PRODUCTION MODEL AND CONSUMER PREFERENCES FOR TEXAS PECANS

A Thesis

by

CHRISTOPHER JAMES CHAMMOUN

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

MASTER OF SCIENCE

August 2012

Major Subject: Agricultural Economics

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Approved by:

Co-Chairs of Committee,	Joe Outlaw
	Marco A. Palma
Committee Members,	Leonardo Lombardini
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ABSTRACT

Production Model and Consumer Preferences for Texas Pecans. (August 2012)

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High prices in any industry, agricultural especially, tend to spur new investment opportunities. Recent prices for pecans have been high relative to their historical pattern, suggesting investment opportunities for pecans. Prior to any investment, the investor needs to know what products consumers are demanding and how profitable it is to grow those products. This study assessed Texas consumers' preferences for pecan products and the profitability of growing pecans in the central Texas region.

A choice experiment was conducted amongst Texas consumers to reveal consumers' preferences and determine their willingness-to-pay for the attributes comprising pecan products. A stochastic production model was formulated to determine the profitability of three different types of pecan orchards: a native orchard with no irrigation, an improved varieties orchard with irrigation, and an improved varieties orchard without irrigation.

Results from the choice experiment indicated that consumers preferred large size pecans, native variety pecans, pecan halves, United States-grown pecans, and Texas-grown pecans. The choice experiment also found that consumers were heterogeneous in their preferences for all attributes except pecan variety and U.S. origin. Results from the stochastic production model indicated that the most profitable pecan orchard in central Texas was the irrigated improved orchard.

DEDICATION

To the farmers of the United States, and particularly those in the South, may the Lord grant his good graces upon your operation and may you find joy and prosperity in all you do.

ACKNOWLEDGEMENTS

I would like to thank my committee chairs, Drs. Palma and Outlaw, for their patience and guidance throughout the course of my research. I would also like to thank my committee members, Drs. Lombardini and Harris, for the insights into the Texas pecan industry as well as the practices of producers in central Texas. Thanks also to the countless people within the agricultural industry and pecan producers without whose expertise this research would not have been possible. A special thanks to all the research and extension personnel in the Departments of Agricultural Economics, Horticulture, and Entomology for their assistance in this research.

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CHAPTER I

INTRODUCTION

Pecan, *Carya illinoinesis*, is native to North America. Many pecan cultivars are produced extensively throughout the southern portion of the United States and the northern regions of Mexico. Propagation has spread the pecan to other countries throughout the world but the United States has remained the largest producer of pecans in the world (USDA Foreign Agricultural Service 2012b). Georgia has been the top U.S. commercial pecan producer over the past century with Texas and New Mexico now in second and third place, even though pecan is not a native species of Georgia or New Mexico. Native U.S. pecans are found in the floodplains and tributaries along the Mississippi, Ohio, Missouri, and Red Rivers, as well as many rivers scattered throughout central Texas and northern Mexico (Santerre 1994). Texas has traditionally been the largest producer of native pecans in the United States.

Pecan production has been well documented to follow a cyclical pattern of production (Chung and Harris 1995). Production changes from "on" and "off" years, with "on" years producing a relatively higher amount than the "off" years. Prices for pecans have traditionally followed the supply and demand changes of the "on" and "off" cycle of production. As suggested by economic theory, and proved with empirical data, prices and production are inversely related. When pecans are in an "on" year and production is high, prices tend to gravitate down relative to the previous year. In an "off"

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

year of production and supplies are lower, prices tend to rise. This pattern has held throughout most of the life of the commercial pecan industry until the mid-2000s. With the introduction of pecans into the Chinese market, the additional impact on the demand function has altered the traditional structure with an overall rise in prices due to the increase in demand.

As with any industry, excess profits, usually attained by high prices, tend to spur investments. In agriculture, high prices tend to shift acreage away from the relatively low price crops to high price crops because of the higher expected profits. Perennial crops are not as easily shifted to other more profitable crops because of their different nature from annual crops, such as corn or soybeans. Revenue from perennial crops typically lag several years behind initial investment. Because of the nature of the supply function, it is often hard to predict if there are any potential profits by investing in a perennial or tree crop.

This study avoids many of these complicating factors by focusing on the profitability of investing in an established pecan orchard in central Texas. United States Department of Agriculture (USDA) data indicate that there are over 10,000 acres of both native and improved varieties in Texas that are currently non-bearing (USDA National Agricultural Statistics Service 2012). This study evaluated three different types of orchards in central Texas: a native orchard with no irrigation, an improved varieties orchard with irrigation, and an improved varieties orchard without irrigation. It was assumed that each orchard was currently not in production, representing USDA non-bearing acreage. These orchards were formulated into a stochastic production model and simulated using Monte Carlo simulation.

Prior to determining which type of orchard was the most profitable, this study also assessed Texas consumers' preferences for different variety types, sizes, conditions, and origins of pecans. This was done by using a conjoint analysis choice experiment in which consumers answered questions relating to different pecan product attributes.

Merging the choice experiment and production model together, what consumers are demanding and willing to pay for pecans as well at what type of orchard to grow these pecans is most profitable was determined. This study took the approach of investing in pecans as a business investment with a life of 15 years. For forecast and prediction purposes, only the years of 2012 – 2015 were evaluated. The models formulated terminate at 2015 because of the diminished confidence in the prediction methods that forecast past five years.

Outline for the Study

Chapter II reviews the pecan industry by looking at past and current data for the world, U.S., and Texas markets. Chapter III provides a review of the literature pertaining to conjoint analysis, choice experiments, and the use of Monte Carlo simulation as a tool for analyzing business investments. The methods used to conduct the research for this study are provided in the methodology, Chapter IV. Results from the choice experiment and production model are discussed in Chapter V. Concluding remarks and further suggestions are made in Chapter VI.

CHAPTER II

REVIEW OF PECAN INDUSTRY

Pecans are native to North America and are produced extensively throughout the southern regions of the United States and the northern parts of Mexico (Santerre 1994). The United States is the largest producer of pecans in the world and Mexico is second (USDA Foreign Agricultural Service 2012b). Historically Georgia has been the largest pecan producing state in the U.S. with Texas and New Mexico constantly vying for second place each year (USDA National Agricultural Statistics Service 2012). Texas is the largest producer of native and seedling pecans as the various river bottoms found throughout central and east Texas are one of the native habitats for pecans (Santerre 1994). The pecan industry in the U.S. competes to a degree with of almonds, walnuts, and pistachios in the market place, but less so in farm location (USDA Foreign Agricultural Service 2012a; Harris 2011).

World

On average the United States and Mexico produce over 200,000 metric tons of pecans per year (figure 1). World demand for pecans is primarily in North America, Europe and some emerging markets in Asia. In recent years China has become a major purchaser of pecans.

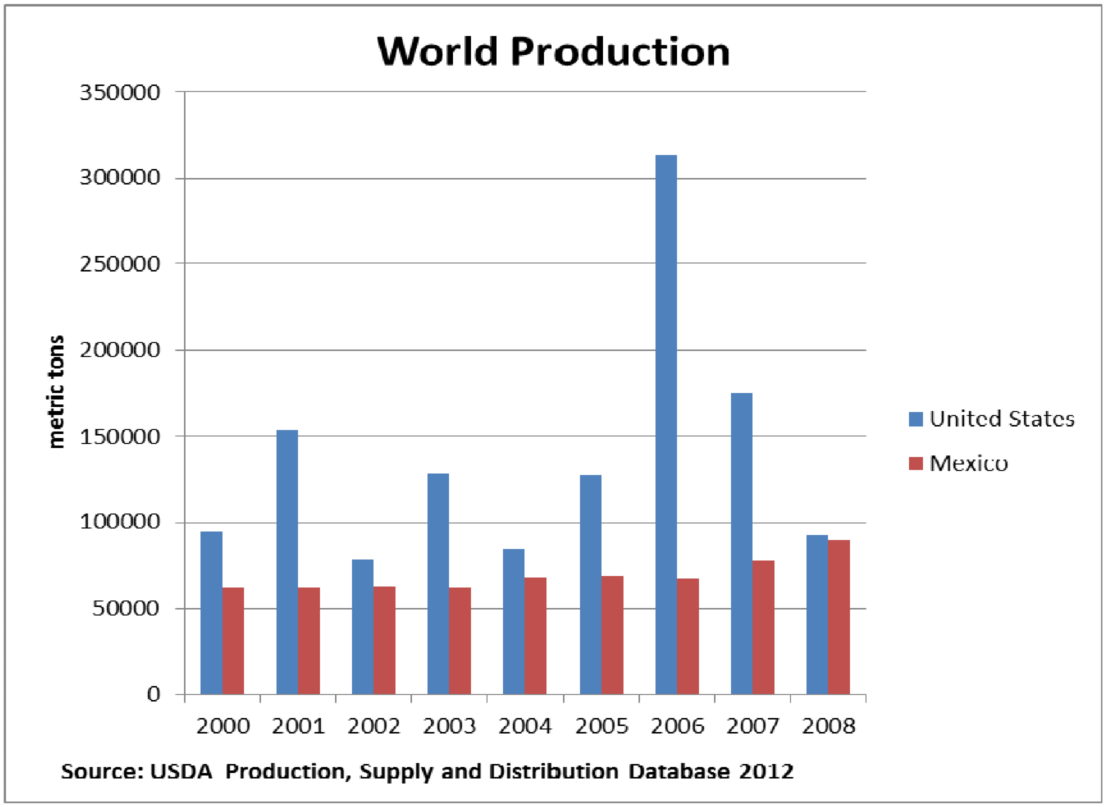

Figure 1. World Production of Pecans

United States

It must be recognized that the United States is a large exporter of other tree nuts as well as pecans. In 2011, $5.4 billion of edible tree nuts were exported from the United States. The largest single tree nut exported was almonds, with over 50% of export value. Walnuts and pistachios totaled 20% and 14% respectively. Pecans were the fourth largest tree nut by export valued at 7% (figure 2).

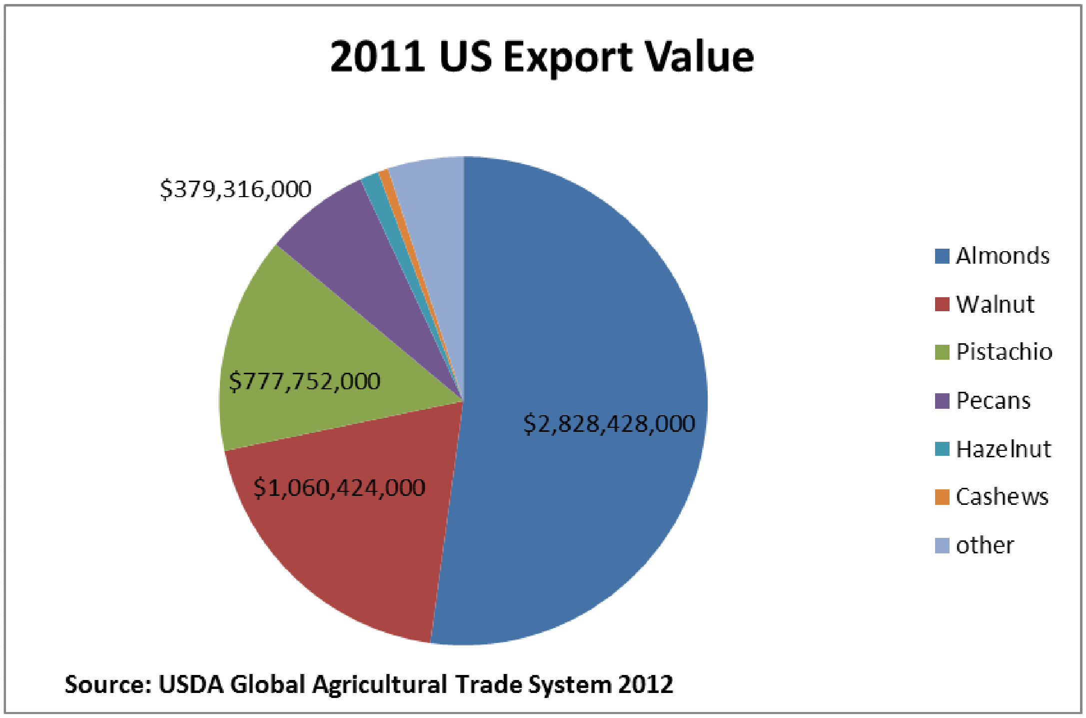

Figure 2. 2011 Value of U.S. Edible Tree Nuts

The United States pecan industry consists of many producers throughout the southern United States, with most of the production coming from Georgia, Texas, New Mexico, and Arizona. Also located in these pecan production areas are various accumulators and shellers who purchase nuts directly from producers and sometimes purchase nuts from each other. Food processors then purchase shelled pecans from the shellers to put in their finished products. A growing number of retail stores can also be found throughout the United States that sell pecans directly to the consumer from the producer. This option usually allows producers to capture a higher price for their nuts.

The United States exported almost $2 billion of in-shell pecans in 2011 with the largest single purchaser of United States pecans being China. Mexico and Vietnam are also large purchasers of United States in-shell pecans (figure 3). In 2007, China purchased 41% of the United States in-shell pecan exports. This percentage grew to 83% of in-shell pecan exports in 2009 and has remained over 50% in 2010 and 2011. The total dollar value of in-shell exports to China in 2011 was $192.8 million. Shelled pecan exports from the United States primarily go to Canada and Europe (figure 4). In the last five years, Canada has purchased approximately 30% of United States shelled pecan exports. In 2011 the dollar value of United States shelled pecan exports to Canada was $186.5 million.

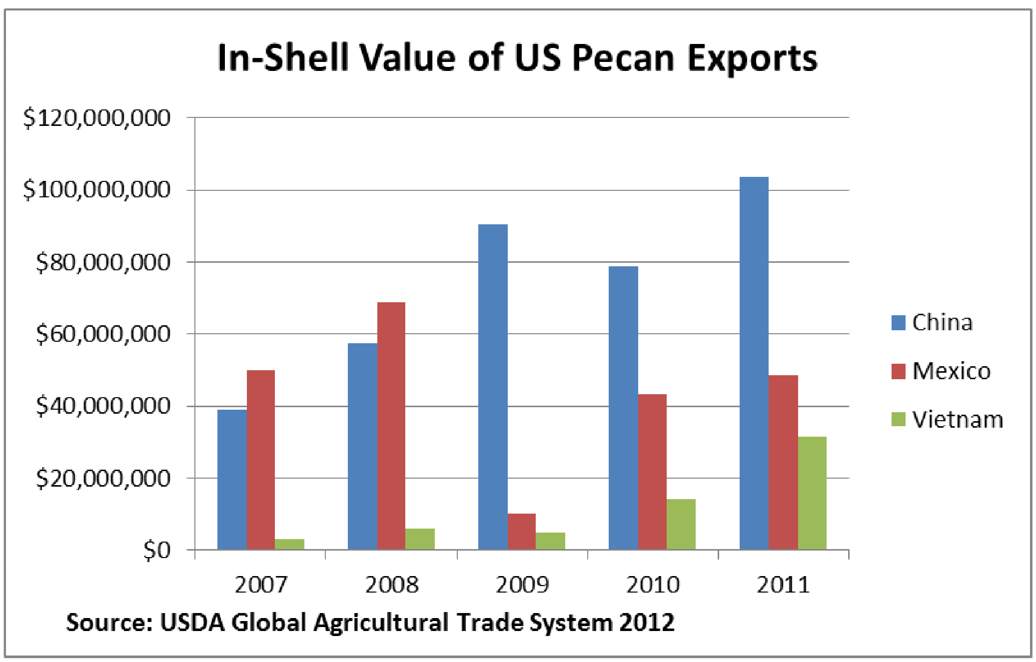

Figure 3. Value of U.S. Exports of In-Shell Pecans

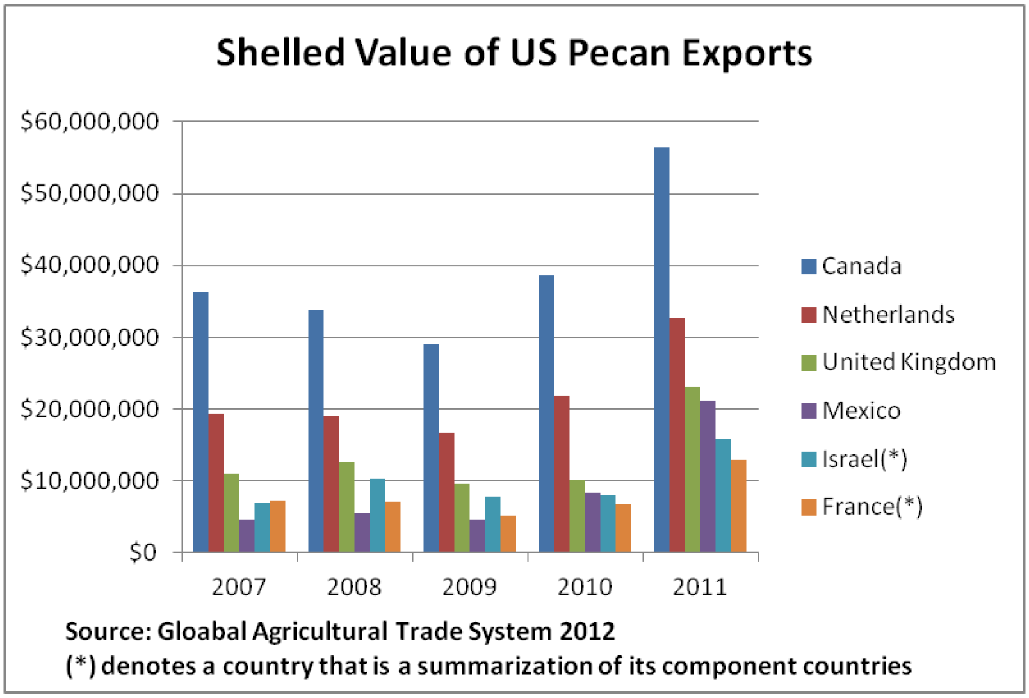

Figure 4. Value of U.S. Exports of Shelled Pecans

Production of pecans in the United States is concentrated in the southern states from Georgia on the eastern coast to the southern portion of California on the western coast. Georgia traditionally is the largest producer by volume with Texas and New Mexico currently fluctuating as the second largest producer in the United States. In 2010 Georgia was the largest pecan producing state with 75 million pounds, which accounted for 26% of the total production in the United States (figure 5). In the same year Texas and New Mexico had 24% and 23% of total production respectively. In 2011, drought stricken Texas only produced 15% of the total United States pecans while Georgia produced almost 41% of the total. New Mexico produced 22% of total U.S. production in 2011. Texas is the largest producer of native and seedling pecans with Georgia and

Oklahoma as the second and third most producing states of native and seedling pecans (figure 6).

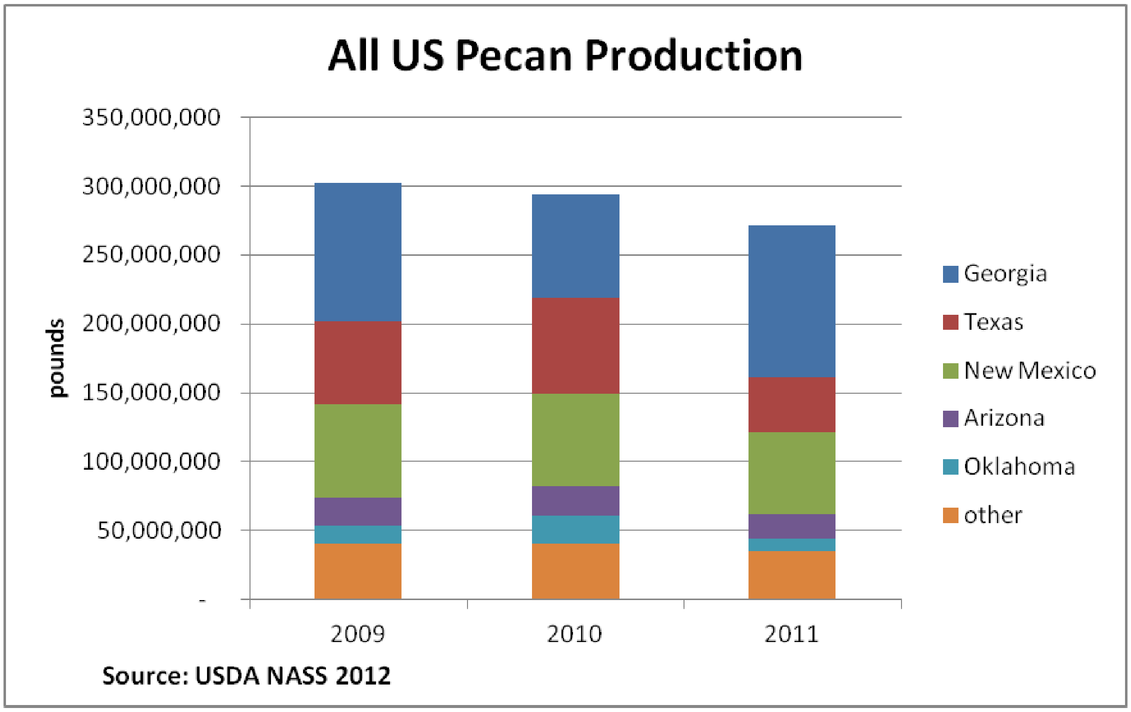

Figure 5. Pecan Production in the U.S.

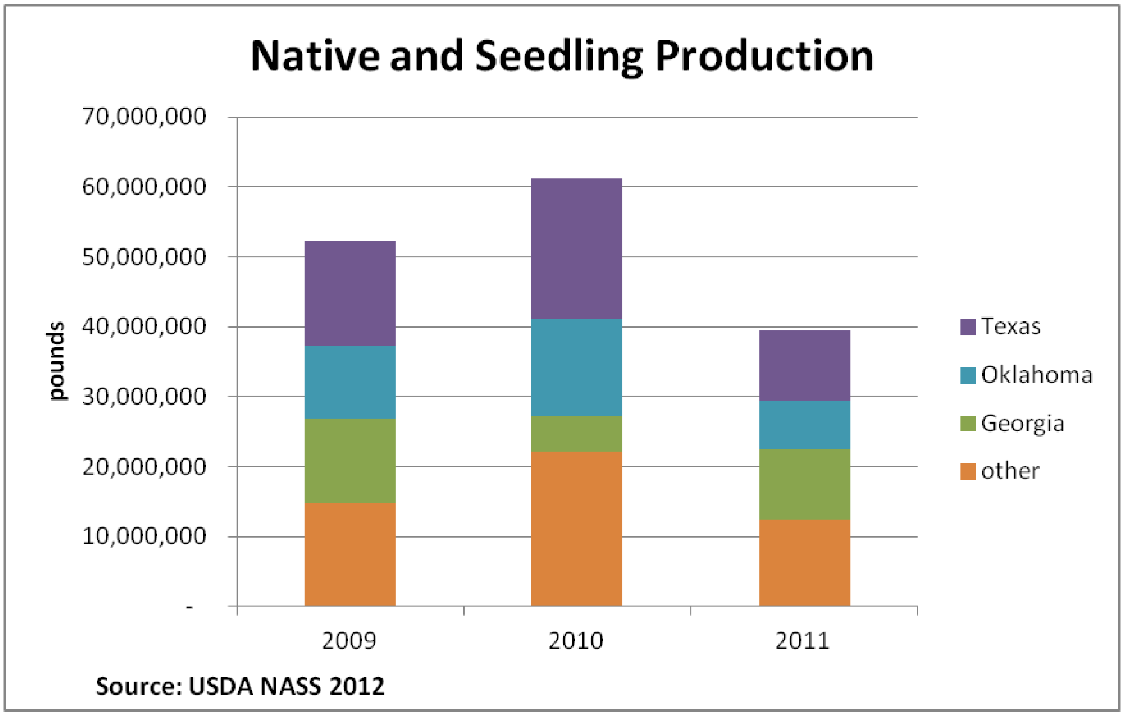

Figure 6. Native and Seedling Production in the U.S.

Texas

Pecans are produced in 106 of Texas' 254 counties. Comanche is the largest pecan producing county with over 14,000 acres per the 2007 USDA Census of Agriculture. San Saba, El Paso, and Mills are the next largest pecan producing counties (table 1). Production within Texas is throughout the state but mainly concentrated in three regions: west, central, and east. Native pecans are only found in the central and east regions and are typically found in close proximity to rivers and streams (Santerre 1994). Production in the west region is all improved varieties and relies extensively on irrigation.

Table 1. Top Ten Pecan Counties in Texas by Acreage

Rank	County	Acres
1	Comanche	14,571
2	San Saba	9,504
3	El Paso	8,658
4	Mills	5,303
5	Montague	4,108
6	Cooke	3,451
7	Houston	3,438
8	Bell	3,317
9	De Witt	3,074
10	Hood	3,031

Source: USDA NASS 2012

Operation size in Texas is very diverse. According to the 2007 USDA Census of Agriculture, there are 6,625 pecan operations in Texas; 18 of these operations are larger than 1000 acres. The largest number of operations category of operations (2,267) is the smallest, 1 – 4.9 acre, size operation (figure 7). Texas acreage consists of a considerable amount of native and improved varieties that are non-bearing or not currently in production (figure 8).

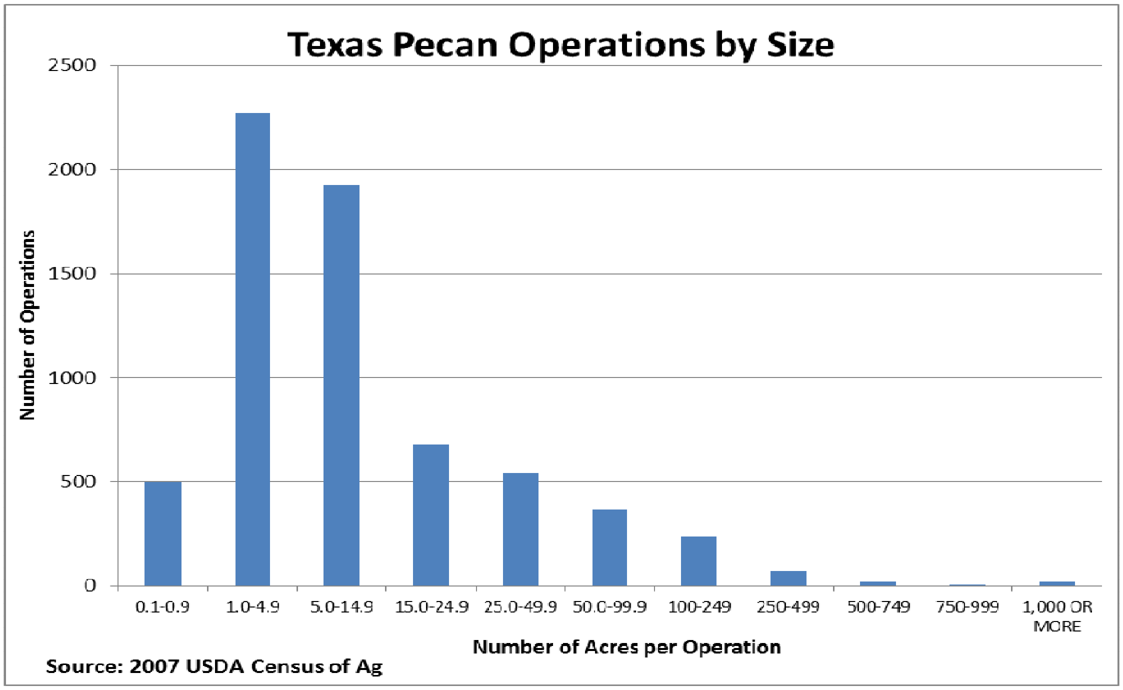

Figure 7. Texas Pecan Operations by Size

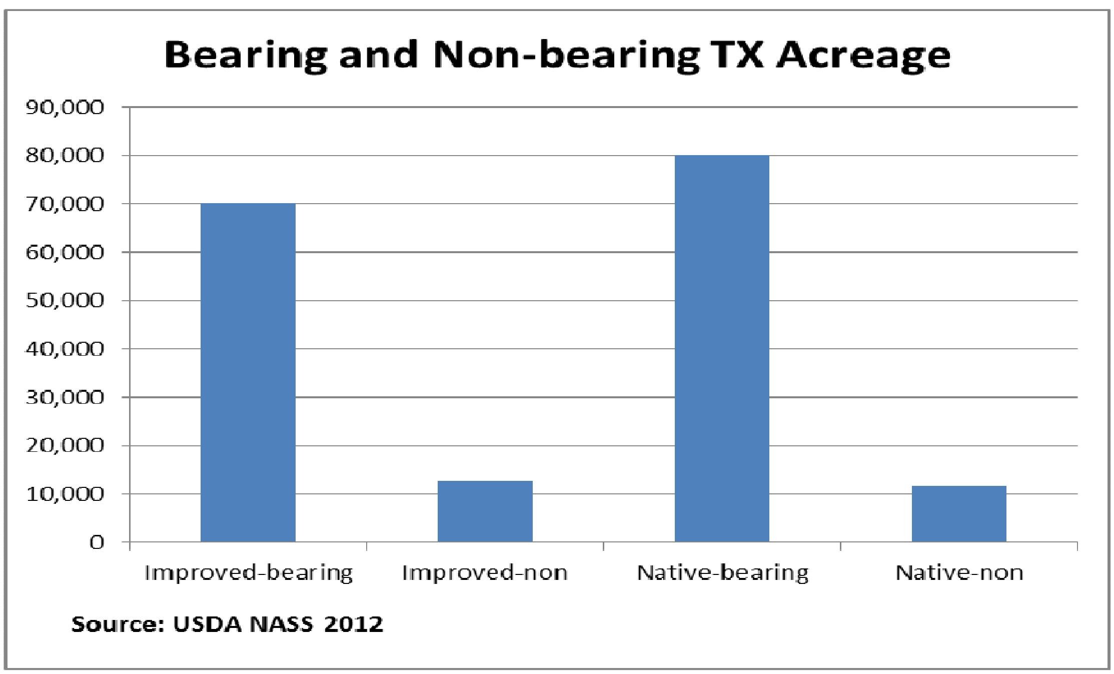

Figure 8. Bearing and Non-Bearing Acres in Texas

CHAPTER III

REVIEW OF LITERATURE

A unique review of the literature is required to understand both the concept of a conjoint analysis and a stochastic production model. Conjoint analyses have been conducted for several decades and have made good use of modern computation abilities to analyze more complex models. Several conjoint analyses evaluating consumer preferences for agricultural products have been conducted and are discussed.

Stochastic production models have also taken advantage of the growing computational power of computers. This advantage is captured in newer model developments and the use of Monte Carlo simulation techniques. Discussion of several production models relating to agriculture and agribusiness are found below.

Conjoint Analysis

A conjoint analysis is a way to measure consumers' preferences regarding different product attributes. The analysis starts by capturing the consumers' overall judgments about a set of product alternatives and then dissects comparable utility scales for each attribute (Green and Wind 1975). This is done to separate the relevant value of various attributes of a product from the value of the overall product. Green and Wind (1975) state this is advantageous to planning and marketing for businesses, particularly businesses introducing new products into the marketplace. Conjoint analyses are also relevant in evaluating package design, brand name, product promotions, pricing, and brand alternatives (Green and Wind 1975). The design of any conjoint analysis first starts by choosing the appropriate product attributes that are relevant to the consumer (Green and Srinivasan 1978). This can be done by questioning consumers directly, focus group interviews, and the knowledge of a product manager regarding consumer preferences.

An orthogonal array is the main component of any conjoint analysis. An orthogonal array "represents the most parsimonious set of designs available for main-effect parameter estimation" (Green 1974). One important understanding of the orthogonal array is that the main effects of any two factors be uncorrelated and independent from each other (Palma et al. 2010).

One type of conjoint analysis is the choice experiment. This analysis gives consumers a choice between a set of products (Adamowicz et al. 1998). As Adamowicz et al. (1998) explains this differs from traditional conjoint analysis where consumers are asked to rank or rate each alternative. Given that most products consist of multifactor attributes, listing all possible product choices, a full factorial design, becomes increasingly large (Green 1974; Green and Srinivasan 1978). Because of the large number of choices that would have to be evaluated by the consumer, a fractional factorial design can be used to capture the same main-effects as a full factorial design but with reduced burden (Green and Srinivasan 1978; Green 1974). Green (1978) states that a large full factorial design set of products is "not representative of the real life behavior of the individual where he/she may have more time and motivation to deliberate on the choice from among a small set of alternatives." For this reason a fractional factorial design can be used to reduce the number of combinations tested and still maintain orthogonally.

In recent years, several conjoint analyses have been done using agricultural products. Lusk, Roosen, and Fox (2003) use a contingent valuation choice experiment to determine beef demand from cattle administered growth hormones or fed genetically modified corn. Palma et al. (2010) reveals consumer preferences for potted orchids in the Hawaiian market by using a conjoint experiment. Chinese consumers' demand for food safety attributes was assessed by Ortega et al. (2012) using a choice experiment.

Lusk, Roosen, and Fox (2003) use a choice experiment to determine consumers' willingness-to-pay (WTP) for cattle that were administered growth hormones or fed genetically modified corn. They state that such product attributes are credence attributes, meaning that "consumers cannot judge quality prior to purchase" (Lusk, Roosen, and Fox 2003). This differs from experience goods, in which the product has an established quality reputation recognized by the consumer. Lusk, Roosen, and Fox (2003) used a mail survey sent to consumers in France, Germany, the United Kingdom, and the United States. Consumers were asked to make a choice between two rib-eye[1] steaks with varying levels of price, marbling, tenderness, and the use or non-use of growth hormones and genetically modified corn as feed in the production of the livestock. As previously mentioned, a full factorial design would require consumers to answer a burdensome amount of choice questions about rib-eye steaks. Because of this, Lusk, Roosen, and Fox (2003) used a computer generated fractional factorial design of 18 choice sets that

[1] Lusk, Roosen, and Fox (2003) used rib-eye steaks for being high value cuts of meat recognized by most consumers.

produces a D-efficiency score of 97. The D-efficiency score is a measure of the orthogonal balance of a survey design. A perfectly orthogonally balanced design has a D-efficiency of 100. Lusk, Roosen, and Fox (2003) also stated that "most attributes were perfectly uncorrelated" with only a significant correlation between two levels of the marbling attribute. For estimation of the results, Lusk, Roosen, and Fox (2003) used a random parameters logit model with effects coding. Effects coding is similar to dummy variable coding except that effects coding contrasts the parameter estimates with one of the levels of the attribute (Williams 1994). This internalizes the constant term, whereas dummy variable coding allows for the dummy variable that is absent the model to be captured in the constant term. The random parameters logit model is useful because it allows coefficients to "vary randomly over individuals to capture the potential variation in taste for specific steak attributes" (Lusk, Roosen, and Fox 2003).

The results indicated that all consumers in the four countries (France, Germany, the United Kingdom, and the United States) showed the price attribute as negative, which was expected, although United States consumers were slightly more price sensitive than European consumers (Lusk, Roosen, and Fox 2003). Preferences for steaks from cattle administered growth hormones were similar across all four countries with consumers in the United Kingdom being somewhat less concerned than consumers in the United States. Results also showed that French and German consumers are relatively homogeneous in the preferences for steak attributes, but attribute preference in the United Kingdom and the United States vary. WTP calculations were based on the results of the random parameters logit model and were multiplied by two to account for the use of effects coding. WTP calculations were made by taking the coefficient of the desired attribute and dividing it by the coefficient for price. WTP calculation results indicated French consumers were willing to pay higher premiums for hormone free beef, while German and United Kingdom consumers' WTP for beef not administered growth hormones was not statistically different from United States consumers. In contrast to this, Lusk, Roosen, and Fox (2003) found that European consumers were willing to pay a significantly higher amount for beef not feed genetically modified corn when compared to United States consumers.

Another study using conjoint analysis was done to assess consumer preferences for potted orchids in Hawaii (Palma et al. 2010). Instead of a survey by mail as done by Lusk, Roosen, and Fox (2003), Palma et al. (2010) used a written questionnaire distributed to randomly selected consumers at various garden center locations in the Akatsuka Orchid Gardens on the Island of Hawaii. This study also used a fractional factorial design for the orthogonal array and effects coding in the evaluation of the model. The survey asked consumers to rate their preferences of different orchids from 0 to 10, with 0 being least preferred and 10 being most preferred. The orchid attributes being examined were pot size, color, species, and purchase price. For analyzing consumer preferences, Palma et al. (2010) used a two-limit probit model for estimation. The two-limit probit regression is similar to the standard probit model except that the dependent variable is bounded by an upper and lower limit (Rosett and Nelson 1975).

General survey results from this study indicated, as does the negative coefficient for price in the tobit regression, that consumers were sensitive to price and preferred to pay a lower price for orchids rather than a higher price (Palma et al. 2010). The results from the conjoint analysis showed that all variables were statistically significant except for pot size. This suggests that the attribute of pot size does not statistically influence the consumer's utility for orchid products. Moth orchid, one level of the species attribute, also had a negative coefficient, which suggests that it lowers consumers' utility. Besides revealing how each attribute level affected consumer utility, Palma et al. (2010) also calculated the relative importance of each attribute. Price was the most relevant at 30.90%, while pot size, species, and color had a relevant importance of 26.28%, 25.58%, and 17.23% respectively. Palma et al. (2010) exerts that the results can also be applied to new products of interest by combining attribute levels and summing up their utility values. This would not result in a set price for a new orchid product, but would show a relative utility that could be compared to similar products.

Another study using conjoint analysis was conducted by Ortega et al. (2012) assessing Chinese consumers' demand for food safety attributes. This was done by examining WTP for ultra-high temperature (UHT) pasteurized milk. UHT milk was used because it is known to the Chinese consumer that the labeling of UHT milk has met various safety related certifications. Five two-level attributes of UHT were selected for the choice experiment: price, shelf-life, government certification, private certification, and brand (Ortega et al. 2012). Similar to Lusk, Roosen, and Fox (2003), this study used a fractional factorial design to obtain a D-optimal value of orthogonally. This design yielded sixteen choice sets. Along with Palma et al. (2010), this study randomly selected survey participants at the location in which the product was normally purchased, in this case supermarkets and convenience stores. To evaluate the consumers' preferences for food safety attributes associated with UHT milk, a random parameters logit model was used. Similar to Lusk, Roosen, and Fox (2003), Ortega et al. (2012) used a random parameters logit model because "unlike the traditional logit model, where consumers are assumed to be homogenous, heterogeneity in consumer preferences" is allowed in the random parameters logit model. The estimation results of the model were then used to calculate WTP for each product attribute. Analogous to the WTP calculations performed on beef demand by Lusk, Roosen, and Fox (2003), Ortega et al. (2012) multiplied the WTP calculation by two because of the use of effects coding.

The results of the Chinese consumers' demand for food safety attributes indicated that consumers are willing to pay the most for government certification, followed by product brand, and private certification (Ortega et al. 2012). Interestingly Ortega et al. (2012) found that there was a negative WTP for UHT milk with a shelf-life longer than three months. They report that this indicated "consumers do not positively value longer-shelf life UHT milk" (Ortega et al. 2012).

Production Model

Stochastic production models are used to help business managers and potential investors analyze investment decisions under conditions of risk and uncertainty (Richardson and Mapp 1976). Richardson and Mapp's (1976) approach is to form a stochastic production model using several steps: identify critical variables that influence the success or failure of the investment, link probability distributions to for stochastic variables to known variables that influence the outcome of the investment, specify accounting relationships, input model into a computer program and simulate the model. Richardson and Mapp (1976) state several ways to incorporate risk and uncertainty into developing a stochastic production model. Using objective probabilities offers improvement over subjective probabilities for analyzing investments. Net returns can be discounted using a certainty equivalent ratio to discount net returns where the “ratio is the coefficient relating an investor’s indifference between a certain cash flow and a risky one” (Richardson and Mapp 1976).

Simulation techniques, such as Monte Carlo simulation, offer an alternative to analyzing investments in uncertain conditions. Simulation is useful because it repeats a process many times allowing the model to generate probability distributions for the desired key output variables of the model.

Richardson and Mapp (1976) used the model development and design process to generate results for a proposed ice manufacturing facility. They found that the cumulative distribution function (CDF) of the net present value (NPV) of the investment indicated a 23% chance of yielding a negative NPV. They showed how useful a graphical representation of the CDF was in evaluating investments. The rate of return on the investment was also calculated and was graphically shown in their results. Rate of return was calculated by dividing each NPV of the CDF by the initial investment. This shows the rate of return on the investment as a distribution instead of a single value. Richardson and Mapp’s (1976) results also showed the usefulness of cash flows in investment analysis. They found that their ice manufacturing model yielded a 1% chance of having less than $22,400 cash flows in the first year. Results for year one also showed that cash flows exceeding $25,200 had a 1% chance of occurring as well. This type of information is extremely useful to an investor who places high value in yearly cash flows of an investment.

Furthermore, several investments can be analyzed at one time using the techniques explained by Richardson and Mapp (1976). Using simulation techniques and graphically displaying the results allows an investor to compare which distribution yields the most desired results. This allows a manager or investor to change aspects of the model, such as input cost and management decisions, to see how changes within the model yield different results. Richardson and Mapp (1976) concluded by stating formulating stochastic production models for analyzing risk and uncertainty in investments can be used in all types of business environments, both large and small, and agricultural and non-agricultural.

In regards to ranking different scenarios within a production model, Richardson and Outlaw (2008) explain several different methods that can be applied to any simulated production model. Mean variance was the first of several methods described to rank alternatives under conditions of risk and uncertainty. The mean variance method is simple in that it finds the scenario that yields the highest average mean and the lowest average risk, with risk being the variance of each scenario. The disadvantage of using the mean variance method is that it does not always show a dominant scenario, meaning that the method does not always produce a scenario with the highest average mean and the lowest average variance.

An alternative method to rank risky alternatives makes use of cumulative distribution functions (CDF) is first degree stochastic dominance (Richardson and Outlaw 2008). By graphically displaying each CDF for each alternative scenario, one is able to visually see if one scenario dominates another. This means that the scenario furthest to the right, associated with higher probabilities of a positive NPV, is dominant, given that the CDF graphs do not intersect. If the graphs intersect then first degree stochastic dominance does not yield a single dominant scenario.

If first degree stochastic dominance does not return a single dominant choice for a scenario, second degree stochastic dominance can be used. Second degree stochastic dominance is similar to first degree stochastic dominance in its use of CDFs except that second degree stochastic dominance calculates the sum of the difference between each CDF. This is beneficial in that it can be used to rank similar risky alternatives whose CDFs cross one or more times (Richardson and Outlaw 2008). The downside to using second degree stochastic dominance is that it "makes an assumption about the decision maker's risk preferences but does not take into consideration utility when ranking risky alternatives" (Richardson and Outlaw 2008).

To account for a decision maker's risk preferences, Richardson and Outlaw (2008) proposed the use of stochastic dominance with respect to a function (SDRF). Each simulated result of the stochastic production model is evaluated over a range of risk aversion coefficients. Upper and lower risk aversion coefficients are chosen based on the range of risk the decision maker is willing to undertake. SDRF is useful because it can effectively rank multiple risky alternatives if the decision maker has different preferences about risk aversion (Richardson and Outlaw 2008; McCarl 1988). Richardson and Outlaw (2008) note that SDFR is computationally difficult because it has to be evaluated over all possible combinations of the risky alternatives, but they used a Microsoft Excel add-on, Simetar, to calculate and tabulate SDRF.

Another approach used by Richardson and Outlaw (2008) that accounts for a decision maker's risk preferences is stochastic efficiency with respect to a function (SERF). SERF is a more transparent method than SDRF and is easily seen graphically (Richardson and Outlaw 2008). SERF calculates the certainty equivalent over the range of risk aversion coefficients. This means that at each level of risk, the highest certainty equivalent yields the highest utility and is thereby preferred over the other alternatives. SERF is advantageous to SDRF because the analyst does not have to know the decision makers level of risk and SERF ranks all risky alternatives concurrently. Richardson and Outlaw (2008) also use Simetar, as with SDRF, to graphically display SERF results.

The simplest and most easily understood method of ranking risky alternatives proposed by Richardson and Outlaw (2008) is the use of StopLight charts. StopLight is a function within Simetar that easily displays the probability of risky alternatives falling within a range of probabilities of success and failure. Richardson and Outlaw (2008) note that StopLight was originally developed for use in communicating probabilities to policy makers who are not well verse in statistics, but that StopLight is useful for any audience as long as there is a general understanding of probabilities. StopLight charts "display the probabilities for a favorable outcome and an unfavorable outcome for each policy as different colors in a stacked bar chart" with green being favorable, red being unfavorable, and yellow being the probability of an outcome between favorable and unfavorable (Richardson and Outlaw 2008). The interpretation of StopLight charts for a risk adverse decision maker is simple and straightforward: the most preferred alternative has the least amount of red and the most amount of green. Richardson and Outlaw (2008) point out that StopLight is advantageous to other ranking methods in that the analyst does not need to know the decision maker’s degree of risk. The “decision maker ranks the risky alternatives based on his/her own utility function for income and risk after setting minimum and maximum target outcome levels and observing the green and red probabilities in the alternative bars” (Richardson and Outlaw 2008).

Use of a stochastic production model in an agribusiness investment was done by Richardson et al. (2007), in which a proposed ethanol plant in Texas was analyzed. Similar to Richardson and Outlaw (2008) the feasibility study on a proposed ethanol plant in Texas used Monte Carlo simulation techniques making use of the Latin hypercube sampling procedure. Monte Carlo simulation offered an improvement to analyzing a proposed ethanol plant because it allowed for price and cost risk which had not been previously done in similar studies for proposed ethanol plants in Texas (Richardson et al. 2007). The objective of Richardson et al. (2007) was to show the benefits of using Monte Carlo simulation techniques in analyzing the economic viability of a risky investment. The model was developed using the same procedures described in Richardson and Mapp (1976). Unlike Richardson and Mapp (1976), the proposed ethanol plant model made use of multivariate empirical (MVE) distributions to simulate stochastic variables. Data for putting the model together came from multiple sources. All simulated stochastic variables were validated using Student-t test and Box's M test to check the mean and covariance of the simulated data (Richardson et al. 2007). Stochastic variables were used to create the pro forma financial statements to analyzing the economic viability of the model. The six key output variables under consideration by Richardson et al. (2007) were variable cost per gallon, average net returns over 10 years, average ending cash reserves over ten years, NPV, rate of return on investment (ROI), and present value of ending net worth (PVENW).

The results of Richardson et al. (2007) showed that variable cost per gallon ranged from a minimum of $1.14 per gallon to a maximum of $2.07 per gallon, with an average of $1.47. The deterministic, non-stochastic, forecast of variable cost yielded $1.46 per gallon. Similarly, the stochastic analysis of average annual net returns resulted in a minimum of negative $15.08 million and a maximum of $12.95 million with an average of $1.97 million per year. The deterministic forecast for average annual net returns was found to be $3.67 million per year. Richardson el al. (2007) stated how not incorporating risk into the model yielded lower cost per gallon and higher expected annual net returns versus the stochastic model. They also find that "the deterministic forecast of NPV, ROI, and PVENW were also biased with higher values than forecasted by the stochastic analysis" (Richardson et al. 2007). For example, they found that the stochastic NPV for the model had a 65% chance of being lower than the deterministic forecast and that there was only a 10% chance of yielding a positive NPV.

Regarding pecan production, Springer, Swinford, and Rohla (2011) analyzed the profitability of improved irrigated pecan orchards in the Southern Plains. They do not specify which states constitute the Southern Plains region, but given certain implications within their work, the reader can conjecture that the Southern Plains is the region of Texas and Oklahoma east to the Mississippi River. Unlike Richardson and Mapp (1976), Richardson et al. (2007), and Richardson and Outlaw (2008), this production model did not make use of stochastic probabilities or Monte Carlo simulation techniques. The goal of Springer, Swinford, and Rohla (2011) was to “determine if an irrigated improved pecan orchard is economical relative to agronomic systems commonly implemented by producers that have access to irrigation” (Springer, Swinford, and Rohla 2011). Springer, Swinford, and Rohla (2011) make note that 84% of native pecan acreage and 56% of improved pecan acreage in the United States is found in the Southern Plains region. With irrigation being the largest management practice difference between a native and an improved orchard, Springer, Swinford, and Rohla (2011) questioned why the Southern Plains region is not home to a higher percentage of the improved pecan acreage. Their goal was to analyze an improved irrigated pecan orchard with respect to alternative cropping systems to understand the probability of investing in an improved irrigated pecan orchard in the Southern Plains region.

Methods used to generate the model included management data from a 25 acre farm owned and operated by The Samuel Roberts Noble Foundation. Soybeans and wheat were chosen as alternative enterprises because of their high prevalence as irrigated crops in the Southern Plains region (Springer, Swinford, and Rohla 2011). A 20 year time period was used to analyze the model which was representative of a 100 acre operation. Springer, Swinford, and Rohla (2011) note that there would be a three year lag from initial investment and establishment of the orchard until revenue from pecans would be generated.

Results from Springer, Swinford, and Rohla (2011) indicated that the model required a large initial outlay of capital that would take many years to recuperate. The 20 year model showed that after year 18 the NPV for the operation was competitive with the comparable agricultural enterprises being evaluated, soybeans and wheat (Springer, Swinford, and Rohla 2011). Though the model was not made stochastic, Springer, Swinford, and Rohla (2011) conducted a scenario analysis using the minimum and maximum prices from the 2005 – 2009 price range to determine how the NPV changed with optimistic and pessimistic prices received. The NPV for average, minimum, and maximum price scenarios all yielded better than the respective NPVs for soybeans and wheat. Springer, Swinford, and Rohla (2011) noted, without statistical evidence, that an improved irrigated orchard could be considered more risky when compared to other enterprises. The basis for this conjecture lay in the negative cash flows that occurred in the first ten years of the orchard's life. These negative cash flows were created by the large initial outlay of capital.

Given this review of the literature, one can see the importance of understanding conjoint analyses and stochastic production models. Conjoint analyses have been conducted on various agricultural products yielding very useful results to agribusinesses and marketers. Production models have been used to test the economic viability of potential investments, yielding results as distributions of probabilities rather than point estimates.

CHAPTER IV

METHODOLOGY

As seen in the literature review, the two concepts of a conjoint analysis and a stochastic production model are not synonymous. Each analysis approached the problem from different sides of the pecan industry, the consumer and the producer. A choice experiment with random parameters logistic regression techniques were determined to be the optimal methods to estimate consumers' willingness to pay for each pecan attribute. A stochastic production model, making use of empirical distributions and simulation software, was determined to be the optimal method to assess the profitability of investing on one of the three orchard scenarios.

Conjoint Analysis

The first step in conducting any conjoint analysis is selecting the proper attributes and attribute levels of the desired product (Palma et al. 2010). Unlike Palma et al. (2010) and Ortega et al. (2012), in which a survey was conducted to determine which product attributes are desirable, this conjoint analysis used methods similar to Lusk, Roosen, and Fox (2003) in which research into the products' industry and market determined the desirable product attributes. Industry and market research concluded five major attributes affect consumers' preferences for pecans (Lombardini, Waliczek, and Zajicek 2008; Moore et al. 2009). With pecans being sold both in the shell and shelled, there is a large difference in price per pound between shelled and unshelled pecans (Crawford 2009). For this reason, this conjoint analysis only examined consumer's preferences for shelled pecans. The five attributes and their respective levels can be seen in table 2. Variety described the pecan variety, whether native or improved. The improved variety category incorporated all improved varieties and was not specific to any particular improved variety. Price described the purchase price of an 8 ounce bag of pecans. Market research determined that \$3, \$5, and \$7 were reasonable levels of purchase price of an 8 ounce bag of pecans. Origin described where the pecans were grown. The United States is the largest pecan producer in the world, but Mexico exports a substantial amount of pecans to the United States; therefore, imported was added as a level for origin. Texas was added to access consumers' recognition of Texas grown pecans. Status described the condition in which pecans can be purchased. Again, market research determined pecan halves and pecan pieces where the most common form of pecans sold. Size described the size in which pecans were purchased. Size small and size large were also determined by market and industry research (Stein and McEachern 2007; Texas AgriLife Extension Horticulture 2012).

Table 2. Attributes and Levels

Attribute	Levels
Size	Small and Large
Variety	Native and Improved
Status	Pieces and Halves
Origin	Imported, U.S., and Texas
Price	\$3, \$5, and \$7

A full factorial design with two attributes of three levels and three attributes of two levels yielded ($2 \times 2 \times 2 \times 3 \times 3 = 72$) seventy-two possible product combinations. Palma et al. (2010) stated it is impractical and burdensome to ask a consumer to answer such a large number of questions or make a large number of product selections. Thus, a fractional factorial design was used. The survey design was programmed in SAS 9.3 using the *%mktruns* and *%choiceff* program macros. The *%mktruns* macro determined that 36 or 72 choice sets yielded a 100 percent efficient orthogonal design. Due to this large number of questions, 12 choice sets were determined to be a reasonable amount for respondents to answer. The *%choiceff* macro was used to group the choice sets into pairs with a third option of choosing neither of the two pecan products. The 12 choice set orthogonal fractional factorial design yielded a relative D-efficiency of 90.04. The complete SAS code can be found in Appendix A. The results of the SAS model to find the optimal survey design can be found in Appendix B. The choice sets designated in this design can be found in table 3.

Table 3. Choice Sets for Survey

Set	Option	Variety	Price	Origin	Status	Size
1	1	native	$7	us	pieces	lg
	2	improved	$5	Imported	halves	sm
	none	.	.	.	.	.
2	1	native	$5	tx	pieces	sm
	2	improved	$7	Imported	halves	lg
	none	.	.	.	.	.
3	1	native	$3	Imported	halves	sm
	2	improved	$5	tx	pieces	lg
	none	.	.	.	.	.
4	1	improved	$3	tx	halves	sm
	2	native	$5	Imported	pieces	lg
	none	.	.	.	.	.
5	1	native	$3	Imported	pieces	lg
	2	improved	$7	us	halves	sm
	none	.	.	.	.	.
6	1	native	$7	tx	halves	lg
	2	improved	$5	Imported	pieces	sm
	none	.	.	.	.	.
7	1	native	$7	Imported	halves	sm
	2	improved	$3	us	pieces	lg
	none	.	.	.	.	.
8	1	native	$3	tx	pieces	sm
	2	improved	$5	us	halves	lg
	none	.	.	.	.	.
9	1	native	$3	us	halves	lg
	2	improved	$7	tx	pieces	sm
	none	.	.	.	.	.
10	1	improved	$3	tx	halves	lg
	2	native	$7	us	pieces	sm
	none	.	.	.	.	.
11	1	improved	$3	us	pieces	sm
	2	native	$5	tx	halves	lg
	none	.	.	.	.	.
12	1	native	$5	us	halves	sm
	2	improved	$7	Imported	pieces	lg
	none	.	.	.	.	.

The opt out product was included to allow for no purchase in order to closely resemble a retail setting. As suggested by Lusk, Roosen, and Fox (2003), the third option may have little influence in model estimates and it is unclear how to handle the third option if it dominates the choices of the respondents; yet it was determined for this conjoint analysis that it was relevant to include a third option of choosing neither pecan products in the choice experiment.

The survey was designed in the form of a choice experiment, which differs from other methods of conjoint analysis in which survey participants are asked to rank each product. Choice experiments also differ from other conjoint analyses in that the choices are products described by their attributes, not a base product and a specific alternative for each choice set (Adamowicz et al. 1998). Choice experiments operate on the assumption that consumers derive utility from consuming the product attributes rather than the product itself, and that consumers are rational, meaning that a consumer prefers more utility to less (Lusk, Roosen, and Fox 2003).

The random parameters logit is useful and relevant because it makes use of random utility theory (Ortega et al. 2012; Train 2009). The random utility model can be written as

(1) $$U_{nj} = \beta' x_{nj} + \varepsilon_{nj}$$

where β_n is a vector of coefficients for respondent n and ε_{nj} is a random term. The coefficients vary over respondents in the population with density $f(\beta)$, with this density being a function of θ that represents the parameters of the β's in the population as specified in (6).

Prior to conducting the survey, the survey was submitted and approved by Texas A&M University's Institutional Review Board. MarketTools, Inc. was used to distribute the survey online using their pre-established database of consumers. A random sample population of 501 consumers, who were residents of Texas, over the age of 18, were selected. Survey results were tabulated by MarketTool, Inc. into an Excel spreadsheet. A copy of the survey can be found in Appendix C.

For estimation purposes, variety, origin, status, and size were treated as non-continuous variables, while price was treated as a continuous variable. Survey results were coded using effects coding. With *L* number of attributes, effects coding, similar to dummy variable coding, uses *L-1* attributes (Bech and Gyrd-Hansen 2005). The difference between effects coding and dummy variable is that -1 is used as the reference level instead of 0. This means that the reference point is internalized in the parameter coefficient estimates and not represented in the intercept coefficient (Williams 1994). Therefore effects coding yields results absent of an intercept term.

Choice experiments can be evaluated using several different econometric methods. Since the dependent variable to be determined is a probability of choice, a probit or logit model can be used (Hill, Griffiths, and Judge 2001; Wooldridge 2009). Neither model yields a well-defined value for the dependent variable, the choice probability, but both are extremely useful in determining how each attribute affects the probability of choosing a product. The probit model is specified in the equation

(2) $$G(z) = \Phi(z) \equiv \int_{-\infty}^{z} \Phi(v)dv$$

where G is a CDF function that takes on values strictly between $0 < G(z) < 1$, for all real numbers z, and where $\Phi(z)$ is the PDF of the standard normal density

(3) $$\Phi(z) = (2\pi)^{-1/2} \exp(-z^2 / 2) .$$

The probit model is useful if $G(z)$ is distributed normally, an assumption that was not made for purposes of this choice experiment.

A second type of model used to analyze choice experiments in consumer research is the logit model. Whereas the probit model assumes a normal distribution, the logit model forms its own probability density function (PDF) with the equation

(4) $$G(z) = \frac{\exp(z)}{[1 + \exp(z)]}$$

where G is the logistic function between zero and one for all real numbers z (Wooldridge 2009; Hill, Griffiths, and Judge 2001; Hosmer 1989). A specific application of logistic regression is the conditional logit model. As specified by Cameron and Trivedi (2010), the conditional logit is used when datasets include alternative-specific variables, such as price and quality measures for all alternatives, not just the chosen alternative. A further application of the conditional logit is the alternative-specific conditional logit, sometimes called McFadden's Choice, which allows for alternative-specific variables and case-specific variables. Thus the conditional logit functional form is

(5) $$P_{ni} = \frac{\exp(\beta' x_{ni})}{\sum_{j=j}^{J} \exp(\beta' x_{nj})}$$

where x_{nj} are observed variables that relate alternative j, among J alternatives, to respondent n. This can be interpreted as the probability of individual n choosing alternative i as a function of parameters that define x_{ni} (Long 2004; McFadden 1973).

A more complex type of logistic regression that takes the integral of standard logit probabilities over a density of parameters is the random parameters logit (Train 2009). Sometimes called the mixed logit, the random parameters logit allows the parameter associated with each variable to vary randomly across respondents (Revelt and Train 1998). Thus the probability of respondent n choosing alternative i takes the form

$$(6) \qquad P_{ni} = \int \left(\frac{\exp(\beta' x_{ni})}{\sum_{j=j}^{J} \exp(\beta' x_{nj})} \right) f(\beta \mid \theta) d\beta$$

where θ describes the density of β. Each individual has a coefficient, β, and the densities of all βs are represented by θ. For example, θ could represent the mean and standard deviation of all the βs determined by the survey population. The mixed logit choice probabilities P_{ni} are functions of θ and do not depend on the values of β, because the βs are removed during integration (Train 2009).

For estimating equations (4), (5), and (6), Stata 12.1 was used. The *reshape* command was used to transform the data into a suitable format for logistic regression in Stata. After the data was reshaped, the dataset consisted of 18,036 observations. Stata's *clogit* command was used to estimate the coefficients of the conditional logistic regression found in equation (4). The command used for the alternative specific logit was *acslogit*. The alternative specific logit follows (4) but was programmed as specified by Cameron and Trivedi (2010) using both alternative and case specific variables. For estimating the random parameters logit model, the user-designed *mixlogit* command was used (Hole 2007). As stated by Hole (2007) the *mixlogit* command fits the model with both individual-specific and alternative-specific explanatory variables similar to the *clogit* command but differs in the fact that it allows for unobserved heterogeneity. The *mixlogit* command relies on simulation and it was determined that 500 draws were adequate for simulation. The Stata code for the choice experiment can be found in Appendix C.

To calculate the willingness-to-pay (WTP) for each attribute, the marginal rate of substitution of price and the other qualitative variables was calculated. That is, how much price would have to change for respondents to be indifferent between qualitative variables (Lusk, Roosen, and Fox 2003; Ortega et al. 2012).

(7) $$WTP = -2 * \left(\frac{\beta_{attribute}}{\beta_{price}} \right)$$

where $\beta_{attribute}$ is the coefficient for each attribute determined in the model and β_{price} was the coefficient for price. This ratio was multiplied by two because of the use of effects coding.

Production Model

The pecan production model was formulated to compare the profitability and economic viability of producing pecans in central Texas. The model assumed that each of the three scenarios, native, improved irrigated, and improved non-irrigated, were mature orchards approximately twenty years old. The models were structured so that the NPV along with other pertinent key output variables could be determined from the time period 2012 – 2015. Four years of production was determined to be optimal because of the small amount of historical price data and the inability to appropriately forecast prices and cost past 2015. For that reason, the production model only goes to the year 2015. Another assumption in the model was that the orchards were previously not managed or not properly managed based on Texas AgriLife Extension's guidelines for growing pecans in the Texas Pecan Handbook or as specified by research and extension personnel.

The stochastic production model comparing the profitability of a native pecan orchard, an improved irrigated pecan orchard, and an improved non-irrigated pecan orchard are based on the production practices of central Texas. For the purposes of this research, central Texas was defined as the counties within the area of Milam, Comanche, San Saba, and Guadalupe Counties and their adjacent counties. This region was used because it was determined to have a considerable amount of native and improved orchards and production practices different than the areas of far west Texas and far east Texas (Harris 2011; Lombardini 2012; Nesbitt 2012; Ree 2011). As mentioned in Chapter II, the USDA reports a large amount of both native and improved non-bearing pecan acres in Texas. Anecdotal evidence suggests that a large portion of these non-bearing orchards are in the specified central Texas region. All data relevant to this specific region of Texas were collected in this region. All fixed cost for each of the three scenarios analyzed, native, improved irrigated, and improved non-irrigated, were the same except the native and improved non-irrigated did not have any fixed irrigation cost. All costs reported are for new unused equipment, other than the land value which is reported as an operational orchard.

The model assumed that the orchard candidates for potential investment were neglected for approximately 20 years and not managed to their full potential. Remediation cost involving factors like crowding, nutritional status, etc. were thus anticipated. Texas AgriLife Research recommendations indicate removing every other tree to avoid crowding at the 20 year mark (Stein and McEachern 2007; Lombardini 2012; Nesbitt 2012). Tree removal cost was determined to be $200 per acre, yielding an expense of $30,000 in the first year of investment (Kaase 2012).

Fixed costs for the production model were collected primarily by direct communication with retailers. The initial capital expenditures required to start managing a mature 20 year old orchard were determined largely from previous research into a deterministic budget for an operating pecan orchard (Texas AgriLife Extension Agricultural Economics 2011). Along with the Texas AgriLife Extension Agricultural Economics (2011) operational budget, capital requirements were also determined by interviewing current pecan producers in central Texas (Sherrod 2012; Berdoll 2011). Pecan land prices were obtained via the Texas Chapter of the American Society of Farm

Managers and Rural Appraisers online resource “Texas Rural Land Value Trends 2010” (Texas Chapter ASFMRA 2011). The average price of pecan land in the specified central Texas region was calculated as $2,375 per acre. Since this research compared three orchards, each 150 acres in size, $2,375 per acre was multiplied by 150 to yield a total land cost of $356,250. It was determined that a small shelter to store equipment and to dry pecans was needed. Average price for a 40 foot by 40 foot shelter without a concrete floor was calculated as $12,400 (Archery Buildings 2012; Krenek 2012).

All equipment cost data were collected via phone interviews or online data sources. Two tractors were needed to manage a 150 acre orchard. A large 150-horsepower tractor with a cab was calculated to be $108,709.50 (Brazos Valley Equipment 2012; Hi-Way Equipment 2012). Another medium sized open station tractor of 90-horsepower was calculated at $42,018. Both 150-horsepower and 90-horsepower tractors were the averages of a John Deere and Case IH brands of tractors of comparable sizes that were available in the central Texas region. A half ton truck was determined to be needed for a pecan operation of 150 acres. Using the three largest light truck manufacturers in the United States, it was determined that a single cab half ton pick-up truck would cost $22,220 (Ford Motor Company 2012; General Motors 2012; Chrysler Group LLC 2012). The cost was calculated from an average of standard single cab, two-wheel drive, half ton pick-up trucks from Ford, Chevrolet, and Dodge. In addition to a truck, it was determined that an orchard of 150 acres would also have a non-highway utility vehicle that would be used in conjunction with the pick-up truck for daily orchard management activities (Nesbitt 2012; Sherrod 2012). Given the wide variety of off-road utility vehicles, an average of several vehicles was needed to obtain a utility vehicle cost. Average of Polaris, Kawasaki, Honda, and John Deere's standard two person utility vehicles was taken to determine a cost of $9,259.63 (Brazos Valley Equipment 2012; Polaris Fun Center 2012; Greathouse Motorsports 2012; Action Sports 2012).

One self-propelled tree shaker was determined to be adequate for a 150 acre orchard. Averages of two Orchard Manufacturing Company shakers and a shaker from Sun Valley, Inc. yielded a cost of $111,750 (Orchard Machinery Corporation 2012; Sun Valley Inc. 2012). For gathering pecans prior to harvest, a ten-foot sweeper and a three-point hitch mounted blower were determined to cost $13,500 and $5,485, respectively (Savage of Georgia LLC 2012).

For harvesting, one pull-type harvester was determined to be sufficient for an orchard of 150 acres. A Savage 8261 pull-type harvester was added to the fixed cost at $23,935 (Savage Equipment 2012). Producer and extension professional interviews indicate that this size harvester will harvest approximately five acres a day, meaning that in optimal conditions an orchard of 150 acres could be harvested in one month (Nesbitt 2012; Sherrod 2012). Allowing for a six day work week and some allotted time for equipment repairs and weather related incidents, this harvester should complete harvest in about two months, consistent with extension personal recommendations (Texas AgriLife Extension Agricultural Economics 2011; Stein and McEachern 2007). Two trailers with false floors capable of facilitating a forced heated air dryer were determined to be needed for an operation of this size. Cost for an eight-ton capacity trailer with a hydraulic dumping body was obtained from Peerless Manufacturing Company. Trailers were $8,250 each yielding a total trailer cost of $16,500 (Peerless Manufacturing Company 2012). Prior to pecans being dried, they must be hauled between the harvester and the cleaner. Costs for a trailer made specifically for this purpose were calculated to be $5,218 each; therefore, two trailers added $10,437 to the initial capital expenditures for a 150 acre operation (Southern Nut N Tree Equipment 2012). The cost of a cleaner was obtained by averaging two cleaners manufactured by Savage Equipment. Calculations determined the cleaner cost to be $13,435 (Savage Equipment 2012). For a pecan dryer, it was determined that the standard peanut wagon dryer was economical and practical for this operation (Savage of Georgia LLC 2012; Cook Industrial Electric Company 2012). This dryer is capable of drying two trailers, like the Peerless Manufacturing Company trailers in the model, at the same time. Total cost for the dryer was calculated at $4,460.

For spraying purposes, it was determined a 150 acre orchard would need one air-blast sprayer to apply zinc, nitrogen, fungicides, and insecticides. An average price of $12,485 was obtained from averaging a 500-gallon capacity sprayer and a 1,000-gallon capacity sprayer (Savage Equipment 2012). For applying herbicides, one boom sprayer with a spray pattern averaging 30 to 40 feet was calculated to cost $3,500 (Wegwert Welding 2012; Washington County Tractor 2012). It was assumed that the entire orchard floor, or 100 percent of each acre, would be sprayed with glyphosate using the boom sprayer for the improved variety orchards. No glyphosate would be sprayed in the native orchard.

Irrigation costs were for a new micro-jet irrigation system operating from a 200 gallon per minute well. Materials and installation costs per acre were obtained and calculated to be $2,400 per acre, or $360,000 for the total 150 acre operation (ATS Irrigation 2012). The 200 gallon per minute well cost was calculated at $22,500 (Siegert Water Wells Inc. 2012). It must be noted that only the improved irrigated orchard scenario incurred these two fixed cost.

Capital expenditures (CAPEX) totaled $1,167,381 for the improved irrigated orchard and $784,881 for the native and improved non-irrigated orchards. The CAPEX amount was inputted into a loan calculator with a life of fifteen years and an interest rate of 5.5% (Richardson 2003; Capital Farm Credit 2012). This produced a constant annual payment of $116,301.04 and $78,194.25 for the orchards with irrigation and for the orchards without irrigation, respectively.

Data used to calculate variable cost were obtained from several different sources. Yield data were obtained from the USDA's State Farm Service Agency (FSA) office in College Station, Texas. Data from 2001 – 2009 for native, improve irrigated, and improved non-irrigated orchards were obtained for Comanche, San Saba, Guadalupe, and Milam counties (Peabody 2008). Price data were obtained for improved and native varieties for the state of Texas from 2002 – 2010 (USDA National Agricultural Statistics Service 2012). Both the price and yield data displayed the alternate bearing cycle of pecans. With increase demand from the Chinese and other Asian markets, it was determined that only prices from 2007 – 2010 would be used to display the new demand for pecans in Asia.

Pastureland cash rents were also obtained from USDA National Agricultural Statistics Service (NASS) for 2008 – 2011. Pastureland cash rents were used to determine revenue from grazing cattle on native orchards, a practice common in the industry (Nesbitt 2012; Ree 2011). Precipitation and temperature data from 1964 – 2010 were obtained from a weather station in Bell County, Texas (National Oceanic and Atmospheric Organization 2012). Chemical costs for generic glyphosate, known by its most popular trade name RoundUp, and chlorpyrifos, known by its trade name as Lorsban, were collected from USDA NASS (2012) for the years of 2001 – 2010. Data for a 32% nitrogen solution were also collected from USDA NASS (2012) but were only available from 2002 – 2008. Enable 2F cost was obtained from Producers Cooperative Association (2012) for the year 2012. No USDA NASS historical data was available for Enable 2F. Producers Cooperative Association (2012) also provided 2012 cost for zinc and granular nitrogen. The granular nitrogen used for a ground application of nitrogen was urea with a nitrogen-phosphorus-potassium mix of 46-0-0. Fuel prices were obtained from USDA NASS (2012) for prices paid by agricultural producers from 2001 – 2011. The three fuels used on the 150 acre pecan orchard were diesel, gasoline, and liquid propane (LP).

Annual and hourly labor was needed for a 150 acre orchard and data were obtained from 2001 – 2010 for average annual pay for fruit and tree nut farming (Bureau of Labor Statistics 2012b). Hired hourly labor data were obtained from 1989 – 2011 for all types of farming operations in the United States (USDA National Agricultural Statistics Service 2012). Electricity prices were obtained for the years 1997 – 2011 for the average retail price per kilowatt-hour to the end user (Energy Information Administration 2012).

Historical data for Producer Price Indexes (PPI) for agricultural chemicals, labor, electricity, pecan prices, repairs, and property insurance were all obtained from the Bureau of Labor Statistics (Bureau of Labor Statistics 2012a). The PPI for ranchland prices was obtained from the Federal Reserve's District 11 office in Dallas, Texas (Federal Reserve Bank of Dallas 2012). PPIs were used to inflate input cost. See table 4.

Table 4. PPI Used to Inflate Input Cost

PPI Used to Inflate Input Cost	
Input	PPI used
Glyphosate	PPI-Ag Chemicals
Chlorpyrifos	PPI-Ag Chemicals
Diesel	PPI-Diesel
Gas	PPI-Gas
LP	PPI-LP
Pecan Price	PPI-Pecan
Labor	PPI-Labor
Cattle Rents	PPI-Ranchland
Electricity	PPI-Electricity
Nitrogen 32%	PPI-Nitrogen
Granular Nitrogen	PPI-Nitrogen
Maintenance	PPI-Repairs
Insurance	PPI-Insurance

All input variables used to calculate variable cost were made stochastic using multivariate empirical (MVE) probability distributions or univariate empirical probability distributions. MVE distributions were used because of the limited amount of historical data that could be collected (Richardson 2000). Empirical distributions offer an advantage of other probability distributions because empirical distributions are defined by their data, not by a specific known distribution (Richardson 2000; Richardson 2010). Similar to Richardson et al. (2007), this stochastic production model used Simetar and its related functions for making variables stochastic and simulated those variables using MVE distributions. The first step in estimating the parameters for a MVE distribution was to determine the random and non-random components of each variable (Richardson 2000). This was done by using ordinary least squares (OLS) regression to identify any systematic variability in the data. When OLS resulted in a statistically significant variable, the standard OLS equation was used to find the estimation of the variable:

(8) $$\hat{X}_{it} = \beta_0 + \beta_1(t) + \varepsilon_{it}$$

for each variable i and each year t and

(9) $$\varepsilon_{it} = X_{it} - \hat{X}_{it}$$

is the random component. Where OLS failed to show a statistically significant trend in the data, the mean of each variable was used. Thereby $\hat{X}_{it} = \overline{X}_{it}$. Next observations were put into Simetar's Empirical Distribution Function using either percent deviations from mean or percent deviations from trend. Table 5 shows which variables were made stochastic as percent deviations from the mean and which were made stochastic as percent deviations from the trend and the corresponding R^2 and $p-values$ for the trend variables. All linear trend forecasts were found to be statistically significant at the 99% level unless otherwise noted.

Table 5. Empirical Distributions as % Deviations from Mean and Trend

Empirical Distributions as % Deviations from				
Mean	**Trend**	R^2	$p-values$	
Glyphosate	Nitrogen 32%	0.910617	0.000381	
Chlorpyrifos	Diesel	0.663618	0.001789	
Precipitation	Gas	0.714111	0.000179	
Yields	LP	0.826342	0.000065	
Pastureland Rents	Prices:Improved	0.753005	0.090122	*
PPI-Ag Chemicals	Prices:Native	0.862806	0.038185	**
PPI-LP	Annual Labor	0.887348	0.000024	
PPI-Gas	Hourly Labor	0.994635	2.97E-26	
PPI-Diesel	Electricity	0.910334	1.63E-08	
PPI-Nitrogen	PPI-Labor	0.706227	0.000906	
PPI-Electricity				
PPI-Ranchland				
PPI-Pecan Prices				
PPI-Repairs				
PPI-Insurance				

**Statistically significant at 90% confidence level*

***Statistically significant at 95% confidence level*

Next correlated uniform standard deviates (CUSD) were created for each stochastic variable using Simetar's $=CUSD$ function. Where univariate distributions were used, a uniform standard deviate (USD) was used instead of a CUSD. These CUSDs and USDs were used in the calculation of the stochastic deviate (SD) using Simetar's $=EMP$ function for empirical distributions:

(10) $SD_{it} = EMP(S_i, F(X_i), CUSD_{it})$

where S_i are the fractional deviations and $F(X_i)$ are the respective probabilities of the fractional deviations (Richardson 2010). Finally the stochastic value (SV) was calculated:

(11) $SV_{it} = \overline{X}_{it} * (1 + SD_{it})$

for variables where percent deviations from mean were used and

(12) $SV_{it} = \hat{X}_{it} * (1 + SD_{it})$

where percent deviations from trend were used.

Once all variables i were made stochastic for t years, the first year of each variable was simulated for validation testing. Validation of the data was determined using Simetar's Hypothesis Testing for Data dialog box (Richardson 2010). For MVE distributions that were made stochastic with the means of the historical data, a two-sample Hotelling T^2 test was conducted to test the means of the simulated data with the historical data. A Box's M test was conducted to test the covariance matrices of the simulated data and the historical data. A third test was done to check the simulated correlation matrix with that of the historical correlation matrix. The Hotelling T^2 test and Box's M test can be done using the "Compare Two Series" tab in the Simetar's Hypothesis Testing for Data dialog box. The testing of correlation matrices can be done using the "Check Correlation" tab in Simetar's Hypothesis Testing for Data dialog box. The null hypothesis for the Hotelling T^2 test was

(13) $H_0 : \overline{X}_{it} = \widetilde{X}_{it}$

where $\widetilde{X}_{it}$ is the mean for the simulated variable *i* in year *t*. The null hypothesis for the Box's M test was

(14) $H_0 : \mathrm{cov}(X_i, X_j) = \mathrm{cov}(\widetilde{X}_i, \widetilde{X}_j)$

where $\widetilde{X}_i$ and $\widetilde{X}_j$ are the simulated variables. The null hypothesis for the correlation test was

(15) $H_0 : \rho(X_i, X_j) = \rho(\widetilde{X}_{,}, \widetilde{X}_j)$.

No variable rejected the null hypothesis (15), meaning that all simulated variables were statistically correlated with their historical values. Validation results for testing the simulated MVE distributions as percent deviations from the means are found in table 6. A failure to reject the null hypothesis indicates that the simulated variables reproduce their historical data. In the process of model validation, it was discovered that Simetar was unable to validate datasets with large amounts of columns as in the precipitation data for this model. Precipitation data was validated only by checking its correlation with its historical data. All means and covariances successfully replicated their historic data.

Table 6. Validation of MVE Distributions with Mean

Validation of MVE Distributions with Mean			
p-values for	Hotelling T2	Box's M	Complete Homogeneity
Yields	0.999	0.999	1.000
Pastureland	0.999	0.997	1.000
Precipitation	N/A	N/A	N/A
Glyphosate/Chlorpyrifos	0.996	0.990	1.000
PPI-LP,Gas,Diesel,Nitrogen	1.000	0.993	0.993

Validation of MVE distributions that were made stochastic using percent deviations from trend used the forecasted value instead of the historical means in calculating the stochastic value. The correlations of these distributions were also checked using the "Check Correlation" tab in Simetar's Hypothesis Testing for Data dialog box using equation (15). The means and standard deviations were tested using the "Test Parameters" tab also in Simetar's Hypothesis Testing for Data dialog box. The means test was done using a Student's t-test that follows (13). Standard deviations were tested with a Chi-Squared test will null hypothesis

(16) $H_0 : \sigma_{X_{it}} = \tilde{\sigma}_{X_{it}}$,

where $\sigma_{X_{it}}$ is the standard deviation of the historical data and $\tilde{\sigma}_{X_{it}}$ is the standard deviation of the simulated data. No variable rejected the null hypothesis found in (15), meaning that all simulated variables were statistically correlated with their historical values. To test the standard deviations, a special test standard deviation had to be calculated in order to account for the use of forecasted values (Richardson 2012). The test standard deviation was calculated as

$$(17) \qquad \sigma_{test} = \frac{\hat{X}_{hist}}{\overline{X}_{hist}} * \overline{X}_{hist} * (CV_{Sim} / 100)$$

where $\hat{X}_{hist}$ is the forecasted variable from the historical data and $\overline{X}_{hist}$ is the mean of the historical data. The CV_{Sim} is equal to the simulated standard deviation divided by the simulated mean multiplied by 100, and thus must be divided by 100 in calculation. All variables were found to be statistically similar in their means and variances as their respective historical data. Results for the mean and standard deviation test can be found in table 7.

Table 7. Validation of MVE Distributions with Trend

Validation of MVE Distributions with Trend		
p-values for	Student's T	Chi-Squared
Prices:Native	0.970	0.972
Prices:Improved	0.954	0.997
Diesel	0.626	0.902
Gas-bulk	0.557	0.924
Gas	0.558	0.923
LP	0.998	0.984

For variables that were made stochastic using regular univariate empirical distributions using the means as forecast, the first year of each variable was also simulated for validation testing. The “Compare Two Series” tab in Simetar’s Hypothesis Testing for Data dialog box was used to compare the means and variances of the historical and simulated data. A two-sample Student’s t-test was done to test the means of the simulated data versus the historical data. An F-Test was conducted to test that the variances of the simulated data and historical data were statistically the same. The null hypothesis for the Student's t-test follows (13) while the null hypothesis for the F-Test of the variance was

(18) $H_0 : \sigma^2{}_{X_{it}} = \tilde{\sigma}^2{}_{X_{it}}$,

where $\sigma^2{}_{X_{it}}$ is the variance of the historical data and $\tilde{\sigma}^2{}_{X_{it}}$ is the variance of the simulated data for variable i in year t. All tests indicated that the historical means and variances were correctly reproduced. Validation results for testing the simulated empirical distributions are found in table 8.

Table 8. Validation of Univariate Empirical Distributions with Mean

Validation of Univariate Empirical with Mean		
p-values for	Student's T	F-test
PPI-Ag Chemicals	1.000	0.256
PPI-Electricity	1.000	0.416
PPI-Ranchland	0.999	0.385
PPI-Pecan Price	1.000	0.375
PPI-Repairs	0.985	0.382
PP-Insurance	0.981	1.000

For validation of univariate empirical distributions as percent deviations from trend, or where a forecasted value was used to calculate the stochastic value, the "Test Parameter" tab in Simetar's Hypothesis Testing for Data dialog box was used to test the means and standard deviations of the data. To test the means, a Student's t-test was done with null hypothesis following (11). A Chi-Squared test was done to test the historical and simulated standard deviations. The null hypothesis for the Chi-Squared test follows (14). Similar to MVE with trend, a special test standard deviation was calculated to account for the use of forecasted data. The same calculation was used as in (18). All simulated data was found to fail to reject the null hypotheses, meaning that simulated data correctly fit the historical data. Results are shown in table 9.

Table 9. Validation of Univariate Empirical Distributions with Trend

Validation of Univariate Empirical with Trend		
p-values for	Student's T	Chi Squared
Nitrogen 32%	0.088	0.808
Annual Labor	0.632	0.962
Hourly Labor	0.214	0.956
Electricity	0.861	0.975
PPI-Labor	0.496	0.883

Given the nature of pecan production and adverse weather conditions, a deterministic number of chemical sprays would not be representative of a pecan orchard in central Texas. To simulate the number of sprays needed for the 150 acre orchards, a uniform distribution was used to determine the number of sprays per year. Prior research and producer surveys conducted by Texas A&M University's Entomology Department gave a uniform distribution of sprays per year (Harris and Ree 1998; Ree, Gomezplata, and Harris 2006). This was programmed into the model using Simetar's *=UNIFORM( )* function inside Excels' *=INT* function to ensure that a whole number would be selected from the uniform distribution.

Equipment maintenance costs were also calculated using a uniform distribution of costs as a percentage of the initial cost of each piece of equipment. These percentages were obtained from prior research done by extension economist at the University of Minnesota and Iowa State University (Lazarus 2011; Edwards 2009). For maintenance costs not given in these extension publications, costs were determined by using the percentages of similar equipment. Pick-up truck maintenance percentages were determined to be similar to percentages of the large 150 horsepower tractor. For calculating the maintenance cost of the off-road utility vehicle, the percentages for the medium sized 90 horsepower tractor were used. No data were available for shelter maintenance cost, so it was determined that costs were minimal with the lower part of the uniform distribution being zero and the upper part of the uniform distribution being one percent (Sherrod 2012). Maintenance costs for irrigation were determined by interviews with an irrigation specialist (ATS Irrigation 2012).

Intermediate calculations were done to determine variable costs per acre for each operation input. Revenue was calculated for each of the three orchards as

$$(19)\qquad REVENUE_{Nat,II,IN} = (PRICE_{Nat,I} * (1 + PPI : Pecan)) * YIELD_{Nat,II,IN}$$

where Nat equals native, II equals improved irrigated, and IN equals improved non-irrigated. Yield is in units of pounds of pecans per acre. Revenue for grazing cattle on the native orchard was calculated as

$$(20)\qquad REVENUE_{Cattle} = RENTAL_{Cattle} * (1 + PPI : Ranchland)\,.$$

Revenue from the Noninsured Crop Disaster Assistance Program (NAP) must be added as potential revenue source. NAP is a voluntary program administered by the

USDA Farm Service Agency to protect against low yields, loss of inventory, or prevented planting due to natural disasters (USDA Farm Service Agency 2011). NAP is only available for crops in which there are currently no other government program and catastrophic risk protection crop insurance is not available. A NAP payment is triggered by a fifty percent or higher loss in yields due to a natural disaster. NAP payments are made for an entire crop per farm and were calculated as

$$(21)\qquad REVENUE_{NAP} = \begin{bmatrix} \begin{pmatrix} (acres * share * (50\% * YIELD_{AVG})) \\ -(acres * share * YIELD_{Actual}) \end{pmatrix} \\ * (55\% * PRICE_{AVG}) \end{bmatrix} - (YIELD_{Actual} * PRICE_{Actual} * acres)$$

where *share* equals the percent share of risk in the operation of the person receiving a NAP payment.

Tractor variable cost for spraying with both the boom sprayer and the air-blast sprayer were calculated as

$$(22)\quad TRACTOR_{Spray} = \begin{pmatrix} (hrs / ac) * (gal / hr) * \\ (PRICE_{Diesel} * (1 + PPI : Diesel)) * (trips / year) \end{pmatrix} * (1 + \%LUBE)$$

where $\%LUBE$ was determined to be ten percent of the overall fuel cost for a tractor, and thereby added ten percent to the cost of operation; (gal / hr) corresponds to the amount of diesel used per hour of operation. Since tank mixing chemicals occurs, Excel's *=MAX* function was used to determine the number of trips per year the tractor would be used. Variable cost per acre for each spray was calculated as

$$(23)\qquad SPRAY = (rate / ac) * (PRICE_{Chemical} * (1 + PPI)) * (trips / year)$$

where the rate of application per acre and the price of the chemical being sprayed were in the same units. Each was inflated with a PPI found in table 4. Tractor variable cost for using equipment was calculated as

$$(24)\quad TRACTOR_{Equipment} = \begin{pmatrix} (PRICE_{Diesel} * (1 + PPI : Diesel)) * (hrs / ac) \\ * (gal / hr) * (trips / year) \end{pmatrix} * (1 + \%LUBE) .$$

The pecan tree shaker used in the model was self-propelled but followed the same calculation as (4.24). Variable cost for operation of the pick-up truck was calculated as

$$(25)\qquad TRUCK = \left((gal / ac) * (PRICE_{Gas} * (1 + PPI : Gas))\right) * (1 + \%LUBE) .$$

Application of granular nitrogen by a custom applicator was determined to be needed only once at the beginning of the growing season and was calculated as

$$(26)\qquad NITROGEN = (PRICE_{Nitrogen} * (1 + PPI : Nitrogen)) + (fee / ac)$$

where (fee / ac) is the amount charged per acre by a custom applicator. Post-harvest cleaning of pecans was calculated as

(27)

$$CLEANING_{Nat,II,IN} = \frac{(kw / hr) * (PRICE_{Electricity} * (1 + PPI : Electricity))}{(lb / hr)} * YIELD_{Nat,II,IN}$$

where (lb / hr) is the amount of pounds per hour the cleaner can process. After pecans are cleaned they will be dried using the calculation

(28)

$$DRYING_{Nat,II,IN} = \left((kw / hr) * (PRICE_{Electricity} * (1 + PPI : Electicity)) * (hrs / lb)\right) \\ * YIELD_{Nat,II,IN} .$$

Hourly labor variable cost were calculated as

(29) $$LABOR_{Hourly} = (hrs / ac) * (PRICE_{Labor_{Hourly}} * (1 + PPI : Labor) .$$

Irrigation costs per acre per year were calculated by determining the requirement per year and subtracting the amount of stochastic precipitation. This was multiplied by kilowatts per hour of electricity used, how many hours it took to get one inch of irrigation per acre, and the price of electricity. More formally

(30) $$\begin{aligned} IRRIGATION &= \sum_{Jan}^{Dec} (REQ - PRECIP) * (kw / hr) * (hrs / ac) \\ &* (PRICE_{Electricity} * (1 + PPI : Electricity)) \end{aligned}$$

where REQ is the requirement of precipitation per month and $PRECIP$ is the amount of stochastic precipitation received.

Several variable costs were calculated for the whole 150 acre orchard and were not broken down into a per acre cost. These costs were not variable in the traditional sense, meaning they varied with production; however, they were forecasted and made stochastic, allowing year-to-year variation. Equipment maintenance, equipment insurance, and annual labor were calculated this way. Equipment maintenance was calculated as

(31)

$$MAINTENANCE_{Equipment} = \sum (uniform(low, high) * PRICE) * (1 + PPI : Repairs)$$

where $PRICE$ is the is the initial cost of the equipment and *uniform(low,high)* is the uniform distribution of the percentage of maintenance costs relative to the initial cost of each piece of equipment. Insurance on equipment was calculated as

(32) $$INSURANCE_{Equipment} = (PRICE * \%INSUR) * (1 + PPI : INSURANCE)$$

where *%INSUR* is the insurance cost percentage of the total cost for each piece of equipment. It was determined that a fixed rate of .85 percent of total cost was sufficient for all equipment. Annual labor was calculated as

(33) $$LABOR_{Annual} = PRICE_{Labor_{Annual}} * (1 + PPI : Labor).$$

Both variable and fixed costs were used in the calculations of the pro forma financial statements. All three orchard scenarios, native, improved irrigated and improved non-irrigated, each have their own financial statement yet they all follow the same formulas for calculation purposes. The income statement consists of total receipts and total expenses. Total receipts were calculated as

(34) $$TOTALRECEIPTS = REVENUE_{Pecans} + REVENUE_{NAP}.$$

For the native orchard only, revenue from grazing cattle on the orchard was also added to total receipts. Total expenses were calculated as

(35) $$TOTALEXPENSES = \sum expenses$$

Where the summation takes place from equation (22) to (33). Net cash income (NCI) was calculated as

(36) $$NCI = TOTALRECEIPTS - TOTALEXPENSES.$$

The cash flow statement is a combination of cash inflows and outflows. Cash inflows (*CASHIN*) were calculated as

(37) $$CASHIN = BEGCASH + NCI + INT_{Cash}$$

where *BEGCASH* is the beginning cash amount at the time of initial investment and INT_{Cash} is the interest earned on cash. Previous research did not indicate an amount of beginning cash need for a pecan orchard, so the model assumed a beginning cash of $50,000. Cash outflows (*CASHOUT*) were calculated as

$$(38) \qquad CASHOUT = CAPEX_{Principal} + DEFICITLOAN + TAXES$$

where $CAPEX_{Principal}$ is the principal amount of the capital expenditure loan for each year. *DEFICITLOAN* is the amount of operating loan plus interest that must be repaid if there was negative ending cash in the previous year. *TAXES* indicate the amount of income taxes due for each year. For taxes purposes, equipment was depreciated using Modified Accelerated Cost Recovery System (MACRS) on a ten year 150% declining balance method (Internal Revenue Service 2011). Ending cash (*EC*) was calculated as the difference of cash inflows and outflows, or more formally as

$$(39) \qquad EC = CASHIN - CASHOUT \ .$$

The balance sheet consisted of total assets and total liabilities of each respective orchard operation. Total assets were calculated as

$$(40) \qquad TOTALASSETS = EC + LAND + CAPEX$$

where *LAND* is the appreciated value of the original purchase price of the orchard and *CAPEX* is the depreciated value of the capital expenditures less the original land value. Land value was set to appreciate at 13.12%, the average rate of PPI for pecan prices.

Capital expenditures depreciated at 12% using the useful life method for fifteen years, the same as the life of the capital expenditures loan. More formally,

(41) $$DEPRECIATION_t = \left(PRICE - DEPRECIATION_{t-1}\right) * \%DEPRECIATION$$

where *PRICE* is the initial cost of the equipment. This allowed for a 15% recovery of the initial capital outlay after 15 years. MACRS depreciation was used for tax purposes only. Ending cash was made zero if calculated as negative in (37). Total liabilities were calculated as

(42) $$TOTALLIABILITIES = CAPEX_{Debt} + CF_{deficits}$$

Where $CAPEX_{Debt}$ is the total debt for each year of the capital expenditures loan and $CF_{Deficits}$ was the amount of cash needed to operate if *EC* was negative. $CF_{Deficit}$ plus interest was repaid in (36) as *DEFICITLOAN*. Net worth of each operation was calculated as

(43) $$NETWORTH = TOTALASSETS - TOTALLIABILITIES\ .$$

The pro forma financial statements were used to give an indication of the investments profitability, but there were several other key output variables that had to be calculated. Beginning net worth (*BNW*) was calculated as

(44) $$BNW = BEGCASH + CAPEX - DEBT_{Jan1}$$

where $DEBT_{Jan1}$ is the amount of debt the operation had on January 1st of the first year of investment. The present value of ending net worth (*PVENW*) is calculated as

(45) $$PVENW = NW * \left(1/(1 + discountrate)^{N}\right)$$

where the discount rate was determined to be 7.75% and *N* equals the number of years into the operation investment. The discount rate was determined by averaging the discount rates of previous stochastic models (Richardson and Mapp 1976; Richardson et al. 2007). The final key output variable calculated was net present value (*NPV*) which was calculated as

(46) $$NPV = -BNW + PVENW\ .$$

The NPV, the probability of NPV being greater than zero, and each year's EC was simulated for each of the three scenarios using Simetar's simulation engine. The simulation engine used Latin Hypercube sampling as opposed to the less accurate Monte Carlo sampling method, and 500 iterations was determined to be sufficient.

CHAPTER V

RESULTS

Results from the conjoint analysis choice experiment and the stochastic production models are presented in this chapter. Each model was researched and developed separately but shared the same basic principle: What the consumers are demanding and what is profitable to produce. For the choice experiment, using Stata 12.1, different models were examined for a conditional logit, alternative-specific conditional logit, and a random parameters logit model. Simetar, a Microsoft Excel add-on, was used to make the production model stochastic, and key output variables were simulated in order to report estimates as probability distributions.

Conjoint Analysis

For estimating logistic regressions specified in Chapter IV, the third option was removed from the dataset. This was done for ease of estimation as the dataset was not properly coded to handle the third option of choosing neither. The dataset could have been recoded to incorporate the neither option as an independent variable and allowing its estimation to be incorporated into the constant term in the regression. As mentioned in Chapter IV, logistic regression coefficients have little interpretable meaning but show the relative magnitude of each attribute preference.

Of the original 18,036 observations 6,012 were dropped to rid the model of the third option and 1,552 were dropped by Stata because of all positive or negative outcomes, yielding 10,472 observations used in the conditional logit model. All six variable attributes tested were statistically significant at greater than the 99% level.

Results from the conditional logit model showed a negative coefficient for price as expected. Price was expected to be negative according to economic theory which suggests a rational consumer would rather pay less than more to consume a product; therefore price has a negative effect on the consumption of any good. Variables for large pecans, pecan halves, U.S. origin, and Texas origin all had positive coefficients indicating these attributes increase the probability of a pecan product to be chosen. Base attributes and their respective improvements were determined from industry, market and prior research (Santerre 1994; Lombardini, Waliczek, and Zajicek 2008).

The only variable tested that yielded a negative coefficient, other than price, was *varimp* which represents improved varieties. Prior research and market data suggested that improved varieties were in higher demand and received a higher price. The negative coefficient for improved varieties indicated that consumers prefer native varieties over improved varieties. This result was opposite of economic intuition, which suggest, as market research suggest, that the higher priced improved varieties should yield a higher utility than the lower priced native varieties because of they are perceived as higher quality products (Moore et al. 2009). This result suggests that consumers may prefer native varieties over improved varieties because of the consumers' preferences for native or natural origin products. No post-estimation calculations were done on the conditional logit model since the model assumes homogeneity of preferences across the sample population's preferences. Results from the conditional logit regression using Stata's *clogit* command can be found in table 10.

Table 10. Conditional (fixed-effects) Logistic Regression Results

Conditional (fixed-effects) logistic regression				Number of obs		=	10472
				LR	chi2(6)	=	1538.79
				Prob >	chi2	=	0.0000
Log likelihood	=	-2859.92		Pseudo	R2	=	0.2120

choice	|	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sizelg	|	0.082525	0.0162569	5.08	0.000	0.0506623	0.1143882
varimp	|	-0.05814	0.016362	-3.55	0.000	-0.0902102	-0.0260722
stahalf	|	0.132891	0.0163006	8.15	0.000	0.1009421	0.1648391
orgus	|	0.118474	0.0255373	4.64	0.000	0.0684216	0.168526
orgtx	|	0.685195	0.0270677	25.31	0.000	0.6321434	0.7382468
price	|	-0.18522	0.011553	-16.03	0.000	-0.207864	-0.1625772

Similar to the conditional logit model, 10,472 observations were used for the alternative-specific, McFadden's Choice, logit model. All variables were statistically significant at the 99% level. Results for the alternative-specific logit yielded identical coefficients, standard errors, z-values, and p-values as the conditional logit model. Results were identical because the alternatives order did not matter, meaning that each alternative in the choice set was not specific to a brand. A respondent choice of the first or second alternative had no effect on the model. Because of the nature of the data, the "group" function of the *clogit* command and the "case" function of the *asclogit* command both used the "groupcount" variable to identify each individual. The difference in the two commands is that the *asclogit* command has the “alternatives” function in which the case-specific alternatives are to be specified. For this model, the “option” variable was specified as the case-specific alternatives. Since the data were grouped by individual respondent, both models were essentially specified as identical models. The calculation of both the *clogit* and *asclogit* used the same formula specified in (4) and the results of the two models were identical. Results for the alternative-specific logit can be found in table 11.

Table 11. Alternative-Specific Logistic Regression Results

Alternative-specific conditional logit			Number of obs		=		10472
Case variable: groupcount			Number of cases		=		5236
Alternative variable: option			Alts per case:	min	=		2
				avg	=		2
				max	=		2
			Wald	chi2(6)	=		1188.54
Log likelihood	=	-2859.92	Prob >	chi2	=		0.0000

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
option						
sizelg	0.082525	0.0162569	5.08	0.000	0.0506623	0.1143882
varimp	-0.05814	0.016362	-3.55	0.000	-0.0902102	-0.0260722
stahalf	0.132891	0.0163006	8.15	0.000	0.1009421	0.1648391
orgus	0.118474	0.0255373	4.64	0.000	0.0684216	0.168526
orgtx	0.685195	0.0270677	25.31	0.000	0.6321434	0.7382468
price	-0.18522	0.011553	-16.03	0.000	-0.207864	-0.1625772

For the full random parameters logit model, the user written *mixlogit* command for Stata was used (Hole 2007). Again, 10,472 observations out of the 18,036 were used for similar reasons as the *clogit* and *asclogit* models. 500 draws were specified as the *mixlogit* command uses simulation to estimate the parameters of the model. As previously mentioned, the random parameters logistic model is an improvement over the conditional logistic model because it does not assume homogeneity of preferences across the population of respondents. Random parameters logit models allow for heterogeneity of preferences. All variables tested were found to be statistically significant at greater than the 99% level. The signs of the coefficients from the random parameters logit model were identical to the signs of coefficients for the conditional logit models. Both variables *price* and *varimp* had negative coefficients. Like the conditional logit results, this indicated that a consumer's utility would be diminished by increasing price or by moving from natives to improved variety pecans. Price was expected to have a negative coefficient since the consumers were assumed to behave rationally. Improved varieties were expected to have a positive coefficient, since the *a priori* was that natives are a base product and improved varieties are an improvement over natives. Results of the random parameters logit can be found in table 12.

An important feature of the *mixlogit* command is the estimation of random effects of the slopes of the independent variables standard deviations to test the heterogeneity of preferences. These standard deviations are coefficients for each variable. As noted by Hole (2007), a statistically significant standard deviation of a variable indicates that there is preference heterogeneity in that attribute. Results from the *mixlogit* model showed that variables *sizelg, stahalf,* and *orgtx* all had statistically significant standard deviations. This means consumers' preferences for large pecans, pecan halves, and Texas origin pecans were heterogeneous across the sample population of Texas consumers. What is interesting is that *varimp*, improved varieites, and *orgus*, U.S. origin, were found not to be heterogeneous across the sample population. This means that the sample population of Texas consumers were homogeneous in their preferences for improved variety pecans and pecans from the United States. As previously mentioned, the estimated coefficient for improved varieties was negative, meaning that consumers preferred native pecans over improved variety pecans. Merging the interpretation of the sign of the estimated coefficient with the interpretation of the standard deviations for each attribute, it was found that Texas consumers were homogenous in their preference of consuming native variety pecans over improved variety pecans. This was opposite of the *a priori* that natives are inferior to improved variety pecans. The non-significant standard deviation of the attribute for U.S. origin pecans also showed that consumers were homogenous in their preference of consuming U.S. pecans over the base attribute of imported pecans. Standard deviation results are also reported in table 12. All results from all three Stata models can be found in Appendix D.

Table 12. Random Parameters Logistic Regression Results

Mixed logit model							
			Number of obs		=	10472	
			LR	chi2(5)	=	531.64	
Log likelihood	=	-2594.1	Prob >	chi2	=	0.0000	
choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	
Mean							
price	-0.26164	0.0151358	-17.29	0.000	-0.291309	-0.2319779	
sizelg	0.119123	0.026847	4.44	0.000	0.0665038	0.1717421	
varimp	-0.07882	0.0201573	-3.91	0.000	-0.1183313	-0.039316	
stahalf	0.193059	0.0274054	7.04	0.000	0.1393449	0.2467722	
orgus	0.176929	0.0316449	5.59	0.000	0.114906	0.2389518	
orgtx	1.146483	0.0711762	16.11	0.000	1.00698	1.285986	
SD							
sizelg	0.358451	0.0323041	11.10	0.000	0.2951365	0.4217663	
varimp	-0.04176	0.0923877	-0.45	0.651	-0.2228394	0.1393138	
stahalf	0.369675	0.0325781	11.35	0.000	0.3058229	0.4335265	
orgus	0.030859	0.1679733	0.18	0.854	-0.2983628	0.3600804	
orgtx	1.101091	0.0686488	16.04	0.000	0.9665416	1.23564	

The sign of the estimated standard deviation is irrelevant: interpret them as being positive

Further investigation into the homogeneity of preferences was done by dividing the consumers into two separate groups, those who purchased pecans often and those who did not purchase pecans often. This was done to test whether there was a difference in preference for improved varieties and U.S. origin pecans across consumption habits. The premise being that there was not equal knowledge across consumers regarding native and improved varieties and U.S. grown pecans versus imported pecans. Using question 5 from the Pecan Consumer Survey (Appendix C), consumers were divided into two groups according to their response to question 5. Question 5 reads “How often do you purchase pecans?” For this test we assumed that purchasing pecans and consuming pecans were directly related. Respondents that answered either “Less than once a year,” “Once a year,” or “Several times a year” were grouped into the not often consumers group. Respondents that answered either “Once a month,” “Twice a month,” “Once a week,” or “More than once a week” were grouped into the often consumers category. The same three models, conditional logit, alternative-specific conditional logit, and the random parameters logit, were run for each of the two groups. For sake of comparison, only the random parameters logit models were compared since the random parameters logit models tested for heterogeneity of preferences.

For the group specified as not often consumers, 8,728 observations were used out of the previously ran 10,472 observations. This means that 83.3% of respondents in the sample population were not often consumers of pecans. All variables tested were found to be statistically significant at greater than the 99% level. The *mixlogit* model yielded similar results to the full model with *price* and *varimp* having negative coefficients. The coefficient values were also very similar. The standard deviations for improved varieties and U.S. origin were also similar to the full model with neither standard deviation being statistically significant. This confirms the results found in the full model that consumers are homogeneous in their preferences for improved varieties and U.S. origin pecans. Results for the random parameters logit with only not often pecan consumers can be found in table 13.

Table 13. Random Parameter Logistic Regression Results for Not Often Consumers

Mixed logit model				Number of obs	=		8728
				LR chi2(5)	=		486.93
Log likelihood	=	-2078.39		Prob > chi2	=		0.0000
choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	
Mean							
price	-0.30609	0.018279	-16.75	0.000	-0.3419148	-0.2702622	
sizelg	0.114957	0.031477	3.65	0.000	0.0532639	0.1766503	
varimp	-0.0871	0.023677	-3.68	0.000	-0.1335093	-0.0406955	
stahalf	0.207304	0.033228	6.24	0.000	0.1421784	0.2724301	
orgus	0.194956	0.03698	5.27	0.000	0.1224773	0.2674353	
orgtx	1.27452	0.086284	14.77	0.000	1.105406	1.443634	
SD							
sizelg	0.39333	0.038105	10.32	0.000	0.3186467	0.4680135	
varimp	-0.09063	0.06557	-1.38	0.167	-0.2191484	0.0378799	
stahalf	0.437637	0.039499	11.08	0.000	0.3602209	0.5150538	
orgus	0.062825	0.19917	0.32	0.752	-0.3275412	0.4531908	
orgtx	1.195188	0.083403	14.33	0.000	1.031722	1.358654	

The sign of the estimated standard deviations is irrelevant: interpret them as positive

For the group classified as often pecan consumers, 1,744 observations were used out of the 10,472 used in the full model. This means that only 16.7% of consumers were classified as often consumers of pecans. Variables for large size pecans, improved varieties, and U.S. origin were not statistically significant at the 99% level, although *sizelg* was found to be statistically significant at the 95% level. These failures were somewhat expected, since the number of respondents in this group of often consumers was much lower than the group of not often consumers. With the failure to yield significant coefficients, standard deviation results could not be compared to results for the often consumers group. Since variables *sizelg, varimp,* and *orgus* were not statistically significant, this means often consumers of pecans are indifferent in their preferences for pecan size, pecan variety, or whether a pecan product originates from the U.S. or was imported. Therefore, it was conclusive that a majority of respondents were not often consumers of pecans and had homogenous preferences for improved varieties of pecans and pecans from the United States. Results for the often consumers random parameter logit model with the non-significant variables bolded can be found in table 14. The full results from the Stata models comparing the two consumption groups can be found in Appendix E.

Further non-statistical aspects of these results were also examined. In the Pecan Consumer Survey (Appendix C), descriptions of each attribute were specified prior to the respondents answering the choice questions. For native pecans, the description read "Native Variety: Pecan varieties that are native to their country of origin." For improved varieties the description read "Improved Variety: Pecan varieties that are bred from native varieties using traditional plant breeding techniques." While these descriptions may have been clear to those familiar with agriculture, for those who were not familiar with agriculture these descriptions may have been opaque or somewhat deceiving. For those who were unfamiliar with "traditional plant breeding techniques," respondents may have related pecans that were "native to their country of origin" with being more natural or true to pecans in their natural environment. Although improved varieties are bred from natural variety pecans, they are not genetically modified organisms as may have been thought by the respondents. This misunderstanding was not fully assessed by the survey designers in the original creation of the survey. Though this raised a valid point, statistically there was no way to validate this suggestion.

Table 14. Random Parameters Logistic Results for Often Consumers

Mixed logit model				Number of obs		=	1744
				LR chi2(5)		=	57.06
Log likelihood	=	-497.306		Prob > chi2		=	0.0000
choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	
Mean							
price	-0.11784	0.029704	-3.97	0.000	-0.1760626	-0.0596242	
sizelg	0.130251	0.052279	**2.49**	**0.013**	0.0277853	0.2327165	
varimp	-0.05772	0.042452	**-1.36**	**0.174**	-0.1409291	0.0254809	
stahalf	0.157007	0.047465	3.31	0.001	0.0639772	0.2500364	
orgus	0.123415	0.066428	**1.86**	**0.063**	-0.0067813	0.2536115	
orgtx	0.72991	0.125841	5.80	0.000	0.4832649	0.9765541	
SD							
sizelg	0.254549	0.067852	3.75	0.000	0.1215606	0.3875367	
varimp	0.035313	0.175431	0.20	0.840	-0.3085258	0.3791517	
stahalf	0.167356	0.077107	2.17	0.030	0.0162283	0.3184831	
orgus	-0.02956	0.239096	-0.12	0.902	-0.4981803	0.4390594	
orgtx	0.815638	0.128356	6.35	0.000	0.5640655	1.06721	

The sign of the estimated standard deviations is irrelevant: interpret them as being positive

Looking at the full random parameters logit model with 10,472 observations, the estimation of the consumer willingness-to-pay (WTP) for each attribute was done using equation (7) specified in Chapter IV. This equation was multiplied by two because the respondents answered questions based on an eight ounce bag of pecans. Multiplying by two allows all WTP estimates to be compared on a per pound basis. WTP calculations were done with the *ceteris paribus* assumption. This means that each WTP calculation assumed that the WTP dollar amount calculated was for two identical products other than the specified attribute of the calculation.

As noted by the positive coefficient, consumers were willing to pay more for large pecans than small pecans. Calculations indicated a mean WTP of $1.82 per pound equivalent for large pecans over small pecans. Pecan halves and U.S. origin also had positive coefficients' and were determined to have a mean WTP of $2.95 per pound equivalent versus pecan pieces and $2.70 per pound equivalent versus imported pecans respectively. Texas origin, the *orgtx* variable, had a positive coefficient greater than one, causing a larger magnitude for the WTP estimate. Calculations revealed consumers' mean WTP for Texas pecans versus imported pecans at $17.53 per pound equivalent. This result indicated a strong demand by Texas consumers for Texas grown pecans. As previously noted, improved varieties had a negative coefficient thereby making natives preferred over improved varieties. Calculations revealed a -$1.21 per pound equivalent mean WTP for improved varieties, therefore it was conceived that consumers are willing to pay on average $1.21 per pound more for native variety than improved variety pecans. Mean WTP calculation results are found in table 15.

Table 15. Mean WTP Results

Mean Willingness-to-Pay (WTP)	WTP	in dollars
sizelg	1.821	$1.82
varimp	-1.205	-$1.21
stahalf	2.951	$2.95
orgus	2.705	$2.70
orgtx	17.53	$17.53

values reported in per pound equivalents

In order to compare two pecan products, product utilities were calculated. Utility calculations differ from WTP calculations in that WTP calculations determine the WTP for each attribute versus its base. Product utilities show the utility derived from consuming the product, which is a combination of attributes. Utility calculations by themselves are meaningless, as the calculations result in a number that is uninterruptable without other utility calculations for comparison. Calculations were done by adding each attribute coefficient multiplied by its variable, as specified in (1). The best product, large native halves from Texas at a price of $3 per pound, yielded a product utility of .7526. The calculation to derive this utility is as follows:

(47) $$UTIL_{Best} = \beta_{sizelg}(1) + \beta_{varimp}(-1) + \beta_{stahalf}(1) + \beta_{orgus}(0) + \beta_{orgtx}(1) + \beta_{price}(3)\,.$$

The worst product, small improved pieces that were imported at a price of $7 per pound, yielded a product utility of -3.5460. Its calculation is as follows:

(48) $$UTIL_{Worst} = \beta_{sizelg}(-1) + \beta_{varimp}(1) + \beta_{stahalf}(-1) + \beta_{orgus}(-1) + \beta_{orgtx}(-1) + \beta_{price}(7)\,.$$

As previously mentioned, each utility's raw value is uninterruptable, but comparing the two values is useful. By taking the ratio of best and worst product utilities, it was found that the consumer derives 4.7 times as much utility from the best product than the worst product. These calculations could be used to derive the utility for an assortment of different products as desired. For more product utilities see Appendix D.

Production Model

The production model was created to test the profitability of growing pecans in central Texas. Three different orchard scenarios were tested: native, improved irrigated, and improved non-irrigated.

Yields and prices were forecasted and made stochastic for the four years being evaluated, 2012 – 2015. Yields were made stochastic by using percent deviations from the mean and prices were made stochastic using percent deviations from the trend. As with other stochastic results, only the means of the stochastic values can be shown. See table 16 for stochastic prices and yields for 2012 – 2015.

Table 16. Average Stochastic Prices and Yields

Average Stochastic Prices and Yields					
	PriceNat	PriceImp	YieldNat	YieldImp-Irr	YieldImp-Non
2012	$1.89	$2.67	255	653	251
2013	$2.17	$3.01	255	653	251
2014	$2.45	$3.35	255	653	251
2015	$2.73	$3.69	255	653	251

Prices are in $ per pound and Yields are in pound per acre

As explained in Chapter IV, the stochastic production model was formulated to determine the profitability of a native orchard with no irrigation, an improved variety orchard with irrigation, and an improved variety orchard without irrigation. Profitability was not determined by a single concept, but was determined by making use of pro forma financial statements, probability density functions, cumulative distribution functions, and an assortment of stochastic dominance tools for evaluating each of the three scenarios.

The pro forma statements, like the entire model, were stochastic and cannot be shown in their stochastic mode. Simulation of the results of the pro forma statements gave probability distributions for analyzing the model stochastically. For purposes of discussion here, the averages of the stochastic values are reported in the financial statements by using Simetar's Expected Value Mode. The financial statements included an income statement showing receipts minus expenses, a cash flow statement showing cash inflows minus cash outflows, and a balance sheet showing assets minus liabilities for each of the three scenarios in each of the four years simulated. For comparison purposes, the financial statements for each scenario are reported separately but the other key output variables are reported comparing all three scenarios together.

The model for a native orchard with no irrigation resulted in negative net cash income (NCI) for all 4 years evaluated. NCI slowly increased, became more positive, in the years evaluated from -$116,180.68 in 2012 to -$47,823.51 in 2015. The NAP expense in the income statement was set to $0 because simulation of the NAP calculation determined that a NAP payment would never be received by the orchard. Ending cash (EC) was calculated in the cash flow statement and was also found to be negative for all four years evaluated for the native orchard. Opposite of NCI, EC grew more negative over time, going from -$101,186.27 in 2012 to -$441,373.29 in 2015. Net worth was determined in the balance sheet by subtracting the liabilities from the assets. Net worth for the native orchard was found to be negative and growing more negative over time going from -$136,656.68 in 2012 to -$314,404.23 in 2015. Financial statements for the native orchard can be found in table 17.

The income statement for the improved irrigated orchard yielded opposite results as the native orchard. For the improved irrigated orchard, NCI grew over time from $61,704.26 in 2012 to $219,862.95 in 2015. Cash flows for the improved irrigated orchard also grew over time with EC at $54,952.17 in 2012 to $278,132.23 in 2015. The balance sheet showed that the orchard had a net worth of -$9,348.96 in 2012 but grew positively to $326,104.17 in 2015. Financial statements for the improved irrigated orchard can be found in table 18.

Table 17. Financial Statements for the Native Orchard

Financial Statements

Income Statement:Native	**2012**	**2013**	**2014**	**2015**
Receipts				
Rev:Nat	$ 91,134.27	$ 104,417.10	$ 119,635.91	$ 137,072.86
Rev:Cattle	$ 1,679.25	$ 1,790.40	$ 1,908.90	$ 2,035.25
Rev:NAP Nat	$ -	$ -	$ -	$ -
Total Receipts	$ 92,813.52	$ 106,207.50	$ 121,544.81	$ 139,108.11
Expenses				
tree removal	$ 30,000.00			
total sprays	$ 24,557.16	$ 25,712.32	$ 26,869.90	$ 28,029.95
shredder(tractor1)	$ 4,927.66	$ 5,254.84	$ 5,582.01	$ 5,909.18
shaker	$ 9,595.89	$ 10,233.01	$ 10,870.13	$ 11,507.25
sweeper(tractor1)	$ 5,397.69	$ 5,756.07	$ 6,114.45	$ 6,472.83
harvest(tractor2)	$ 8,996.14	$ 9,593.44	$ 10,190.74	$ 10,788.04
truck	$ 1,295.79	$ 1,367.45	$ 1,439.11	$ 1,510.78
Ground Nitro	$ 3,018.75	$ 3,316.16	$ 3,654.60	$ 4,039.72
cleaning	$ 9.16	$ 9.40	$ 9.64	$ 9.89
drying	$ 2,261.09	$ 2,375.51	$ 2,490.04	$ 2,604.66
equip maintenance	$ 41,363.14	$ 42,325.07	$ 42,325.07	$ 42,325.07
labor-annual	$ 21,473.36	$ 22,091.45	$ 22,706.15	$ 23,317.46
labor-hourly	$ 6,251.87	$ 6,386.53	$ 6,520.42	$ 6,653.55
irrigation	$ -	$ -	$ -	$ -
equip insurance	$ 6,678.04	$ 6,684.59	$ 6,691.15	$ 6,697.72
NAP	$ -	$ -	$ -	$ -
CAPEX debt interest	$ 43,168.46	$ 41,242.04	$ 39,209.67	$ 37,065.52
Total Expenses	$ 208,994.19	$ 182,347.88	$ 184,673.08	$ 186,931.62
Net Cash Income	$ (116,180.68)	$ (76,140.38)	$ (63,128.27)	$ (47,823.51)

Cash Flow Statement	**2012**	**2013**	**2014**	**2015**
Beginning Cash Jan 1	$ 50,000.00	$ -	$ -	$ -
Net Cash Income	$ (116,180.68)	$ (76,140.38)	$ (63,128.27)	$ (47,823.51)
interest earned on cash	$ 20.20	$ -	$ -	$ -
Cash Inflows	$ (66,160.48)	$ (76,140.38)	$ (63,128.27)	$ (47,823.51)
Principal on CAPEX loan	$ 35,025.79	$ 36,952.21	$ 38,984.58	$ 41,128.73
Repay deficit loans		$ 106,751.51	$ 231,935.53	$ 352,421.04
Income taxes	$ -	$ -	$ -	$ -
Cash Outflows	$ 35,025.79	$ 143,703.72	$ 270,920.11	$ 393,549.77
Ending Cash Dec 31	$ (101,186.27)	$ (219,844.10)	$ (334,048.38)	$ (441,373.29)

Balance Sheet	**2012**	**2013**	**2014**	**2015**
Cash Dec 31	$ -	$ -	$ -	$ -
Land	$ 356,250.00	$ 402,997.43	$ 455,879.10	$ 515,699.95
CAPEX less land	$ 358,134.92	$ 315,158.73	$ 277,339.68	$ 244,058.92
Total Assets	$ 714,384.92	$ 718,156.16	$ 733,218.79	$ 759,758.87
CAPEX debt	$ 749,855.34	$ 712,903.13	$ 673,918.55	$ 632,789.82
cash flow deficits	$ 101,186.27	$ 219,844.10	$ 334,048.38	$ 441,373.29
Total Liabilities	$ 851,041.60	$ 932,747.23	$ 1,007,966.93	$ 1,074,163.10
Net Worth	$ (136,656.68)	$ (214,591.07)	$ (274,748.14)	$ (314,404.23)

Table 18. Financial Statements for the Improved Irrigated Orchard

Financial Statements

Income Statement:Imp-Irr	**2012**	**2013**	**2014**	**2015**
Receipts				
Rev:Imp-Irr	$ 328,964.41	$ 376,911.02	$ 431,845.85	$ 494,787.45
Rev:NAP Imp-Irr	$ -	$ -	$ -	$ -
Total Receipts	$ 328,964.41	$ 376,911.02	$ 431,845.85	$ 494,787.45
Expenses				
tree removal	$ 30,000.00			
total sprays	$ 30,068.00	$ 31,461.75	$ 32,857.91	$ 34,256.54
shredder(tractor1)	$ 4,927.66	$ 5,254.84	$ 5,582.01	$ 5,909.18
shaker	$ 2,628.09	$ 2,802.58	$ 2,977.07	$ 3,151.56
sweeper(tractor1)	$ 8,096.53	$ 8,634.10	$ 9,171.67	$ 9,709.24
harvest(tractor2)	$ 13,494.22	$ 14,390.17	$ 15,286.12	$ 16,182.07
truck	$ 1,295.79	$ 1,367.45	$ 1,439.11	$ 1,510.78
Ground Nitro	$ 3,018.75	$ 3,316.16	$ 3,654.60	$ 4,039.72
cleaning	$ 23.45	$ 24.06	$ 24.69	$ 25.33
drying	$ 5,790.15	$ 6,083.17	$ 6,376.45	$ 6,669.98
equip maintenance	$ 93,922.74	$ 96,106.99	$ 96,106.99	$ 96,106.99
labor-annual	$ 21,473.36	$ 22,091.45	$ 22,706.15	$ 23,317.46
labor-hourly	$ 6,251.87	$ 6,386.53	$ 6,520.42	$ 6,653.55
irrigation	$ 2,131.10	$ 2,186.46	$ 2,243.25	$ 2,301.51
equip insurance	$ 9,932.48	$ 9,942.22	$ 9,951.98	$ 9,961.75
NAP	$ -	$ -	$ -	$ -
CAPEX debt interest	$ 64,205.96	$ 61,340.73	$ 58,317.92	$ 55,128.84
Total Expenses	$ 267,260.15	$ 271,388.65	$ 273,216.32	$ 274,924.50
Net Cash Income	$ 61,704.26	$ 105,522.37	$ 158,629.53	$ 219,862.95

Cash Flow Statement	**2012**	**2013**	**2014**	**2015**
Beginning Cash Jan 1	$ 50,000.00	$ 54,952.17	$ 98,181.22	$ 172,464.72
Net Cash Income	$ 61,704.26	$ 105,522.37	$ 158,629.53	$ 219,862.95
interest earned on cash	$ 20.20	$ 22.20	$ 39.67	$ 69.68
Cash Inflows	$ 111,724.46	$ 160,496.73	$ 256,850.41	$ 392,397.35
Principal on CAPEX loan	$ 52,095.08	$ 54,960.31	$ 57,983.13	$ 61,172.20
Repay deficit loans		$ -	$ -	$ -
Income taxes	$ 4,677.21	$ 7,355.21	$ 26,402.56	$ 53,092.92
Cash Outflows	$ 56,772.29	$ 62,315.52	$ 84,385.69	$ 114,265.12
Ending Cash Dec 31	$ 54,952.17	$ 98,181.22	$ 172,464.72	$ 278,132.23

Balance Sheet	**2012**	**2013**	**2014**	**2015**
Cash Dec 31	$ 54,952.17	$ 98,181.22	$ 172,464.72	$ 278,132.23
Land	$ 356,250.00	$ 402,997.43	$ 455,879.10	$ 515,699.95
CAPEX less land	$ 694,734.92	$ 611,366.73	$ 538,002.72	$ 473,442.40
Total Assets	$ 1,105,937.09	$ 1,112,545.38	$ 1,166,346.55	$ 1,267,274.58
CAPEX debt	$ 1,115,286.04	$ 1,060,325.73	$ 1,002,342.61	$ 941,170.41
cash flow deficits	$ -	$ -	$ -	$ -
Total Liabilities	$ 1,115,286.04	$ 1,060,325.73	$ 1,002,342.61	$ 941,170.41
Net Worth	$ (9,348.96)	$ 52,219.64	$ 164,003.94	$ 326,104.17

Table 19. Financial Statements for the Improved Non-Irrigated Orchard

Financial Statements

Income Statement:Imp-Non	**2012**	**2013**	**2014**	**2015**
Receipts				
Rev:Imp-Non	$ 126,447.27	$ 144,876.98	$ 165,992.82	$ 190,186.29
Rev:NAP Imp-Non	$ -	$ -	$ -	$ -
Total Receipts	$ 126,447.27	$ 144,876.98	$ 165,992.82	$ 190,186.29
Expenses				
tree removal	$ 30,000.00			
total sprays	$ 30,068.00	$ 31,461.75	$ 32,857.91	$ 34,256.54
shredder(tractor1)	$ 4,927.66	$ 5,254.84	$ 5,582.01	$ 5,909.18
shaker	$ 14,393.83	$ 15,349.51	$ 16,305.19	$ 17,260.87
sweeper(tractor1)	$ 8,096.53	$ 8,634.10	$ 9,171.67	$ 9,709.24
harvest(tractor2)	$ 13,494.22	$ 14,390.17	$ 15,286.12	$ 16,182.07
truck	$ 1,295.79	$ 1,367.45	$ 1,439.11	$ 1,510.78
Ground Nitro	$ 3,018.75	$ 3,316.16	$ 3,654.60	$ 4,039.72
cleaning	$ 9.02	$ 9.25	$ 9.49	$ 9.74
drying	$ 2,225.62	$ 2,338.25	$ 2,450.98	$ 2,563.81
equip maintenance	$ 41,363.14	$ 42,325.07	$ 42,325.07	$ 42,325.07
labor-annual	$ 21,473.36	$ 22,091.45	$ 22,706.15	$ 23,317.46
labor-hourly	$ 6,251.87	$ 6,386.53	$ 6,520.42	$ 6,653.55
irrigation	$ -	$ -	$ -	$ -
equip insurance	$ 6,678.04	$ 6,684.59	$ 6,691.15	$ 6,697.72
NAP	$ -	$ -	$ -	$ -
CAPEX debt interest	$ 43,168.46	$ 41,242.04	$ 39,209.67	$ 37,065.52
Total Expenses	$ 196,464.28	$ 200,851.15	$ 204,209.54	$ 207,501.26
Net Cash Income	$ (70,017.01)	$ (55,974.17)	$ (38,216.72)	$ (17,314.96)

Cash Flow Statement	**2012**	**2013**	**2014**	**2015**
Beginning Cash Jan 1	$ 50,000.00	$ -	$ -	$ -
Net Cash Income	$ (70,017.01)	$ (55,974.17)	$ (38,216.72)	$ (17,314.96)
interest earned on cash	$ 20.20	$ -	$ -	$ -
Cash Inflows	$ (19,996.81)	$ (55,974.17)	$ (38,216.72)	$ (17,314.96)
Principal on CAPEX loan	$ 35,025.79	$ 36,952.21	$ 38,984.58	$ 41,128.73
Repay deficit loans		$ 58,048.84	$ 159,278.86	$ 249,486.57
Income taxes	$ -	$ -	$ -	$ -
Cash Outflows	$ 35,025.79	$ 95,001.05	$ 198,263.44	$ 290,615.30
Ending Cash Dec 31	$ (55,022.60)	$ (150,975.22)	$ (236,480.16)	$ (307,930.27)

Balance Sheet	**2012**	**2013**	**2014**	**2015**
Cash Dec 31	$ -	$ -	$ -	$ -
Land	$ 356,250.00	$ 402,997.43	$ 455,879.10	$ 515,699.95
CAPEX less land	$ 694,734.92	$ 611,366.73	$ 538,002.72	$ 473,442.40
Total Assets	$ 1,050,984.92	$ 1,014,364.16	$ 993,881.83	$ 989,142.35
CAPEX debt	$ 749,855.34	$ 712,903.13	$ 673,918.55	$ 632,789.82
cash flow deficits	$ 55,022.60	$ 150,975.22	$ 236,480.16	$ 307,930.27
Total Liabilities	$ 804,877.94	$ 863,878.35	$ 910,398.71	$ 940,720.08
Net Worth	$ 246,106.98	$ 150,485.81	$ 83,483.12	$ 48,422.26

The improved non-irrigated orchard yielded a negative NCI for the four years simulated but grew over time, going from -$70,017.01 in 2012 to -$17,314.96 in 2015. EC for the improved non-irrigated orchard was also negative but decreased over the time period simulated. In 2012 EC was -$55,022.60 for the improved non-irrigated orchard and ended with -$307,930.27 in 2015. Net worth for the improved non-irrigated orchard decreased as well but remained above zero for the four years simulated. Net worth was found to be $246,106.98 in 2012 and $48,422.26 in 2015. Financial statements for the improved non-irrigated orchard can be found in table 19.

By looking just at the pro forma financial statements for each orchard scenario, several implications about profitability were made. The native orchard appears to be the least profitable with an average NCI, EC, and net worth all less than zero for the 4 projected years. The improved non-irrigated orchard shows an average negative NCI and EC for the 4 project years and a positive yet diminishing average net worth over the 4 years. By just evaluating the averages of the output variables in the financial statements, the improved irrigated orchard appeared to be the most profitable. Both average NCI and average EC were positive and growing over the four year period. Average net worth was negative in the first projected year but became positive in the second year and increasing over the 4 years.

For comparing the net present value (NPV) of the three scenarios, each NPV was simulated 500 times using Latin Hypercube Sampling method of Monte Carlo simulation in Simetar. This allowed each NPV to be seen as a distribution of outcomes rather than a single point estimate. The native orchard was found to have the lowest probability, 19%, of having a positive NPV. The improved irrigated orchard had the highest probability of having a positive NPV at 68%. The improved non-irrigated orchard had a 58% chance of yielding a positive NPV. These probabilities can easily be seen in a cumulative distribution function (CDF) of each NPV. The probability of each NPV being zero or less can be seen where the CDF crosses the vertical axis at zero. The CDF for the native orchard can easily been seen to be the highest on the axis, with improved irrigated being the lowest and improved non-irrigated in between the two. If only comparing the positive portion of the CDFs, the improved irrigated CDF shows first degree stochastic dominance over the improved non-irrigated and the native orchards. Looking at the CDFs over the full range of the distribution, only the improved irrigated was first degree stochastic dominant over the native orchard. Calculations of second degree stochastic dominance indicated that the improved irrigated orchard was preferred over the native and improved non-irrigated orchards. Second degree stochastic dominance results also yielded that the improved non-irrigated orchard was preferred over the native orchard. The CDFs can be seen in figure 9.

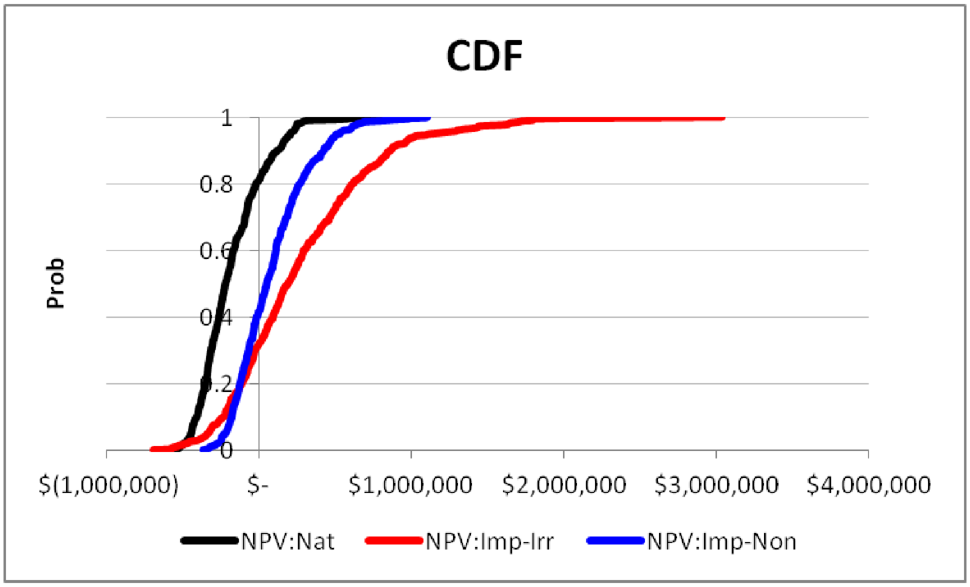

Figure 9. CDF of the NPV of Each Scenario

Looking at the means and standard deviations of the simulated NPVs also revealed implications of profitability. The mean simulated NPV for the native orchard was found to be -$174,284.63 with a standard deviation of 206,970.20. The mean and standard deviation for the simulated NPV for the improved irrigated orchard was $275,853.47 and 487,818.61 respectively. The improved non-irrigated orchard yielded a simulated mean NPV of $89,123.73 and a standard deviation of 242,915.31. These means and standard deviations can be seen in the probability density function (PDF) of each NPV in figure 10. The relatively wide PDF for the improved irrigated orchard reflects its large standard deviation and the narrowness of the native orchard PDF reflects it having the smallest standard deviation. The PDF of the improved non-irrigated orchard was wider than the native but not as wide as the improved irrigated, indicated by its standard deviation falling between that of the native and improved irrigated orchard.

Though the improved irrigated PDF displayed the most risk because of its high standard deviation, the skewness of the PDF was to the positive and therefore the accompanying risk was associated with a higher NPV. By looking at the means of the simulated values, it was found that the native PDF was centered to the left of zero, indicating its negative mean NPV. Both PDFs for improved non-irrigated and improved irrigated are centered to the right of zero, but the large standard deviation and skewness of the improved irrigated PDF pulled its mean higher than that of the improved non-irrigated.

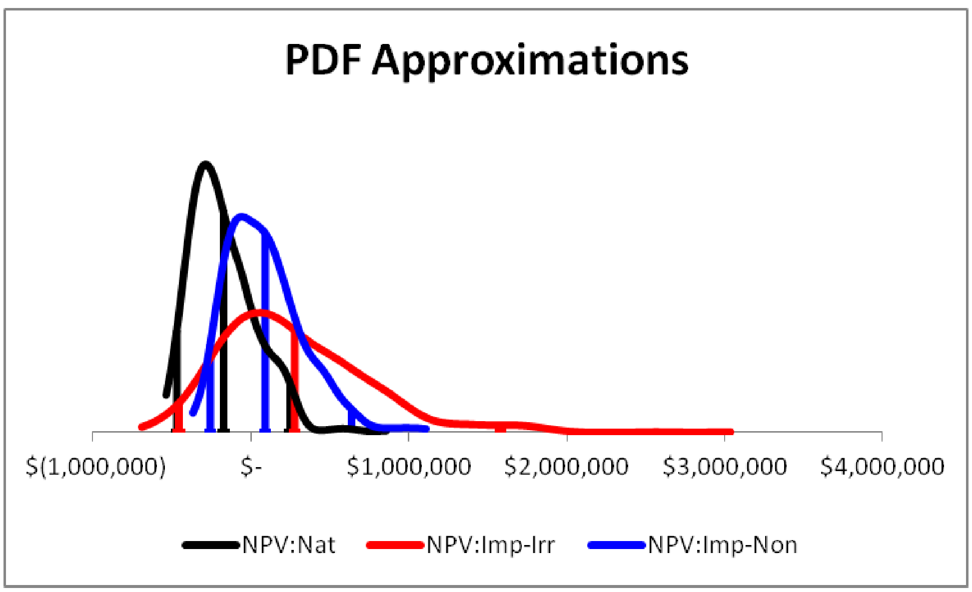

Figure 10. PDF of the NPV for Each Scenario

Several other statistical methods were used to determine the most profitable of the three scenarios. Stochastic dominance with respect to a function (SDRF) was calculated using Simetar, as done by Richardson and Outlaw (2008). The lower risk aversion coefficient was set to zero, for a risk neutral decision maker, and the upper risk aversion coefficient, for an extremely risk averse decision maker, was set to four divided by beginning net worth, which yielded an upper risk aversion coefficient of 0.00008. SDRF results for the lower risk aversion coefficient, a risk neutral decision maker, yielded the improved irrigated orchard as the most preferred and the native orchard as least preferred. Results for the upper risk aversion coefficient, an extremely risk averse decision maker, yielded the improved non-irrigated orchard as most preferred with the improved irrigated orchard as least preferred. SDRF results can be seen in table 20.

Table 20. SDRF Results Comparing the NPV of Each Scenario

Analysis of Stochastic Dominance with Respect to a Function (SDRF)

© 2008

	Efficient Set Based on SDRF at			Efficient Set Based on SDRF at	
	Lower RAC	**0**		Upper RAC **$**	**0.00**
	Name	Level of Preference		Name	Level of Preference
1	NPV:Imp-Irr	Most Preferred	1	NPV:Imp-N	Most Preferred
2	NPV:Imp-Non	2nd Most Preferred	2	NPV:Nat	2nd Most Preferred
3	NPV:Nat	3rd Most Preferred	3	NPV:Imp-Ir	3rd Most Preferred

*The efficient sets are not the same for both RAC values. This result suggests that the efficient set changes between the two RACs. Use SERF analysis to determine the RAC(s) where the efficient set changes.

Stochastic efficiency with respect to a function (SERF) was also calculated in Simetar and results can be seen in figure 11. Both lower and upper risk aversion coefficients were set to the same values as used in SDRF. The horizontal axis represents the average risk aversion coefficient. SERF results indicated that a risk neutral decision maker would prefer the improved irrigated orchard and an extremely risk averse decision maker would prefer the improved non-irrigated orchard. This can be seen in figure 11 by the improved irrigated NPV being of the highest magnitude to the far left, risk aversion coefficient equal to zero, and the improved non-irrigated NPV being of the highest magnitude to the far right, risk aversion coefficient equal to 0.00008.

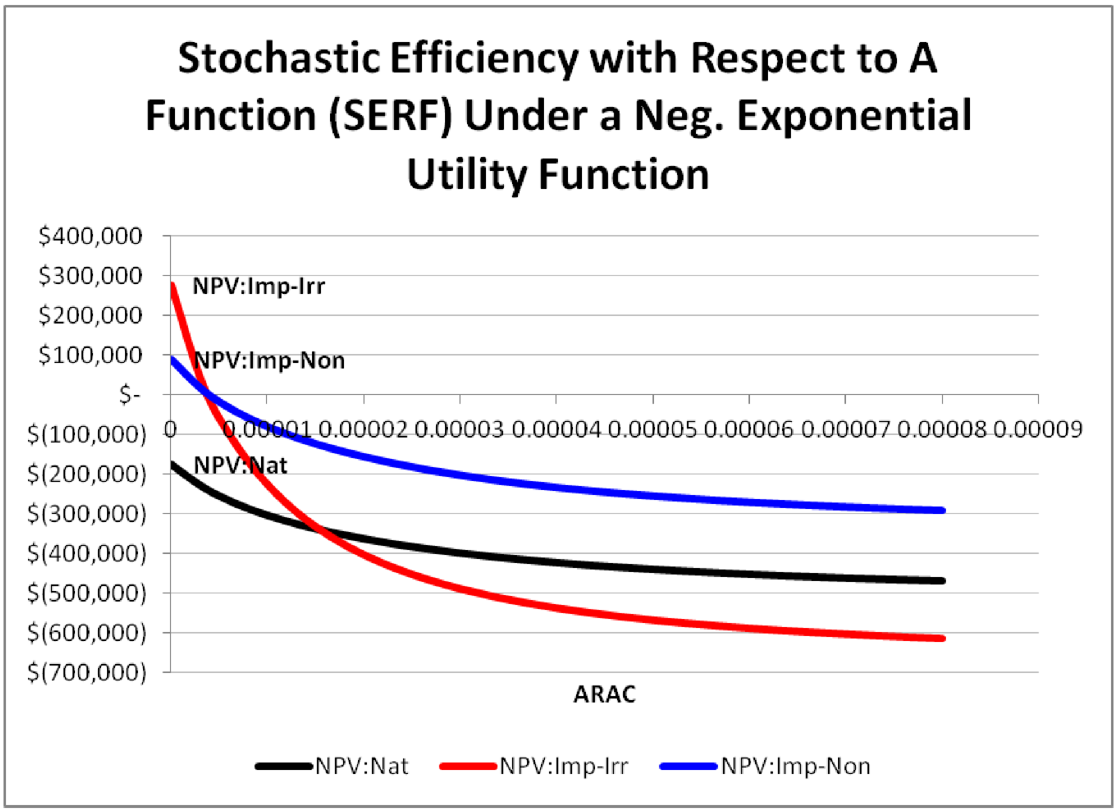

Figure 11. SERF Results Comparing the NPV of Each Scenario

StopLight charts, as introduce by Richardson and Outlaw (2008), were also calculated in Simetar to compare the NPV of each of the three scenarios. As mentioned in Chapter III, StopLight charts do not have to assume a risk aversion coefficient of the decision maker. StopLight charts display the probability of success or failure of a value, in this case NPV, falling within a specified range. For this analysis, the lower cut-off value was set to $0 and the upper cut-off value was set to the opportunity cost of the initial investment. The initial investment was calculated future value of the sum of average of the CAPEX loans for the operations with and without irrigation, or $976,131.13, and the $50,000 beginning cash. The loan rate for the operating loan was used in calculating the future value of the initial investment. The cut-off values were chosen to allow the decision maker to see the probability of the NPV for each orchard scenario falling between zero and opportunity cost of the initial investment, which was calculated as $1,277,996. Since the native and improved non-irrigated orchards did not have the initial capital outlay of irrigation, the averages of the loans for irrigation and no irrigation were taken to give midpoint value of $976,131.13. The StopLight chart indicated that the least preferred orchard, based on the specified cut-off values, was the native orchard and the most preferred was the improved irrigated orchard. It can be seen in figure 12 that the native orchard had an 81.00% probability of yielding a NPV lower than $0 and a 0.00% probability of yielding an NPV greater than $1,277,996. Also, there was only a 19.00% chance that the NPV would fall between the upper and lower cut-off values. The improved irrigated was the most preferred because it displayed the most green and the least amount of red, opposite of the NPV for the native orchard. The probability of a NPV greater than $1,277,996 was found to be 4.40% for the improved irrigated orchard, and the probability of the improved irrigated orchard having a NPV lower than $0 was 32.20%. The improved non-irrigated orchard was not least or most preferred by the StopLight results. The improved non-irrigated orchard yielded a 0.00% probability of the NPV being greater than the upper cut-off and a 41.60% chance of the NPV falling below the lower cut-off. It was found that the improved non-irrigated had a 58.40% chance of yielding a NPV between the upper and lower cut-off values.

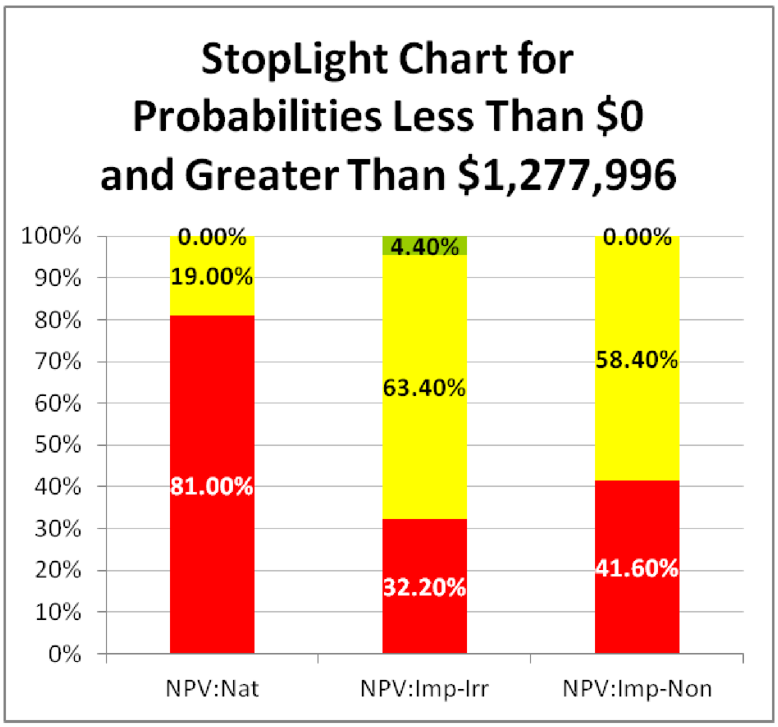

Figure 12. StopLight Chart for the NPV of Each Scenario

Results from the analysis of the NPV indicated that the improved irrigated orchard was first degree stochastic dominant over the native orchard. The irrigated improved orchard was second degree stochastic dominant over both the improved non-irrigated and native orchards. SDRF and SERF indicated that a risk neutral decision maker would prefer the improved irrigated orchard. Also mentioned by SDRF and SERF were that an extremely risk averse decision maker would prefer the improved non-irrigated orchard. StopLight results for the given cut-off values indicated that the improved irrigated orchard was the most preferred and the native orchard was the least preferred.

The average ending cash (EC) and net cash income (NCI) for each the three scenarios was reported in their respective pro forma financial statements. Both EC and NCI were simulated with 500 iterations using Simetar and results were put into fan graphs. Fan graphs allow the analyst or decision maker to see how a value explodes or implodes over time. Fan graph results indicated that the EC of the native orchard steadily fanned out over time and the majority of values remained negative with only the 95^{th} percentile remaining positive. The improved non-irrigated EC fan graph displayed similar results, but was not as negative as that of the native EC fan graph. The 75^{th} percentile of the improved non-irrigated remained close to zero. The improved irrigated fan graph displayed the majority of values in the positive sector, as expected by the positive averages from the financial statements. Over time the 25^{th} percentile of the fan graph for the improved irrigated EC dropped below zero. Fan graphs for the EC of the native, improve irrigated, and improved non-irrigated can be seen in figures 13, 14, and 15 respectively.

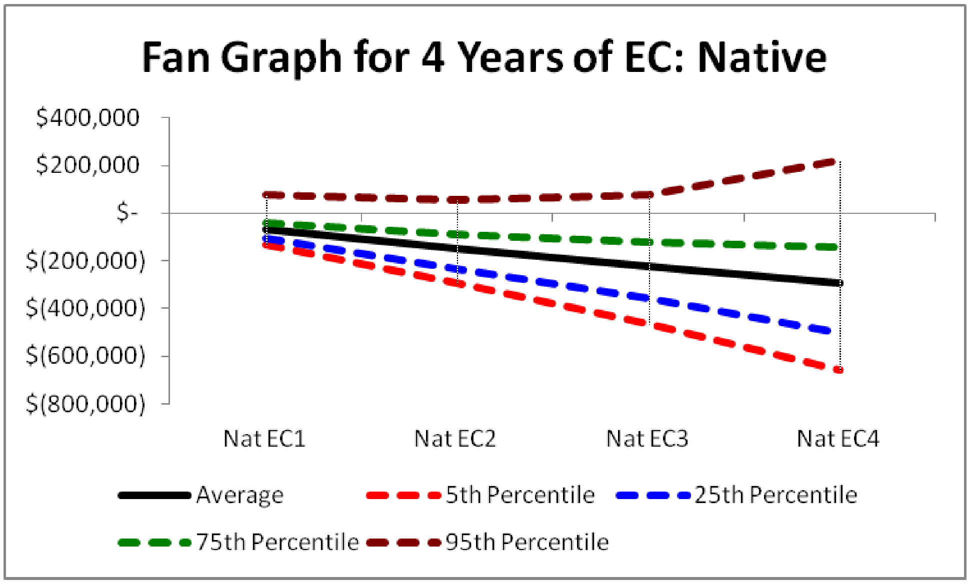

Figure 13. Fan Graph of Ending Cash for the Native Orchard

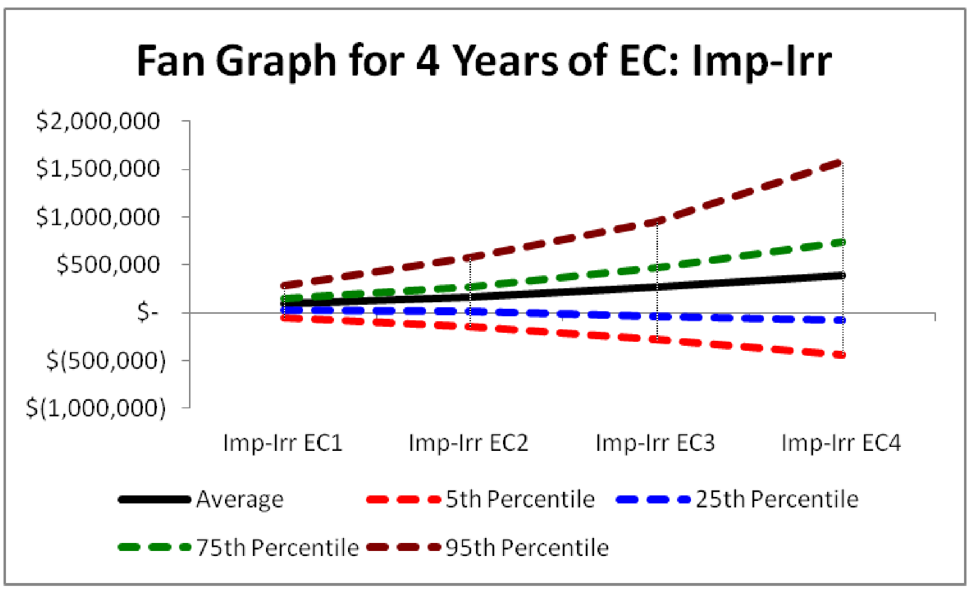

Figure 14. Fan Graph of Ending Cash for the Improved Irrigated Orchard

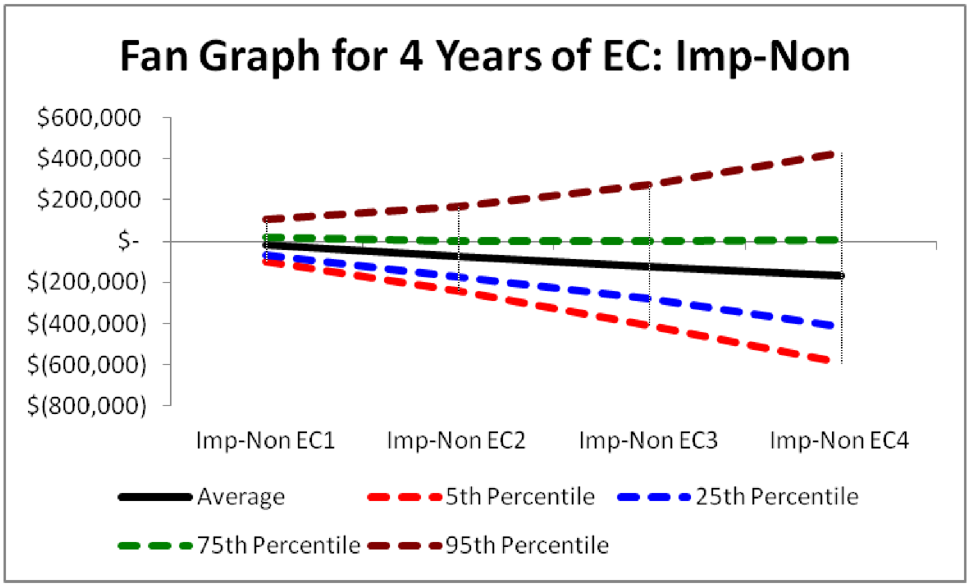

Figure 15. Fan Graph of Ending Cash for the Improved Non-Irrigated Orchard

For simulating NCI, each NCI was divided by the number of acres to yield a profit per acre. Since NCI is calculated as receipts minus expenses, with expenses being both variable and fixed cost, it was determined that this would yield a reasonable profit per acre calculation. As with EC, each NCI per acre was simulated with 500 iterations and put into a fan graph. For the native orchard, NCI per acre fanned out over time but the averaged never exceeded zero, as seen in the averages reported in the financial statements. The NCI per acre for the improved non-irrigated yielded an average close to zero but its 95th percentile was as high as $2,500 per acre in year four and the 5th percentile was as low as -$1,000 per acre in year four. The NCI per acre for the improved irrigated orchard yielded only negative values at the 25th percentile. The average NCI per acre reached approximately $2,000 by year four. The 95th percentile of the improved irrigated NCI per acre reached $7,500 per acre in year four. Fan graph results for the native, improved irrigated, and improved non-irrigated orchards' NCI per acre can be seen in figures 16, 17, and 18 respectively.

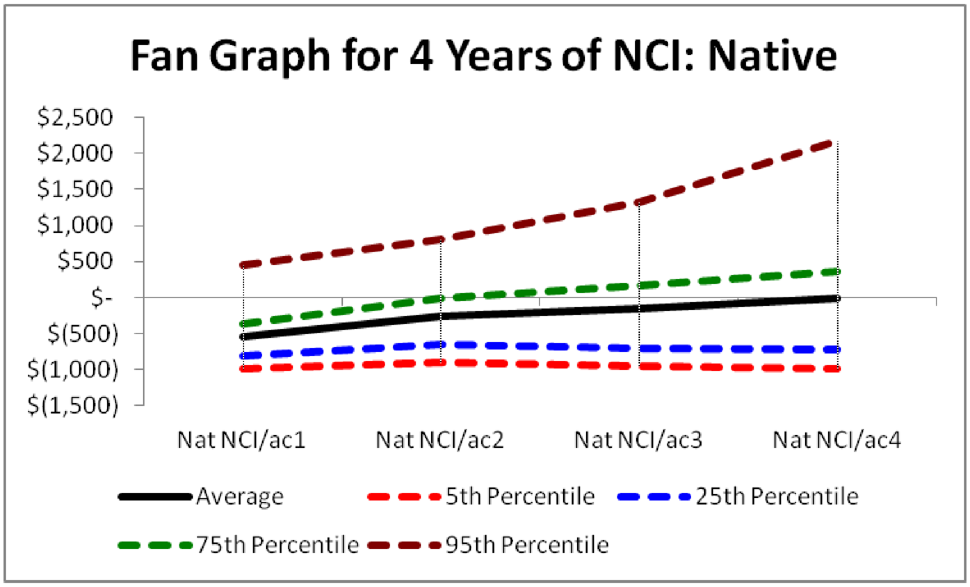

Figure 16. Fan Graph of NCI Per Acre for the Native Orchard

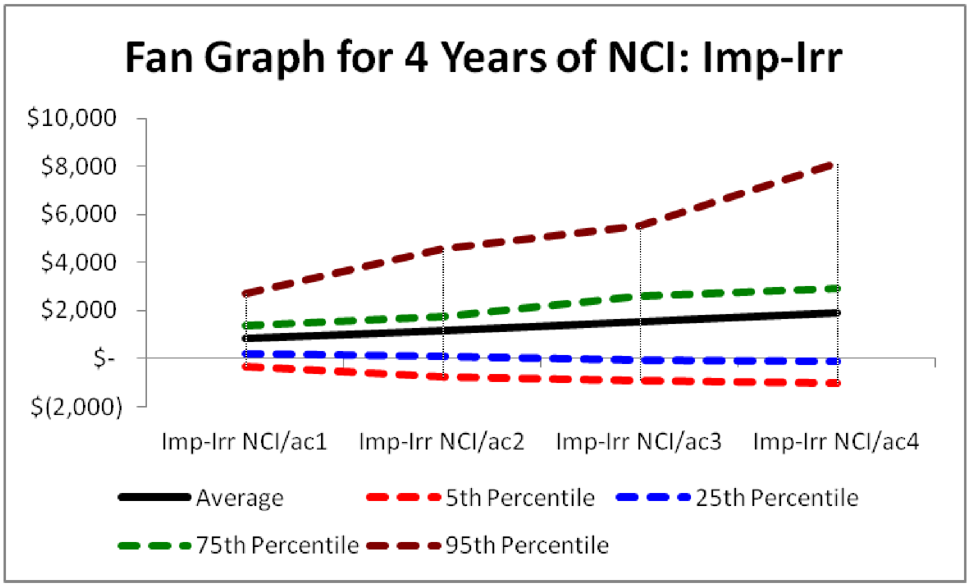

Figure 17. Fan Graph of NCI Per Acre for the Improved Irrigated Orchard

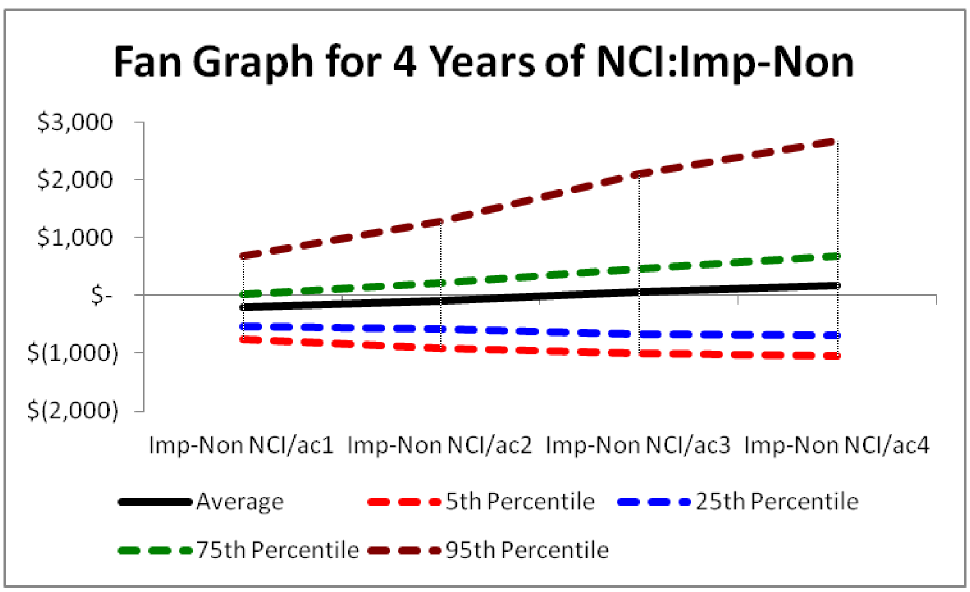

Figure 18. Fan Graph of NCI Per Acre for the Improved Non-Irrigated Orchard

Fan graphs for EC and NCI per acre indicated that the improved irrigated orchard yielded the highest amount of ending cash and net cash income per acre for the three orchard scenarios. EC fan graph results indicated that both native and improved non-irrigated orchards yielded EC that averaged below zero, while the improved irrigated orchard had an average EC above zero and exploded mainly in the positive section of the graph. Comparing the three scenarios, it can be seen that all yielded 5th percentile NCI per acre levels around -$1,000 per year but the improved irrigated had the highest average and the most percentiles in the positive section.

Results from analysis of the NPV, EC, and NCI for the three orchard scenarios indicate that the improved irrigated orchard had the highest amount of favorable outcomes. This result was contrary to the results from the choice experiment, which found that consumers derived higher utility and were willing to pay more for native varieties than improved variety pecans. Economic intuition suggests that if consumers are willing to pay more for a certain variety of pecans, then that variety should receive a higher price and therefore be more profitable to produce, *ceteris paribus*. Since the major difference between the three scenarios was price and yield, further investigation into these two aspects were taken to examine profitability.

Microsoft Excel is extremely useful in making business and production models, and allows an analyst to easily update and change input data. For this reason, yields were adjusted for each scenario to compare all three scenarios with a NPV as close to zero as possible. For the native scenario to have a NPV close to zero, at $498, average yields were increased by 81% to 520 pounds per acre. The improved irrigated scenario yields were dropped by 20% to 532 pound per acre and still yielded an NPV of $1,070. For the improved non-irrigated scenario, yields were increased by 3% to yield an NPV of $716.

For formulating another model yields were changed based on information received from Dr. George Ray McEachern, a professor and retired pecan horticultural Extension specialist at Texas A&M University, to form a new model. Communications with Dr. McEachern indicated yields different from those collected from USDA FSA and were inputted into the stochastic production model (McEachern 2012). For sake of brevity, this model will be referred to as the GRM model and yield data can be seen in figure 19. No data were given for improved non-irrigated pecan yields, therefore data were created using *=IF* statements and Simetar's *=UNIFORM* command to force the improved non-irrigated yields to follow native yields in good years and to be a percent of improved irrigated yields in bad years. All data other than yields remained that same as in the previous model.

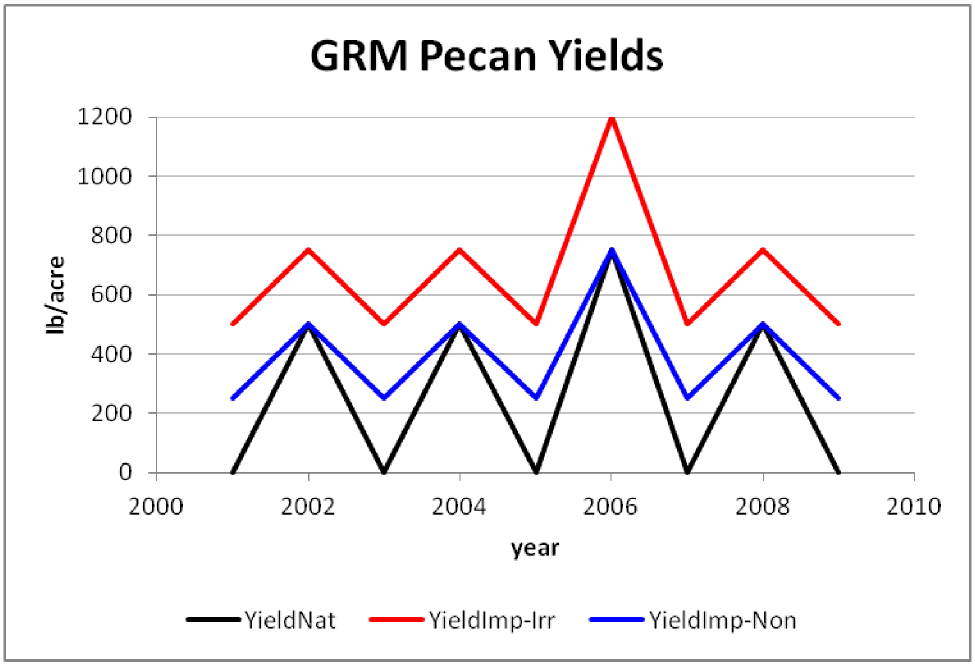

Figure 19. Yields from GRM Pecan Model

CDF and PDF results of the simulated NPV of the GRM model produced similar results to the original model. Both the native and improved non-irrigated scenarios had higher probabilities of being greater than zero, from 19% to 33% in the native orchard, and from 58% to 80% in the improved non-irrigated, when compared to the original model. The probability of having a NPV greater than zero for the improved irrigated orchard actually decreased from 68% in the full model to 66% in the GRM model. First degree stochastic dominance could not be determined by looking at the CDF for the GRM model because of the overlapping CDFs for improved irrigated and improved non-irrigated. CDF results of the NPVs for the GRM model can be seen in figure 20.

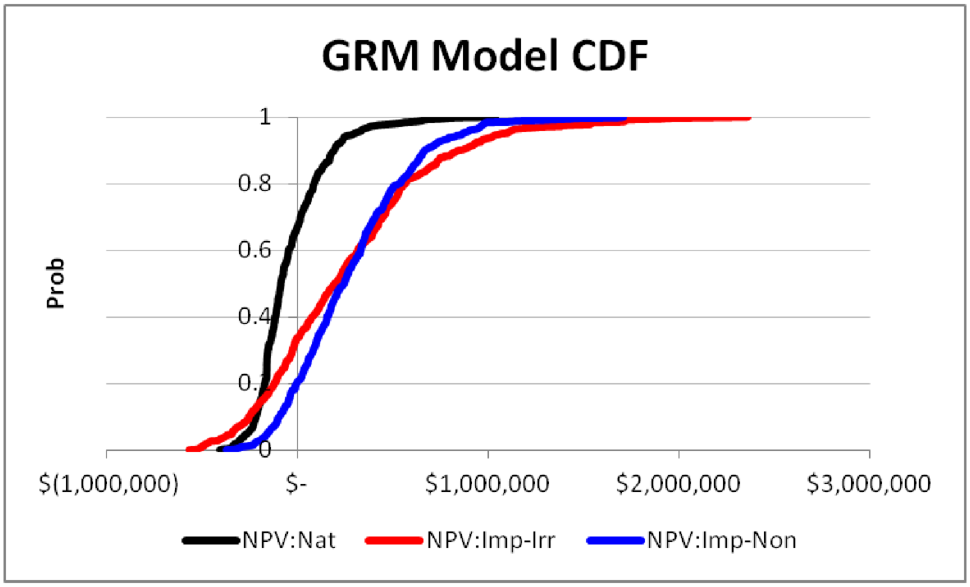

Figure 20. CDF of NPV for the GRM Model

PDF results indicated an increase in standard deviation of the NPV for the improved non-irrigated orchard as the new PDF was wider than the PDF for the original model. Though not as visible on the PDF graph, summary statistics of the simulated data indicated a decrease in standard deviation from the original model for both the native and improved irrigated. Both improved irrigated and improved non-irrigated showed large positive skewness. PDF results can be seen in figure 20.

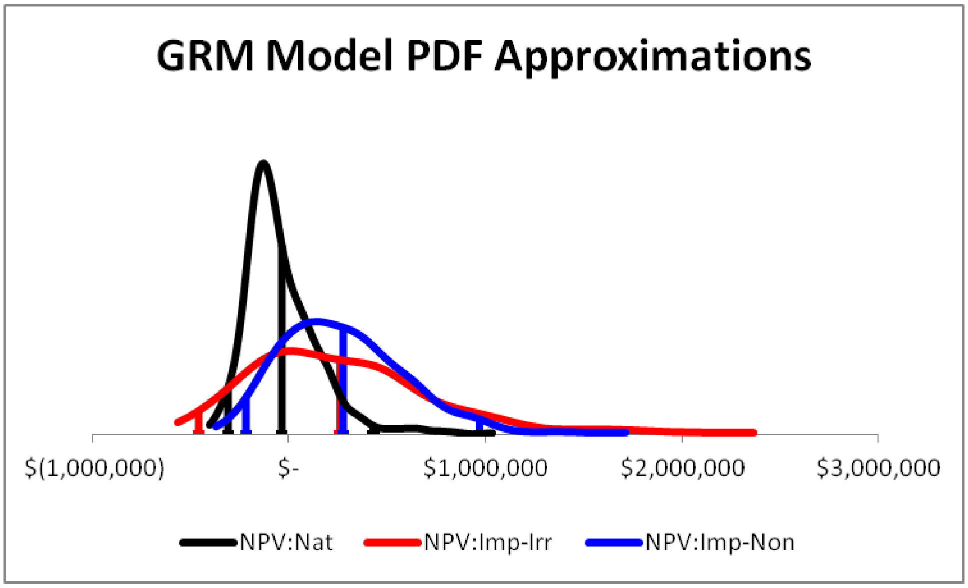

Figure 21. PDF of the NPV for the GRM Model

Contrary to the SDRF results of the original model, SDRF results for the GRM model indicated the improved non-irrigated was preferred for both the risk neutral decision maker and the extremely risk averse decision maker. The native orchard was found to be least preferred for the risk neutral decision maker, and the improved irrigated was found to be least preferred for the extremely risk averse decision maker. SDRF results for the GRM model can be seen in table 21.

Table 21. SDRF Results Comparing the NPVs for the GRM Model

Analysis of Stochastic Dominance with Respect to a Function (SDRF)

© 2008

Efficient Set Based on SDRF at			Efficient Set Based on SDRF at		
	Lower RAC	**0**		Upper RAC **$**	**0.00**
	Name	Level of Preference		Name	Level of Preference
1	NPV:Imp-Non	Most Preferred	1	NPV:Imp-N	Most Preferred
2	NPV:Imp-Irr	2nd Most Preferred	2	NPV:Nat	2nd Most Preferred
3	NPV:Nat	3rd Most Preferred	3	NPV:Imp-Ir	3rd Most Preferred

*The efficient sets are not the same for both RAC values. This result suggests that the efficient set changes between the two RACs. Use SERF analysis to determine the RAC(s) where the efficient set changes.

SERF results for the GRM model replicated the results given by SDRF where both a risk neutral and extremely risk averse decision maker both would prefer the improved non-irrigated scenario. SERF results for the GRM model can be seen in figure 22.

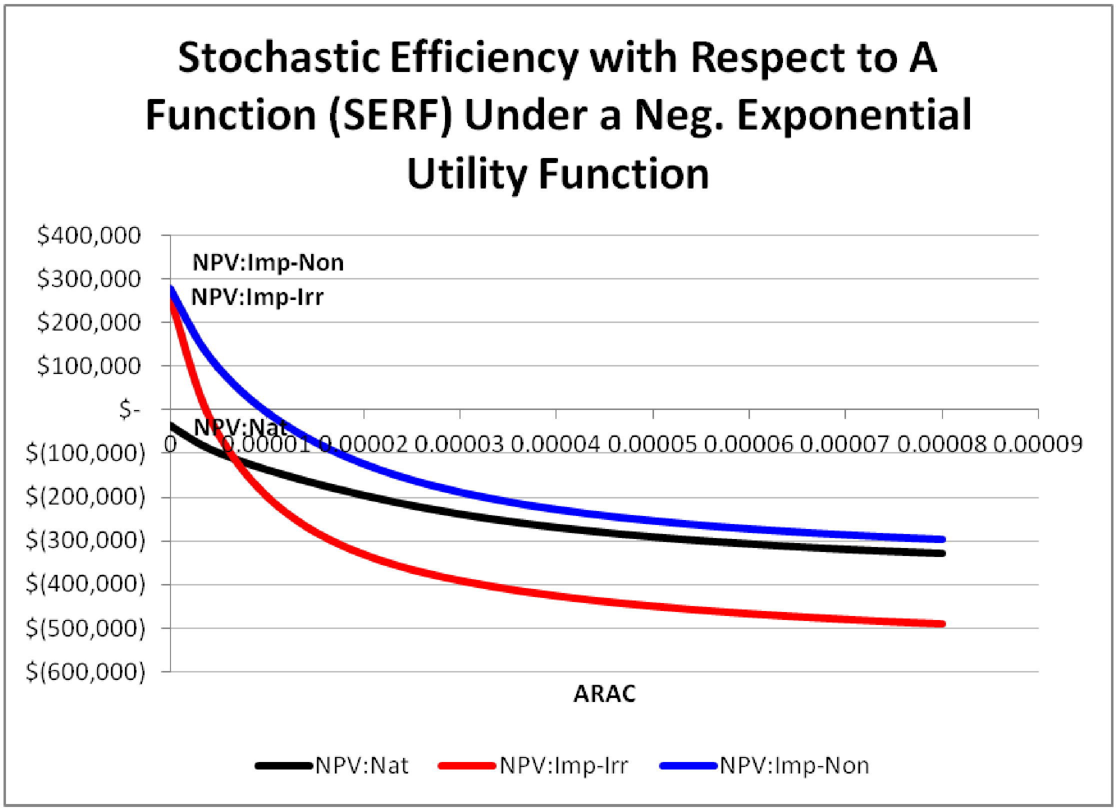

Figure 22. SERF Results Comparing the NPVs for the GRM Model

StopLight chart results for the GRM model were not as conclusive as the results for the original model. The StopLight chart indicated that the native orchard produced the lowest probability of exceeding the upper cut-off and the highest probability of falling below the lower cut-off; Therefore, it was determined to be least desirable in the GRM model. The improved irrigated and improved non-irrigated scenarios did not produce a single preferred orchard according to the StopLight results. The improved irrigated scenario had the highest probability, 3.00%, of exceeding the upper cut-off, but also had a higher probability at 33.80% than the improved non-irrigated scenario at 20.40% of falling below the lower cut-off. The improved non-irrigated only had a 1.00%

probability of exceeding the upper cut-off value of $1,277,996, but had a lower probability of failure as previously mention. Therefore, for the optimistic decision maker, the improved irrigated orchard was preferred since it yielded the highest probability of exceeding the upper cut-off. The pessimistic decision maker preferred the improved non-irrigated scenario since it yielded the lowest probability of falling below the lower cut-off value. StopLight chart results for the GRM model can be found in figure 23.

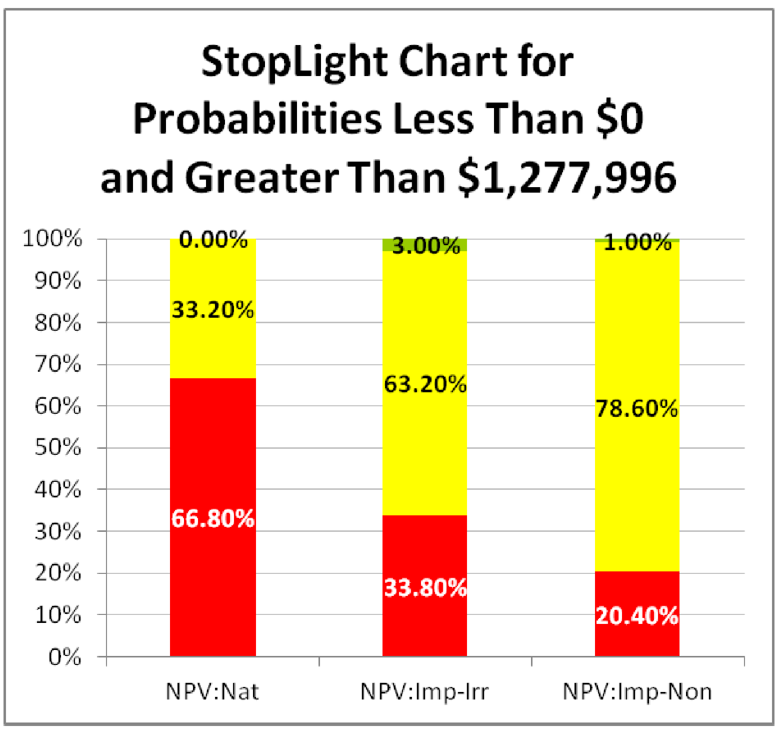

Figure 23. StopLight Chart for the NPVs for the GRM Model

Also, it must be noted that under the yield conditions specified in the GRM model, NAP payments for the native and improved irrigated scenarios had a probability greater than zero of occurring. In the original model, NAP payments were simulated for all three scenarios to determine their probability of occurrence, and it was found that NAP payments had a 0% chance of occurring in any of the scenarios. Under the new yields specified in the GRM model, the native orchard had a 2% chance of receiving a NAP payment and the improved non-irrigated scenario had a 10% chance of receiving a NAP payment over the four years evaluated.

In comparison, the GRM model preferred the improved non-irrigated scenario versus the original model preferring the improved irrigated scenario. Neither model showed preference for the native orchard scenario. Since the GRM model adjusted yields for comparison purposes, another model was generated from the original model with adjustments made to price. With improved varieties collecting a premium over native varieties, the third model created, labeled the Equal Prices model, equated the price of natives to the price of improved varieties. This adjustment took away the premium received by improved varieties and allowed for analysis without price as a major contributing factor.

A CDF graph of all three models failed to yield a first degree stochastic dominant scenario as all three models intersected each other at least once. The probability of having a positive NPV for the native orchard rose from 19% in the original model to 38% in the Equal Prices model. The improved irrigated orchard's probability of having a positive NPV remained unchanged, as expected, at 68%. Similar results were expected and found in the improved non-irrigated orchard with a new probability of having an NPV greater than zero at 58%, the same result from the original model. As expected, both the CDF for native and improved non-irrigated orchards closely followed each other in the Equal Prices model. This was expected since yields for the two scenarios were similar and prices were made exactly the same. CDF results from the Equal Prices model can be seen in figure 24.

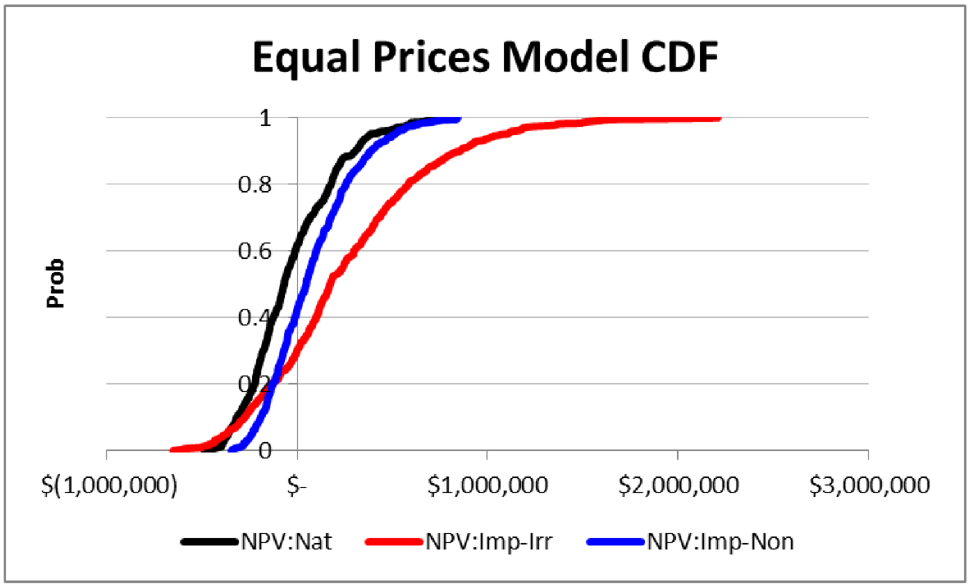

Figure 24. CDF of NPV for the Equal Prices Model

Like the CDF graph, PDFs for native and improved non-irrigated orchards closely mimicked each other. Both were closely grouped around zero with similar widths and kurtosis. This result can also be seen in the standard deviations for the simulated data. The native orchard scenario yielded a standard deviation of 238,197.66 and the improved non-irrigated scenario had a standard deviation of 228,558.04. PDF results can be seen in figure 25 for the Equal Prices model.

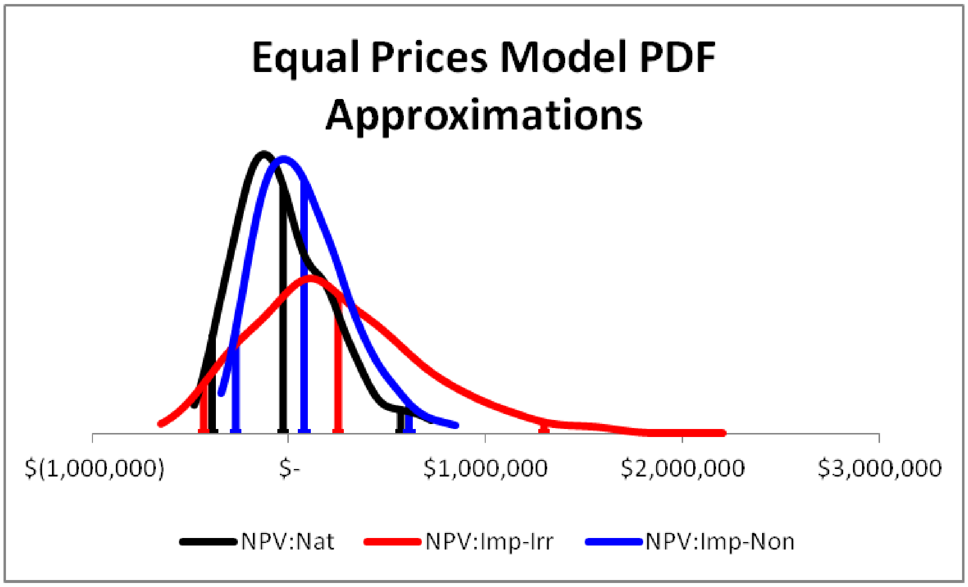

Figure 25. PDF of the NPV for the Equal Prices Model

SDRF results for the Equal Prices model yielded identical results to the original model. For the lower risk aversion coefficient, a risk neutral decision maker, the improved irrigated orchard was found to be preferred and the native orchard was found to be least preferred of the three scenarios. For the upper risk aversion coefficient, an extremely risk averse decision maker, the improved non-irrigated orchard was preferred and the improved irrigated was least preferred. SDRF results for the Equal Prices model can be found in table 22.

Table 22. SDRF Results Comparing the NPVs for the Equal Prices Model

Analysis of Stochastic Dominance with Respect to a Function (SDRF)

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	Efficient Set Based on SDRF at			Efficient Set Based on SDRF at	
	Lower RAC	0		Upper RAC $	0.00
	Name	Level of Preference		Name	Level of Preference
1	NPV:Imp-Irr	Most Preferred	1	NPV:Imp-N	Most Preferred
2	NPV:Imp-Non	2nd Most Preferred	2	NPV:Nat	2nd Most Preferred
3	NPV:Nat	3rd Most Preferred	3	NPV:Imp-Ir	3rd Most Preferred

*The efficient sets are not the same for both RAC values. This result suggests that the efficient set changes between the two RACs. Use SERF analysis to determine the RAC(s) where the efficient set changes.

Like SDRF, SERF results for the Equal Prices model yielded the same results as the original model. For a risk neutral decision maker, the improved irrigated orchard is the most preferred scenario. The improved non-irrigated orchard was the most preferred scenario for an extremely risk averse decision maker. SERF results for the Equal Prices model can be found in figure 26.

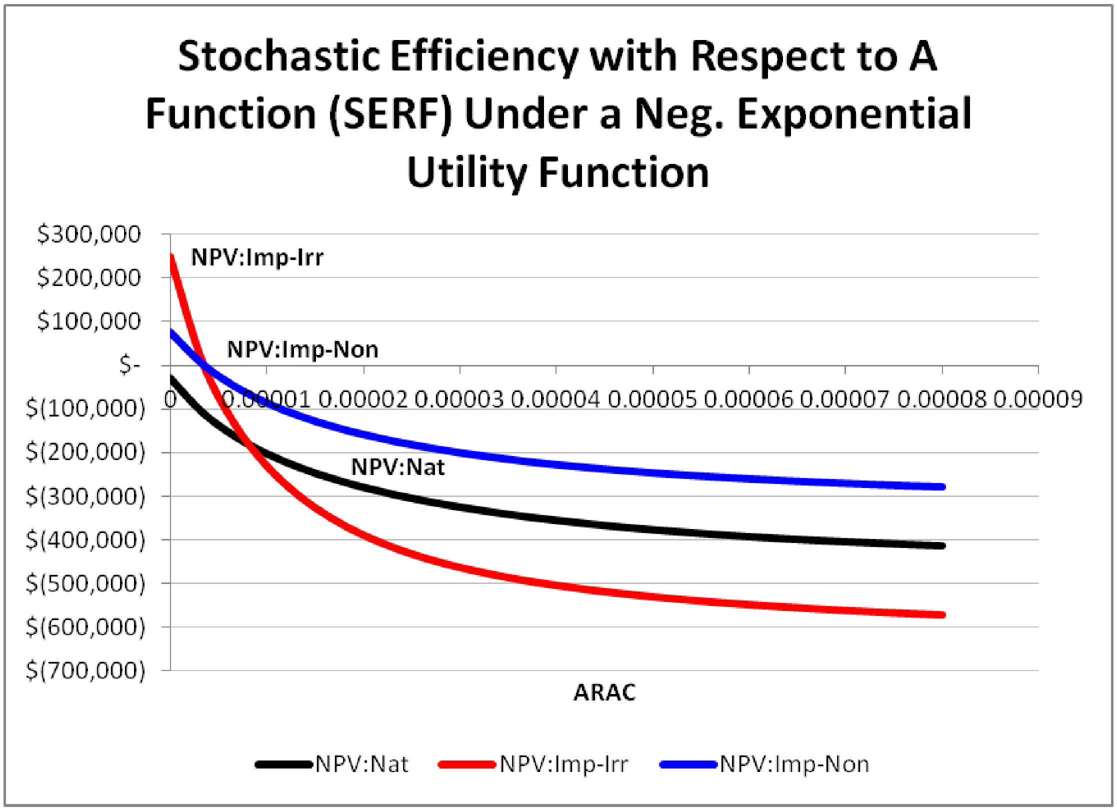

Figure 26. SERF Results Comparing the NPVs for the Equal Prices Model

StopLight chart results for the Equal Prices model yielded an obvious choice preference of the improved irrigated model. The improved irrigated orchard was determined to be the most preferred because it yielded the highest amount of green and the lowest amount of red. It was found to have a probability of 2.60% of exceeding the upper cut-off and a 30.00% probability of falling below the lower cut-off. The native orchard was determined to be the least preferred according to the StopLight chart with a 0.00% chance of yielding a NPV higher than the upper cut-off and having a 61.60% chance of yielding a NPV lower than the bottom cut-off value. StopLight results for the Equal Prices model can be seen in figure 27.

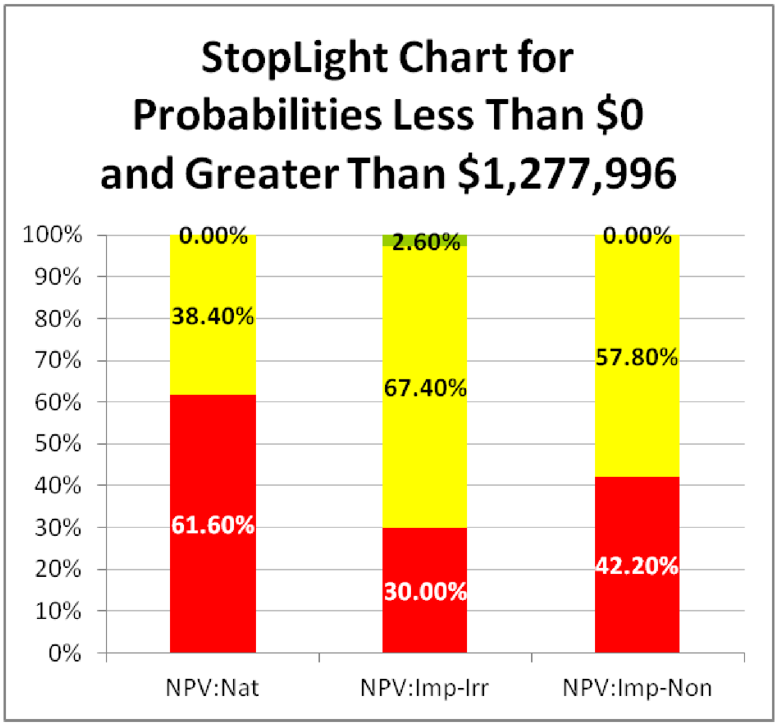

Figure 27. StopLight Chart for the NPVs for the Equal Prices Model

Comparing the Equal Prices model, where natives received the same price as the improved models, to the original model offers only a small improvement for the native scenario. In both situations the improved irrigated orchard is the preferred choice and offered the highest NPV of the three scenarios. Both the GRM model and the Equal Prices model were examined to see how the profitability of the orchards changed when yields or prices were different.

Recalling the results from the choice experiment, it was determined that consumers were homogenous in their preference for native variety pecans over improved variety pecans. It was also calculated that consumers are willing to pay $1.21 more for native pecans than improved pecans at the retail level. Merging this concept of WTP at the retail level and the profitability of a pecan orchard, it was determined that the retail price for natives could be adjusted and inserted into the production model to assess the profitability of producing natives at the new price specified by the choice experiment. USDA data on the farm share of fresh vegetables and fresh fruit was used to determine the farm share of the retail price of pecans. Calculations indicated an average of 27% farm share of the retail price for fresh fruits and vegetables from 2000 – 2009 (USDA Economic Research Service 2011). Multiplying the 27% farm share by the $1.21 retail price yields 0.32535, which can be interpreted as $0.33 premium for natives. Native prices were adjusted in the model by adding the premium to the stochastic price for improved varieties, thus creating the new native price. This new model was labeled as CE Prices model, indicating the prices determined by the choice experiment. New prices can be found in table 23.

Table 23. Average Stochastic Prices for the CE Prices Model

Average Stochastic Prices for the CE Prices Model

	PriceImp	PriceNat
2012	$2.67	$2.99
2013	$3.01	$3.34
2014	$3.35	$3.68
2015	$3.69	$4.02

Prices reported in $ per pound

The CE Prices Model was simulated with 500 iterations, and similar graphs and statistics were developed as in previous models. The CDF of the NPVs for the CE Prices model indicated a large improvement in the probability of the native orchard scenario yielding a positive NPV. The newly calculated probability was found to be 51%, more than double that of the original 19%. The new probabilities for the improved irrigated orchard and the improved non-irrigated orchard of producing a NPV greater than zero were found to be 71% and 62% respectively. As with the Equal Prices model, the CDF for native and improved non-irrigated orchards were extremely similar, almost overlaying each other. With all of the CDFs intersecting each other at least once, first degree stochastic dominance could not be determined. CDF results for the CE Prices model can be found in figure 28.

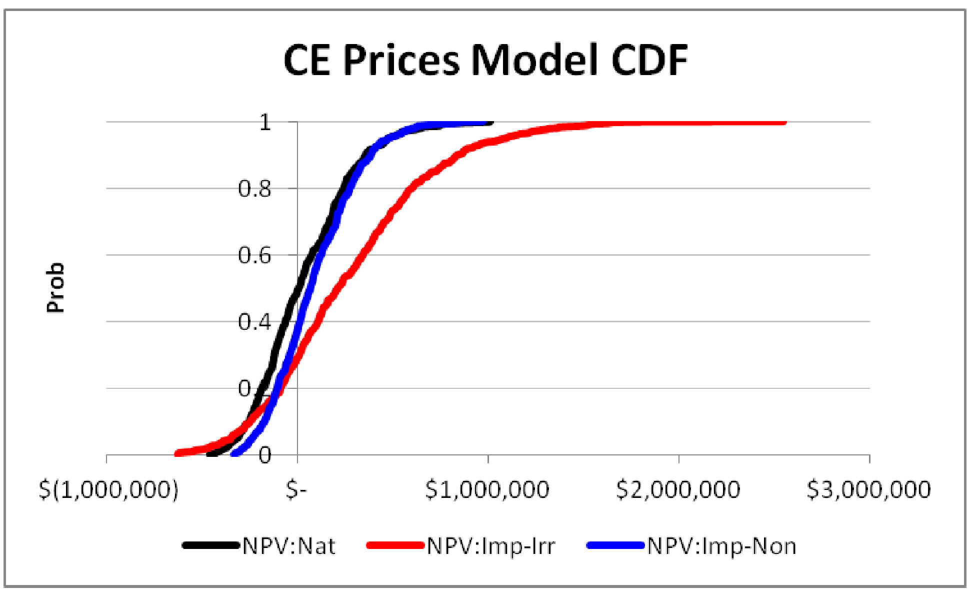

Figure 28. CDF of NPV for the CE Prices Model

PDF results of the CE Prices model indicated, as with the CDF, a very close relationship between the native orchard scenario and the improved non-irrigated orchard scenario. The PDFs for native and improved non-irrigated orchards have similar width and kurtosis, indicating similar densities for their respective probabilities. The mean of the simulated NPV for the native scenario was half that of the improved non-irrigated scenario; $38,864 and $91,056 respectively. Their standard deviations were found to be similar; the standard deviation for the simulated NPV was 253,844.52 and 223,910.96 for the native and improved non-irrigated orchards respectively. PDF results for the CE Prices model can be found in figure 29.

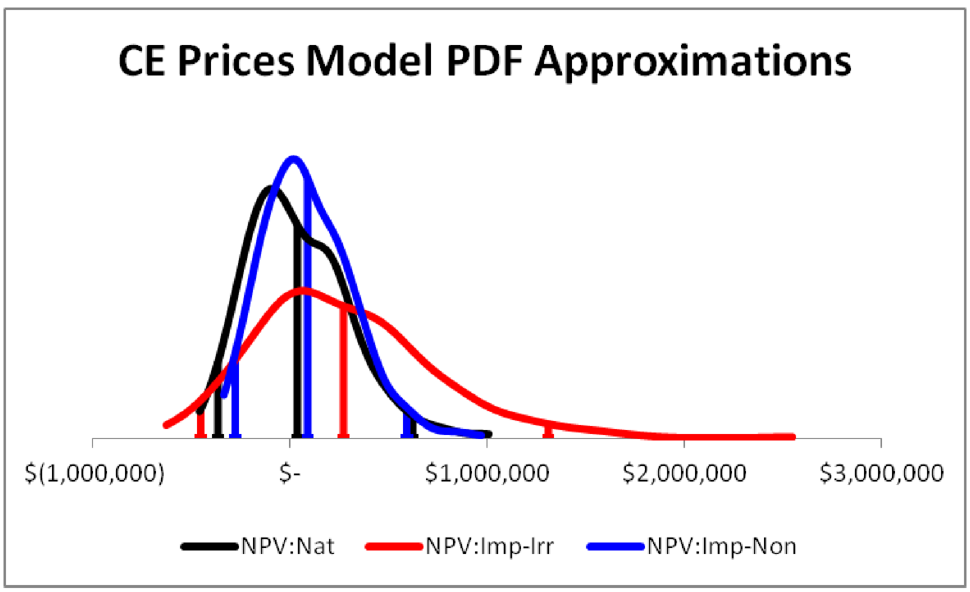

Figure 29. CDF of the NPV for the CE Prices Model

Second degree stochastic dominance results were found to be identical to the original model. The improved irrigated orchard was second degree stochastic dominant over both the native and improved non-irrigated orchard scenarios. The improved non-irrigated orchard was second degree stochastic dominant over the native orchard.

SDRF results of the CE Prices model were also identical to the results generated from the original model. The most preferred scenario for a risk neutral decision maker, determined by the lower risk aversion coefficient, was found to be the improved irrigated orchard scenario and the least preferred was the native orchard scenario. For an extremely risk averse decision maker, determined by the upper risk aversion coefficient, the most preferred scenario was the improved non-irrigated orchard and the least preferred scenario was the improved irrigated orchard. SDRF results for the CE Prices model can be found in table 24.

Table 24. SDRF Results Comparing the NPVs for the CE Prices Model

Analysis of Stochastic Dominance with Respect to a Function (SDRF)

© 2008

Efficient Set Based on SDRF at			Efficient Set Based on SDRF at		
	Lower RAC	**0**		Upper RAC **$**	**0.00**
	Name	Level of Preference		Name	Level of Preference
1	NPV:Imp-Irr	Most Preferred	1	NPV:Imp-N	Most Preferred
2	NPV:Imp-Non	2nd Most Preferred	2	NPV:Nat	2nd Most Preferred
3	NPV:Nat	3rd Most Preferred	3	NPV:Imp-Ir	3rd Most Preferred

*The efficient sets are not the same for both RAC values. This result suggests that the efficient set changes between the two RACs. Use SERF analysis to determine the RAC(s) where the efficient set changes.

Results from the SERF analysis were also identical to the original model. For a risk neutral decision maker, the improved irrigated orchard was most preferred. The improved non-irrigated orchard was most preferred for an extremely risk averse decision maker. SERF results for the CE Prices model can be found in figure 30.

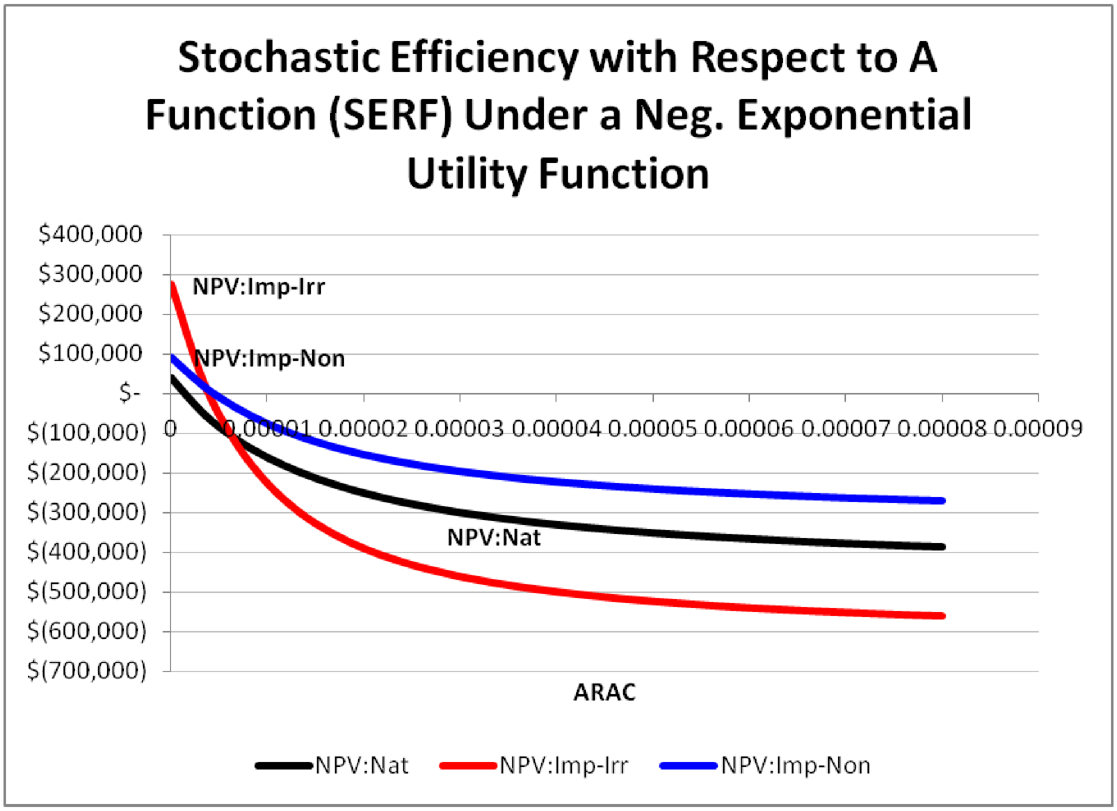

Figure 30. SERF Results Comparing the NPVs for the CE Prices Model

Stoplight results for the CE Prices model indicated an improvement for the native orchard scenario from the original model. Although the probability of generating an NPV greater than the upper cut-off did not change, the probability of the native orchard scenario achieving an NPV lower than the lower cut-off value decreased from 81.00% to

49.00%. Despite this improvement from the original model, the native scenario was still not preferred to either of the other two models. The improved non-irrigated orchard yielded slightly better results than the native orchard with a probability of 0.00% for exceeding the upper cut-off value and a probability of 37.60% for falling below the lower cut-off value. The most preferred scenario according to the StopLight chart was the improved irrigated orchard. The improved irrigated orchard yielded a probability of 2.80% of the NPV exceeding the upper cut-off value and a probability of 29.00% of the NPV falling below the lower cut-off value. StopLight chart results for the CE Prices model can be found in figure 31.

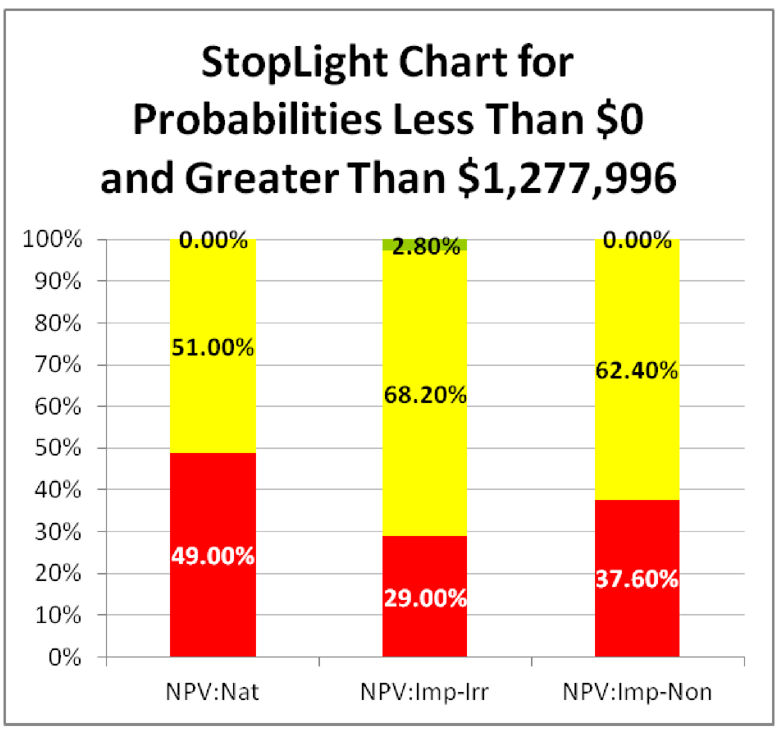

Figure 31. StopLight Chart for the NPVs for the CE Prices Model

Given the importance of the prices calculated in the CE Prices model and their potential effect on ending cash and net cash income, EC and NCI per acre were simulated and put into fan graphs similar to the original model.

Since prices for improved varieties did not change from the original to the CE Prices model, EC fan graphs were nearly identical to those in the original model. The fan graph for the native orchard scenario indicated, as expected, an improvement over the original fan graph for natives found in figure 13. The EC fan graph for the native orchard in the original model indicated a negative average, as the fan grew more negative over time. The native orchard scenario EC fan graph for the CE Prices model indicated the average EC remained close to zero and exploded over the four years evaluated. EC fan graph results for the native, improved irrigated, and improved non-irrigated orchard scenarios can be found in figures 32, 33, and 34 respectively.

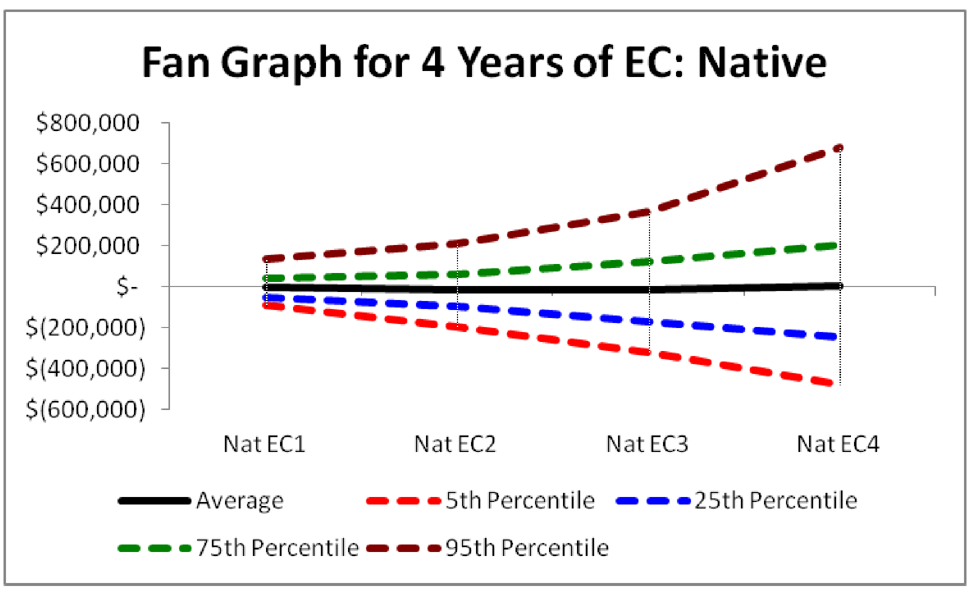

Figure 32. Fan Graph of Ending Cash in the CE Prices model Native

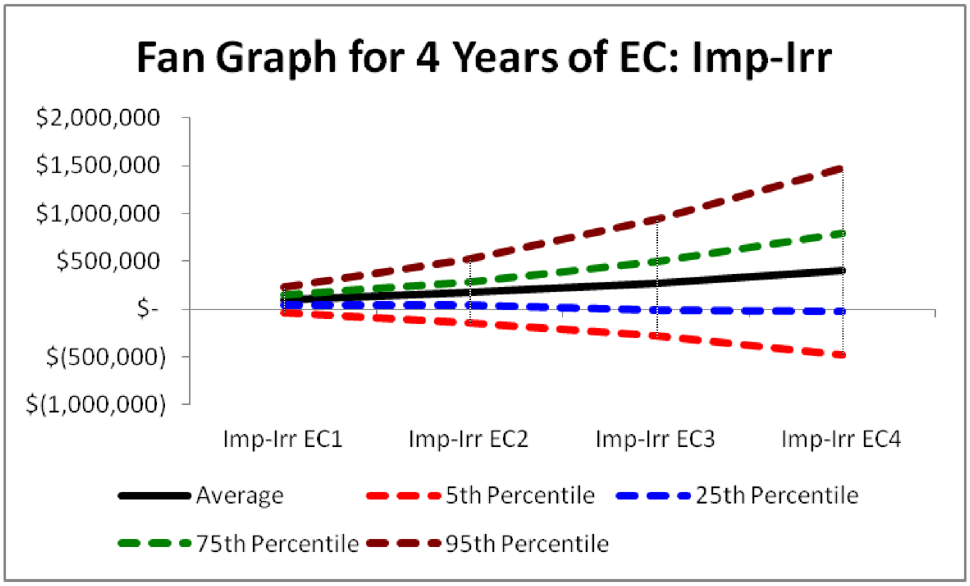

Figure 33. Fan Graph of EC in the CE Prices model for Improved Irrigated

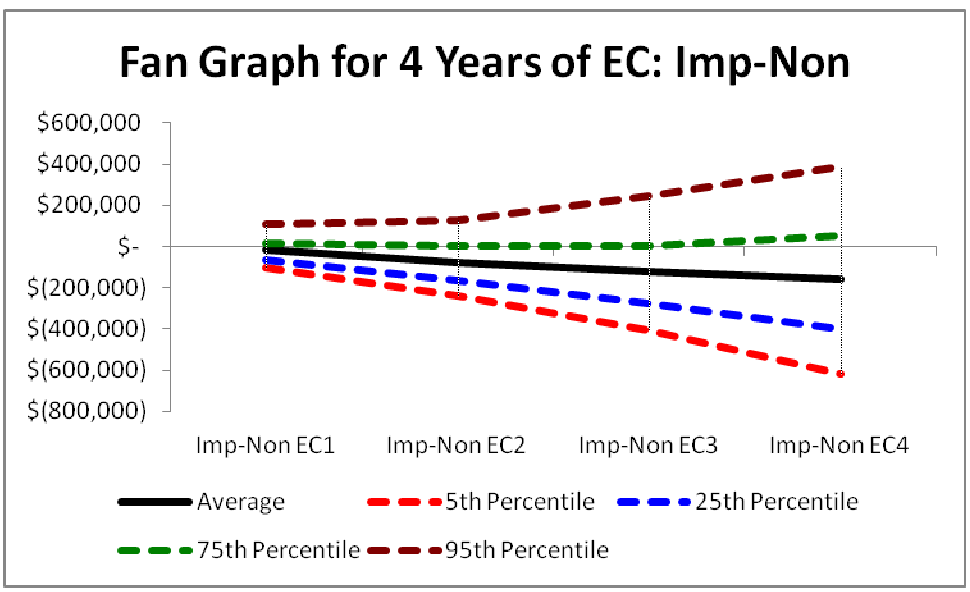

Figure 34. Fan Graph of EC in the CE Prices model for Improved Non-Irrigated

NCI per acre for the CE Prices model was also put into fan graphs to see how the NCI per acre grew over time. As with the EC fan graphs, fan graphs for NCI per acre for the improved irrigated and improved non-irrigated orchards were nearly identical to those of the original model. As expect with the new higher prices, NCI per acre for the native orchard scenario showed improvement over the original model. Average NCI per acre for the native orchard started around zero in year one and rose to about $700 per acre in the fourth year. As with the original model the 25th percentile for the NCI per acre for the native orchard remained below zero throughout the years evaluated. NCI per acre fan graph results for the native, improved irrigated, and improved non-irrigated orchards can be found in figures 35, 36, and 37 respectively.

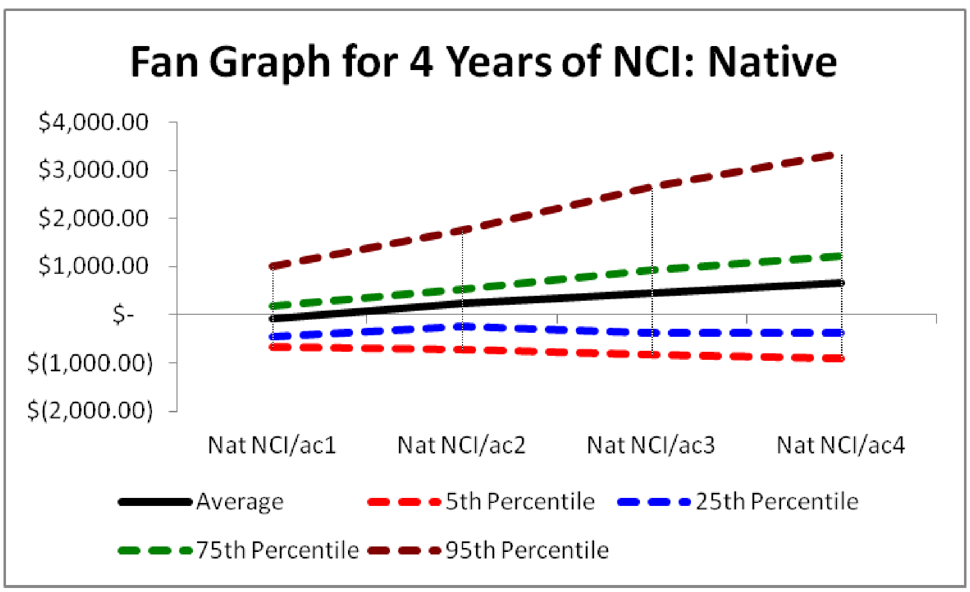

Figure 35. Fan Graph of NCI Per Acre in the CE Prices Model for Native

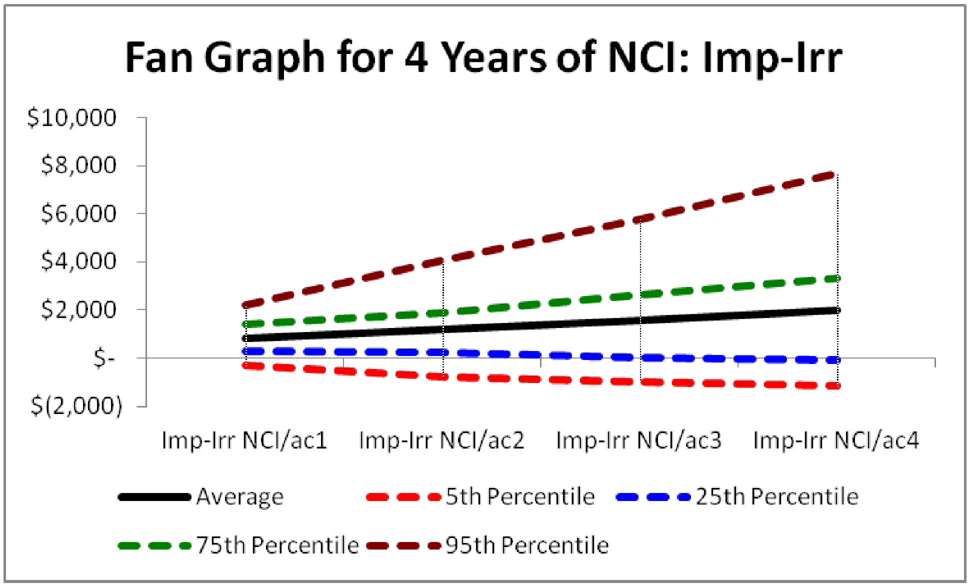

Figure 36. Fan Graph of NCI Per Acre in the CE Prices Model for Improved Irrigated

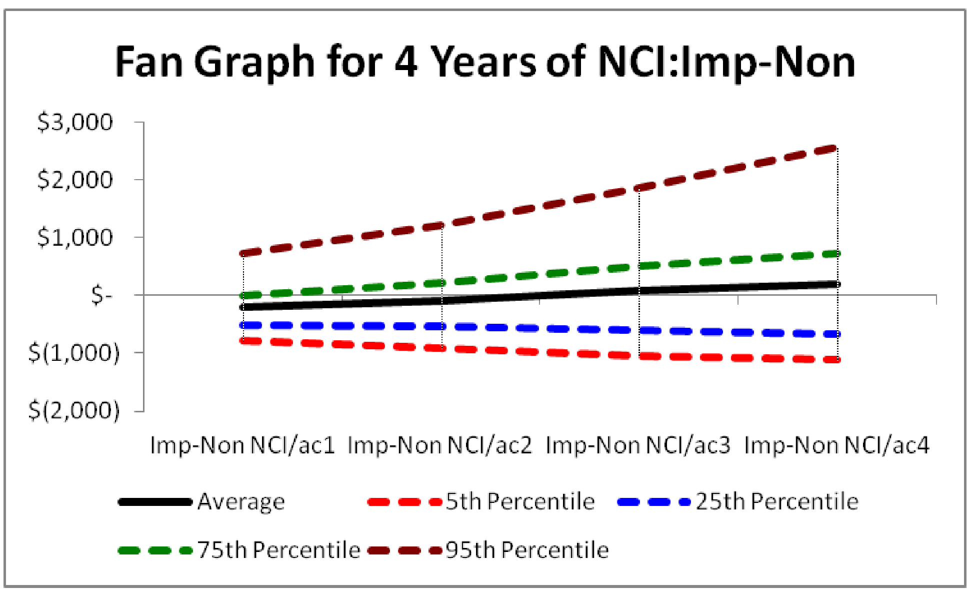

Figure 37. Fan Graph of NCI Per Acre in the CE Prices Model for Improved Non-Irrigated

Results from the EC and NCI per acre fan graphs of the CE Prices model showed improvements for the native orchard scenario over its counterpart in the original model. Improvements were not great enough though for the native orchard scenario to be preferred over the other two orchard scenarios. As with the original model, EC and NCI per acre results indicated that the improved irrigated orchard was the most profitable.

Overall the CE Prices model yielded improvements for the native orchard over the original model in NPV, EC, and NCI per acre. Even with the price premium of $0.33 per pound for natives, the improved irrigated orchard was determined to be the most profitable scenario for CE Price model.

In conclusion, results from the conjoint analysis choice experiment found that consumers derived higher utility from large size pecans, native pecans, pecan halves, and pecans that originated in the U.S. or Texas. Results also indicated that consumers were heterogeneous in their preferences for large pecans, pecan halves, and pecans from Texas. Consumers were found to be homogeneous in their preferences for native varieties and U.S. origin pecans. WTP calculations indicated consumers were willing to pay greater than $1 per pound for large pecans and native pecans and over $2 per pound for pecan halves and U.S. origin pecans. Texas-origin pecans were found to have the highest WTP at $17.53 per pound. These results suggest that any pecan products marketed as native, U.S.-grown, or Texas-grown will receive a higher retail price because of consumer recognition or belief in the superiority of these products, given that the consumer is rational. Results from the stochastic production model indicated that an improved irrigated orchard was more profitable than a native orchard or and improved non-irrigated orchard. Prices were adjusted to reflect the $0.33 price premium for natives at the farm level and the model was re-simulated with the new native price. Even with the native orchard receiving a price premium, it was determined that the native orchard was not as profitable as the improved irrigated or improved non-irrigated orchards. Therefore, the improved irrigated orchard prevailed as the most profitable scenario across all evaluated models.

CHAPTER VI

CONCLUSION

In conclusion, it was found that the pecan industry has a strong and viable market across the world. The United States is the leading nation in pecan production, with Mexico second. In the U.S., Georgia has traditionally been the largest pecan producing state, with Texas and New Mexico vying for second place. In regards to native pecan production, Texas is the largest producer. Native prices traditionally are lower than improved variety prices, and both of these prices have followed a cyclical pattern relating to pecan production.

A review of the literature found that a conjoint analysis can be conducted in several ways to reveal the preferences consumers have regarding different product attributes. Several different conjoint analyses have been conducted regarding agricultural products and ideas from those studies were used in conducting the choice experiment in this study. Reviewing the literature also gave a foundation for building a stochastic production model. Building on the work of Richardson and Mapp (1976), and continuing through the work of Richardson and Outlaw (2008), several different methods were used to analyze the profitability of the three different orchard scenarios.

Using a random parameters logit model to analyze the preferences in the choice experiment was found to be the most useful and pertinent for this study. The random parameters logit model allowed for calculations of utility and WTP, as well as testing for heterogeneity among preferences. It was found that consumers derived the most utility from large pecans, native pecans, pecan halves, and U.S.-grown or Texas-grown pecans. WTP calculations indicated that consumers mean WTP for large pecans was \$1.82, \$1.21 for native pecans, \$2.95 for pecan halves, \$2.70 for U.S. grown pecans, and \$17.53 for Texas-grown pecans over each attributes' respective base attribute. It was also found that consumers are heterogeneous in their preferences for large pecans, pecan halves, and Texas grown pecans, but showed homogeneous preferences for pecan variety and U.S. origin pecans. Results showed a negative coefficient for improved varieties and price. Price was expected to have a negative coefficient but improved varieties were expected to show a positive coefficient. The results found were interesting since the *a priori* assumption stated natives were inferior to improved varieties. This *a priori* was formed from prior industry and market research.

The stochastic production model used several methods to assess the profitability of the three orchard scenarios. First CDF and PDF graphs were formulated to visually see the distribution of probabilities for each of the three scenarios. Stochastic dominance (SDRF) and stochastic efficiency (SERF) with respect to a function were ran to assess profitability under different risk aversion coefficients. It was found that a risk neutral decision maker would prefer the improved irrigated orchard while an extremely risk averse decision maker would prefer the improved non-irrigated orchard. StopLight charts, EC fan graphs, and NCI per acre fan graphs all indicated that the improved irrigated orchard was most profitable.

Results from the choice experiment indicated a higher WTP for native varieties. Initial results from the stochastic production model indicated the native orchard was the least preferred and least profitable orchard of the three orchard scenarios. For this reason, several other models were analyzed to see how the three orchards would be preferred under different yield and price situations. Neither the GRM model with new yields, nor the Equal Prices model equating native and improved prices, suggested an improvement over the original model. Therefore it was determined that the WTP calculation found for the retail price of pecans could be scaled back to the farm level wholesale price and put into the model. Results from the CE model, using the WTP found in the choice experiment, offered improvements for the native orchard over the original model, but the improved irrigated orchard was still found to be most profitable.

Further research in this area should be conducted expanding the choice experiment survey beyond the borders of Texas to reveal the preferences of consumers across the entire U.S. for pecan products. Results for this study suggest that product promotion, such as “Go Texan”, that market Texas produced products would be extremely useful in the Texas pecan market. Also suggested by the choice experiment results is the strong demand for native varieties. Product promotions labeling products as natural or native also have potential in the Texas pecan market. The stochastic production model could easily be updated in future years to reflected updated cost, yields, and prices as the pecan industry changes and progresses with the new markets for pecan products in Asia.

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APPENDIX A

SAS CODE FOR SURVEY

```
Pecan Consumer Survey Code
*/D-eff is about 91. MP code;
*use seed=3658934;


title 'Looking at the number of runs needed';
%mktruns(2 3 3 2 2); /*factor level list for all attribute levels*/
title2 'using the number of optimal runs to create linear design';
%mktex (2 3 3 2 2, /*factor level list of all attribute levels first 3
is for option 1,2, and no prod*/
n=72, /*number of runs from %mktruns*/
Seed = 3658934); /*seed of 3658934 gives D=90.04; 500000 gives D=90.04;
5000000 gives D=89.97 */
                        /* seed of 5000 gives D=89.78; 2500000 D=89.84
3500000 D=89.44; 36000000 D=89.97*/
                        /*seed of 3658935 gives D=90.04; 3659000
D=89.97; 3658940 D=89.78 */


proc format;
value variety 1='native' 2='improved';
value price 1='$3' 2='$5' 3='$7';
value origin 1='us' 2='Imported' 3='tx';
value status 1='halves' 2='pieces';
value size 1='sm' 2='lg';

run;

%mktlab(data=design, /*input data set*/
            vars= Variety Price Origin Status Size, /*new attribute
names*/
            int=f1-f3,                                  /*create 3
columns of 1's in f1-f3*/
            out=final,
/*output design*/
            stmts=format Variety variety. Price price. Origin origin.
Status status. Size size. );

            data final;
            retain f1-f3 0;
            length option $ 10 variety price origin status size 8;
            if _n_ = 1 then do; f3=1; option='none'; output; f3=0;end;
            set design(rename=(x1=variety x2=price x3=origin x4=status
x5=size));
            f1=1; option='1'; output; f1=0;
            f2=1; option='2'; output; f2=0;
            format Variety variety. Price price. Origin origin. Status
status. Size size.;
            run;
```

```
proc print; run;

%choiceff   (data=final,                   /*candidate set of
alternatives */
                  bestout=sasuser.pecan, /*choice design stored
permantly */
                                                       /*model with stdz
orthog coding */
                  model=class(variety price origin status size/ sta) /
                  cprefix=0                    /*lpr=0 labels from
just levels */
                  lprefix=0,                   /*cpr=0 names from just
levels*/
                  nsets=12,                    /*number of choice sets
*/
                                         /* random number seed*/
                  flags=f1-f3,                 /* flag which
alternative can go where */
                  maxiter=20,
                  rscale=partial=2 of 3,
                  options=relative,            /*relative d-
efficiency*/
                  beta=zero,                  /*assumed beta vector*/
                          Seed = 3658934);


proc format;
value zer -1e-12 - 1e-12 = 0;
run;
proc print data=bestcov label;
title 'Variance-Covariance Matrix';
id __label;
label __label = '00'x;
var native _3 _5 us imported halves sm;
format _numeric_ zer5.2;
run;
title;


proc print data=sasuser.pecan;
var option -- size;
id set; by set;
run;

%mktblock(data=sasuser.pecan, nalts=3, nblocks=1, Seed = 3658934,
factors=variety price origin status size) /* add seed*/
```

APPENDIX B

SAS SURVEY DESIGN

```
                 Looking at the number of runs needed                  660
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                           Design Summary

                       Number of
                       Levels       Frequency

                            2           3
                            3           2

                 Looking at the number of runs needed                  661
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            Saturated      = 8
            Full Factorial = 72

            Some Reasonable                        Cannot Be
               Design Sizes       Violations       Divided By

                         36 *              0
                         72 *              0
                         12                1     9
                         24                1     9
                         48                1     9
                         60                1     9
                         18                3     4
                         54                3     4
                         30                4     4 9
                         42                4     4 9
                          8 S              9     3 6 9

      * - 100% Efficient design can be made with the MktEx macro.
      S - Saturated Design - The smallest design that can be made.
          Note that the saturated design is not one of the
          recommended designs for this problem.  It is shown
          to provide some context for the recommended sizes.

                 Looking at the number of runs needed                  662
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      n    Design                                      Reference

     36    2 ** 20  3 **  2                         Orthogonal Array
     36    2 ** 16  3 **  4                         Orthogonal Array
     36    2 ** 13  3 **  2   6 **  1               Orthogonal Array
     36    2 ** 11  3 ** 12                         Orthogonal Array
     36    2 ** 10  3 **  8   6 **  1               Orthogonal Array
     36    2 **  9  3 **  4   6 **  2               Orthogonal Array
     36    2 **  4  3 ** 13                         Orthogonal Array
     36    2 **  3  3 **  9   6 **  1               Orthogonal Array
     36    2 **  3  3 **  2   6 **  3               Orthogonal Array
     72    2 ** 56  3 **  2                         Orthogonal Array
     72    2 ** 53  3 **  2   4 **  1               Orthogonal Array
     72    2 ** 52  3 **  4                         Orthogonal Array
     72    2 ** 49  3 **  4   4 **  1               Orthogonal Array
```

n	Design	Reference
72	2 ** 49 3 ** 2 6 ** 1	Orthogonal Array
72	2 ** 47 3 ** 12	Orthogonal Array
72	2 ** 46 3 ** 8 6 ** 1	Orthogonal Array
72	2 ** 46 3 ** 2 4 ** 1 6 ** 1	Orthogonal Array
72	2 ** 45 3 ** 4 6 ** 2	Orthogonal Array
72	2 ** 44 3 ** 12 4 ** 1	Orthogonal Array
72	2 ** 43 3 ** 8 4 ** 1 6 ** 1	Orthogonal Array
72	2 ** 42 3 ** 4 4 ** 1 6 ** 2	Orthogonal Array
72	2 ** 40 3 ** 13	Orthogonal Array
72	2 ** 39 3 ** 9 6 ** 1	Orthogonal Array
72	2 ** 39 3 ** 2 6 ** 3	Orthogonal Array
72	2 ** 38 3 ** 12 6 ** 1	Orthogonal Array
72	2 ** 38 3 ** 5 6 ** 2	Orthogonal Array
72	2 ** 37 3 ** 13 4 ** 1	Orthogonal Array
72	2 ** 37 3 ** 8 6 ** 2	Orthogonal Array
72	2 ** 37 3 ** 3 6 ** 3	Orthogonal Array
72	2 ** 36 3 ** 12 12 ** 1	Orthogonal Array
72	2 ** 36 3 ** 9 4 ** 1 6 ** 1	Orthogonal Array
72	2 ** 36 3 ** 7 6 ** 3	Orthogonal Array
72	2 ** 36 3 ** 2 4 ** 1 6 ** 3	Orthogonal Array
72	2 ** 35 3 ** 12 4 ** 1 6 ** 1	Orthogonal Array
72	2 ** 35 3 ** 5 4 ** 1 6 ** 2	Orthogonal Array
72	2 ** 34 3 ** 8 4 ** 1 6 ** 2	Orthogonal Array
72	2 ** 34 3 ** 3 4 ** 1 6 ** 3	Orthogonal Array
72	2 ** 29 3 ** 11 6 ** 2	Orthogonal Array
72	2 ** 28 3 ** 2 6 ** 4	Orthogonal Array
72	2 ** 27 3 ** 11 6 ** 1 12 ** 1	Orthogonal Array
72	2 ** 27 3 ** 6 6 ** 4	Orthogonal Array
72	2 ** 23 3 ** 24	Orthogonal Array
72	2 ** 22 3 ** 20 6 ** 1	Orthogonal Array
72	2 ** 21 3 ** 16 6 ** 2	Orthogonal Array

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n	Design	Reference
72	2 ** 20 3 ** 24 4 ** 1	Orthogonal Array
72	2 ** 20 3 ** 12 6 ** 3	Orthogonal Array
72	2 ** 19 3 ** 20 4 ** 1 6 ** 1	Orthogonal Array
72	2 ** 19 3 ** 8 6 ** 4	Orthogonal Array
72	2 ** 18 3 ** 16 4 ** 1 6 ** 2	Orthogonal Array
72	2 ** 18 3 ** 7 6 ** 5	Orthogonal Array
72	2 ** 17 3 ** 12 4 ** 1 6 ** 3	Orthogonal Array
72	2 ** 17 3 ** 3 6 ** 6	Orthogonal Array
72	2 ** 16 3 ** 25	Orthogonal Array
72	2 ** 16 3 ** 8 4 ** 1 6 ** 4	Orthogonal Array
72	2 ** 15 3 ** 21 6 ** 1	Orthogonal Array
72	2 ** 15 3 ** 7 4 ** 1 6 ** 5	Orthogonal Array
72	2 ** 14 3 ** 24 6 ** 1	Orthogonal Array
72	2 ** 14 3 ** 17 6 ** 2	Orthogonal Array
72	2 ** 14 3 ** 3 4 ** 1 6 ** 6	Orthogonal Array
72	2 ** 13 3 ** 25 4 ** 1	Orthogonal Array
72	2 ** 13 3 ** 20 6 ** 2	Orthogonal Array
72	2 ** 13 3 ** 13 6 ** 3	Orthogonal Array
72	2 ** 12 3 ** 24 12 ** 1	Orthogonal Array
72	2 ** 12 3 ** 21 4 ** 1 6 ** 1	Orthogonal Array
72	2 ** 12 3 ** 16 6 ** 3	Orthogonal Array
72	2 ** 12 3 ** 9 6 ** 4	Orthogonal Array
72	2 ** 11 3 ** 24 4 ** 1 6 ** 1	Orthogonal Array
72	2 ** 11 3 ** 20 6 ** 1 12 ** 1	Orthogonal Array
72	2 ** 11 3 ** 17 4 ** 1 6 ** 2	Orthogonal Array
72	2 ** 11 3 ** 12 6 ** 4	Orthogonal Array
72	2 ** 11 3 ** 8 6 ** 5	Orthogonal Array
72	2 ** 10 3 ** 20 4 ** 1 6 ** 2	Orthogonal Array

```
     72    2 ** 10  3 ** 16   6 **  2  12 **  1    Orthogonal Array
     72    2 ** 10  3 ** 13   4 **  1   6 **  3    Orthogonal Array
     72    2 ** 10  3 **  4   6 **  6              Orthogonal Array
     72    2 **  9  3 ** 16   4 **  1   6 **  3    Orthogonal Array
     72    2 **  9  3 ** 12   6 **  3  12 **  1    Orthogonal Array
     72    2 **  9  3 **  9   4 **  1   6 **  4    Orthogonal Array
     72    2 **  9  3 **  7   6 **  6              Orthogonal Array
     72    2 **  8  3 ** 12   4 **  1   6 **  4    Orthogonal Array
     72    2 **  8  3 **  8   4 **  1   6 **  5    Orthogonal Array
     72    2 **  8  3 **  8   6 **  4  12 **  1    Orthogonal Array
     72    2 **  8  3 **  3   6 **  7              Orthogonal Array
     72    2 **  7  3 **  7   6 **  5  12 **  1    Orthogonal Array
     72    2 **  7  3 **  4   4 **  1   6 **  6    Orthogonal Array
     72    2 **  6  3 **  7   4 **  1   6 **  6    Orthogonal Array
     72    2 **  6  3 **  3   6 **  6  12 **  1    Orthogonal Array
     72    2 **  5  3 **  3   4 **  1   6 **  7    Orthogonal Array

               Looking at the number of runs needed                 664
        using the number of optimal runs to create linear design
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                     Algorithm Search History

                              Current          Best
       Design    Row,Col  D-Efficiency  D-Efficiency  Notes
       ----------------------------------------------------------
            1      Start      100.0000      100.0000  Tab
            1        End      100.0000


               Looking at the number of runs needed                 665
        using the number of optimal runs to create linear design
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                        The OPTEX Procedure

                       Class Level Information

                        Class  Levels  Values

                        x1       2     1 2
                        x2       3     1 2 3
                        x3       3     1 2 3
                        x4       2     1 2
                        x5       2     1 2

               Looking at the number of runs needed                 666
        using the number of optimal runs to create linear design
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                                                             Average
                                                            Prediction
Design                                                       Standard
Number     D-Efficiency     A-Efficiency     G-Efficiency      Error
ƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒƒ
     1       100.0000         100.0000         100.0000         0.3333

               Looking at the number of runs needed                 667
        using the number of optimal runs to create linear design
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Obs   f1   f2   f3   option   variety    price    origin    status   size

  1    0    0    1    none          .      .           .        .     .
  2    1    0    0    1      native      $3     us         halves    sm
  3    0    1    0    2      native      $3     us         halves    sm
```

4	1	0	0	1	native	$3	us	halves	lg
5	0	1	0	2	native	$3	us	halves	lg
6	1	0	0	1	native	$3	us	pieces	sm
7	0	1	0	2	native	$3	us	pieces	sm
8	1	0	0	1	native	$3	us	pieces	lg
9	0	1	0	2	native	$3	us	pieces	lg
10	1	0	0	1	native	$3	Imported	halves	sm
11	0	1	0	2	native	$3	Imported	halves	sm
12	1	0	0	1	native	$3	Imported	halves	lg
13	0	1	0	2	native	$3	Imported	halves	lg
14	1	0	0	1	native	$3	Imported	pieces	sm
15	0	1	0	2	native	$3	Imported	pieces	sm
16	1	0	0	1	native	$3	Imported	pieces	lg
17	0	1	0	2	native	$3	Imported	pieces	lg
18	1	0	0	1	native	$3	tx	halves	sm
19	0	1	0	2	native	$3	tx	halves	sm
20	1	0	0	1	native	$3	tx	halves	lg
21	0	1	0	2	native	$3	tx	halves	lg
22	1	0	0	1	native	$3	tx	pieces	sm
23	0	1	0	2	native	$3	tx	pieces	sm
24	1	0	0	1	native	$3	tx	pieces	lg
25	0	1	0	2	native	$3	tx	pieces	lg
26	1	0	0	1	native	$5	us	halves	sm
27	0	1	0	2	native	$5	us	halves	sm
28	1	0	0	1	native	$5	us	halves	lg
29	0	1	0	2	native	$5	us	halves	lg
30	1	0	0	1	native	$5	us	pieces	sm
31	0	1	0	2	native	$5	us	pieces	sm
32	1	0	0	1	native	$5	us	pieces	lg
33	0	1	0	2	native	$5	us	pieces	lg
34	1	0	0	1	native	$5	Imported	halves	sm
35	0	1	0	2	native	$5	Imported	halves	sm
36	1	0	0	1	native	$5	Imported	halves	lg
37	0	1	0	2	native	$5	Imported	halves	lg
38	1	0	0	1	native	$5	Imported	pieces	sm
39	0	1	0	2	native	$5	Imported	pieces	sm
40	1	0	0	1	native	$5	Imported	pieces	lg
41	0	1	0	2	native	$5	Imported	pieces	lg
42	1	0	0	1	native	$5	tx	halves	sm
43	0	1	0	2	native	$5	tx	halves	sm

Looking at the number of runs needed 668
using the number of optimal runs to create linear design
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Obs	f1	f2	f3	option	variety	price	origin	status	size
44	1	0	0	1	native	$5	tx	halves	lg
45	0	1	0	2	native	$5	tx	halves	lg
46	1	0	0	1	native	$5	tx	pieces	sm
47	0	1	0	2	native	$5	tx	pieces	sm
48	1	0	0	1	native	$5	tx	pieces	lg
49	0	1	0	2	native	$5	tx	pieces	lg
50	1	0	0	1	native	$7	us	halves	sm
51	0	1	0	2	native	$7	us	halves	sm
52	1	0	0	1	native	$7	us	halves	lg
53	0	1	0	2	native	$7	us	halves	lg
54	1	0	0	1	native	$7	us	pieces	sm
55	0	1	0	2	native	$7	us	pieces	sm
56	1	0	0	1	native	$7	us	pieces	lg
57	0	1	0	2	native	$7	us	pieces	lg
58	1	0	0	1	native	$7	Imported	halves	sm
59	0	1	0	2	native	$7	Imported	halves	sm
60	1	0	0	1	native	$7	Imported	halves	lg
61	0	1	0	2	native	$7	Imported	halves	lg

62	1	0	0	1	native	$7	Imported	pieces	sm
63	0	1	0	2	native	$7	Imported	pieces	sm
64	1	0	0	1	native	$7	Imported	pieces	lg
65	0	1	0	2	native	$7	Imported	pieces	lg
66	1	0	0	1	native	$7	tx	halves	sm
67	0	1	0	2	native	$7	tx	halves	sm
68	1	0	0	1	native	$7	tx	halves	lg
69	0	1	0	2	native	$7	tx	halves	lg
70	1	0	0	1	native	$7	tx	pieces	sm
71	0	1	0	2	native	$7	tx	pieces	sm
72	1	0	0	1	native	$7	tx	pieces	lg
73	0	1	0	2	native	$7	tx	pieces	lg
74	1	0	0	1	improved	$3	us	halves	sm
75	0	1	0	2	improved	$3	us	halves	sm
76	1	0	0	1	improved	$3	us	halves	lg
77	0	1	0	2	improved	$3	us	halves	lg
78	1	0	0	1	improved	$3	us	pieces	sm
79	0	1	0	2	improved	$3	us	pieces	sm
80	1	0	0	1	improved	$3	us	pieces	lg
81	0	1	0	2	improved	$3	us	pieces	lg
82	1	0	0	1	improved	$3	Imported	halves	sm
83	0	1	0	2	improved	$3	Imported	halves	sm
84	1	0	0	1	improved	$3	Imported	halves	lg
85	0	1	0	2	improved	$3	Imported	halves	lg
86	1	0	0	1	improved	$3	Imported	pieces	sm

Looking at the number of runs needed 669
using the number of optimal runs to create linear design
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Obs	f1	f2	f3	option	variety	price	origin	status	size
87	0	1	0	2	improved	$3	Imported	pieces	sm
88	1	0	0	1	improved	$3	Imported	pieces	lg
89	0	1	0	2	improved	$3	Imported	pieces	lg
90	1	0	0	1	improved	$3	tx	halves	sm
91	0	1	0	2	improved	$3	tx	halves	sm
92	1	0	0	1	improved	$3	tx	halves	lg
93	0	1	0	2	improved	$3	tx	halves	lg
94	1	0	0	1	improved	$3	tx	pieces	sm
95	0	1	0	2	improved	$3	tx	pieces	sm
96	1	0	0	1	improved	$3	tx	pieces	lg
97	0	1	0	2	improved	$3	tx	pieces	lg
98	1	0	0	1	improved	$5	us	halves	sm
99	0	1	0	2	improved	$5	us	halves	sm
100	1	0	0	1	improved	$5	us	halves	lg
101	0	1	0	2	improved	$5	us	halves	lg
102	1	0	0	1	improved	$5	us	pieces	sm
103	0	1	0	2	improved	$5	us	pieces	sm
104	1	0	0	1	improved	$5	us	pieces	lg
105	0	1	0	2	improved	$5	us	pieces	lg
106	1	0	0	1	improved	$5	Imported	halves	sm
107	0	1	0	2	improved	$5	Imported	halves	sm
108	1	0	0	1	improved	$5	Imported	halves	lg
109	0	1	0	2	improved	$5	Imported	halves	lg
110	1	0	0	1	improved	$5	Imported	pieces	sm
111	0	1	0	2	improved	$5	Imported	pieces	sm
112	1	0	0	1	improved	$5	Imported	pieces	lg
113	0	1	0	2	improved	$5	Imported	pieces	lg
114	1	0	0	1	improved	$5	tx	halves	sm
115	0	1	0	2	improved	$5	tx	halves	sm
116	1	0	0	1	improved	$5	tx	halves	lg
117	0	1	0	2	improved	$5	tx	halves	lg
118	1	0	0	1	improved	$5	tx	pieces	sm
119	0	1	0	2	improved	$5	tx	pieces	sm

120	1	0	0	1	improved	$5	tx	pieces	lg
121	0	1	0	2	improved	$5	tx	pieces	lg
122	1	0	0	1	improved	$7	us	halves	sm
123	0	1	0	2	improved	$7	us	halves	sm
124	1	0	0	1	improved	$7	us	halves	lg
125	0	1	0	2	improved	$7	us	halves	lg
126	1	0	0	1	improved	$7	us	pieces	sm
127	0	1	0	2	improved	$7	us	pieces	sm
128	1	0	0	1	improved	$7	us	pieces	lg
129	0	1	0	2	improved	$7	us	pieces	lg

Looking at the number of runs needed 670
using the number of optimal runs to create linear design
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Obs	f1	f2	f3	option	variety	price	origin	status	size
130	1	0	0	1	improved	$7	Imported	halves	sm
131	0	1	0	2	improved	$7	Imported	halves	sm
132	1	0	0	1	improved	$7	Imported	halves	lg
133	0	1	0	2	improved	$7	Imported	halves	lg
134	1	0	0	1	improved	$7	Imported	pieces	sm
135	0	1	0	2	improved	$7	Imported	pieces	sm
136	1	0	0	1	improved	$7	Imported	pieces	lg
137	0	1	0	2	improved	$7	Imported	pieces	lg
138	1	0	0	1	improved	$7	tx	halves	sm
139	0	1	0	2	improved	$7	tx	halves	sm
140	1	0	0	1	improved	$7	tx	halves	lg
141	0	1	0	2	improved	$7	tx	halves	lg
142	1	0	0	1	improved	$7	tx	pieces	sm
143	0	1	0	2	improved	$7	tx	pieces	sm
144	1	0	0	1	improved	$7	tx	pieces	lg
145	0	1	0	2	improved	$7	tx	pieces	lg

Looking at the number of runs needed 671
using the number of optimal runs to create linear design
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n	Name	Beta	Label
1	native	0	native
2	_3	0	$3
3	_5	0	$5
4	us	0	us
5	Imported	0	Imported
6	halves	0	halves
7	sm	0	sm

Looking at the number of runs needed 672
using the number of optimal runs to create linear design
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Design	Iteration	D-Efficiency	D-Error
1	0	4.450889	0.224674
	1	6.939359	0.144106
	2	7.018381	0.142483
	3	7.108520	0.140676
	4	7.108520	0.140676

Design	Iteration	D-Efficiency	D-Error
2	0	4.616565	0.216611

	1	6.917050	0.144570
	2	7.082254	0.141198
	3	7.124815	0.140355
	4	7.124815	0.140355

Design	Iteration	D-Efficiency	D-Error
3	0	3.889246	0.257119
	1	6.823340	0.146556
	2	6.997314	0.142912
	3	6.997314	0.142912

Design	Iteration	D-Efficiency	D-Error
4	0	4.636420	0.215684
	1	7.043832	0.141968
	2	7.087509	0.141093
	3	7.087509	0.141093

Looking at the number of runs needed 673
using the number of optimal runs to create linear design
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Design	Iteration	D-Efficiency	D-Error
5	0	4.554331	0.219571
	1	6.945340	0.143981
	2	7.033203	0.142183
	3	7.033203	0.142183

Design	Iteration	D-Efficiency	D-Error
6	0	4.774942	0.209427
	1	6.959908	0.143680
	2	7.030701	0.142233
	3	7.030701	0.142233

Design	Iteration	D-Efficiency	D-Error
7	0	4.514446	0.221511
	1	6.943670	0.144016
	2	7.028965	0.142268
	3	7.182512	0.139227
	4	7.182512	0.139227

Design	Iteration	D-Efficiency	D-Error
8	0	4.229214	0.236451
	1	6.922187	0.144463
	2	7.038774	0.142070
	3	7.076830	0.141306
	4	7.076830	0.141306

Looking at the number of runs needed 674
using the number of optimal runs to create linear design
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Design	Iteration	D-Efficiency	D-Error
9	0	4.528691	0.220814
	1	7.046156	0.141921
	2	7.107647	0.140694
	3	7.107647	0.140694

Design	Iteration	D-Efficiency	D-Error
10	0	4.376472	0.228495
	1	6.877864	0.145394
	2	7.047435	0.141896
	3	7.123323	0.140384
	4	7.124815	0.140355

Design	Iteration	D-Efficiency	D-Error
11	0	4.229347	0.236443
	1	6.906424	0.144793
	2	7.019415	0.142462
	3	7.075523	0.141332
	4	7.075523	0.141332

Design	Iteration	D-Efficiency	D-Error
12	0	3.943603	0.253575
	1	6.965330	0.143568
	2	7.044270	0.141959
	3	7.203324	0.138825
	4	7.203324	0.138825

Looking at the number of runs needed 675
using the number of optimal runs to create linear design
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Design	Iteration	D-Efficiency	D-Error
13	0	4.162137	0.240261
	1	6.942175	0.144047
	2	7.035263	0.142141
	3	7.035263	0.142141

Design	Iteration	D-Efficiency	D-Error
14	0	3.987928	0.250757
	1	7.011885	0.142615
	2	7.117329	0.140502
	3	7.117329	0.140502

Design	Iteration	D-Efficiency	D-Error
15	0	4.499970	0.222224
	1	6.765570	0.147807
	2	7.098258	0.140880
	3	7.098258	0.140880

Design	Iteration	D-Efficiency	D-Error
16	0	4.665308	0.214348
	1	6.966452	0.143545
	2	7.099727	0.140850
	3	7.133693	0.140180

Looking at the number of runs needed 676
using the number of optimal runs to create linear design
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Design	Iteration	D-Efficiency	D-Error
17	0	4.180029	0.239233
	1	6.799821	0.147063
	2	7.151099	0.139839
	3	7.151099	0.139839

Design	Iteration	D-Efficiency	D-Error
18	0	4.671800	0.214050
	1	6.812550	0.146788
	2	7.129665	0.140259
	3	7.129665	0.140259

Design	Iteration	D-Efficiency	D-Error
19	0	4.185723	0.238907
	1	6.766689	0.147783
	2	7.059406	0.141655
	3	7.059406	0.141655

Design	Iteration	D-Efficiency	D-Error
20	0	4.399786	0.227284
	1	6.964038	0.143595
	2	7.070107	0.141441
	3	7.076830	0.141306

Looking at the number of runs needed 677
using the number of optimal runs to create linear design
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Final Results

Design 12

```
                    Choice Sets           12
                    Alternatives           3
                    Parameters             7
                    Maximum Parameters    24
                    D-Efficiency      7.2033
                    Relative D-Eff   90.0416
                    D-Error           0.1388
                    1 / Choice Sets   0.0833

              Looking at the number of runs needed                  678
         using the number of optimal runs to create linear design
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```

n	Variable Name	Label	Variance	DF	Standard Error
1	native	native	0.12500	1	0.35355
2	_3	$3	0.15038	1	0.38778
3	_5	$5	0.15038	1	0.38778
4	us	us	0.15038	1	0.38778
5	Imported	Imported	0.15038	1	0.38778
6	halves	halves	0.12500	1	0.35355
7	sm	sm	0.12500	1	0.35355
				==	
				7	

```
                ’Variance-Covariance Matrix’                       679
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```

’00’x	native	$3	$5	us	Imported	halves	sm
native	0.13	0	0	0	0	0	0
$3	0	0.15	0	0.00	0.01	0	0
$5	0	0	0.15	0.01	-0.00	0	0
us	0	0.00	0.01	0.15	0	0	0
Imported	0	0.01	-0.00	0	0.15	0	0
halves	0	0	0	0	0	0.13	0
sm	0	0	0	0	0	0	0.13

```
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```

Set	option	variety	price	origin	status	size
1	1	native	$7	us	pieces	lg
	2	improved	$5	Imported	halves	sm
	none	.	.	.	.	.
2	1	native	$5	tx	pieces	sm
	2	improved	$7	Imported	halves	lg
	none	.	.	.	.	.
3	1	native	$3	Imported	halves	sm
	2	improved	$5	tx	pieces	lg
	none	.	.	.	.	.
4	1	improved	$3	tx	halves	sm
	2	native	$5	Imported	pieces	lg
	none	.	.	.	.	.
5	1	native	$3	Imported	pieces	lg
	2	improved	$7	us	halves	sm
	none	.	.	.	.	.
6	1	native	$7	tx	halves	lg
	2	improved	$5	Imported	pieces	sm

	none	.	.	.	.	.
7	1	native	$7	Imported	halves	sm
	2	improved	$3	us	pieces	lg
	none	.	.	.	.	.
8	1	native	$3	tx	pieces	sm
	2	improved	$5	us	halves	lg
	none	.	.	.	.	.
9	1	native	$3	us	halves	lg
	2	improved	$7	tx	pieces	sm
	none	.	.	.	.	.
10	1	improved	$3	tx	halves	lg
	2	native	$7	us	pieces	sm
	none	.	.	.	.	.
11	1	improved	$3	us	pieces	sm

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Set	option	variety	price	origin	status	size
11	2	native	$5	tx	halves	lg
	none	.	.	.	.	.
12	1	native	$5	us	halves	sm
	2	improved	$7	Imported	pieces	lg
	none	.	.	.	.	.

Canonical Correlations Between the Factors 682
There are 16 Canonical Correlations Greater Than 0.316
C - Constant Factor
21:16 Tuesday, October 25, 2011

	Block	Alt1_ variety	Alt1_ price	Alt1_ origin	Alt1_ status	Alt1_ size	Alt2_ variety	Alt2_ price
Block	C	C	C	C	C	C	C	C
Alt1_variety	C	1	0.49	0.37	0.10	0.10	1.00	0.23
Alt1_price	C	0.49	1	0.27	0.11	0.43	0.49	0.70
Alt1_origin	C	0.37	0.27	1	0.13	0.13	0.37	0.52
Alt1_status	C	0.10	0.11	0.13	1	0.03	0.10	0.27
Alt1_size	C	0.10	0.43	0.13	0.03	1	0.10	0.36
Alt2_variety	C	1.00	0.49	0.37	0.10	0.10	1	0.23
Alt2_price	C	0.23	0.70	0.52	0.27	0.36	0.23	1
Alt2_origin	C	0.12	0.71	0.55	0.13	0.13	0.12	0.49
Alt2_status	C	0.10	0.11	0.13	1.00	0.03	0.10	0.27
Alt2_size	C	0.10	0.43	0.13	0.03	1.00	0.10	0.36
Alt3_variety	C	C	C	C	C	C	C	C
Alt3_price	C	C	C	C	C	C	C	C
Alt3_origin	C	C	C	C	C	C	C	C
Alt3_status	C	C	C	C	C	C	C	C
Alt3_size	C	C	C	C	C	C	C	C

	Alt2_ origin	Alt2_ status	Alt2_ size	Alt3_ variety	Alt3_ price	Alt3_ origin	Alt3_ status	Alt3_ size
Block	C	C	C	C	C	C	C	C
Alt1_variety	0.12	0.10	0.10	C	C	C	C	C
Alt1_price	0.71	0.11	0.43	C	C	C	C	C
Alt1_origin	0.55	0.13	0.13	C	C	C	C	C
Alt1_status	0.13	1.00	0.03	C	C	C	C	C
Alt1_size	0.13	0.03	1.00	C	C	C	C	C

Alt2_variety	0.12	0.10	0.10	C	C	C	C	C
Alt2_price	0.49	0.27	0.36	C	C	C	C	C
Alt2_origin	1	0.13	0.13	C	C	C	C	C
Alt2_status	0.13	1	0.03	C	C	C	C	C
Alt2_size	0.13	0.03	1	C	C	C	C	C
Alt3_variety	C	C	C	C	C	C	C	C
Alt3_price	C	C	C	C	C	C	C	C
Alt3_origin	C	C	C	C	C	C	C	C
Alt3_status	C	C	C	C	C	C	C	C
Alt3_size	C	C	C	C	C	C	C	C

Canonical Correlations > 0.316 Between the Factors 683
There are 16 Canonical Correlations Greater Than 0.316
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		r	r Square
Alt1_variety	Alt2_variety	1.00	1.00
Alt1_status	Alt2_status	1.00	1.00
Alt1_size	Alt2_size	1.00	1.00
Alt1_price	Alt2_origin	0.71	0.50
Alt1_price	Alt2_price	0.70	0.49
Alt1_origin	Alt2_origin	0.55	0.30
Alt1_origin	Alt2_price	0.52	0.27
Alt2_price	Alt2_origin	0.49	0.24
Alt1_variety	Alt1_price	0.49	0.24
Alt1_price	Alt2_variety	0.49	0.24
Alt1_price	Alt1_size	0.43	0.18
Alt1_price	Alt2_size	0.43	0.18
Alt1_variety	Alt1_origin	0.37	0.13
Alt1_origin	Alt2_variety	0.37	0.13
Alt1_size	Alt2_price	0.36	0.13
Alt2_price	Alt2_size	0.36	0.13

Summary of Frequencies 684
There are 16 Canonical Correlations Greater Than 0.316
* - Indicates Unequal Frequencies
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		Frequencies
	Block	12
*	Alt1_variety	9 3
*	Alt1_price	7 2 3
*	Alt1_origin	4 3 5
*	Alt1_status	7 5
*	Alt1_size	7 5
*	Alt2_variety	3 9
*	Alt2_price	1 6 5
*	Alt2_origin	4 5 3
*	Alt2_status	5 7
*	Alt2_size	5 7
	Alt3_variety	12
	Alt3_price	12
	Alt3_origin	12
	Alt3_status	12
	Alt3_size	12
*	Block Alt1_variety	9 3
*	Block Alt1_price	7 2 3
*	Block Alt1_origin	4 3 5
*	Block Alt1_status	7 5
*	Block Alt1_size	7 5
*	Block Alt2_variety	3 9
*	Block Alt2_price	1 6 5

```
*    Block Alt2_origin           4 5 3
*    Block Alt2_status           5 7
*    Block Alt2_size             5 7
     Block Alt3_variety          12
     Block Alt3_price            12
     Block Alt3_origin           12
     Block Alt3_status           12
     Block Alt3_size             12
*    Alt1_variety Alt1_price     4 2 3 3 0 0
*    Alt1_variety Alt1_origin    3 3 3 1 0 2
*    Alt1_variety Alt1_status    5 4 2 1
*    Alt1_variety Alt1_size      5 4 2 1
*    Alt1_variety Alt2_variety   0 9 3 0
*    Alt1_variety Alt2_price     1 4 4 0 2 1
*    Alt1_variety Alt2_origin    3 4 2 1 1 1
*    Alt1_variety Alt2_status    4 5 1 2
*    Alt1_variety Alt2_size      4 5 1 2
*    Alt1_variety Alt3_variety   9 3
*    Alt1_variety Alt3_price     9 3

                Summary of Frequencies                         685
 There are 16 Canonical Correlations Greater Than 0.316
           * - Indicates Unequal Frequencies
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                                 Frequencies

*    Alt1_variety Alt3_origin    9 3
*    Alt1_variety Alt3_status    9 3
*    Alt1_variety Alt3_size      9 3
*    Alt1_price Alt1_origin      2 2 3 1 0 1 1 1 1
*    Alt1_price Alt1_status      4 3 1 1 2 1
*    Alt1_price Alt1_size        4 3 2 0 1 2
*    Alt1_price Alt2_variety     3 4 0 2 0 3
*    Alt1_price Alt2_price       0 4 3 0 0 2 1 2 0
*    Alt1_price Alt2_origin      3 1 3 0 2 0 1 2 0
*    Alt1_price Alt2_status      3 4 1 1 1 2
*    Alt1_price Alt2_size        3 4 0 2 2 1
*    Alt1_price Alt3_variety     7 2 3
*    Alt1_price Alt3_price       7 2 3
*    Alt1_price Alt3_origin      7 2 3
*    Alt1_price Alt3_status      7 2 3
*    Alt1_price Alt3_size        7 2 3
*    Alt1_origin Alt1_status     2 2 2 1 3 2
*    Alt1_origin Alt1_size       2 2 2 1 3 2
*    Alt1_origin Alt2_variety    1 3 0 3 2 3
*    Alt1_origin Alt2_price      0 2 2 1 1 1 0 3 2
*    Alt1_origin Alt2_origin     0 2 2 2 0 1 2 3 0
*    Alt1_origin Alt2_status     2 2 1 2 2 3
*    Alt1_origin Alt2_size       2 2 1 2 2 3
*    Alt1_origin Alt3_variety    4 3 5
*    Alt1_origin Alt3_price      4 3 5
*    Alt1_origin Alt3_origin     4 3 5
*    Alt1_origin Alt3_status     4 3 5
*    Alt1_origin Alt3_size       4 3 5
*    Alt1_status Alt1_size       4 3 3 2
*    Alt1_status Alt2_variety    2 5 1 4
*    Alt1_status Alt2_price      1 3 3 0 3 2
*    Alt1_status Alt2_origin     2 3 2 2 2 1
*    Alt1_status Alt2_status     0 7 5 0
*    Alt1_status Alt2_size       3 4 2 3
*    Alt1_status Alt3_variety    7 5
*    Alt1_status Alt3_price      7 5
*    Alt1_status Alt3_origin     7 5
*    Alt1_status Alt3_status     7 5
```

```
*    Alt1_status Alt3_size       7 5
*    Alt1_size Alt2_variety      2 5 1 4
*    Alt1_size Alt2_price        1 4 2 0 2 3
*    Alt1_size Alt2_origin       2 3 2 2 2 1

                Summary of Frequencies                        686
 There are 16 Canonical Correlations Greater Than 0.316
           * - Indicates Unequal Frequencies
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                                 Frequencies

*    Alt1_size Alt2_status       3 4 2 3
*    Alt1_size Alt2_size         0 7 5 0
*    Alt1_size Alt3_variety      7 5
*    Alt1_size Alt3_price        7 5
*    Alt1_size Alt3_origin       7 5
*    Alt1_size Alt3_status       7 5
*    Alt1_size Alt3_size         7 5
*    Alt2_variety Alt2_price     0 2 1 1 4 4
*    Alt2_variety Alt2_origin    1 1 1 3 4 2
*    Alt2_variety Alt2_status    1 2 4 5
*    Alt2_variety Alt2_size      1 2 4 5
*    Alt2_variety Alt3_variety   3 9
*    Alt2_variety Alt3_price     3 9
*    Alt2_variety Alt3_origin    3 9
*    Alt2_variety Alt3_status    3 9
*    Alt2_variety Alt3_size      3 9
*    Alt2_price Alt2_origin      1 0 0 1 3 2 2 2 1
*    Alt2_price Alt2_status      0 1 3 3 2 3
*    Alt2_price Alt2_size        0 1 2 4 3 2
*    Alt2_price Alt3_variety     1 6 5
*    Alt2_price Alt3_price       1 6 5
*    Alt2_price Alt3_origin      1 6 5
*    Alt2_price Alt3_status      1 6 5
*    Alt2_price Alt3_size        1 6 5
*    Alt2_origin Alt2_status     2 2 2 3 1 2
*    Alt2_origin Alt2_size       2 2 2 3 1 2
*    Alt2_origin Alt3_variety    4 5 3
*    Alt2_origin Alt3_price      4 5 3
*    Alt2_origin Alt3_origin     4 5 3
*    Alt2_origin Alt3_status     4 5 3
*    Alt2_origin Alt3_size       4 5 3
*    Alt2_status Alt2_size       2 3 3 4
*    Alt2_status Alt3_variety    5 7
*    Alt2_status Alt3_price      5 7
*    Alt2_status Alt3_origin     5 7
*    Alt2_status Alt3_status     5 7
*    Alt2_status Alt3_size       5 7
*    Alt2_size Alt3_variety      5 7
*    Alt2_size Alt3_price        5 7
*    Alt2_size Alt3_origin       5 7
*    Alt2_size Alt3_status       5 7
*    Alt2_size Alt3_size         5 7

                Summary of Frequencies                        687
 There are 16 Canonical Correlations Greater Than 0.316
           * - Indicates Unequal Frequencies
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                                 Frequencies

     Alt3_variety Alt3_price     12
     Alt3_variety Alt3_origin    12
     Alt3_variety Alt3_status    12
```

Alt3_variety Alt3_size	12
Alt3_price Alt3_origin	12
Alt3_price Alt3_status	12
Alt3_price Alt3_size	12
Alt3_origin Alt3_status	12
Alt3_origin Alt3_size	12
Alt3_status Alt3_size	12
N-Way	1 1 1 1 1 1 1 1 1 1 1 1

Block	Set	Alt	variety	price	origin	status	size
0	1	1	native	$7	us	pieces	lg
		2	improved	$5	Imported	halves	sm
		3	.	.	.	.	.
0	2	1	native	$5	tx	pieces	sm
		2	improved	$7	Imported	halves	lg
		3	.	.	.	.	.
0	3	1	native	$3	Imported	halves	sm
		2	improved	$5	tx	pieces	lg
		3	.	.	.	.	.
0	4	1	improved	$3	tx	halves	sm
		2	native	$5	Imported	pieces	lg
		3	.	.	.	.	.
0	5	1	native	$3	Imported	pieces	lg
		2	improved	$7	us	halves	sm
		3	.	.	.	.	.
0	6	1	native	$7	tx	halves	lg
		2	improved	$5	Imported	pieces	sm
		3	.	.	.	.	.
0	7	1	native	$7	Imported	halves	sm
		2	improved	$3	us	pieces	lg
		3	.	.	.	.	.
0	8	1	native	$3	tx	pieces	sm
		2	improved	$5	us	halves	lg
		3	.	.	.	.	.
0	9	1	native	$3	us	halves	lg
		2	improved	$7	tx	pieces	sm
		3	.	.	.	.	.
0	10	1	improved	$3	tx	halves	lg
		2	native	$7	us	pieces	sm
		3	.	.	.	.	.
0	11	1	improved	$3	us	pieces	sm

Block	Set	Alt	variety	price	origin	status	size
0	11	2	native	$5	tx	halves	lg
		3	.	.	.	.	.
0	12	1	native	$5	us	halves	sm
		2	improved	$7	Imported	pieces	lg
		3	.	.	.	.	.

APPENDIX C

PECAN CONSUMER SURVEY

Pecan Consumer Survey

Thank you for your participation in this survey. All information you provide will be reported anonymously and will be kept strictly confidential. Results from this survey will be reported in summary format only. If you have any questions regarding this survey, please feel free to contact the principal investigators:

Dr. Marco Palma	Chris Chammoun
Texas A&M University	Texas A&M University
mapalma@tamu.edu	cchammoun@tamu.edu

You will be asked to answer several questions about your consumption of pecans as well as other types of nuts. Next you will be asked to make a choice between two different types of pecan products. And finally you will be asked some basic household demographic questions.

Do you wish to proceed? YES NO

Consumption questions

(Please select one unless otherwise noted)

1. How often to you purchase nuts?

   a. Less than once a year
   b. Once a year
   c. Several times a year
   d. Once a month
   e. Twice a month
   f. Once a week
   g. More than once a week

2. Where do you normally purchase nuts?
   a. Retail store/supermarket
   b. Farmers market/roadside markets
   c. Wholesale/farmer direct
   d. Internet
3. In what package size do you normally purchase nuts?
   a. 4oz
   b. 8oz
   c. 12oz
   d. 16oz
   e. Other, please specify:________
4. Please rank all of the following nuts from 1 to 7, where 1 is the most preferred and 7 is the least preferred. Please rank all products even those that you may prefer at the same preference level.
   a. ___Almonds

b. ___Cashews

c. ___Peanuts

d. ___Pecans

e. ___Pistachios

f. ___Macadamias

g. ___Walnuts

5. How often to you purchase pecans?

    a. Less than once a year

    b. Once a year

    c. Several times a year

    d. Once a month

    e. Twice a month

    f. Once a week

    g. More than once a week

6. In what condition do you normally purchase nuts?

    a. Whole - in-shell

    b. Whole - out of shell

    c. Cracked in shell

    d. Halves

    e. Pieces

    f. Meal

7. Where do you normally purchase pecans?

a. Retail store/supermarket
b. Farmers market/roadside markets
c. Wholesale/farmer direct
d. Internet

8. In what package size do you normally purchase pecans?
   a. 4oz
   b. 8oz
   c. 12oz
   d. 16oz
   e. Other, please specify:__________
9. In what condition do you normally purchase pecans?
   a. Whole - in-shell
   b. Whole - out of shell
   c. Cracked in shell
   d. Halves
   e. Pieces
   f. Meal
10. How important are the following factors when purchasing pecans? Rank each factor on a scale of 1 to 6, where 1 means that the factor is very important and 6 means that the factor in not important at all.
    a. ___Price
    b. ___Size

c. ___Origin

d. ___Variety

e. ___Condition (in-shell, halves, pieces, meal, etc.)

f. ___Organic versus non-organic

11. How often do you complete surveys?

a. Less than once a year

b. Once a year

c. Several times a year

d. Once a month

e. Twice a month

f. Once a week

g. More than once a week

12. Do you receive compensation for completing surveys?

a. Yes

b. No (then skip to Question #14)

13. What type of compensation do you receive for completing surveys? (circle all that apply)

a. Money

b. Coupons

c. Products

d. Gift cards

e. Other

14. How much compensation per month do you receive from participating in surveys?
    a. Less than $100
    b. $101 - $200
    c. $201 - $300
    d. $301 - $400
    e. $401 - $500
    f. More than $500

Choice questions

(Please choose which of the two products you prefer based off of the pecan attributes that are given. If you do not prefer one versus the other, or you do not prefer either of the choices given, then choose the "Neither" answer. All bags referred to are 8 ounce bags.)

<u>Attribute descriptions</u>:

Halves:

Pieces:

Large: Halves that are 1 inch in length or greater. Pieces that are ½ inch or greater.

Small: Halves that are smaller than 1 inch. Pieces that are smaller than ½ inch.

Native Variety: Pecan varieties that are native to their country of origin.

Improved Variety: Pecan varieties that are bred from native varieties using traditional plant breeding techniques.

Texas: Pecans were that are grown in the state of Texas.

United States: Pecans that are grown in the United States.

Imported: Pecans that are grown outside of the United States.

1.

a. A bag of large native variety pecan pieces from the United States for $7.00 per bag.
b. A bag of small improved variety pecan halves that are imported for $5.00 per bag.
c. Neither

2.

a. A bag of small native variety pecan pieces from Texas for $5.00 per bag.
b. A bag of large improved variety pecan halves that are imported for $7.00 per bag.
c. Neither

3.

a. A bag of small native variety pecan halves that are imported for $3.00 per bag.
b. A bag of large improved variety pecan pieces from Texas for $5.00 per bag.
c. Neither

4.

a. A bag of small improved variety pecan halves from Texas for $3.00 per bag.

b. A bag of large native variety pecan pieces that are imported for $5.00 per bag.
c. Neither

5.

a. A bag of large native variety pecan pieces that are imported for $3.00 per bag.
b. A bag of small improved variety pecan halves from the United States for $7.00 per bag.
c. Neither

6.

a. A bag of large native variety pecan halves from Texas for $7.00 per bag.
b. A bag of small improved variety pecan pieces that are imported for $5.00 per bag.
c. Neither

7.

a. A bag of small native variety pecan halves that are imported for $7.00 per bag.
b. A bag of large improved variety pecan pieces from the United States for $3.00 per bag.
c. Neither

8.

a. A bag of small native variety pecan pieces from Texas for $3.00 per bag.

b. A bag of large improved variety pecan halves from the United States for $5.00 per bag.
c. Neither

9.
a. A bag of large native variety pecan halves from the United States for $3.00 per bag.
b. A bag of small improved variety pecan pieces from Texas for $7.00 per bag.
c. Neither

10.
a. A bag of large improved variety pecan halves from Texas for $3.00 per bag.
b. A bag of small native variety pecan pieces from the United States for $7.00 per bag.
c. Neither

11.
a. A bag of small improved variety pecan pieces from the United States for $3.00 per bag.
b. A bag of large native variety pecan halves from Texas for $5.00 per bag.
c. Neither

12.

a. A bag of small native variety pecan halves from the United States for $5.00 per bag.
b. A bag of large improved variety pecan pieces that are imported for $7.00 per bag.
c. Neither

Demographic questions

(Please select one unless otherwise noted)

1. Which of the following best describes where you live?
    a. Rural
    b. Suburban
    c. Urban
2. What is your gender?
    a. Male
    b. Female
3. What is your age?
    a. 18 - 35
    b. 36 - 50
    c. 51 – 65
    d. 66 or older
4. What is your marital status?
    a. Single

b. Married

c. Divorced

d. Widowed

5. What is your ethnic origin?

a. White/Caucasian

b. Hispanic

c. Black/African-American

d. Asian or Pacific Islander

e. Native American

f. Other

6. What is the highest level of education you completed?

a. Grades lower than high school

b. High school/GED

c. Associate degree/technical school/other 2 year school

d. Bachelor degree/other 4 year school

e. Advanced/professional degree

7. What is your employment status?

a. Employed-part time

b. Employed-full time

c. Retired

d. Homemaker

e. Unemployed-seeking employment

f. Unemployed-not seeking employment

8. Including yourself, how many adults live in your household?

    a. One
    b. Two
    c. Three
    d. Four
    e. Five
    f. Six
    g. More than six

9. How many children live in your household?

    a. None
    b. One
    c. Two
    d. Three
    e. Four
    f. Five
    g. Six
    h. More than six

10. What is your annual household income before taxes?

    a. Less than $25,000
    b. $25,000 - $39,999
    c. $40,000 - $54,999

d. $55,000 - $69,999

e. $70,000 - $84,999

f. $85,000 - $99,999

g. $100,000 - $114,999

h. $115,000 - $129,999

i. $130,000 or greater

APPENDIX D

STATA CODE FOR CHOICE EXPERIMENT

```
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                                                      ___  ____  ____  ____  ____(R)
                                                     /__    /   ____/   /   ____/
                                                    ___/   /   /___/   /   /___/
                                                      Statistics/Data Analysis

                                                         User: cchammoun
                                                       Project: Pecan Survey

  ___  ____  ____  ____  ____ (R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/   12.1   Copyright 1985-2011 StataCorp LP
  Statistics/Data Analysis             StataCorp
                                      4905 Lakeway Drive
     Special Edition                   College Station, Texas 77845 USA
                                      800-STATA-PC        http://www.stata.com
                                      979-696-4600        stata@stata.com
                                      979-696-4601 (fax)

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Notes:
      1.  (/v# option or -set maxvar-) 5000 maximum variables

 1 . use "C:\Users\Chris\Desktop\Stata12\FILES\peconsum model 2-23-12 results.dta", clear

 2 . do "C:\Users\Chris\Desktop\Stata12\FILES\pecan_all models 2-23-12.do"

 3 . /*Chris Chammoun
   > Pecan Choice Experiment
   > data file to use: pecan_data_all.dta
   >
   > 3 Models: conditional logit(clogit), alternative-specific(McFaddens choice),
   > mixed-effects logit(mixlogit)*/
 4 .
 5 . use "C:\Users\Chris\Desktop\Stata12\FILES\pecan_data_all.dta", clear

 6 .
 7 . **drop option #3(neither choice of products)
 8 . drop if option==3
   (6012 observations deleted)

 9 .
10 . **fix multiple option error, creates indentifier
11 . gen alt1= option==1

12 . gen groupcount=sum(alt1)

13 .
14 . **the clogit model
15 . clogit choice sizelq varimp stahalf orgus orgtx price, group(groupcount)
   note: 776 groups (1552 obs) dropped because of all positive or
         all negative outcomes.

   Iteration 0:   log likelihood =  -2973.3837
   Iteration 1:   log likelihood =  -2872.3917
   Iteration 2:   log likelihood =  -2859.9627
   Iteration 3:   log likelihood =  -2859.9232
   Iteration 4:   log likelihood =  -2859.9232

   Conditional (fixed-effects) logistic regression   Number of obs   =      10472
                                                     LR chi2(    6)     =    1538.79
                                                     Prob > chi2     =     0.0000
   Log likelihood =  -2859.9232                        Pseudo R2       =     0.2120
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
sizelq	.0825252	.0162569	5.08	0.000	.0506623	.1143882
varimp	-.0581412	.016362	-3.55	0.000	-.0902102	-.0260722
stahalf	.1328906	.0163006	8.15	0.000	.1009421	.1648391
orgus	.1184738	.0255373	4.64	0.000	.0684216	.168526
orgtx	.6851951	.0270677	25.31	0.000	.6321434	.7382468
price	-.1852206	.011553	-16.03	0.000	-.207864	-.1625772

```
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16 . est store clogitresults

17 .
18 . **the asclogit model
19 . asclogit choice sizelg varimp stahalf orgus orgtx price, case(groupcount) alternatives(option) noconstant
   note: 776 cases (1552 obs) dropped due to no positive outcome per case

   Iteration 0:   log likelihood =  -2973.3837
   Iteration 1:   log likelihood =  -2872.3917
   Iteration 2:   log likelihood =  -2859.9627
   Iteration 3:   log likelihood =  -2859.9232
   Iteration 4:   log likelihood =  -2859.9232

   Alternative-specific conditional logit         Number of obs      =      10472
   Case variable: groupcount                      Number of cases    =       5236

   Alternative variable: option                   Alts per case: min =          2
                                                                 avg =        2.0
                                                                 max =          2

                                                     Wald chi2(    6)    =    1188.54
   Log likelihood =  -2859.9232                         Prob > chi2      =     0.0000

   ------------------------------------------------------------------------------
         choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
   -------------+----------------------------------------------------------------
   option       |
         sizelg |   .0825252   .0162569     5.08   0.000     .0506623    .1143882
         varimp |  -.0581412    .016362    -3.55   0.000    -.0902102   -.0260722
        stahalf |   .1328906   .0163006     8.15   0.000     .1009421    .1648391
          orgus |   .1184738   .0255373     4.64   0.000     .0684216     .168526
          orgtx |   .6851951   .0270677    25.31   0.000     .6321434    .7382468
          price |  -.1852206    .011553   -16.03   0.000     -.207864   -.1625772
   ------------------------------------------------------------------------------

20 . est store asclogitresults

21 .
22 . **the mixlogit model, 500 draws
23 . ****NOTE: MORE THAN 50 DRAWS NEEDED FOR FINAL MODEL****
24 . global randvars "sizelg varimp stahalf orgus orgtx"

25 . mixlogit choice price, group(groupcount) id(id) rand($randvars) nrep(500)

   Iteration 0:   log likelihood =  -2837.5357  (not concave)
   Iteration 1:   log likelihood =  -2818.3635  (not concave)
   Iteration 2:   log likelihood =  -2638.6579
   Iteration 3:   log likelihood =  -2608.6468
   Iteration 4:   log likelihood =  -2594.3177
   Iteration 5:   log likelihood =  -2594.1301
   Iteration 6:   log likelihood =  -2594.1032
   Iteration 7:   log likelihood =  -2594.1026
   Iteration 8:   log likelihood =  -2594.1026

   Mixed logit model                                 Number of obs    =      10472
                                                     LR chi2(    5)      =     531.64
   Log likelihood =  -2594.1026                        Prob > chi2      =     0.0000

   ------------------------------------------------------------------------------
         choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
   -------------+----------------------------------------------------------------
   Mean         |
          price |  -.2616435   .0151358   -17.29   0.000     -.291309   -.2319779
         sizelg |   .1191229    .026847     4.44   0.000     .0665038    .1717421
         varimp |  -.0788237   .0201573    -3.91   0.000    -.1183313    -.039316
```

stahalf	.3696747	.0325781	11.35	0.000	.3058229	.4335265
orgus	.0308588	.1679733	0.18	0.854	-.2983628	.3600804
orgtx	1.101091	.0686488	16.04	0.000	.9665416	1.23564

```
The sign of the estimated standard deviations is irrelevant: interpret them as
being positive

26 . est store mixlogitresults

27 .
28 . ***POSTESTIMATION***
29 .
30 . /*  use "_b[varname]" for retreving betas
> WTP(effects coding)= -2*beta(attribute)/beta(price) */
31 .
32 . ***NOTE: WTP ESTIMATES ARE FOR 8OZ BAG (.5 LBS), THEREFORE 2X IS PER LB***
33 . **WTP for large pecans
34 . display 2*(-2*_b[sizelg]/_b[price])
1.821149

35 . **WTP for improved varieties
36 . display 2*(-2*_b[varimp]/_b[price])
-1.2050545

37 . **WTP for halves
38 . display 2*(-2*_b[stahalf]/_b[price])
2.9514749

39 . **WTP for US origin
40 . display 2*(-2*_b[orgus]/_b[price])
2.7048857

41 . **WTP for TX origin
42 . display 2*(-2*_b[orgtx]/_b[price])
17.527406

43 .
44 . **Product Utilities(using effects coding)
45 . **Best product: Large, native, halves, Tx, $3
46 . display _b[sizelg]*(1)+_b[varimp]*(-1)+_b[stahalf]*(1)+_b[orgus]*(0)+_b[orgtx]*(1)+_b[price]*(3)
.75255757

47 .
48 . **Worst product: small, improved, pieces, Imported, $7
49 . display _b[sizelg]*(-1)+_b[varimp]*(1)+_b[stahalf]*(-1)+_b[orgus]*(-1)+_b[orgtx]*(-1)+_b[price]*(7)
-3.5459212

50 .
51 . ***PRODUCT COMPARISONS***
52 . **Base product: small, improved, pieces, Imported, $5
53 . display _b[sizelg]*(-1)+_b[varimp]*(1)+_b[stahalf]*(-1)+_b[orgus]*(-1)+_b[orgtx]*(-1)+_b[price]*(5)
-3.0226342

54 .
55 . **Typical TX pieces product: large, improved, pieces, Texas, $5
56 . display _b[sizelg]*(1)+_b[varimp]*(1)+_b[stahalf]*(-1)+_b[orgus]*(0)+_b[orgtx]*(1)+_b[price]*(5)
-.31449375

57 .
58 . **Typical TX halves product: large, improved, halves, Texas, $5
```

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```
. display _b[sizelg]*(1)+_b[varimp]*(1)+_b[stahalf]*(1)+_b[orgus]*(0)+_b[orgtx]*(1)+_b[price]*(5)
.07162332

.
. **Typical US pieces product: large, improved, pieces, US, $5
. display _b[sizelg]*(1)+_b[varimp]*(1)+_b[stahalf]*(-1)+_b[orgus]*(1)+_b[orgtx]*(0)+_b[price]*(5)
-1.2840477

.
. **Typical US halves product: large, improved, halves, US, $5
. display _b[sizelg]*(1)+_b[varimp]*(1)+_b[stahalf]*(1)+_b[orgus]*(1)+_b[orgtx]*(0)+_b[price]*(5)
-.89793061

.
. **Native TX pieces product: small, native, pieces, Texas, $5
. display _b[sizelg]*(-1)+_b[varimp]*(-1)+_b[stahalf]*(-1)+_b[orgus]*(0)+_b[orgtx]*(1)+_b[price]*(5)
-.39509229

.
. **Native TX halves product: small, native, halves, Texas, $5
. display _b[sizelg]*(-1)+_b[varimp]*(-1)+_b[stahalf]*(1)+_b[orgus]*(0)+_b[orgtx]*(1)+_b[price]*(5)
-.00897523

.
. **Native US pieces product: small, native, pieces, US, $5
. display _b[sizelg]*(-1)+_b[varimp]*(-1)+_b[stahalf]*(-1)+_b[orgus]*(1)+_b[orgtx]*(0)+_b[price]*(5)
-1.3646462

.
. **Native US halves product: small, native, halves, US, $5
. display _b[sizelg]*(-1)+_b[varimp]*(-1)+_b[stahalf]*(1)+_b[orgus]*(1)+_b[orgtx]*(0)+_b[price]*(5)
-.97852915

.
. **mixlpred returns predicted probability of a single choice set, not the choice sequence
. mixlpred p

.
. **mixlbeta calculates individual level(by id) parameters per variable
. mixlbeta sizelg varimp stahalf orgus orgtx price, nrep(500) saving("C:\Users\Chris\Desktop\Stata12\FILES\lbetar
file C:\Users\Chris\Desktop\Stata12\FILES\lbetaresults.dta saved

.
. **Marginal Effects:
. **use dydx() and eydx() for dummy variables
.
. margins, dydx(*)
Warning: cannot perform check for estimable functions.

Average marginal effects                          Number of obs   =      10472
Model VCE    :  OIM

Expression   :  Linear prediction, predict()
dy/dx w.r.t. :  price sizelg varimp stahalf orgus orgtx
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
price	-.2616435	.0151358	-17.29	0.000	-.291309	-.2319779
sizelg	.1191229	.026847	4.44	0.000	.0665038	.1717421
varimp	-.0788237	.0201573	-3.91	0.000	-.1183313	-.039316
stahalf	.1930585	.0274054	7.04	0.000	.1393449	.2467722
orgus	.1769289	.0316449	5.59	0.000	.114906	.2389518
orgtx	1.146483	.0711762	16.11	0.000	1.00698	1.285986

```
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89 .
90 . **indivdual utilities(linear probability that each alt is chosen)
91 . predict util

92 .
93 .
94 .
   end of do-file

95 .
```

APPENDIX E

STATA CODE FOR CHOICE EXPERIMENT OF CONSUMPTION GROUPS

```
peconsum models 2-23-12  Thursday February 23 18:01:37 2012   Page 1

                                                     Statistics/Data Analysis

                                                        User: cchammoun
                                                     Project: Pecan Survey

. do "C:\Users\Chris\Desktop\Stata12\FILES\peconsum model 2-23-12.do"

.
. ******************Model comparison by pecan consumption habits**************
.
. ***Not often consumers***
. ***peconsum1 peconsum2 peconsum3: less than once a year, once a year, several times a year***
. use "C:\Users\Chris\Desktop\Stata12\FILES\pecan_data_all.dta", clear

.
. drop if option==3
(6012 observations deleted)

.
. **dropping peconsum not wanted
. drop if peconsum4==1
(1032 observations deleted)

. drop if peconsum5==1
(480 observations deleted)

. drop if peconsum6==1
(336 observations deleted)

. drop if peconsum7==1
(48 observations deleted)

.
. gen alt1= option==1

. gen groupcount=sum(alt1)

.
. **the clogit model: not often consumers
. clogit choice sizelg varimp stahalf orgus orgtx price, group(groupcount)
note: 700 groups (1400 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood =  -2417.5653
Iteration 1:   log likelihood =  -2333.2122
Iteration 2:   log likelihood =  -2321.8852
Iteration 3:   log likelihood =  -2321.8539
Iteration 4:   log likelihood =  -2321.8539

Conditional (fixed-effects) logistic regression   Number of obs   =       8728
                                                  LR chi2(    6)     =    1406.08
                                                  Prob > chi2     =     0.0000
Log likelihood =  -2321.8539                       Pseudo R2       =     0.2324
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sizelg	.0767556	.0181344	4.23	0.000	.0412128	.1122984
varimp	-.0590619	.018268	-3.23	0.001	-.0948665	-.0232573
stahalf	.1365751	.0181691	7.52	0.000	.1009643	.1721859
orgus	.1234077	.0283618	4.35	0.000	.0678196	.1789957
orgtx	.726407	.0302876	23.98	0.000	.6670443	.7857697
price	-.2050922	.012935	-15.86	0.000	-.2304443	-.1797401

```
22 . est store clogitresults1

23 .
24 . **the asclogit model: not often consumers
25 . asclogit choice sizelg varimp stahalf orgus orgtx price, case(groupcount) alternatives(option) noconstant
   note: 700 cases (1400 obs) dropped due to no positive outcome per case

   Iteration 0:   log likelihood =  -2417.5653
   Iteration 1:   log likelihood =  -2333.2122
   Iteration 2:   log likelihood =  -2321.8852
   Iteration 3:   log likelihood =  -2321.8539
   Iteration 4:   log likelihood =  -2321.8539

   Alternative-specific conditional logit         Number of obs      =       8728
   Case variable: groupcount                      Number of cases    =       4364

   Alternative variable: option                   Alts per case: min =          2
                                                                 avg =        2.0
                                                                 max =          2

                                                     Wald chi2(    6)    =    1051.13
   Log likelihood =  -2321.8539                      Prob > chi2         =     0.0000
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
option						
sizelg	.0767556	.0181344	4.23	0.000	.0412128	.1122984
varimp	-.0590619	.018268	-3.23	0.001	-.0948665	-.0232573
stahalf	.1365751	.0181691	7.52	0.000	.1009643	.1721859
orgus	.1234077	.0283618	4.35	0.000	.0678196	.1789957
orgtx	.726407	.0302876	23.98	0.000	.6670443	.7857697
price	-.2050922	.012935	-15.86	0.000	-.2304443	-.1797401

```
26 . est store asclogitresults1

27 .
28 . **the mixlogit model: not often consumers
29 . ****NOTE: MORE THAN 50 DRAWS NEEDED FOR FINAL MODEL****
30 . global randvars "sizelg varimp stahalf orgus orgtx"

31 . mixlogit choice price, group(groupcount) id(id) rand($randvars) nrep(500)

   Iteration 0:   log likelihood =  -2301.9537  (not concave)
   Iteration 1:   log likelihood =  -2284.6237  (not concave)
   Iteration 2:   log likelihood =  -2121.6256
   Iteration 3:   log likelihood =  -2087.6828
   Iteration 4:   log likelihood =  -2078.6868  (not concave)
   Iteration 5:   log likelihood =  -2078.4874
   Iteration 6:   log likelihood =    -2078.39
   Iteration 7:   log likelihood =  -2078.3893
   Iteration 8:   log likelihood =  -2078.3893

   Mixed logit model                                 Number of obs   =       8728
                                                     LR chi2(    5)      =     486.93
   Log likelihood =  -2078.3893                       Prob > chi2      =     0.0000
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Mean						
price	-.3060885	.0182791	-16.75	0.000	-.3419148	-.2702622
sizelg	.1149571	.0314767	3.65	0.000	.0532639	.1766503
varimp	-.0871024	.0236774	-3.68	0.000	-.1335093	-.0406955
stahalf	.2073042	.0332281	6.24	0.000	.1421784	.2724301
orgus	.1949563	.0369798	5.27	0.000	.1224773	.2674353
orgtx	1.27452	.0862841	14.77	0.000	1.105406	1.443634
SD						
sizelg	.3933301	.0381045	10.32	0.000	.3186467	.4680135
varimp	-.0906343	.0655696	-1.38	0.167	-.2191484	.0378759

```
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     stahalf |   .4376374   .0394989    11.08   0.000     .3602209    .5150538
       orgus |   .0628248     .19917     0.32   0.752    -.3275412    .4531908
       orgtx |   1.195188   .0834026    14.33   0.000     1.031722    1.358654
------------------------------------------------------------------------------
The sign of the estimated standard deviations is irrelevant: interpret them as
being positive

32 . est store mixlogitresults1

33 .
34 .
35 . ***often consumers***
36 . ***peconsum4 peconsum5 peconsum6 peconsum7:once a month, twice a month, once a week, >once a week***
37 . use "C:\Users\Chris\Desktop\Stata12\FILES\pecan_data_all.dta", clear

38 .
39 . drop if option==3
   (6012 observations deleted)

40 .
41 . **dropping peconsum not wanted
42 . drop if peconsum1==1
   (2304 observations deleted)

43 . drop if peconsum2==1
   (2568 observations deleted)

44 . drop if peconsum3==1
   (5256 observations deleted)

45 .
46 . gen alt1= option==1

47 . gen groupcount=sum(alt1)

48 .
49 . **the clogit model: often consumers
50 . clogit choice sizelq varimp stahalf orgus orgtx price, group(groupcount)
   note: 76 groups (152 obs) dropped because of all positive or
         all negative outcomes.

   Iteration 0:   log likelihood =  -543.28361
   Iteration 1:   log likelihood =  -527.21059
   Iteration 2:   log likelihood =   -525.8383
   Iteration 3:   log likelihood =  -525.83533
   Iteration 4:   log likelihood =  -525.83533

   Conditional (fixed-effects) logistic regression   Number of obs   =       1744
                                                     LR chi2(    6)      =     157.18
                                                     Prob > chi2     =     0.0000
   Log likelihood =  -525.83533                       Pseudo R2       =     0.1300

------------------------------------------------------------------------------
      choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      sizelq |   .1052815   .0372657     2.83   0.005      .032242     .178321
      varimp |  -.0511585   .0373645    -1.37   0.171    -.1243915    .0220746
     stahalf |   .1196447   .0373503     3.20   0.001     .0464395    .1928499
       orgus |    .100415   .0593536     1.69   0.091     -.015916     .216746
       orgtx |   .5100205   .0615076     8.29   0.000     .3894679    .6305731
       price |  -.1000205   .0261993    -3.82   0.000    -.1513703   -.0486707
------------------------------------------------------------------------------
```

```
   peconsum models 2-23-12  Thursday February 23 18:01:37 2012   Page 4

51 . est store clogitresults2

52 .
53 . **the asclogit model: often consumers
54 . asclogit choice sizelg varimp stahalf orgus orgtx price, case(groupcount) alternatives(option) noconstant
   note: 76 cases (152 obs) dropped due to no positive outcome per case

   Iteration 0:   log likelihood =  -543.28361
   Iteration 1:   log likelihood =  -527.21059
   Iteration 2:   log likelihood =   -525.8383
   Iteration 3:   log likelihood =  -525.83533
   Iteration 4:   log likelihood =  -525.83533

   Alternative-specific conditional logit         Number of obs      =      1744
   Case variable: groupcount                      Number of cases    =       872

   Alternative variable: option                   Alts per case: min =         2
                                                                 avg =       2.0
                                                                 max =         2

                                                     Wald chi2(    6)    =    135.78
   Log likelihood =  -525.83533                       Prob > chi2        =    0.0000

   ------------------------------------------------------------------------------
         choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
   -------------+----------------------------------------------------------------
   option       |
         sizelg |   .1052815   .0372657     2.83   0.005      .032242     .178321
         varimp |  -.0511585   .0373645    -1.37   0.171    -.1243915    .0220746
        stahalf |   .1196447   .0373503     3.20   0.001     .0464395    .1928499
          orgus |    .100415   .0593536     1.69   0.091     -.015916     .216746
          orgtx |   .5100205   .0615076     8.29   0.000     .3894679    .6305731
          price |  -.1000205   .0261993    -3.82   0.000    -.1513703   -.0486707
   ------------------------------------------------------------------------------

55 . est store asclogitresults2

56 .
57 . **the mixlogit model: often consumers
58 . ****NOTE: MORE THAN 50 DRAWS NEEDED FOR FINAL MODEL****
59 . global randvars "sizelg varimp stahalf orgus orgtx"

60 . mixlogit choice price, group(groupcount) id(id) rand($randvars) nrep(500)

   Iteration 0:   log likelihood =  -523.44266  (not concave)
   Iteration 1:   log likelihood =  -515.81813
   Iteration 2:   log likelihood =   -500.4739
   Iteration 3:   log likelihood =  -498.30593
   Iteration 4:   log likelihood =  -497.31867
   Iteration 5:   log likelihood =   -497.3064
   Iteration 6:   log likelihood =  -497.30639

   Mixed logit model                                  Number of obs   =       1744
                                                      LR chi2(    5)     =      57.06
   Log likelihood =  -497.30639                        Prob > chi2     =     0.0000

   ------------------------------------------------------------------------------
         choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
   -------------+----------------------------------------------------------------
   Mean         |
          price |  -.1178434   .0297042    -3.97   0.000    -.1760626   -.0596242
         sizelg |   .1302509   .0522793     2.49   0.013     .0277853    .2327165
         varimp |  -.0577241   .0424523    -1.36   0.174    -.1409291    .0254809
        stahalf |   .1570068    .047465     3.31   0.001     .0639772    .2500364
          orgus |   .1234151   .0664279     1.86   0.063    -.0067813    .2536115
          orgtx |   .7299095   .1258414     5.80   0.000     .4832649    .9765541
   -------------+----------------------------------------------------------------
   SD           |
         sizelg |   .2545486   .0678523     3.75   0.000     .1215606    .3875367
         varimp |   .0353129   .1754311     0.20   0.840    -.3085258    .3791517
        stahalf |   .1673557   .0771072     2.17   0.030     .0162283    .3184831
          orgus |  -.0295605   .2390962    -0.12   0.902    -.4581803    .4390594
```

```
       orgtx |   .8156379   .1283556     6.35   0.000     .5640655    1.06721
--------------------------------------------------------------------------------
The sign of the estimated standard deviations is irrelevant; interpret them as
being positive

61 . est store mixlogitresults2

62 .
63 .
64 .
end of do-file
```

VITA

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