33 displays the WTP estimates from a Random Parameter Tobit model in which Classes 1, 2, and 4 (*Ambitious Shoppers*, *Utilitarian Buyers*, and *Prestige Lovers*, respectively) were compared to Class 3 (*Affluent Elitists* acted as the baseline). The coefficient estimates in Table 33 indicate that all classes' WTP for lettuce were significantly different from Class 3. For instance, compared to the *Affluent Elitists* in Class 3, the *Ambitious Shoppers* in Class 1 were willing to pay $0.19 more for lettuce. In contrast, the *Utilitarian Buyers* consumers in Class 2 and the *Prestige Lovers* in Class 4 were willing to pay around $0.30 and $0.42 less than the *Affluent Elitists* in Class 3.

Latent Class Analyses Conclusion

In general, the classes defined by the prestige scale, the health scale, and a combination of the two scales varied in terms of their prestige and health related behavior, socio-economic characteristics, preferences, and willingness to pay for lettuce. Ignorance of the differences in the peripheral characteristics of consumers may lead to flawed conclusions about consumers' product valuation. By recognizing the differences in consumers' complex behavior, researchers can gain valuable insight into the sources of unobserved individual heterogeneity, which may have subsequent effects on the marketing and promotion efforts of agribusinesses.

Table 32. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products by Latent Class: Prestige Scale Only

	Class 1			**Class 2**			**Class 3**			**Class 4**			**All Participants**		
	Ambitious Shoppers			*Utilitarian Buyers*			*Affluent Elitists*			*Prestige Lovers*					
E[y]	1.61			1.41			1.60			1.48			1.45		
Class Membership	12.07%			69.48%			9.19%			9.26%			100%		
	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x
Means of Random Parameters															
Constant	2.072 ***	0.146		1.406 ***	0.047		2.363 ***	0.683		0.934 ***	0.133		1.519 ***	0.038	
Organic	-0.102	0.175	-0.102	0.100 *	0.058	0.099	0.178	0.638	0.178	0.319 *	0.187	0.319	0.099 **	0.047	0.098
Hydroponic	0.032	0.157	0.032	-0.041	0.053	-0.041	0.055	0.920	0.055	0.193	0.173	0.193	-0.005	0.046	-0.005
Red	-0.571 ***	0.123	-0.570	-0.218 ***	0.047	-0.218	-0.575	0.466	-0.575	-0.391 ***	0.142	-0.390	-0.292 ***	0.039	-0.290
Mixed	0.245	0.188	0.244	0.031	0.076	0.031	0.196	0.951	0.196	-0.171	0.251	-0.171	0.051	0.062	0.050
Tasting	-0.184	0.213	-0.183	0.060	0.063	0.060	0.671	0.740	0.671	-0.111	0.179	-0.111	0.036	0.052	0.036
Production Information	0.424	0.260	0.423 *	0.026	0.089	0.026	0.109	1.250	0.109	0.000	0.427	0.000	0.069	0.066	0.069
Tasting x Organic	-0.077	0.363	-0.077	-0.091	0.094	-0.090	0.618	0.910	0.618	-0.038	0.298	-0.038	-0.082	0.080	-0.081
Tasting x Hydroponic	0.019	0.294	0.019	-0.047	0.090	-0.047	0.310	1.479	0.310	0.080	0.315	0.080	-0.030	0.076	-0.030
Tasting x Red	0.081	0.201	0.081	-0.013	0.077	-0.013	0.325	1.029	0.325	0.292	0.314	0.292	0.034	0.064	0.034
Tasting x Mixed	-0.342	0.374	-0.341	-0.006	0.131	-0.006	-0.443	1.288	-0.443	0.346	0.635	0.346	-0.038	0.112	-0.038
Info x Organic	-0.120	0.344	-0.119	0.240 **	0.117	0.239	0.748	1.479	0.747	-0.029	0.700	-0.029	0.209 **	0.091	0.208
Info x Hydroponic	-0.602	0.389	-0.600	0.201 *	0.105	0.201	0.188	2.061	0.188	-0.014	0.380	-0.014	0.061	0.089	0.061
Info x Red	-0.039	0.438	-0.039	0.066	0.118	0.066	0.185	0.910	0.185	0.285	0.479	0.284	0.079	0.103	0.079
Info x Mixed	0.330	0.613	0.329	0.311 **	0.146	0.310	0.185	2.135	0.185	0.330	0.861	0.330	0.284 **	0.137	0.282
Demographics/ Behaviors															
HHSIZE	-0.177 ***	0.034	-0.176	-0.009	0.009	-0.009	-0.141 *	0.074	-0.141	0.485 ***	0.041	0.485	-0.014 *	0.008	-0.014
AWFV	0.003	0.002	0.003	0.005 ***	0.001	0.005	-0.017 ***	0.005	-0.017	-0.023 ***	0.002	-0.023	-0.001 **	0.001	-0.001
Standard Deviations of Random Parameters															
Constant	0.570 ***	0.046		0.746 ***	0.013		0.851 ***	0.187		0.596 ***	0.037		0.642 ***	0.010	
Organic	0.531 ***	0.083		0.172 ***	0.023		0.134	0.172		0.023	0.072		0.221 ***	0.020	
Hydroponic	0.129 **	0.061		0.202 ***	0.019		0.078	0.124		0.131 **	0.057		0.187 ***	0.016	
Red	0.325 ***	0.079		0.135 ***	0.021		0.583 **	0.237		0.084	0.057		0.191 ***	0.017	
Mixed	0.385 ***	0.119		0.033	0.038		0.271	0.258		0.225 **	0.089		0.016	0.032	
Tasting	0.461 ***	0.103		0.136 ***	0.022		0.460	0.416		0.349 ***	0.069		0.148 ***	0.016	
Production Information	0.229 **	0.114		0.176 ***	0.029		0.056	0.117		0.325 ***	0.079		0.001	0.025	
Tasting x Organic	0.295 **	0.132		0.000	0.047		1.070	0.754		0.006	0.132		0.159 ***	0.038	
Tasting x Hydroponic	0.267 **	0.122		0.144 ***	0.036		0.721	0.734		0.172	0.105		0.127 ***	0.029	
Tasting x Red	0.330 **	0.134		0.008	0.039		0.458	0.280		0.024	0.131		0.021	0.035	
Tasting x Mixed	0.046	0.161		0.003	0.077		0.499	0.908		0.041	0.198		0.040	0.064	
Info x Organic	0.248	0.206		0.323 ***	0.056		0.002	0.273		0.000	0.202		0.279 ***	0.047	
Info x Hydroponic	0.101	0.197		0.496 ***	0.044		0.003	0.201		0.203	0.133		0.424 ***	0.035	
Info x Red	0.020	0.182		0.030	0.046		0.001	0.259		0.020	0.143		0.023	0.046	
Info x Mixed	0.028	0.406		0.319 ***	0.074		0.030	0.504		0.016	0.298		0.218 ***	0.068	
σ(e)	0.538 ***	0.022		0.542 ***	0.004		0.427 ***	0.050		0.463 ***	0.019		0.554 ***	0.004	
Log-Likelihood	-349.405			-2008.468			-142.143			-227.693			-2804.041		

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 33. Random Parameters Tobit Estimates for Willingness to Pay (WTP) for Lettuce Products: Class 3 as Baseline, Prestige Scale Only

	Parameter		Standard Error	∂y/∂x
Means of Random Parameters				
Constant	1.585	***	0.059	
Organic	0.095	**	0.048	0.094
Hydroponic	-0.003		0.046	-0.003
Red	-0.286	***	0.039	-0.284
Mixed	0.051		0.061	0.050
Tasting	0.028		0.052	0.028
Production Information	0.071		0.067	0.070
Tasting x Organic	-0.088		0.079	-0.087
Tasting x Hydroponic	-0.038		0.075	-0.038
Tasting x Red	0.032		0.063	0.032
Tasting x Mixed	-0.041		0.110	-0.041
Info x Organic	0.176	**	0.089	0.175
Info x Hydroponic	0.080		0.090	0.080
Info x Red	0.083		0.100	0.082
Info x Mixed	0.314	**	0.135	0.312
Demographics, Behavioral Characteristics, and Classes				
HHSIZE	0.039	***	0.008	0.038
AWFV	-0.001		0.001	-0.001
CLASS1	0.192	***	0.057	0.191
CLASS2	-0.297	***	0.049	-0.295
CLASS4	-0.423	***	0.059	-0.421
Standard Deviations of Random Parameters				
Constant	0.620	***	0.010	
Organic	0.258	***	0.020	
Hydroponic	0.201	***	0.016	
Red	0.199	***	0.018	
Mixed	0.020		0.033	
Tasting	0.188	***	0.017	
Production Information	0.192	***	0.025	
Tasting x Organic	0.120	***	0.040	
Tasting x Hydroponic	0.041		0.031	
Tasting x Red	0.024		0.035	
Tasting x Mixed	0.034		0.061	
Info x Organic	0.253	***	0.040	
Info x Hydroponic	0.385	***	0.037	
Info x Red	0.009		0.047	
Info x Mixed	0.257	***	0.076	
σ(e)	0.550	***	0.004	
Log-Likelihood	-2800.539			

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Secondary Market Results

After the auction rounds were completed, the external validity of the Vickrey 2nd price auction was tested through the use of an on-site secondary market. Recall from the methodology chapter that a farmers' market-like stand was revealed following the conclusion of the auction rounds and participants used their assigned price to either make or forego a purchase in the secondary market. Similar to purchases made in the auction rounds, subjects were made aware that any transactions made in the secondary market would be deducted from their participation fee. Theoretically, an individual should make a purchase if their WTP value, or their bid, is greater or equal to the price they are offered in the secondary market, also known as their assigned values, v_i, whereas those whose last bid was not greater or equal to their assigned value were hypothesized to forego a purchase in the secondary market. Consumers whose last bid was equivalent to their assigned price (previously referred to as induced value) were expected to make a purchase in the secondary market, because they were being offered a good for the maximum amount they were willing to pay to obtain it. Table 34 shows the breakdown of observed behavior in the secondary market by gender and Table 35 displays secondary market behavior by income level.

It can be seen in Table 34 that 35% of the 71 participants who had a consumer surplus (that is, their last bid was greater or equal to their assigned price) made purchases and of this group, 84% were female. Alternatively, most of the 119 individuals who had negative consumer surplus (that is, their last bid was less than their assigned price and resulted in a net loss, or consumer deficit) were female. Of the 5 individuals who made purchases even though their net consumer welfare was in the negative, 60% were female. As Table 34 points out, the majority of participants (119 individuals, 59.20% of the sample) had a loss of consumer welfare, which means that these participants' valued the binding product less than the price that was being offered to them.

Table 34. Secondary Market Behavior: Gender Statistics

Secondary Market Behavior	All Participants	Gender: Male	Gender: Female	All Gender Categories
All Participants (N=201)	201 (100%)	110 (42.41%)	81 (57.59%)	191 (100%)
People with (+) consumer surplus	71 (35.5%)	22 (32.35%)	46 (67.65%)	68 (100%)
Participants with (+) consumer surplus & made purchase	25 (35.21%)	4 (16.00%)	21 (84.00%)	25 (100%)
People with (-) consumer surplus	119 (59.20%)	55 (48.25%)	59 (51.75%)	114 (100%)
Participants with (-) consumer surplus & made purchases	5 (2.49%)	2 (40%)	3 (60%)	5 (100%)
People with (0) zero consumer surplus	11 (5.47%)	5 (55.56%)	4 (44.44%)	9 (100%)
Participants with (0) consumer surplus & made purchases	2 (18.18%)	1 (50%)	1 (50%)	2 (100%)

With regard to income, Table 35 shows of those who experienced a gain in consumer welfare (positive consumer surplus) and those who experienced a loss in consumer welfare (negative consumer surplus), 62.31% and 64.1% were considered low income, respectively. Over a third of the individuals who had positive consumer surplus made purchases (25 individuals), while 2.5% of the individuals who had a negative consumer surplus made purchases anyway (5 individuals).

Table 35. Secondary Market Behavior: Income Statistics

Secondary Market Behavior	All Participants	Income			All Income Categories
		Low Income[(a)]	Middle Income	High Income	
All Participants (N=201)	201 (100%)	126 (63.96%)	30 (15.23%)	41 (20.81%)	197 (100%)
People with (+) consumer surplus	71 (35.5%)	43 (62.31%)	8 (11.6%)	18 (26.09%)	69 (100%)
Participants with (+) consumer surplus & made purchase	25 (35.21%)	11 (45.83%)	5 (20.83%)	8 (33.33%)	24 (100%)
People with (-) consumer surplus	119 (59.20%)	75 (64.1%)	21 (17.95%)	21 (17.94%)	117 (100%)
Participants with (-) consumer surplus & made purchases	5 (2.49%)	1 (20%)	2 (40%)	2 (40%)	5 (100%)
People with (0) zero consumer surplus	11 (5.47%)	8 (72.72%)	1 (9.09%)	2 (18.18%)	11 (100%)
Participants with (0) consumer surplus & made purchases	2 (18.18%)	2 (100%)	0 (0%)	0 (0%)	2 (100%)

[(a)] Average annual income specified as follows: Low Income = less than $44,999.50; Middle Income = $54,999.5 < x ≤ $74,999.5; High Income = more than $84,999.5

Table 36 displays a tabulation of the number of participants who should have made a purchase in the secondary market (those who received an assigned price that was less than their last bid), those who should not have made a purchase (their assigned price was greater than last bid), the number of individuals who actually made a purchase, and those who did not make a purchase. If consumers' their last bid equaled their assigned price, individuals should have made a purchase because it would be irrational for an individual to refuse a product if it was being offered to them for the maximum amount they were willing to pay. Table 36 shows that a majority of the 82 participants who were theoretically expected to make a purchase did not. Additionally, recall that the distribution of assigned prices reflected retail prices of the auction products in local grocery stores. Clearly, 119 participants theoretically should have not made a purchase, which means their maximum WTP (last bid) for the product for sale in the secondary market was less than their assigned price, which represented the price of a lettuce product in local grocery stores. This implies that a majority participants valued the lettuce products less than what they would normally face in a retail environment. However, because the full selection of lettuce products was not offered in the secondary market, this conclusion should be further investigated.

Table 36. Tabulation of Individuals' Expected Behavior versus Actual Behavior

	Should not have purchased	Should have purchased	Total
Did not purchase	114	55	169
Did purchase	5	27	32
Total	119	82	201

Probit Model

The probability that an individual made a purchase in the secondary market was analyzed using several probit-style models. The probability of an individual making a purchase in the secondary market was estimated twice under each model, first as a function of several factors and secondly as a function of a subset of those factors.

To identify what motivates an individual to purchase in the secondary market, the probability that an individual actually made a purchase is first estimated using a ratio of the compensation fee to the subject's average hourly income and whether or not they had purchased fruits and vegetables within the last four days. Four days was used as an indicator for new fruit and vegetable purchases because many fruits and vegetables, especially lettuce, deteriorate in quality after four days following preparation. Other factors used include consumer surplus, age, whether or not the individual was a female, household size, and whether or not the individual was a student. With this standard probit estimation, individuals who value the fee relatively more are 17% less likely to purchase in the secondary market. As expected, those who have greater consumer surplus would be more likely to make a purchase and this is true – individuals with greater consumer surplus are have a 52% higher probability of making a purchase. This could imply that the more of a discount being offered to an individual, the more likely they are to purchase an item, which is in line with consumer theory. While older individual, females, and students were not revealed to be significant factors, larger households were significantly less likely to purchase in the secondary market. Household size may have a negative effect on the probability of making a purchase in the secondary market as a result of individuals choosing to purchase longer-lasting, less perishable food items.

Table 37. Probit Model: Full Set

	Parameter		Standard Error
feetoinc	-0.172	*	0.093
dlast1	-0.140		0.320
csurplus	0.522	***	0.114
age	-0.003		0.007
female	0.129		0.272
hhsize	-0.133	*	0.080
student	-0.556		0.366

Note: *, **, ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 38 shows the estimated probit model using a subset of the variables used in Table 37. The condensed set of factors include the relative importance of the fee, whether or not the individual had purchased fruits and vegetables recently, consumer surplus, and whether or not the individual was a student. It was expected that the greater relative importance of the fee was the less likely individuals would be willing to make a purchase in the secondary market, which would decrease the total value of the compensation fee they received. This expectation held true – the more an individual valued the compensation fee, the probability that they would make a purchase in the secondary market decreased. It was also hypothesized that if an individual had recently purchased fruits and vegetables, the probability of them making a purchase in the secondary market would decrease. This hypothesis also came true. Greater consumer surplus, or larger of a discount, was expected to increase the probability of an individual making a purchase in the market. Table 38 points out that as consumer surplus increases, the probability that an individual makes a purchase in the market increases by 50%.

Table 38. Probit Model: Condensed Set

	Parameter		Standard Error
feetoinc	-0.207	**	0.085
dlast1	-0.496	***	0.190
csurplus	0.505	***	0.108
student	-0.544		0.344

Note: *, **, ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Random Effects Probit Model

Tables 39, 40, 41 and 42 investigate whether random effects are present at the individual level and also at the session level using both the full set and the condensed set of variables. Results from the four models reflect the findings of the standard probit model in Tables 37 and 38. Generally, ρ is a statistic that describes the percentage of variance in the model that is due to random effects at a specified and was used in the discussion of the random effects tobit WTP model. In the case of the random effects at the individual level, ρ in Table 39 and Table 40 takes the value of 0.000. This implies that 0% of the variance in the model is explained by random effects at the individual level. A similar result is found in Table 41 and Table 42, when random effects by session are investigated.

Table 39. Random Effects Probit by Individual: Full Set

	Parameter		Standard Error
feetoinc	-0.172	*	0.093
dlast1	-0.140		0.320
csurplus	0.522	***	0.114
age	-0.003		0.007
female	0.129		0.272
hhsize	-0.133	*	0.080
student	-0.556		0.366
$\ln(\sigma_u^2)$	-14.611		135.390
$\sigma(u)$	0.001		0.045
ρ	0.000		0.000

Note: *, **, ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 40. Random Effects Probit by Individual: Condensed Set

	Parameter		Standard Error
feetoinc	-0.207	**	0.082
dlast1	-0.496	***	0.181
csurplus	0.505	***	0.103
student	-0.544		0.334
$\ln(\sigma_u^2)$	-15.903		74.580
$\sigma(u)$	0.004		0.036
ρ	0.000		0.000

Note: *, **, ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 41. Random Effects Probit by Sessions: Full Set

	Parameter		Standard Error
feetoinc	-0.172	*	0.093
dlast1	-0.140		0.320
csurplus	0.522	***	0.114
age	-0.003		0.007
female	0.129		0.272
hhsize	-0.133	*	0.080
student	-0.556		0.366
$\ln(\sigma_u^2)$	-16.461		62.640
$\sigma(u)$	0.000		0.008
ρ	0.000		0.000

Note: *, **, ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 42. Random Effects Probit by Sessions: Condensed Set

	Parameter		Standard Error
feetoinc	-0.207	**	0.084
dlast1	-0.496	***	0.185
csurplus	0.505	***	0.105
student	-0.544		0.347
$\ln(\sigma_u^2)$	-15.125		8.069
$\sigma(u)$	0.001		0.383
ρ	0.000		0.072

Note: *, **, ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Heteroskedastic Probit Model

Many times, the variance of the unobservable factors is different for different groups of people. When variances of the error terms for two groups of people are assumed to be different, one can apply a heteroskedastic probit model, which uses maximum likelihood estimation and normalization to detect whether heteroskedasticity exists in the model. As discussed in the methodology chapter, normalization allows the variances of the unobservable factors for two groups to be compared against each other. A heteroskedastic probit model was estimated using the full set of variables and the condensed set to identify whether the variances of the unobservable factors of the individuals who should have made purchases and the group of individuals who actually made purchases are heteroskedastic, or different.

Results from the maximum-likelihood estimation of a heteroskedastic probit model, shown in Table 43, indicate that the variance of the individuals who should have purchased is heteroskedastic. This was confirmed when a likelihood ratio test that tested the model with heteroskedasticity against the model without rejects the null hypothesis at the 95% confidence interval that the two models are equal, therefore heteroskedasticity exists. The only factor that has a significant effect on the probability of an individual making a purchase in the secondary market is consumer surplus.

Table 43. Heteroskedastic Probit: Full Set

	Parameter		Standard Error
feetoinc	-0.362		0.257
dlast1	0.033		0.626
csurplus	0.493	*	0.259
age	-0.004		0.010
female	0.257		0.461
hhsize	-0.236		0.197
student	-1.513		1.511
ln σ^2(should)	1.089	*	0.668

Note: *, **, ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

The heteroskedastic probit model was also estimated using the condensed set of variables. A likelihood ratio test that tested the null hypothesis that the model with heteroskedasticity is equal to the model without heteroskedasticity was rejected ($P < 0.01$). This implies that the variance of the unobservable factors is different and this should be taken into account. The relative importance of the fee had a negative effect on the probability of an individual making a purchase in the secondary market, while the opposite is true for consumer surplus.

Table 44. Heteroskedastic Probit: Condensed Set

	Parameter		Standard Error
feetoinc	-0.470	*	0.230
dlast1	-0.463		0.324
csurplus	0.488	*	0.214
student	-2.001		1.385
ln σ^2(should)	1.305	*	0.567

Note: *, **, ***, represent statistical significance at the 10%, 5%, and 1% levels, respectively.

In conclusion, the secondary market analysis indicates that while random effects are not present within individuals or sessions, the importance of unobservable factors vary for the participants. If the compensation fee was relatively larger than the individual's average hourly income, the individual was less likely to make a purchase in the secondary market. This implies that the compensation fee has a significant effect on individual's actions in the experiment and may be the primary reason they are participating. Further research may study the effect of different compensation levels and the effect of distribution on individual's behavior. Additionally, the positive effect of consumer surplus on the probability of an individual making a purchase in the secondary market suggests that those consumers who value lettuce are more likely to purchase it when it is being offered at a discount. Likelihood ratio tests were performed in each probit analysis to compare the full model with the condensed model. In each test, the null hypothesis was not rejected, which means that the condensed set was a preferred representation of the data.

CHAPTER VI

SUMMARY AND CONCLUSIONS

A succinct summary and any final conclusions of this study will be presented in this chapter. First, readers will be provided with an abbreviated background of the study. Next, economic and marketing implications will be explored. Finally, this chapter will conclude with a nod to the limitations of this research and suggestions for future research.

Summary and Conclusions

Experimental auctions are among the most coveted methods used to elicit consumers' valuations of goods. This study employed a non-hypothetical Vickrey second-price auction and an on-site site secondary market in an effort to analyze consumers' willingness to pay for vegetable products and assess the external validity of the auction mechanism. More precisely, panel data, a number of econometric models, and a Latent Class Analysis (LCA) were used to accomplish the following objectives:

- Estimate the impact of a blind tasting, production information, growing method, and color on consumers' valuations of lettuce products
- Segment experiment participants into different latent classes based on their response to scale-style questions relating to health-consciousness and prestige-

seeking behavior, and compare the effects of product attributes and treatments across classes

- Identify motivations and the factors associated with the probability of an individual participating in an secondary market in an effort to study the external validity of consumers' valuations elicited in the experimental auction

Regarding the study, a total of 201 individuals from the Bryan-College Station area of Texas participated in nine sessions over the course of three days. Individuals from the community were recruited to best represent the overall demographics of grocery shoppers in Texas. The primary requirements to participate in this study were that the participant had to be the primary shopper of their household, be at least 18 years of age, and have no known allergies to lettuce. Approximately 84% of participants were the primary grocery shopper of their household.

Once participants arrived to the experiment, they were asked to review and sign a consent form to sign and thereafter randomly assigned an identification number that ensured anonymity throughout the duration of the experiment. Before being seated, each participant was provided with a participation packet that contained instructions and the survey, as well as a packet that of blank bid sheets and an order form. The session monitor read aloud instructions and explained that because the experiment was non-hypothetical, the participants would have to pay real money if they purchased any of the goods at the experiment site.

Four examples (two verbal and two numerical) were provided in an effort to provide participants' with a sound understanding of the intricacies of the Vickrey second-price auction. Following these examples, subjects completed one of two practice auction rounds, and completed a brief knowledge quiz while the market price (the second-highest submitted bid) for the was determined. Following the discussion of the answers to the knowledge quiz, subjects submit bids in the second practice round of auctions. After this, the monitor provided instructions for the first vegetable auction round and explained to participants that the next auction rounds would be real. Eight vegetable products that varied in production method and color are considered close substitutes were used in the two vegetable auction rounds: conventionally grown green leaf lettuce, conventionally grown red leaf lettuce, organically grown green leaf lettuce, organically grown red leaf lettuce, hydroponically grown green leaf lettuce, hydroponically grown green leaf lettuce, hydroponically grown mixed leaf lettuce, and spinach as a reference good. Conventional and organic varieties of lettuce reflected the general choice set of leaf lettuce available to consumers as they purchased at a local grocery store and the hydroponic varieties were considered a novel good as they were produced using water-efficient methods by Texas A&M AgriLife Research and Extension Center in Uvalde, Texas.

Participants in each session completed two rounds of vegetable auctions, with the first round acting as a baseline in which they received no information and the second round acted as a treatment. Half of the sessions received a baseline as the first round and a blind tasting as the treatment round. Participants who received a blind tasting treatment were given sample-sized amounts of each of the seven lettuce products to taste. The other half of the sessions received a baseline round and a treatment of production information, in which they learned about hydroponic vegetable production and the production method of each product was revealed. Participants were allowed to examine each vegetable product prior to submitting their bids in each round. Upon the completion of the two vegetable auction rounds and the collection of bids, participants were asked to complete a consumer survey regarding demographic information, fruit and vegetable purchasing behavior, perceptions about health-consciousness and prestige-seeking behavior. While participants were completing the survey, one of the two rounds was randomly selected to be binding. The hydroponic red leaf lettuce product was chosen to be binding for all sessions due to availability. Following the announcement of the auction buyer, the market price, and the binding product, participants were given the opportunity to purchase the binding product in a secondary market at a stand at the back of the room. This stand was not revealed to participants until after the conclusion of the auction and they were instructed to treat it like they would a stand at a farmers market. Subjects were referred to their order form, which listed the price they could purchase one unit of the binding product for, and were asked to indicate how many, if any, units they would like to purchase. Finally, after participants filled out their individual order form, they collected the $30, minus any purchases, in compensation and signed a receipt of funds form.

Several pieces of information were collected using the aforementioned experimental design. In addition to consumers' valuations of vegetable products and specific product attributes, the aforementioned auction mechanism and survey gathered data on participants' demographic and behavioral characteristics. The results from inquiries about fruit and vegetable purchasing behavior revealed that a mean of around $126 was spent in household weekly food expenditures, of which an average of $29 was spent on fruits and vegetables. Additionally, a mean of 36% of participants' full stock of food at home consisted of fresh vegetables. When buying lettuce, participants considered freshness, taste, and visual appearance as most important.

Because subjects were recruited for the study based on specific criteria relating to vegetable purchasing decisions, age, and allergies, readers should exercise caution when extending these results to the general population. As this study specifically addressed consumers' valuations of lettuce products, readers should be careful not to extend these results to other fruit or vegetable products.

Bids from the vegetable auction rounds were pooled and resulted in a total of 3,193 WTP observations. Valuations for one head of lettuce ranged from $0.00 to $5.50 and participants were willing to pay an average price of $1.47 for all lettuce products across all rounds. Organic green lettuce commanded the highest average WTP in every round and became tied with hydroponic mixed lettuce in the production information treatment.

Individuals were allowed to bid any value for the auction products, including $0.00. Although the percentage of bids censored at zero was relatively low across all products and the auction rounds, these bids were not left out of the econometric analysis. Several models were estimated and each one provided a more refined representation of the WTP data than the last: ordinary least squares, constant parameters tobit, random effects tobit, random parameters linear, and random parameters tobit. Although results varied from model to model, the product attribute of red color often decreased consumers' WTP for lettuce and consumers significantly increased their WTP for organic and mixed lettuce after they learned of its production method on a consistent basis. The WTP models also revealed that tasting the products had no significant effect on consumers' valuations. Heterogeneity was detected at the individual level by random effects tobit, random parameters linear, and random parameters tobit. This detection led to the inclusion of ordinary least square and tobit estimations strictly for comparison purposes as they do not account for the heterogeneous nature of the data.

Because the random parameters tobit model accounts for heterogeneity while simultaneously accommodating the censored nature of the data, it was considered the paramount model. This econometric model revealed several important findings. This model accounts suggests that unobserved heterogeneity exists and it should not be ignored. Other findings indicate that consumers express deep discounts for red lettuce. This may be due to the fact that consumers associate lettuce as being green in color and not red. Alternatively, this may suggest that consumers view red leaf lettuce as a complementary good to green lettuce. They may view red lettuce only as an ingredient in salad and thus may not value it as much as they do green lettuce. Additionally, this model's findings reveal that consumers value organic lettuce, especially after are willing to pay premiums for organic lettuce before and after they know it is produced organically. Increased value was also seen in mixed lettuce, which was hydroponically grown, after consumers learned about production methods. These increased valuation following the production information treatment indicate that consumers value information and they are willing to pay a premium for unconventionally produced lettuce. The increase in WTP seen in mixed lettuce may be a result of participants' aversion to red lettuce. That is, consumers may value mixed lettuce because it is not completely red leaf lettuce, but it provides some variety compared to green lettuce. Factors related to age, income, race, gender, marital status, fruit and vegetable spending habits significantly affected consumers' valuations of lettuce.

In addition to using the full bids to estimate the factors affecting consumers' valuations of lettuce, the implied differences of the bid values were used to investigate the impact of different factors on the change in bid values from the baseline round to the treatment rounds. Results from this treatment indicate that organic varieties and hydroponic varieties negatively affected the change in WTP from the baseline to the blind tasting treatment. Conversely, these same varieties positively influenced the change in WTP from the baseline to the production information treatment. Regarding demographic factors, higher education levels and larger households influenced an increase in the change of WTP from the baseline to the blind tasting treatment, while age and a graduate education decreased the change in bids between the baseline round and the production information treatment. In both applications of implied differences, greater average weekly expenditures on fruits and vegetables contributed to an increase in bids in both implied difference applications.

The third part of this study's analysis included classifying individuals in to separate groups using three applications of Latent Class Analysis (LCA) and estimating WTP through the random parameters tobit model separately for each class in each application. First, following the conjecture that having a healthy lifestyle may be associated with prestige and power, four latent classes of consumers emerged based on observed indicators relating to a combination of health-consciousness and prestige-seeking behaviors, demographics and behavioral characteristics, and valuations of the vegetable products. The four classes for the combination of health and prestige motivations were characterized as follows: "High Health, Low Prestige" (37.38% of participants), "High Health, High Prestige" (24.16% of participants), "Low Health, Low Prestige" (32.60% of participants), and "Low Health, Low Prestige" (5.85% of participants). A second LCA was applied using only observed indicators relating to health-consciousness, demographic and behavioral characteristics, and individuals' WTP estimates. Four latent classes of consumers were identified and characterized as "Health Fanatics" (42.84% of participants), "Health Ponderers" (19.63% of participants), "Vanity Seekers" (19.58% of participants), and "Health Conscious" (17.95% of participants). A third LCA application was used to classify consumers based on observed indicators relating to prestige-seeking tendencies, demographic and behavioral characteristics, and individuals' WTP estimates. In a similar fashion as the other LCA applications, four latent classes of consumers were identified and characterized. Consumers were classified as "Ambitious Shoppers" (12.07% of participants), "Utilitarian Buyers" (69.48% of participants), "Affluent Elitists" (9.19% of participants), or “Prestige Lovers” (9.26% of participants). The random parameters tobit models for each LCA application revealed similarities and differences between each application’s classes in their WTP estimates, socio-demographic profile, and motivations related to prestige and health. By recognizing the differences in consumers’ complex behavior, researchers can gain valuable insight into the sources of unobserved individual heterogeneity, which may have subsequent effects on the marketing and promotion efforts of agribusinesses.

In an effort to fine-tune the external validity of experimental auctions, consumers’ behavior in an on-site secondary market and their valuations in treatment round of auctions was analyzed using several models: probit, random effects probit, and heteroskedastic probit. In estimating the probability that participants made a purchase in the secondary market, it was found that while no random effects existed at the individual or session level, the variance of unobserved effects varied for those who were expected to make a purchase and those who actually did. Consumer surplus and the relative importance of the compensation fee were identified as motivating factors in the secondary market analysis.

Economic and Marketing Implications

A sound understanding of consumers’ preferences and valuations of quality-differentiating attributes is necessary to nurture the increasing demand for unconventionally produced food products. This study provides valuable inferences about the value consumers place on production methods and shows the impact of information on consumers' decisions.

Findings in this study provide valuable information to producers, distributers, and retailers of lettuce and may have profound marketing implications for the fresh fruit and vegetable industry. For example, the most significant finding in this research is the impact of consumer education. In analyzing consumers' willingness to pay for lettuce products that varied in production method and color, it was found that consumers were willing to pay significant premiums for organically grown lettuce and for hydroponically grown lettuce that was mixed in color after they learned about hydroponic production and after the production method of each product was revealed. This implies that consumers are willing to pay more for products that are produced organically and hydroponically and are labeled as such. The impact of information suggests producers, marketers, and distributers of hydroponic and organic lettuce should include production information in the labeling of the product such that it is visible to the targeted consumer. These results are aligned with the growth seen in the organic foods industry recently.

Other results revealed that, ultimately, differences in the taste of the lettuce products did not lead to significantly affect willingness to pay and consumers may perceive red leaf lettuce as less valuable than green leaf lettuce. Additionally, individuals who are concerned about their health and those who view themselves as individuals who purchase goods for their practical use express premiums for organic lettuce after they learn it was produced organically. These results imply that consumers who have different consumption motivations desire the same product, but only after they have been educated on how it was produced. The bottom line is: informing the consumer matters! If consumers know about hydroponic production and how vegetable products are produced, they are likely to make more informed choices which could result in higher revenues for the producers of those goods.

Regarding the efforts made in advancing the field of experimental economic, this study contributed the external validity of experimental auctions by suggesting that the relative importance of the compensation fee matters when eliciting truthful valuations and incentivizing behavior. Furthermore, this study revealed that participants of experiments who place greater importance on the compensation fee are less likely to conform to utility maximizing behavior and suggested that participants have a combined utility for the fee and the auction products.

Limitations and Suggestions for Future Research

Limitations of this study and suggestions for future research are listed below: This experiment consisted of seven lettuce products varying in production method and color. The choice set was imbalanced as the mixed color was only grown hydroponically, not conventionally or organically. Therefore, it is unclear whether the effects seen in the mixed product were due to its method of production or mixed color. Although the tasting treatment had no significant effect on participants' valuations, more information might have been gained had the tasting occurred in a sensory analysis laboratory

To further contribute to the external validity of experimental auction mechanisms, future research should consider conducting a field experiment in a grocery store when consumers have an intention to purchase fruits and vegetables. Because this study found that the relative importance of the compensation fee matters to participants, future research may investigate how the timing and magnitude of payment affect participants' behavior

REFERENCES

Abidoye, B.O., H. Balut, J.D. Lawrence, B. Mennecke, and A.M. Townsend. 2011."U.S. Consumers' Valuation of Quality Attributes in Beef Products." *Journal of Agricultural and Applied Economics.* 43: 1-12.

Alfnes, F., A.G. Guttormsen, G. Steine, and K. Kolstad. 2006. "Consumers' Willingness to Pay for the Color of Salmon: A Choice Experiment with Real Economic Incentives." *American Journal of Agricultural Economics* 88:1050-1061.

Alfnes, F. 2007. "Willingness to Pay versus Expected Consumption Value in Vickrey Auctions for New Experience Goods." *American Journal of Agricultural Economics* 89:921-931.

—. 2009. "Valuing product attributes in Vickrey auctions when market substitutes are available." *European Review of Agricultural Economics* 36:133-149.

Allen, E.I. and C.A. Seaman. 2007. "Likert Scales and Data Analyses." *Quality Progress* 40(7):64-65.

Akaike, H. 1973. "Information Theory and an Extension of the Maximum Likelihood Principle. In B.N. Petrov & F. Csaki (Eds.), Second International Symposium on Information Theory (p. 267-281). Budapest, Hungary: Akademai Kiado.

Amarowicz, R., R. Carle, G. Dongowski, A. Durazzo, R. Galensa, D. Kammerer, G. Maiani, and M.K. Piskula. 2009. "Influence of postharvest processing and storage on the content of phenolic acids and flavonoids in foods." *Molecular Nutrition and Food Research* 53: S151-S183.

American Cancer Society. 2013. "Phytochemicals." Accessed on 10 Apr 2014. Available online at <http://www.cancer.org/treatment/treatmentsandsideeffects/complementaryandalternativemedicine/herbsvitaminsandminerals/phytochemicals>.

Arnade, C., L. Calvin, and F. Kuchler. 2009 "Consumer Response to a Food Safety Shock: The 2006 Food-Borne Illness Outbreak of *E. coli* O157:H7 Linked to Spinach." *Review of Agricultural Economics* 31(4):734-750.

Auspitz, R., and R. Lieben. 1889. *Untersuchungen uber die Theorie des Prices*, Leipzig: Verlag von Duncker & Humblot.

Batt, P.J. and A. M. S. Lim. 1999. "Consumer attitudes towards hydroponic produce in Western Australia." *Food Australia* 51(11) 547-548.

Bearden, W.O., R.G. Netemeyer, K.L. Haws. 2011. *Handbook of Marketing Scales: Multi-Item Measures for Marketing and Consumer Behavior Research*, 3rd. ed. Thousand Oaks, California: SAGE Publications, Inc. 174-175.

—. 2011. *Handbook of Marketing Scales: Multi-Item Measures for Marketing and Consumer Behavior Research,* 3rd. ed. Thousand Oaks, California: SAGE Publications, Inc. 379.

Bentham, J. 1789. *An introduction to the principles of morals and legislation*, reprinted by Oxford: The Clarendon press, 1876.

Bishop, R. and T. Heberlein. 1979. “Measuring values of extra market goods: Are indirect measures biased?” *American Journal of Agricultural Economics* 61: 926-930.

—. 1986. “Does contingent valuation work?” In: Cummings, R. Brookshire, D., Schulze, W. (Eds.), *Valuing Environmental Goods: A State of the Arts Assessment of the Contingent Valuation Method.* Rowman & Allenheld, Totowa, NJ.

Blasco, B., J.J. Rios, L.M. Cervilla, E. Sánchez-Rodrigez, J.M. Ruiz, and L. Romero. 2008. “Iodine biofortification and antioxidant capacity of lettuce: potential benefits for cultivation and human health.” *Annals of Applied Biology* 152: 289-299.

Bohm, P. 1972. “Estimating the demand for public goods: An experiment.” *European Economic Review* 3:111-130.

Boriss, H. and H. Brunke. 2005. Revised by Jore, L. 2012. “Lettuce Profile.” AgMRC: Agricultural Marketing Center. Accessed 10 Apr 2014. Available online at <http://www.agmrc.org/commodities__products/vegetables/lettuce-profile/>.

Bourn, D. and J. Prescott. 2002. “A Comparison of the Nutritional Value, Sensory Qualities, and Food Safety of Organically and Conventionally Produced Foods.” *Critical Reviews in Food Science and Nutrition* 42(1): 1-34.

Brezosky, L. 2014. “Marketing packaged produce bears fruit to tune of $4.8 billion.” Houston Chronicle. Sunday, May 4, 2014.

Brookshire, D.S., D.L. Coursey, and W.D. Schulze. 1987. “The External Validity of Experimental Economics Techniques: Analysis of Demand Behavior.” *Economic Inquiry* 25: 239-250.

Buhr, B.L., D.J. Hayes, J. F. Shogren, and J.B. Kliebenstein. 1993. “Valuing Ambiguity: The Case of Genetically Engineered Growth Enhancers.” *Journal of Agricultural Resource Economics* 18: 175-184.

Campbell, D. T., and J. C. Stanley. 1963. *Experimental and quasi-experimental designs for research on teaching.* American Educational Research Association. Pages 1-32.

Carson, R.T., N.E. Flores, K.M. Martin, and J.L. Wright. 1996. “Contingent Valuation and Revealed Preference Methodologies: Comparing the Estimates for Quasi-Public Goods.” *Land Economics* 72:80-99.

Chang, J.B., J.L. Lusk, and F.B. Norwood. 2009. “How Closely do Hypothetical Surveys and Laboratory Experiments Predict Field Behavior?” *American Journal of Agricultural Economics* 91:518-534.

Cherry, T.L., P. Frykblom, J.F. Shogren, J.A. List, and M.B. Sullivan. 2004. “Laboratory Testbeds and Non-Market Valuation: The Case of Bidding Behavior in a Second-Price Auction with an Outside Option.” *Environmental & Resource Economics* 29:285-294.

Collart, A.J. and M.A. Palma. 2013. "Modeling Unobserved Consumer Heterogeneity in Experimental Auctions: A Censored Random Parameters Approach." *Annual Meeting, Washington, D.C.* Agricultural and Applied Economics Association.

Collart, A.J. 2013. *Econometric Methods to Analyze Consumer Behavior using Hypothetical and Non-Hypothetical Approaches*. PhD dissertation, Texas A&M University.

Coolong, T. and S. Foran. 2012. "Hydroponic Lettuce." University of Kentucky College of Agriculture Cooperative Extension Service. CDBREC Crop Profiles. Accessed 25 Sept 2013. Available online at <http://www.uky.edu/Ag/CCD/introsheets/hydrolettuce.pdf>.

Coppinger, V. M., V. L. Smith, and J. A. Titus. 1980. "Incentives and Behavior in English, Dutch, and Sealed-Bid Auctions." *Economic Inquiry* 43:1-22.

Corrigan, J.R. 2005. "Is the Experimental Auction a Dynamic Market?" *Environmental & Resource Economics* 31:35-45.

Corrigan, J.R. and M. C. Rousu. 2006. "The Effect of Initial Endowments in Experimental Auctions." *American Journal of Agricultural Economics* 88(2):448-457.

Cummings, R.G., G.W. Harrison, E.E. Rutström. 1995. "Homegrown values and hypothetical surveys: Is the dichotomous choice approach incentive compatible?" *American Economic Review* 85(1):260-266.

Dalrymple, D.G. 1973. "A global review of greenhouse food production." USDA Rpt. 89.

Danovich, T. 2014. “When Farmers Get Arrested for Foodborne Illnesses.” *Modern Farmer*. Accessed 8 Apr 2014. Available online at <http://modernfarmer.com/2014/04/foodborne-illness-case-farmers-rarely-made/>.

Davis, R.M., K.V. Subbarao, R.N. Raid, and E.A. Kurtz. 1997. Excerpted from the *Compendium of Lettuce Diseases*. APS Press, MN. Accessed 10 Apr 2014. Available online at <http://calgreens.org/lettuce/>.

Dempster, A.P., N.M. Laird, and D.B. Rubin. 1977. “Maximum Likelihood from Incomplete Data via the EM Algorithm (With Discussion.” *Journal of the Royal Statistical Society* 39:1-38.

Dickie, M., A. Fisher, and S. Gerking. 1987. “Market Transactions and Hypothetical Demand Data: A Comparative Study.” *Journal of the American Statistical Association* 82:69-75.

Diewert, E. 1971. “An Application of the Shephard Duality Theorem, a Generalized Leontief Production Function.” *Journal of Political Economy* 79:481-507.

Drichoutis, A.C., P. Lazaridis, and R.M. Nayga Jr. 2008. “The role of reference prices in experimental auctions.” *Economic Letters* 99:446-448.

Dubois, D., Rucker, D.D., and A.D. Galinsky. 2012. “Super Size Me: Product Size as a Signal of Status.” *Journal of Consumer Research* 38(6): 1047-1062.

Du Pont, M.S., Z. Mondin, G. Williamson, and K.R. Price. 2000. “Effect of variety, processing and storage on the flavonoid glycoside content and composition of lettuce and endive. *Journal of Agricultural and Food Chemistry* 89:1682-1689.

Dupuit, J. 1844. “On the Measurement of the Utility of Public Works.” *Annales des ponts et chausses.* (English translation, *International Economic Review*, 1952).

Durazzo, A., E. Azzini, M.C. Lazzé, A. Raguzzini, R. Pizzala, G. Maiani, L. Palomba, and G. Maiani. 2014. “Anitoxidants in Italian Head Lettuce (*Latuca Sativa* var. *Capitata L.*) Grown in Organic and Conventional Systems under Greenhouse Condition.” *Journal of Food Biochemistry* 38:56-61.

Dziak, J.J., D.L. Coffman, S.T. Lanza, R. Li. 2012. “Sensitivity and Specificity of Information Criteria.” The Methodology Center. Technical Report Series #12-119, The Pennsylvania State University.

Edgeworth, F. Y. 1881. *Mathematical Psychics; an essay on the application of mathematics to the moral sciences,* London, C.K. Paul & co.

Fallovo, C., Y. Rouphael, E. Rea, A. Battistelli, and G. Colla. 2009 “Nutrient solution concentration and growing season affect yield and quality of *Latuca sativa* L. var. *acephala* in floating raft culture.” *Journal of Science and Food Agriculture* 89:1682-1689.

Fisher, I. 1892. *Mathematical Investigations in the Theory of Value and Prices*, Yale.

Fox, J.A., J.F. Shogren, D.J. Hayes, and J.B. Kliebenstein. 1995. “Experimental Auctions to Measure Willingness to Pay for Food Safety.” *Valuing Food Safety and Nutrition*.

Geweke, J. 1996. “Monte Carlo simulation and numberical integration.” in D. Kendrick and J. Rust, eds., *Handbook of Computational Economics*, Elsevier Science: Amsterdam, 731-800.

Gossen, H. 1854. *Die Entwicktlung*, English translation: *The Laws of Human Relations*, Cambridge: MIT Press, 1983.

Gould, S.J. 1988. "Consumer Attitudes Toward Health and Health Care: A Differential Perspective." *The Journal of Consumer Affairs* 22(1):96-118.

Graves, C.J. 1983. "The nutrient film technique." *Horticultural Review* 5:1-44.

Grebitus, C., G. Colson, L. Menapace, and M. Bruhn. 2010. "Who cares about food origin? A comparison of hypothetical survey responses and actual shopping behavior." Selected paper at AAEA meeting in Denver, Colorado, July 25-27, 2010.

Greene, W.H. 2003. *Econometric Analysis: Fifth Edition.* Upper Saddle River, New Jersey: Prentice Hall.

Guala, F., and L. Mittone. 2005. "Experiments in economics: External validity and the robustness of phenomena." *Journal of Economic Methodology* 12(4):495-515.

Guilkey, D.K. and J.L. Murphy. 1993. "Estimation and testing in the random effects probit model." *Journal of Econometrics* 59:301-317.

Haggerty, J. 2013. "Hydroponic businesses grow after food-safety concerns, popularity of locally grown." The Times-Tribune. Accessed 26 Sept 2013. Available online at <http://thetimes-tribune.com/news/business/hydroponic-businesses-grow-after-food-safety-concerns-popularity-of-locally-grown-1.1483983>.

Haile, P. 2001. "Auctions with Resale Markets: An Application to U.S. Forest Service Timber Sales." *The American Economic Review* 91 (3):399-427.

Hallock, B. 2013. "Leafy greens top source of food-borne illnesses, CDC says." Los Angeles Times. Accessed 20 Mar 2014. Available online at <http://articles.latimes.com/2013/jan/29/news/la-dd-leafy-greens-food-borne-illnesses-cdc-20130129>.

Harrison, G.W. and E.E. Rutström. 2008. *Handbook of Experimental Economics Results, Volume 1*. Elsevier B.V. Chapter 81, pages 752-767.

Harrison, G.W., R.M. Harstad, and E.E. Rutström. 2004. "Experimental Methods and Elicitation of Values." *Experimental Economics* 7:123-140.

Heckman, J.J. 1981. "Statistical models for the analysis of discrete panel data." in C. Manski and D. McFadden, eds., *Structural Analysis of Discrete Data with Econometric Applications*, Cambridge: MIT Press, 114-178.

Hicks, J. 1939. *Value and Capital*, Oxford, Clarendon press.

Hoffman, E., D.J. Menkhaus, D. Chakravarti, R. A. Field, and G. D. Whipple. 1993. "Using Laboratory Experimental Auctions in Marketing Research: A case study of new packaging for fresh beef." *Marketing Science* 12(3):318-338.

Hoffmann, S. and Anekwe, T. 2013. "Making Sense of Recent Cost-of-Foodborne Illness Estimates." U.S. Department of Agriculture, Economic Research Service. Economic Information Bull. No. 118, September.

Hotelling, H. 1935. "Demand Functions with Limited Budgets," *Econometrica* 3:66-78.

Huang, C., K. Kan, and T. Fu. 1999. "Consumer Willingness-to-Pay for Food Safety in Taiwan: A Binary-Ordinal Probit Model of Analysis." *The Journal of Consumer Affairs* 33(1):76-91.

Huang, M., M. Li, J. Rutter, J. Walters, and P. Wiwattarangkul. 2002. "Market Analysis of Hydroponic Lettuce in the Nashville Region." University of Tennessee. Accessed 25 Sept 2013. Available online at <http://www.hort.vt.edu/ghvegetables/documents/Economics/Reference%20Other/TN%20lettuce%20study.pdf>.

Ibrahim, R. and W.A.M. Zuki. 2013. "The Physio-Chemical Properties of Lettuce (*Latuca sativa* 'Grand Rapid') Grown under Different Planting Methods." *7th International Postharvest Symposium* 1012: 201-206.

Jaeger, S.R., and F.R. Harker. 2005."Consumer evaluation of novel kiwifruit: willingness-to-pay." *Journal of the Science of Food and Agriculture* 85:2519-2526.

Jensen, M.H. and W.L. Collins. 1985. "Hydroponic vegetable production." *Horticultural Review* 7:483-558.

Jensen, M.H. 1997. "Food production in greenhouses." *Plant Production in Closed Ecosystems*. Springer Netherlands. 1-14.

Jevons, W. 1871. *Theory of Political Economy,* reprinted by London, Macmillan, 1931.

Johannesson, M., B. Lilijas, and R.M. O'Conor. 1997. "Hypothetical versus real willingness to pay: some experimental results." *Applied Economics Letters* 4(3):149-151.

Johnston, R.J. 2006. "Is Hypothetical Bias Universal? Validating Contingent Responses Using Binding Public Referendum." *Journal of Environmental Economics and Management* 52:469-481.

Kagel, J. H., R. M. Harstad, and D. Levin. 1987. "Information Impact and Allocation Rules in Auctions with Affiliated Private Values: A Laboratory Study." *Econometrica* 55:1275-1304.

Kanter, C., K.D. Messer, and H.M. Kaiser. 2009. "Does Production Labeling Stigmatize Conventional Milk?" *American Journal of Agricultural Economics* 91:1097-1109.

Kimura, M. and D.B. Rodriguez-Amaya. 2003. "Carotenoid composition of Hydroponic Leafy Vegetables." *Journal of Agricultural and Food Chemistry* 51:2603-2607.

Lanza, S.T., L.M. Collins, D.R. Lemmon, J.L. Schafer. 2007. "PROC LCA: A SAS Procedure for Latent Class Analysis." *Structural Equation Modeling: A Multidisciplinary Journal* 14(4):671-694.

Lanza, S.T., X. Tan, and B.C. Bray. 2013. "Structural Equation Modeling: A Multidisciplinary Journal." *Structural Modeling: A Multidisciplinary Journal* 20(1):1-26.

Leskovar, D.I., M.A. Palma, B.S. Patil, P. Rosson, J. Landivar, and M. Dozier. 2013. "SWOT Analysis System of Vegetable and Fruit Industry and Texas A&M AgriLife Programs." SCBS#: 418. ISBN 1-58161-418-7, pp 1-10.

Levitt, S.D., and J.A. List. 2009. "Field experiments in economics: The past, the present, and the future." *European Economic Review* 53:1-18.

Lichtenstein, D.R., N.M. Ridgway, and R.G. Netemeyer. 1993. "Price Perceptions and Consumer Shopping Behavior: A Field Study." *Journal of Marketing Research* 30(2):234-245.

Lima, G.P.P. and Vianello, F. 2011. "Review on the main differences between organic and conventional plant-based foods. *International Journal of Food Science and Technology* 46:1-13

List, J.A. and C.A. Gallet. 2001. "What Experimental Protocol Influence Disparities Between Actual and Hypothetical Stated Values?" *Environmental and Resource Economics* 20:241-254.

List, J. A. and J.F. Shogren. 1998. "Calibration of the Differences Between Actual and Hypothetical Valuations in a Field Experiment." *Journal of Economic Behavior and Organization* 37:193-205.

Little, J. and R. Berrens. 2004. "Explaining Disparities between Actual and Hypothetical Stated Values: Further Investigation Using Meta-Analysis." *Economics Bulletin* 3(6):1-13.

Llorach, R., A. Marti'nez, F.A. Tomas-Barberan, M.I. Gil, and F. Ferreres. 2008. "Characterisation of polyphenols and antioxidant properties of five lettuce varieties and escarole." *Food Chemistry* 108:1028-1038.

Loewenstein, G. 1999. "Experimental Economics from the Vantage-Point of Behavioral Economics." *The Economic Journal* 109 (February):F25-F34.

Lusk, J.L. and D. Hudson. 2004. "Willingness-to-Pay Estimates and Their Relevance to Agribusiness Decision Making." *Review of Agricultural Economics* 26(2):152-169.

Lusk, J.L., and M. Rousu. 2006. “Market Price Endogeneity and Accuracy of Value Elicitation Mechanisms.” *Experimental Methods in Environmental and Resource Economic* John List (ed.) Edward Elgar Publishing.

Lusk, J.L. and Shogren, J.F. 2007. *Experimental Auctions: Methods and Applications in Economics and Marketing Research*. Cambridge, United Kingdom: Cambridge University Press.

Lusk, J.L., C. Alexander, and M.C. Rousu. 2007. “Designing Experimental Auctions for Marketing Research: The Effect of Values, Distributions, and Mechanisms on Incentives for Truthful Bidding.” *Review of Marketing Science* (5)3:1-30.

Lusk, J.L., T. Feldkamp, and T.C. Schroeder. 2004. “Experimental Auction Procedure: Impact on Valuation of Quality Differentiated Goods.” *American Journal of Agricultural Economics* 86:389-405.

Marshall, A. 1895. *Principles of economics*, London; New York: Macmillan.

Massantini, F. 1976. “Floating hydroponics; A method of soilless culture.” In Proc. 4th Intn. Congress on Soilless Culture, Las Palmas, Canary Island, Spain. 91-98.

McAdams, C., M. Palma, C. Hall, and A. Ishdorj. 2013. “A Nonhypothetical Ranking and Auction Mechanism for Novel Products.” *Journal of Agricultural and Applied Economics* 45:35-52.

McAdams, C. P. 2011. *Willingness-to-Pay for Pomegranates: Impact of Product and Health Features using Nonhypothetical Procedures.* Masters thesis. Texas A&M University.

McFadden, D. 1974. “Condtional Logit Analysis of Qualitative Choice Behavior.” In P. Zarembka, ed. *Frontiers in Econometrics.* New York: Academic Press, pp 105-142.

McFadden, D.L. 2013. “The New Science of Pleasure.” *NBER Working Paper Series* National Bureau of Economic Research. Working Paper 18687. Available online at <http://www.nber.org/papers/w18687>.

McKenzie, L. 1957. “Demand Theory Without a Utility Index.” *The Review of Economic Studies*, 24:185-189.

Moeltner, K. and D.F. Layton. 2002. “A Censored Random Coefficients Model for Pooled Survey Data with Application to the Estimation of Power Outage Costs.” *The Review of Economics and Statistics* 84:552-561.

Murphy, J.J., P.G. Allen, T.H. Stevens, and D. Weatherhead. 2005. “A Meta-Analysis of Hypothetical Bias in Stated Preference Valuation.” *Environmental and Resource Economics* 30:313-325.

Murphy, M.T., F. Zhang, Y.K. Nakamura, and S.T. Omaye. 2011. “Comparison between Hydroponically and Conventionally and Organically Grown Lettuces for Taste, Odor, Visual Quality and Texture: A Pilot Study.” *Food and Nutrition Sciences* 2:124-127.

Neeser, C., N. Savidov, and D. Driedger. 2005. “Production of Hydroponically Grown Calcium Fortified Lettuce.” *1st International Symposium on Human Health Effects of Fruits and Vegetables* 744:317-322.

Noussair, C., S. Robin, and B. Ruffieux. 2004. “Revealing Consumers’ Willingness-to-Pay: A Comparison of the BDM Mechanism and the Vickrey Auction.” *Journal of Economic Psychology* 25: 725-741.

Pareto, V. 1906. *Manual of Political Economy*, English translation. Augustus M. Kelley, NY, 1971.

Parkhurst, G.M., J.F. Shogren, and D.L. Dickinson. 2004. “Negative Values in Vickrey Auctions.” *American Journal of Agricultural Economics* 86(1):222-235.

Plott, C.R. 1991. “Will economics become an experimental science?” *Southern Economic Journal* 57: 901-919.

Rattler, S., K. Briviba, B. Birzele, and U. Koepke. 2005. “Effect of agronomic management practices on lettuce quality.” Paper at: Researching Sustainable Systems – International Scientific Conference on Organic Agriculture, September 21-23, 2005, Adelaide, Australia.

Ribera, L., and D. McCorkle. 2012. “Economic Impact Estimate of Irrigation Water Shortages on the Lower Rio Grande Valley Agriculture.” Texas A M AgriLife Extension Service. Accessed 5 Feb 2014. Available online at <http: www.tceq.texas.gov assets public ... economic-impact-LRGV.pdf>.

Roth, A.E. 1986. “Laboratory experimentation in economics.” *Economics and Philosophy* 2:245-73.

—. 1988. “Laboratory experimentation in economics: a methodological overview.” *Economic Journal* 98:974-1031.

—. 1995. “Introduction to experimental economics.” in J.H. Kagel and A.E. Roth (eds) *The Handbook of Experimental Economics*, Princeton: Princeton University Press, pp. 3-109.

Rousu, M., W.E. Huffman, J.F. Shogren, and A. Tegene. 2007. “Effects and Value of Verifiable Information in a Controversial Market: Evidence from Lab Auctions of Genetically Modified Food.” *Economic Inquiry* 45:409-432.

Roy, R. 1942. *Elements d’econometrie.* Presses universitaires de France. 1970.

Samuelson, P. 1947. *Foundations of economic analysis.* Cambridge: Harvard University Press, 1983.

Santa Ana, R. 2013. “Despite rain, South Texas crop losses could hit $100 million.” AgriLife Today. Accessed 5 Feb 2014. Available online at <http://today.agrilife.org/2013/05/01/south-texas-crop-losses-could-hit-100-million/>.

Schram, A. 2005. “Artificiality: The Tension between Internal and External Validity in Economic Experiments.” *Journal of Economic Methodology* 12(2):225-237

Schwarz, G. 1978. “Estimating the Dimension of a Model.” *Annals of Statistics* 6:461-464.

Sclove, S.L. 1987. “Application of Model Selection Criteria to Some Problems in Multivariate Analysis.” *Psychometrika* 52:333-43.

Segovia, M.S. 2014. *Measuring Consumer Acceptance and Willingness-to-Pay for Specialty Tomatoes: Impact of Product, Taste, and Health Features.* Masters Thesis. Texas A&M University.

Shogren, J.F., J.A. Fox, D.J. Hayes, and J. Roosen. 1999. "Observed Choices for Food Safety in Retail, Survey, and Auction Markets." *American Journal of Agricultural Economics* 81:1192-1199.

Shogren, J.F., M. Margolis, C. Koo, and J.A. List. 2001. "A Random *n*th-price Auction." *Journal of Economic Behavior and Organization* 46:409-421.

Shrestha, A., and B. Dunn. 2013. "Hydroponics." Oklahoma Cooperative Extension Service. Fact Sheet No. HLA-6442, March.

Sinden, J.A. 1988. "Empirical Tests of Hypothetical Biases in Consumers' Surplus Surveys." *Australian Journal of Agricultural Economics* 32:98-112.

Slutsky, E. 1915. "Sulla teoria del bilancio del consummatore." *Giornale degli Economisti.* English translation, "On the Theory of the Budget of the Consumer," in G. Stigler and K. Boulding, eds, *Readings in Price Theory*, Homewood: Irving.

Smith, A. 1753. *The Theory of Moral Sentiments*, Oxford University Press, 1984.

—. 1776. *An inquiry into the nature and causes of the wealth of* nations. London, W.

Smith, V. 1976. "Experimental Economics: Induced Value Theory." *The American Economic Review* 66(2):274-279.

—. 1982. "Microeconomic systems as an experimental science." *The American Economic Review* 72.5:923-955.

Smith, V. K. and C. Mansfield. 1998. "Buying time: Real and hypothetical offers." *Journal of Environmental Economics and Management* 36: 209-224.

Stampler, L. 2014. "Organic Food Sales on the Rise." TIME.com. Accessed 20 May 2014. Available online at <http:// http://time.com/97949/organic-food-sales-on-the-rise/>.

StataCorp. 2013. *Stata Statistical Software: Release 13*. College Station, TX: StataCorp LP.

Stone, R. 1954. "Linear Expenditure Systems and Demands Analysis." *Economic Journal*, 64:511-527.

Swamy, P.A. 1970. "Efficient Inference in a Random Coefficient Regression Model." *Econometrica* 38:311-323.

Tietenberg, T. and L. Lewis. 2009. *Environmental and Natural Resource Economics.* Pearson Eduction, Inc., Boston. 8th edition, pp. 34-47.

Tobin, J. 1958. "Estimation of Relationships for Limited Dependent Variables." *Econometrica* 26(1):24-36.

Train, K. 2009. *Discrete Choice Methods with Simulation.* Cambridge, United Kingdom: Cambridge University Press. 2nd edition.

Uzawa, H. 1971. "Preference and Rational Choice in the Theory of Consumption." In J. Chipman, L. Hurwicz, M. Richter, and H. Sonnenschein (eds) *Preferences, Utility, and Demand*, New York: Harcourt.

USDA ERS. 2014. Food Availability (per capita) Data System. Vegetables (Fresh). <http://www.ers.usda.gov/data-products/food-availability-(per-capita)-data-system/food-availability-documentation.aspx>.

USDA NASS. 2014. "Vegetable 2013 Summary." ISSN: 0884-6413. Accessed 10 Apr 2014. Available online at <http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1183>.

USDA NASS. 2013. Accessed 2 Dec 2013. Available online at <http://quickstats.nass.usda.gov/results/B8D63B5D-F188 31DA89498E8CEB0C918E>.

Vickrey, W. 1961. "Counterspeculation, Auctions, and Competitive Sealed Tenders." *Journal of Finance* 16(1):8-37.

Vossler, C.A., and J. Kerkvliet. 2003. "A Criterion Validity Test of the Contingent Valuation Method: Comparing Hypothetical and Actual Voting Behavior for a Public Referendum." *Journal of Environmental Economics and Management* 45:631-649.

Vossler, C.A., J. Kerkvliet, S. Polasky, and O. Gainutdinova. 2003. "Externally Validating Contingent Valuation: An Open Space Survey and Referendum in Corvallis, Oregon." *Journal of Economic Behavior and Organization* 51:261-277.

Watson, E. 2014. "Organic Trade Association: U.S. retail sales of organics grew 11.5% to $35.1 billion in 2013." FOOD navigator-usa.com. Accessed 20 May 2014. Available online at <http://www.foodnavigator-usa.com/Markets/US-retail-sales-of-organics-grew-11.5-in-2013-to-35.1bn>.

Wertenbroch, K., and B. Skiera. 2002. “Measuring Consumers’ Willingness to Pay at the Point of Purchase.” *Journal of Marketing Research* 39(May):228-241.

Withrow, R.B. and A.P. Withrow. 1948. “Nutriculture.” Purdue Univ. Agr. Expt. Sta., Bull. No. 328.

Winsor G.W., R.G. Hurd, and D. Price. 1979. “Nutrient Film Technique.” Glasshouse Crops Research Institute, Littlehampton, England. Grower Bulletin 5.

Wolf, M.M., B. Johnson, K. Cochran, and L. Hamilton. 2002. “Consumer Attitudes Toward Organically Grown Lettuce.” *Journal of Food Distribution Research* 31(1):155-160.

Wooldridge, J.M. 2009. *Introductory Econometrics: A Modern Approach*. Fourth Edition. Mason, Ohio: South-Western Cengage Learning.

Yiridoe, E.K., S. Bonti-Ankomah, and R.C. Martin. 2005. “Comparison of consumer perceptions and preference toward organic versus conventionally produced foods: A review and update of the literature.” *Renewable Agriculture and Food Systems* 20(4):193-205.

Zhao, X., E. Chambers IV, Z. Matta, T.M. Loughin, and E.E. Carey. 2007. “Consumer Sensory Analysis of Organically and Conventionally Grow Vegetables.” *Journal of Food Science* 72(2):S87-S91

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 **vegetable purchasing decisions.** Participants are needed for either **February 26, 27, and 28, 2014.** The study will take place on the campus of Texas A&M University.

Besides an opportunity to contribute to a scientific research project, participants will be awarded a payment of **$30** for their participation. To participate, you must be at least 18 years of age. Participation in the study will take approximately 1 hour.

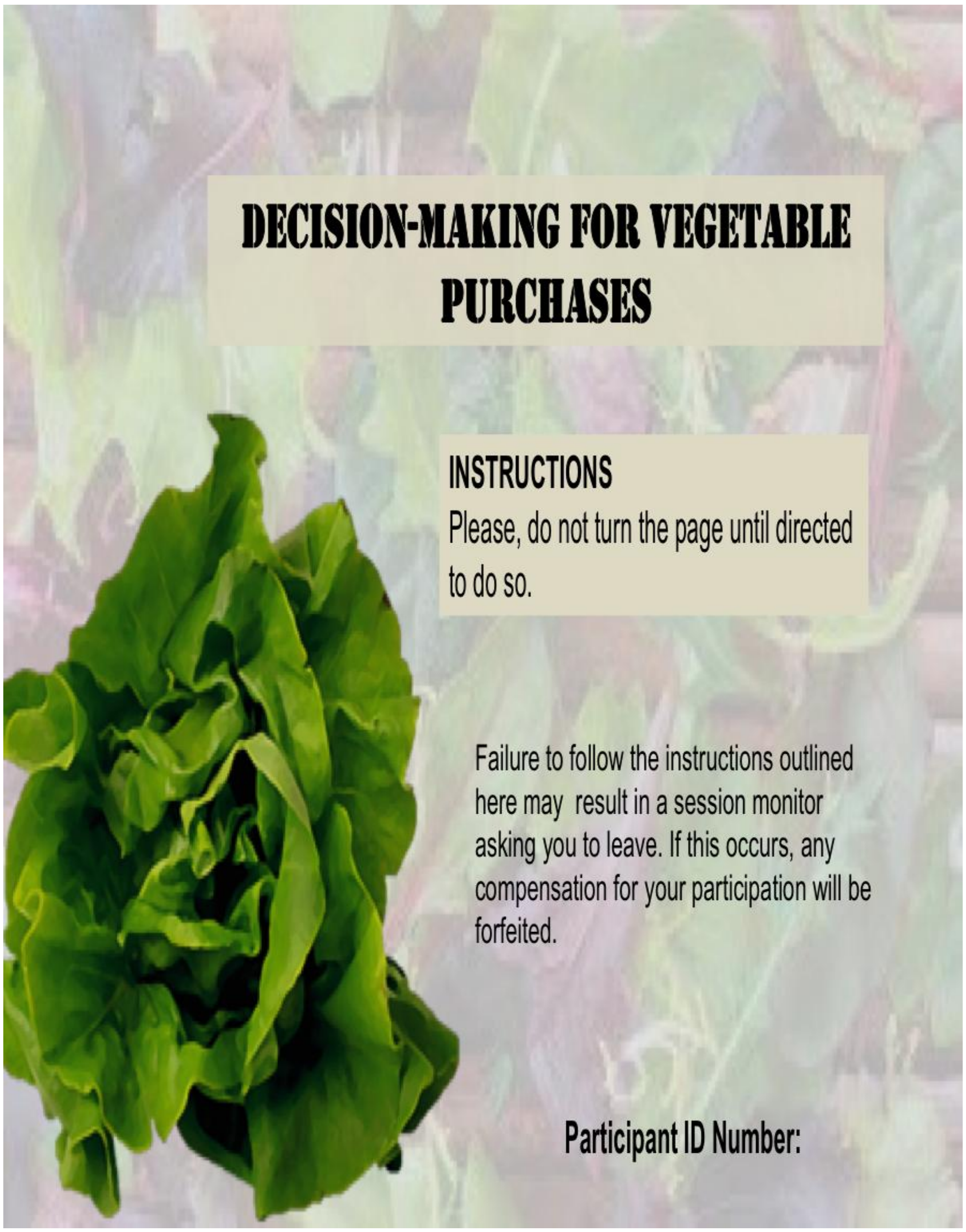
The study includes lettuce tasting. If you have a known lettuce allergy, you may not participate in this study.

Participation in the study is completely voluntary.

If you are interested in participating in this study, please contact **TAMUAgmarketing@gmail.com** or (417) 499-2508 to sign up for the most convenient session.

APPENDIX B

EXPERIMENTAL AUCTION QUESTIONNAIRE



DECISION-MAKING FOR VEGETABLE PURCHASES

INSTRUCTIONS

Please, do not turn the page 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 compensation for your participation will be forfeited.

Participant ID Number:

Introductory Instructions

Welcome! Thank you for agreeing to participate in today's session.

When you entered the room you received this **packet of information**. You should have also been assigned a participant **ID number**, located on the front page of this packet of information. 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. However, in order to receive the participation fee you must complete the session. 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 vegetables. We will now go through a series of instructions. These instructions will be read from a script to make sure the procedures are accurately described. There will be an opportunity for questions once we go through the instructions.

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 may be disqualified from the experiment.

If you have any questions, please direct them to a session monitor who will gladly answer them.

Again, thank you for your participation.

Overview

The purpose of today's experiment is to help us understand purchasing decisions for vegetables and vegetable products. To accomplish this purpose, you will be asked to complete a survey and submit bids for several items. This is a real experiment; if you are one of the buyers of the auctions, you will pay the auction price and in exchange you will receive the item. You will be given more information on the auction procedures shortly.

The experiment will proceed in several stages as described below.

STAGE 1: Learn How Bids Are Submitted

STAGE 2: Learn How Prices and Buyers of the Auction Are Determined

STAGE 3: First Practice Round

STAGE 4: Complete Short Knowledge Quiz

STAGE 5: Second Practice Round

STAGE 6: Submit Bids for Vegetable Products

STAGE 7: Determine Auction Buyer

STAGE 8: Secondary Market

STAGE 9: Complete Survey

STAGE 10: Receive Payment

If you have not already done so, please review and sign the Consent Form. 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 Bids Are Submitted

The Auction: The auction that you will participate in today is called a "sealed bid 2nd-price auction".

1. You will 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.
   Your bid is the **maximum amount of money** that you would be **willing to pay** for each item on the "Bid Sheet."

3. Return to your seat and wait for the Bid Sheets to be collected.

STAGE 2: Learn How the Auction Price and Buyers Are Determined

How The Auction Price is Determined: Today you will be participating in a sealed bid 2nd-price auction. Determining the Market Price:

After all the bids for the items have been collected from all participants, we will sort the bids from highest to lowest. The 2nd highest bid will be the **market price**. The highest bidder will pay the market price for the product.

How the Auction Buyer is Determined:
Determining the Auction Buyers:

You will participate in more than one round of auctions today. However, we will select at random one of these rounds to be binding. All rounds have an equal chance of being drawn. Once the binding round is drawn, a single product from that round will be selected.

For the round that is binding, the highest bidder will purchase the selected product at the market price. This buyer will pay the market price for that round, which will be deducted from the participation fee, and will take home the product.

IMPORTANT REMINDERS:

****Remember, in the auction it is in your best interest to submit a bid of EXACTLY your true value for the good***. If you submit a bid for less than your value, you may end up not winning the auction even though you could have bought the item at a price you were actually willing to pay. If you submit a bid for more than you value the item, then you may end up having to buy the item at a price that is more than you really want to pay.

* ***The practice rounds are hypothetical, but the auction rounds for vegetable products are not***. The buyer of the auction will actually pay money and in exchange receive the vegetable item.

* ***You may bid any value for the item.***

****You will not buy more than one vegetable item from the auctions***. We will randomly select one round and one product to be binding.

****One session participant will take home ONE vegetable product today from the auctions***. There will be a session participant who will buy a product based on the auction bids.

Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

STAGE 3: First Practice Round of Auction

INSTRUCTIONS:

In this stage you will participate in the first hypothetical practice round. First you will be asked to bid on three types of pens. The practice round will proceed as follows:

1. When instructed by a session monitor, you may go to the tables to examine each product. Please do not talk to other participants during bidding. We will be happy to answer any of your questions.
2. On the practice-bidding sheet, you will write down your bid for each item. Then, return to your seat.
3. Wait until a session monitor collects the practice-bidding sheets.

While you wait for the price and buyers of this practice round to be determined, you will complete a short knowledge about the auction procedures. The knowledge quiz starts on the next page (8).

STAGE 4: Short Knowledge Quiz

INSTRUCTIONS:

This is a brief quiz designed for you to check your understanding of how the auctions operate. Please choose the correct answer. Once all participants have completed the quiz, we will go over the answers together.

About the Auction:

1. In a sealed bid 2^{nd}-price auction, the highest bidder is the buyer of the item.
    - **a.** True
    - **b.** False

2. The buyer of the auction for the binding round and product will pay the amount he/she bid for the item.
    - **a.** True
    - **b.** False

3. More than one round of bidding on several products will be done today, but only one round and one product will be randomly selected to be binding.
    - **a.** True
    - **b.** False

4. There will be the opportunity to actually purchase and take home more than one vegetable product today from the auction rounds.
    - **a.** True
    - **b.** False

Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

STAGE 5: Second Practice Round of Auction

INSTRUCTIONS:

You have completed half of the practice. Now you will be asked to bid on four types of glue products. The stage will proceed as follows:

1. When instructed by a session monitor, you may go to the tables to examine each product. Please do not talk to other participants during bidding. We will be happy to answer any of your questions.

2. On the practice-bidding sheet, you will write down your bid for each item. Then, return to your seat.

3. Wait until a session monitor collects the practice-bidding sheets.

Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

STAGE 6A: VEGETABLE AUCTIONS

Thank you for participation so far. The next auction rounds will be for several vegetable products, but only one of the rounds will be binding. The binding round will be selected at random after all rounds have been completed.

INSTRUCTIONS: The stage will proceed as follows:

1. When instructed to do so, you may go to the tables to examine each product. Please do not talk to other participants during bidding. The monitor will be happy to answer any of your questions.
2. On the bidding sheet, write down your bid for each item. Then, return to your seat.
3. Wait until a session monitor collects your sheets.

Please do not turn the page until directed to do so. We will repeat the auction procedure whenever indicated.

Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

STAGE 6B: TASTING

INSTRUCTIONS:

1. Taste samples from left to right following the order of the sample code.
2. Mark with an **"X"** the appropiate box according to your evaluation for the attributes of appearance, color, smell, taste, freshness and overall acceptance.

   1= Extremely Dislike

   9= Extremely Like

3. For each item, please indicate your bid on each bidding sheet. Please do not talk to other participants during bidding.
4. Wait until a session monitor collects your sheets.
5. You can find crackers and water in the table to rinse your palate between each sample.

If you have any questions, please direct them to a session monitor who will gladly answer them.

Please do not turn the page until directed to do so. We will repeat the auction procedure whenever indicated.

Date: February, 2014

Sample: 1

Appearance

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Color

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Smell

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Taste

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Freshness

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Overall Acceptance

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Date: February, 2014

Sample: 2

<u>Appearance</u>

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

<u>Color</u>

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

<u>Smell</u>

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

<u>Taste</u>

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

<u>Freshness</u>

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

<u>Overall Acceptance</u>

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Date: February, 2014

Sample: 3

Appearance

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Color

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Smell

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Taste

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Freshness

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Overall Acceptance

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Date: February, 2014

Sample: 5

Appearance

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Color

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Smell

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Taste

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Freshness

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Overall Acceptance

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Date: February, 2014

Sample: 6

Appearance

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Color

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Smell

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Taste

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Freshness

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Overall Acceptance

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Date: February, 2014

Sample: 7

Appearance

1	2	3	4	5	6	7	8	9

Extremely Dislike — Neither like / Nor dislike — Extremely Like

Color

1	2	3	4	5	6	7	8	9

Extremely Dislike — Neither like / Nor dislike — Extremely Like

Smell

1	2	3	4	5	6	7	8	9

Extremely Dislike — Neither like / Nor dislike — Extremely Like

Taste

1	2	3	4	5	6	7	8	9

Extremely Dislike — Neither like / Nor dislike — Extremely Like

Freshness

1	2	3	4	5	6	7	8	9

Extremely Dislike — Neither like / Nor dislike — Extremely Like

Overall Acceptance

1	2	3	4	5	6	7	8	9

Extremely Dislike — Neither like / Nor dislike — Extremely Like

Date: February, 2014

Sample: 8

Appearance

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Color

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Smell

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Taste

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Freshness

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Overall Acceptance

1	2	3	4	5	6	7	8	9
Extremely Dislike				Neither like / Nor dislike				Extremely Like

Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

STAGE 8: SURVEY

INSTRUCTIONS: Please select **only one** answer by marking an "X" in the blank unless otherwise indicated. There is no right or wrong answer. Your survey responses are very important to the results of today's sessions. **Please remember that all responses will be kept confidential**.

1. **PRIMARY SHOPPER: Are you the PRIMARY grocery shopper for your household?**
   a. ___ Yes **b.** ___ No

2. **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

3. **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

4. **FRESH FRUIT AND VEGETABLE EXPENDITURES: Approximately what portion of your fruit and vegetable purchases are for <u>FRESH</u> 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. ___ 1-24% of the fruits and vegetables purchased are fresh.
   c. ___ 25-49% of the fruits and vegetables purchased are fresh.
   d. ___ 50-75% of the fruits and vegetables purchased are fresh.
   e. ___ 76-100% of the fruits and vegetables purchased are fresh.

5. **LOCATION OF FRUIT AND VEGETABLE PURCHASES: Of the following options, where does your household make the LARGEST PORTION of its fruit and vegetable purchases?**
   a. ___ Mass-merchandiser (e.g., Walmart, Target)
   b. ___ Supermarket/ Grocery Store (e.g. HEB, Kroger, Albertsons)
   c. ___ Roadside Fruit and Vegetable Stand
   d. ___ Farmers' Market
   e. ___ Other (Please Indicate :_______________________________________)

6. **LAST PURCHASE OF FRUIT AND VEGETABLES: When was the last time someone in your household purchased fruits and vegetables?**
   - **a.** ___ Less than 2 days ago
   - **b.** ___ 2-4 days ago
   - **c.** ___ 5-7 days ago
   - **d.** ___ 8- 10 days ago
   - **e.** ___ 11-14 days ago
   - **f.** ___ More than 2 weeks ago

7. **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

8. **FRESH VEGETABLES ON HAND: Please estimate the amount of FRESH VEGETABLES that you currently have on hand in your home as a percentage of your full stock.**
   - **a.** ___ 0%
   - **b.** ___ 1-24%
   - **c.** ___ 25-49%
   - **d.** ___ 50-74%
   - **e.** ___ 75-100%

9. How important are the following factors to you when making lettuce purchasing decisions? (Please select only one level of importance per row).

	Not Important At All	Not Very Important	Somewhat Important	Very Important
A. PRICE				
B. TASTE				
C. NUTRITION				
D. CONVENIENCE				
E. VISUAL APPEARANCE				
F. SIZE				
G. FRESHNESS				
H. GROWING LOCATION				
I. CERTIFIED PRODUCTION PRACTICES				

10. **How often do you exercise? (Include only periods of exercise longer than 20 minutes).**
   - **a.** ___ Never
   - **e.** ___4-6 times per week
   - **b.** ___ Once a month
   - **f.** ___ Once a day
   - **c.** ___ Once a week
   - **g.** ___More than once a day
   - **d.** ___ 2-3 times per week

11. **Do you currently have any serious health issues (including any conditions which require regular doctor visits and/or prescription medication)?**
    - **a.** ___ Yes
    - **b.** ___ No (**Skip to question 14**)

12. **If you have health issues that you would consider serious, are any of them nutrition related?**
    - **a.** ___ Yes
    - **b.** ___ No

13. **If you have health issues that you would consider serious, do any of them require specific diet?**
    - **a.** ___ Yes
    - **b.** ___ No

14. **Have you ever experienced food poisoning from consuming fruits and vegetables?**
    - **a.** ___ Yes
    - **b.** ___ No
    - **c.** ___ Don't Know

15. **Do you believe there are benefits of consuming fruits and vegetables that have been certified for appropriate food safety?**
    - **a.** ___ Yes
    - **b.** ___ No
    - **c.** ___Don't Know/Not Sure

16. **AGE: Please indicate your age in years: __________ years**

17. **WEIGHT: Please indicate your weight in pounds:**

    ___ lb.

18. **HEIGHT: Please indicate your height in feet:**

    ___ ft. ___in

19. **EDUCATION: Please indicate the <u>highest</u> 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/ Bachelor's Degree
   - **f.** ___ Some Graduate School
   - **g.** ___ Graduate Degree

20. **HOUSEHOLD SIZE: Including yourself, <u>how many</u> people live in your household?**
   ___ People

21. **CHILDREN: <u>How many</u> children live in your household, if any?**
   ___ Children

22. **GENDER: Please indicate your gender:**
   - **a.** ___ Female
   - **b.** ___ Male

23. **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: ____)

24. **MARITAL STATUS: What is your current marital status?**
   - **a.** ___ Single
   - **b.** ___ Married

25. **INCOME: Please indicate your household yearly income for 2013.** (Include all forms of income, including salary, interest and dividend payments, tips, scholarship support, student loans, parental support, social security, child support, and allowance).
   - **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

26. **EMPLOYMENT: Which of these best describes your employment status?**
   - **a.** ___ Unemployed
   - **b.** ___ Stay-at-Home Parent
   - **c.** ___ Part-time Employed
   - **d.** ___ Full-time Employed
   - **e.** ___ Retired
   - **f.** ___ Disabled
   - **g.** ___ Student

27. Do you currently participate in any Food and Nutrition Assistance programs? (ex. SNAP, WIC, etc.)

a. ________ No **b.________ Yes**

28. Mark with an "X" the appropiate box according to how strongly you agree or disagree with the following statements

1 = Extremely Disagree
2 = Disagree
3 = Disagree Somewhat
4 = Neutral
5 = Agree Somewhat
6 = Agree
7 = Extremely Agree

A. People notice when you buy the most expensive brand of a product.

1	2	3	4	5	6	7

Extremely Disagree | Neutral | Extremely Agree

B. Buying a high price brand makes me feel good about myself

1	2	3	4	5	6	7

Extremely Disagree | Neutral | Extremely Agree

C. Buying the most expensive brand of a product makes me feel classy.

1	2	3	4	5	6	7

Extremely Disagree | Neutral | Extremely Agree

D. I enjoy the prestige of buying a high priced product.

1	2	3	4	5	6	7

Extremely Disagree | Neutral | Extremely Agree

E. It says something to people when you buy the high priced version of a product.

1	2	3	4	5	6	7

Extremely Disagree — Neutral — Extremely Agree

F. Your friends will think you are cheap if you consistently buy the lowest priced version of a product.

1	2	3	4	5	6	7

Extremely Disagree — Neutral — Extremely Agree

G. I think others make judgments about me by the kinds of products and brands I buy.

1	2	3	4	5	6	7

Extremely Disagree — Neutral — Extremely Agree

H. Even for a relatively inexpensive product, I think that buying a costly brand is impressive.

1	2	3	4	5	6	7

Extremely Disagree — Neutral — Extremely Agree

29. Mark with an "X" the appropiate box according to how well the following statements describe you:

0 = statement does not describe you at all
1 = statement describes you a little
2 = statement describes you about fifty-fifty
3 = statement describes you fairly well
4 = statement describes you well

A. I reflect about my health a lot.

0	1	2	3	4

Does not describe you at all — Describes you well

B. I'm very self-conscious about my health.

0	1	2	3	4

Does not describe you at all — Describes you well

C. I'm generally attentive to my inner feelings about my health.

0	1	2	3	4

Does not describe you at all — Describes you well

D. I'm constantly examining my health.

0	1	2	3	4

Does not describe you at all — Describes you well

E. I'm alert to changes in my health.

0	1	2	3	4

Does not describe you at all — Describes you well

F. I'm usually aware of my health.

0	1	2	3	4

Does not describe you at all — Describes you well

G. I'm aware of the state of my health as I go through the day.

0	1	2	3	4

Does not describe you at all — Describes you well

H. I notice how I feel physically as I go through the day.

0	1	2	3	4

Does not describe you at all — Describes you well

I. I'm very involved with my health.

0	1	2	3	4

Does not describe you at all — Describes you well

Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

STAGE 9: INTRODUCTION OF SECONDARY MARKET

INSTRUCTIONS:

1. You will now be provided with the opportunity to purchase a designated product in a secondary market.
2. To do so, we have assembled a distribution of market prices for lettuce from stores in the Bryan/ College Station area.
3. **WE HAVE ASSIGNED A PRICE TO YOU THAT IS WITHIN THIS RANGE OF RETAIL PRICES.** The price that **YOU** can buy the designated product in the secondary market for is located on the following order form.
4. Please indicate how many units, IF ANY, you want to buy in the secondary market at your assigned price on the following order form. Note that any purchases made will be deducted from your participation fee, in exchange for the good.

Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

Thank you for your participation!

Your responses are very important for us.

WE DONT HAVE ANY
VEGETABLE
JOKES YET

SO IF YOU DO

LETTUCE KNOW

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 participation fee minus any purchases. Please wait for further instructions.

APPENDIX C

BIDDING SHEETS & ORDER FORM

STAGE 3: PRACTICE ROUND 1: Pen Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below.

A. PAPER MATE PEN	B. PILOT B2P PEN	C. BIC PEN
BID:$_______	BID:$_______	BID:$_______

STAGE 3: PRACTICE ROUND 1: Pen Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below.

A. PAPER MATE PEN	B. PILOT B2P PEN	C. BIC PEN
BID:$_______	BID:$_______	BID:$_______

STAGE 5: PRACTICE ROUND 2: Glue Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below.

A. INSTANT KRAZY GLUE	B. ELMER'S GLUE STICK	C. SCOTCH GLUE GEL	D. ELMER'S CLEAR GLUE
BID:$_______	BID:$_______	BID:$_______	BID:$_______

STAGE 5: PRACTICE ROUND 2: Glue Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below.

A. INSTANT KRAZY GLUE	B. ELMER'S GLUE STICK	C. SCOTCH GLUE GEL	D. ELMER'S CLEAR GLUE
BID:$_______	BID:$_______	BID:$_______	BID:$_______

STAGE 6: ROUND 6-A Vegetable Product Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below. **Please be sure to write a bid for ALL products listed.**

A. 1	B. 2	C. 3	D. 4	E. 5	F. 6	G. 7	H. 8
BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____

STAGE 6: ROUND 6-A Vegetable Product Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below. **Please be sure to write a bid for ALL products listed.**

A. 1	B. 2	C. 3	D. 4	E. 5	F. 6	G. 7	H. 8
BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____

STAGE 6: ROUND 6-B Vegetable Product Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below. **Please be sure to write a bid for ALL products listed.**

A. 1	B. 2	C. 3	D. 4	E. 5	F. 6	G. 7	H. 8
BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____

STAGE 6: ROUND 6-B Vegetable Product Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below. **Please be sure to write a bid for ALL products listed.**

A. 1	B. 2	C. 3	D. 4	E. 5	F. 6	G. 7	H. 8
BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____	BID:$_____

ORDER FORM

Participant No. __________

Assigned Price: $__________

Would you like to purchase the product in the Secondary Market?

(Please check one box)

YES ☐

NO ☐

If you answered YES, how many units will you buy? ________ Units

Total Order:

________ UNITS × $ ________ ASSIGNED PRICE = $ _______ TOTAL DUE

ORDER FORM

Participant No. __________

Assigned Price: $__________

Would you like to purchase the product in the Secondary Market?

(Please check one box)

YES ☐

NO ☐

If you answered YES, how many units will you buy? ________ Units

Total Order:

________ UNITS × $ ________ ASSIGNED PRICE = $ _______ TOTAL DUE

APPENDIX D

HYDROPONIC PRODUCTION INFORMATION

- Hydroponic lettuce is grown in greenhouses, without soil.
- Plants are propagated and grown in inert, inorganic material (free of soil borne diseases).
- Roots are constantly exposed to nutrient solution or humidified air.

Compared to field production…

- They have a shorter production cycle (e.g. 60 days vs. 90 days in field).
- They use much less water (The amount of water used per plant is 5 to 10% of what is used in the field...which means that hydroponics have a higher water use efficiency such as 90%)
- Hydroponic systems offer better control of environmental conditions, nutrition and water requirements.
- Hydroponic plants have much lower incidence of pests and diseases, and fewer to minimum pesticide applications.
- Better cleanliness of the final product.