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An analysis of the processor preferences for the adoption of potential crawfish peeling machines

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AN ANALYSIS OF THE PROCESSOR PREFERENCES FOR THE ADOPTION OF POTENTIAL CRAWFISH PEELING MACHINES

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Abstract

Over the past decade, the peeling segment of the Louisiana crawfish industry has faced the challenge of remaining competitive in an increasingly global market. Since the mid-1990's, there has been escalated discussion among Louisiana crawfish processors on the need for a crawfish peeling machine. The International Trade Commission determined that the U.S. crawfish industry had been "materially injured" by the imported tailmeat and ruled China was, in fact, dumping crawfish in the U.S. by selling below fair market value in the host country. The development of a suitable crawfish peeling machine could potentially increase production and lower cost of production, therefore allowing the United States to be more competitive with the imported tailmeat from China.

Using conjoint analysis, the preferences of Louisiana crawfish processors in adopting crawfish peeling machines are analyzed. Theses results were based on the various attributes a peeling machine would possess. According to the industry, whether the crawfish peeling machine deveins is viewed as being most important; devein constitutes 30.6% of the total importance. For this study, cluster analysis was used to categorize processors into homogenous groups to bring together crawfish processors with a relatively high similarity in attribute preference. The analysis suggests processors peeling a higher percentage of crawfish tailmeat tended to be grouped into cluster 2, which considered a machine that deveins and retains fat to be the most important.

Thirty crawfish processors' ex-ante adoption rates of hypothetical crawfish peeling machines are assessed using a polychotomous choice elicitation format. Adoption rates are estimated to range from 23 to 70 percent, depending upon the machine and whether it was purchased or leased. Processors most likely to adopt are determined

using ordered probit analysis. Greater adopters would be larger and more diversified, have greater current resources, and have longer planning horizons. Early adopters of the machine would benefit from the reduced cost of production before the market becomes concentrated while late adopters would most likely experience lower profits or short-term losses prior to adoption.

Chapter 1

Introduction

The Problem

Crawfish is a major industry in the Louisiana economy. The total crawfish economic impact within the state is more than $120 million annually and the industry includes approximately 1,300 farmers (LSU AgCenter 2006, Louisiana Summary). According to the United States International Trade Commission (ITC, 2003), in the early years of its investigations, 1994-1996, peeled crawfish tailmeat consumption in the United States rose 80 percent, from 5.27 million pounds to 9.52 million pounds. Since the United States Department of Commerce ruling of 1997, apparent U.S. consumption has continued to rise. In 1997, 3.78 million pounds of crawfish tailmeat was consumed, and by 2002, that number escalated to 10.55 million pounds. The majority of increased consumption occurred in Louisiana, followed by its adjoining states, and to a lesser degree the broader national market. The consumption was not constant, with declines in 1999 and 2002. However, general U.S. consumption increased 178.7 percent over the 1997-2002 period. Conversely, the share of U.S. consumption accredited to domestically-produced crawfish tailmeat varied significantly over the same time period, with a high of 38.7 percent in 1997, to a low of 4.6 percent in 2000 and 2001 (ITC, 2003). The remainder of evident U.S. consumption was satisfied with imported tailmeat, and those imports were from China. China's imports accounted for 61.8 percent in 1997 and 95 percent in 2005 of U.S. crawfish tailmeat consumption (ITC, 2003).

Crawfish tailmeat is the result of whole, live crawfish being boiled, cooled, picked, and then cleaned. The consequential tailmeat may be sold as fresh, chilled, or frozen. Most of the domestic product is sold as fresh or chilled, while only 20 percent is sold frozen. All imported crawfish tailmeat is sold frozen (ITC, 2003). Discussion with stakeholders suggests different attitudes about the quality of United States as opposed to China's tailmeat, believing the U.S. product may be of higher quality, based on U.S. consumer preference. Some base their reasoning on the fact that imported tailmeat is always frozen while domestic producers offer their product with an option of being fresh. If there were to be any new methods in the production of crawfish tailmeat, it would be beneficial to recognize the product differentiation that the U.S. market presently enjoys.

According to Dellenbarger et al. (1986), processors generally begin purchasing live crawfish in October and can extend purchases to July or August, depending on the yields. March, April, May and June are the peak processing months. The Louisiana crawfish industry has endured many obstacles over the past decade while trying to remain competitive in the global market. The biggest challenge it faces is other countries, China in particular, producing peeled tailmeat at lower cost and shipping the product into the United States (Gillespie and Capdeboscq, 1996).

One way to potentially become more competitive would be via the development and adoption of a crawfish peeling machine that would reduce peeling cost and potentially produce more product than the current peeling process. The lower cost of production could potentially allow early adopters to increase profit in the short run while lowering the price of crawfish tailmeat, making domestic tailmeat more competitive with the already lower-priced imported tailmeat.

Imported crawfish from China is significantly cheaper than crawfish processed in Louisiana. In 1996, the retail price of the imported product was roughly half of the U.S.

product price, frequently ranging from $3.00 - $6.00 per pound for Chinese crawfish compared to $6.00 - $9.00 per pound for Louisiana crawfish. As a result of the price difference, between 1993 and 1996, Louisiana crawfish producers saw the value of their product decline from $13.5 million to $4.9 million (Gillespie and Capdeboscq, 1996).

Gillespie and Capdeboscq (1996) conducted a survey of 80 Louisiana processors to determine the cost associated with crawfish peeling labor. A modified version of the study was administered in the present study. Fewer than half of the processors peeling crawfish remained in business from 1996 to 2005. The attenuation in firm numbers is generally attributed to the lower-priced imported Chinese tailmeat. At present-day prices, domestic product retail prices range from $7.00 to $15.00 per pound while the imported product is being sold from $5.00 to $8.00 per pound (Gillespie and Lewis, 2005). Louisiana crawfish meat is sold primarily to consumers and select restaurants that prefer the domestic product. The price gap between the two products is unlikely to be reduced unless there is a reduction in the cost of production in farming or processing.

By 1996, crawfish from China constituted approximately 70% - 80% of the United States crawfish market (ITC, 2003). This eventually led to an investigation by the ITC at the request of the U.S. House of Representatives. During the investigation, the Crawfish Processors' Alliance filed a petition with the U.S. Department of Commerce (DOC) and the ITC in September, 1996. It proclaimed that Chinese processors were dumping their product into the United States. Dumping occurs when a foreign competitor sells its product below cost in order to "drive out" domestic producers.

The imported product affected by the antidumping order under review, as defined by Commerce, consists of:

> freshwater crawfish tailmeat, in all forms, grades and sizes; whether fresh, chilled, or frozen; and regardless of how it is packed, preserved, or prepared. Excluded from the capacity of the investigation and order are live crawfish and other whole crawfish, whether fresh, frozen, boiled, or chilled. Also excluded are saltwater crawfish of any type, and their correlated parts. Freshwater crawfish tailmeat is currently classifiable in the Harmonized Tariff Schedule of the United States (HTSUS) under HTSUS subheading 0306.19.00.10 and 0306.29.00.00. The written account of the scope of this proceeding is dispositive (ITC, 2003, p.4).

A determination of "dumping" requires rulings by the DOC and the ITC on two conditions: (1) that the imported product has injured the domestic industry and (2) the product itself sells for less in the United States than it does in its home country (ITC, 2003). On August 29, 1997, the ITC determined that the U.S. crawfish industry had been "materially injured" by the imported tailmeat and ruled China was, in fact, dumping crawfish in the U.S. by selling below fair market value in the host country. The result was the imposition of tariffs on imported tailmeat from China ranging between 7.53% and 223.01%, with most of the tariffs in the 200% range. In its 2002 five-year review, the ITC determined that a revocation of the order would be detrimental to the industry because it would "materially injure" the domestic market. Thus, the duties were reinstated (ITC, 2003). The duty partially offsets the advantages China receives by decreasing the margin of prices between the two countries.

Since the mid-1990's, there has been escalated discussion among Louisiana crawfish processors on the need for a crawfish peeling machine. Crawfish tailmeat has been peeled and packaged using manual human labor. Even though the United States' biggest competitor, China, also uses human labor, its wages are lower than in the United States (ITC, 2003). For instance, the United States has a minimum wage law that exceeds wages in China. Other than labor, another point of discussion is the different qualities each country's product holds. U.S. tailmeat generally is thought to be of higher quality based on consumer preferences. Many suggest the major difference is China's product is always frozen, mainly due to shipping procedures, while the domestic product may be purchased fresh. If a machine were to be manufactured, it would likely be important to recognize the product differentiation that the U.S. crawfish tailmeat currently benefits from, such as a fresh product that includes a yellow substance technically known as the hepatopancreas, but commonly referred to as crawfish "fat."

Justification

As stated earlier, the total value of Louisiana's crawfish industry in 2005 was just over $45.2 million annually (LSU Ag Center, 2006). With the implementation of a crawfish peeling machine, the crawfish industry could not only potentially improve economic conditions in the industry, but be a larger contributor to the Louisiana economy. After the 2005 natural disasters of hurricanes Katrina and Rita, the overall Louisiana economy experienced reduced production. Fortunately, most crawfish habitats survived these storms. A peeling machine would serve as a resource in encouraging one of Louisiana's main economic sectors, seafood production, to compete with imports in the domestic market.

There are various segments within the crawfish industry, such as transportation and marketing. One segment capable of realizing significant cost decreases could be processing. Many in the industry believe that the introduction of a crawfish peeling machine would contribute to the reduction in costs for U.S. tailmeat. Little, however, is known about the market for a crawfish peeling machine. Even though some potential investors have expressed interest in developing a machine, they have been hesitant to invest money into the project until more information would be made available. In reality, U.S. costs of production are relatively high compared to China's cost of production, Louisiana processors produce at levels below their potential, and U.S. production share has decreased over time (ITC, 2003). By reducing some of the crawfish tailmeat production cost, the United States might recover some of the market share lost to its foreign competitors.

Many people who live outside of Louisiana do not understand how important crawfish is to the state's culture. The crawfish has become a symbol of the Cajun people, inhabitants of Louisiana since the mid 1700's. They were exiled from New Acadia by the British because they refused to pledge allegiance to the British Crown. More than 10,000 people migrated to Louisiana, where they found a permanent home. They are one of the oldest and most distinctive cultures in America. Today, more than one million people of Cajun or mixed Cajun descent live in Louisiana (Trépanier, 1991). Their form of the French language, a form of provincial French that has been passed down orally for three centuries, has virtually disappeared. However, the accented English and Cajun idioms prevail as do the music and food, in which crawfish plays an important role. An example is a testament of the Crawfish Festival explaining its significance as follows:

> "The Crawfish Festival, for example, officially begins with a 5:00 Mass, said either on the official grounds or in the church which abuts the

grounds. The new Crawfish Queen is already selected, in a competition held the weekend prior to the festival. On the festival grounds are a carnival show (which pays the festival association a prearranged portion of its income, often as much as 60%); food, beer, and souvenir booths; and a contest area. Contests include a crawfish peeling contest, a crawfish eating contest, and crawfish races, scheduled several hours apart. (Esman, 1982, p.203)."

In Louisiana and throughout the United States, the crawfish has become the symbol of the Cajun culture. They can be found on items such as: bumper stickers, T-shirts, postcards, and other souvenirs sold to tourists around the world. Crawfish is a main attraction in various Louisiana activities such as the New Orleans Jazz Festival and Mardi Gras. The most notable would be the annual Breaux Bridge Crawfish Festival that attracts thousands of people who travel from great distances to sample crawfish in Cajun cuisine, participate in crawfish eating contests, or cheer contestants in the crawfish race. The crawfish dispute between Louisiana and China can be argued to represent more than a mere trade disagreement, as crawfish symbolizes a distinct culture.

Objectives

The objectives of this research are to determine:

- The attributes most valued by processors in a crawfish peeling machine, and
- Whether crawfish processors are willing to adopt 3 hypothetical crawfish peeling machines given specific costs and descriptions.

The results of this study may be used by potential crawfish peeling machine developers who are deciding whether or not to allocate resources to machine development.

Problem Statement

One of the biggest challenges with the U.S. crawfish market is the high imports from China, which can produce crawfish at a relatively lower price (ITC, 2003). According to the ITC, China is "dumping" its product into the U.S. economy at a lower price, placing downward pressure on domestic prices. This makes it difficult for Louisiana crawfish producers to remain competitive, as evidenced by the relatively large difference in the two prices being charged. The development of a suitable crawfish peeling machine could potentially increase production and lower cost of production, therefore allowing the United States to be more competitive with the imported tailmeat from China.

Thesis Outline

The thesis will be organized into five chapters. Chapter Two is a review of literature relevant to the research problem. The research methodology is included in Chapter Three. It is comprised of three areas: conjoint analysis, technology adoption, and data collection. Descriptive statistics from the survey with the empirical results are included in Chapter Four. Chapter Five includes the summary, conclusions, and discussion of future research needs in crawfish processing.

Chapter 2

Review of Literature

Conjoint Analysis

In this study, conjoint and technology adoption analyses are used to assess processors' preferences for and willingness to adopt potential crawfish peeling machines. Thus, the literature review in this chapter deals primarily with studies using conjoint analysis or technology adoption questions, and studies analyzing the economics of crawfish processing in general.

It is generally accepted that 1964 marks the beginning of conjoint measurement, with a seminal paper by a mathematical psychologist named Luce and a statistician named Tukey (Luce and Tukey, 1964). There has been much advancement since their contributions. New product acceptance studies typically assume that a respondent's total utility for a hypothetical product is a function of the various attributes the product may possess. Conjoint analysis is a technique that may be used to determine the importance of selected machine attributes, as rated by processors. It can be used to estimate "part-worth" utilities.

Part-worth utilities are the partial effects of utility a respondent receives for a certain attribute level on the total utility. In its most common application, conjoint measurement provides a model for part-worth utilities for a mixture of attributes of multi-attribute alternatives which can be estimated from preference orderings of a set of factorially designed alternatives. The difficulty of this procedure is that it might be impossible for respondents to convey their part-worth utilities. Consequently, any attempt to measure overall utility by summing part-worth utility could produce outcomes with high measurement error. More recently, some authors have assumed the subject's rank orderings are measured on an interval scale. This makes it possible to use ordinary least squares regression (OLS) to estimate the parameters of the model. Therefore, the best hypothetical machine can be determined.

One category of conjoint analysis studies has sought to estimate a respondent's willingness to pay for a bundle of attributes associated with a product. Studies evaluating willingness to pay for new products include Mackenzie (1990); Lin, Payson, and Wertz (1996); Stevens, Barrett, and Willis (1997); and Miquel, Ryan, and McIntosh (2000). Willingness to pay is calculated directly from the marginal rates of substitution between price and non-price attributes projected from conjoint data. This approach requires respondents to rate or rank bundles as price and other attributes are varied.

Rating/Ranking

Greenhalgh and Neslin (1981) criticize self-stated ratings in their study of conjoint analysis for negotiator preferences. "Self-state" requires respondents to indicate the importance of various issues on a multicategory rating scale in order to measure preference (e.g. ranging from unimportant to highly important). Self-stated rating scales are reasonable for simple tradeoffs but not strong enough for more complex, realistic situations. They propose conjoint analysis is a better method for measuring preferences than the self-stated ratings procedure because it is difficult to aggregate self-stated importance measures into an overall preference in a bargaining situation.

Krosnik and Alwin (1988) assess the dissimilarity between rankings versus rating product profiles in conjoint analysis. They suggest ranking may be the preferable technique, after showing the discrepancies occurring when rating measures are used, which are due to the non-differentiation in responses. High ratings among all values stem from respondents' lack of motivation to make difficult choices among products. This makes their answers invalid and decreases the strength of the study. The ranking method forces them to make the complex choices they otherwise would not have made.

Green and Srinivasan (1990) extended their 1978 review of conjoint analysis with an article discussing new developments and data manipulation. When evaluating Wittinik and Cattin (1982), they concluded when using rankings and ratings data, the relative importance of an attribute increases as the levels on which they are defined increases, while holding the minimum and maximum levels constant. An example is price increasing seven percentage points when two intermediate price levels were introduced to the three levels that were already present. They offered the explanation that the addition of intermediate levels to an attribute psychologically makes the respondent pay more attention to it, increasing its overall importance in preferences. More research is needed to develop methods for minimizing or eliminating the problem.

Utility/Attributes

All conjoint applications begin with Zartman's (1977) process; the creation and selection of attributes. While it is possible to have a large number of attributes, only a limited set could be evaluated meaningfully. Although applications have been reported having more than 25 attributes (Green and Srinivasan, 1978), most involve less than seven, due to respondents' inability to evaluate complex multidimensional stimuli.

Periodically, conjoint analysis users criticize economists for accepting too many assumptions of theory. Mandasky (1980), states economists assume no more than the existence of complete, transitive preferences over "bundles." Bundles are groups of products that give its owner satisfaction from usage. Plott (1980) assumes a utility function (for the additive case) $U(i_1,\ldots,i_n) = V(1,i_1) + V(n,i_n)$; in this case, the theory automatically presumes all the assumptions found in the economic theoretic model. As expected, if we are taking into account various factors (n), with the *i*th factor ($i = 1,2,\ldots,n$), then we shall represent a bundle as an n-tuple ($i_1,i_2,\ldots i_n$). The function $U(i_1,\ldots, i_n)$ assumes the indifference curves having straight lines, by virtue of conjoint theory. The second point that needs emphasis is the nature of utility. The individual functions $V(j,i_j)$, when viewed ordinally, are translated within the "marginal rates of substitution" formula:

$$(1) \qquad \frac{V(j,x) - V(j,x-1)}{V(j',x') - V(j',x'-1)}$$

The conjoint model can be viewed as a unique case of ordinal economic preference theory under this interpretation. Thus, cardinal utility is unnecessary. Plott (1980) then discusses the "preference reversal" phenomenon. Preference reversal occurs when respondents express a preference for one bundle in a pair but then place a higher monetary value on another bundle (Gretcher and Plott, 1979). They believed this type of "intransitivity" cannot be included in either the conjoint analysis or quantal choice model.

Conjoint measurement is defined by Timmermans, Heyden, and Westerveld (1984) as being based on the possibility of measuring the relative contributions of two or more independent variables, even though their individual effects may not be measurable. Thus, they were concerned with simultaneously measuring the joint effect of two or more independent variables on the rank ordering of a dependent variable. This is normally accomplished by having respondents rank different alternatives with respect to overall utility.

Finally, expressing the utility function in monetary terms was noted as being important. Accomplishing this shows the incremental utilities that can be aggregated across individuals and weighed against the incremental cost. Srinvasan (1980) assumed the utility function is linear, that is,

$$(2) \qquad U_{ij} = \sum_{p=1}^{t} W_{ip} Y_{jp}$$

where U_{ij} is the estimated utility of the *i*th consumer for the *j*th object, W_{ip} is the estimated weight of the *i*th consumer for the *p*th attribute (p = 1,2,…, t), and Y_{jp} is the value of the Jth stimulus along the *p*th attribute. Then defining p = 1 to be a monetary attribute, such as price, and multiplying the equation by $(-1/w_{i1})$, it gives U'_{ij} denoting the utility in monetary terms.

Model Selection

In an effort to determine which model would best fit the data used in analysis for this study, research led to an evaluation of the work conducted by Srinvasan (1980). His investigations depict conjoint measurement and quantal choice models. Madansky (1980) informs that conjoint analysis deals with each respondent separately. On the other hand, quantal choice models are generally estimated at the aggregate level. Individual differences in preferences are not well represented at the aggregate level in quantal choice analysis. Thus, for marketing analysis, individual utility functions are more relevant. The present study regarding the implementation of a crawfish peeling machine was performed on the individual level. Therefore, it seems conjoint measurement would be the most appropriate choice.

DeSarbo et al. (1982) considers yet another type of analysis, three-way multivariate conjoint analysis. It differs from traditional metric conjoint analysis because it allows a researcher to examine several dependent variables simultaneously, as well as individual differences in response. Traditional metric conjoint analysis involves gathering preferences for various profiles and then decomposing the preference scores using regression, or other methods, to get part-worths for the various levels of the attributes. The assumptions are: (1) the gathered response data is metrically scaled and (2) the form of the constraints on the subject and profile modes is linear.

Recently, choice-based conjoint analysis, proposed by Louviere and Woodworth (1983), has been growing in popularity. It combines conjoint concepts with discrete choice theory and estimates an aggregate multinomial logit model using choice data. Choice-based conjoint models, however, suffer mathematically from the independence of irrelevant alternatives (IIA) property and the aggregated probabilistic representation of customer choice. An example of the IIA property being violated is the "blue bus/red bus paradox." Suppose an individual were given the option of taking a bus or a car for vacation. The probability of selecting either would be ½. Now let's change the choices to deciding between a red bus, blue bus, and a car; one would expect the probabilities to change to 1/4, 1/4, and 1/2 respectively, presuming color has no effect on choice. In this manner, selecting a bus would still have a 50% probability of getting chosen. The argument is adding more buses to the equation should not lower the probability of a respondent choosing that mode of transportation. However, the formulation in choice-based conjoint models would predict a probability of 1/3 for each of the three choices, which is counter-intuitive because it assumes the probability of selecting a bus increases to 66% (the summation of percentages attached to the red and blue bus) and decreases the probability of selecting a car to 33% when considering the addition of another color bus.

These problems collectively weaken the model's capability of assessing market heterogeneity at the individual level. Therefore, results gathered from this model should be applied only to products with monotonic attribute sets (Chen and Hausman, 2000). Mathematically, one possible way to resolve this situation is to use a nested logit model. However, some of the properties may be lost. The best way to alleviate the problem is by carefully selecting candidate products. This task does require more managerial judgment but would aid in correcting for the independence of irrelevant alternatives. The assumptions for customer preferences under choice-based conjoint analysis are:

- the total population size of the potential market is known;
- a potential customer will purchase at least one product from the product line;
- the probability of a potential customer purchasing a product from the product line is independent and identically distributed across customers;
- the production system has no capacity; and
- there are no fixed costs of introducing new products.

Chen and Hausman (2000) examine the mathematical properties behind the selection of products using choice-based conjoint analysis. Choice-based analysis forces consumers to make choices between products, which is the behavior marketers usually seek to predict. The problem of properly selecting/designing successful product lines is commonly formulated using a market response simulator based on traditional ratings/rankings-based conjoint analysis. The simulator estimates how consumers would respond to different products offering various attribute values.

Harrison, Gillespie, and Fields (2005) lend insights on model application. A main concern facing this study was the decision of which econometric model to use for the conjoint analysis: the ordered probit (OP) model or the two-limit tobit (TLT) model. The rank-order method encourages respondents to explicitly rank all hypothetical product choices. In such cases, the dependent variable is ordinal, and ordered regression models such as ordered probit are more suitable for conjoint estimation. On the other hand, the interval-rating method allows respondents to express order and prominence across product choices, which is a feature allowing both metric and nonmetric properties of utility to be drawn out. Model selection becomes less clear if interval-rating scaling is used. However, the obscured nature of the scale can be adjusted for with the two-limit tobit model, which corrects for censoring and retains metric information. While the ordered probit model is theoretically more appealing, the two-limit tobit model could be more useful in practice, if there are limited degrees of freedom, such as for individual level models. They found that two-limit tobit and ordered probit models result in the same attributes having roughly equal significance and signs.

Technology Adoption

No studies have been conducted on adoption rates of crawfish peeling machines, as no commercially available machines are in existence. However, there is some literature on the adoption rates of new technologies in other industries. The evidence that follows explains why some firms are more willing to implement new technological changes at faster rates than others. Of more importance, an analysis of whether or not firms can be successful followers after other firms adopt the new technology first shall be discussed in further detail.

Research and Development and Information Diffusion

Stoneman and Kwon (1996) explore the determinants of the returns to the adoption of new process technologies and calculate measures of that return. They criticize most literature on the return to technological change for inadvertently calculating the return to research and development (R&D), which is not a good proxy for the use of new technology because it is purchased from outside the company instead of being generated from within. Within the realm of their research, they reference Karshenas and Stoneman's (1993) diffusion theory. Diffusion theory hypothesizes the profit gained by the firm from the adoption of new technology will depend on the characteristics of the firm, number of other adopters, and position in order of adoption.

Being adequately informed about technological breakthroughs is vital to a firm's existence. Wozniak (1986) indicates early adopters need to acquire a better quality and larger quantity of information than others to reduce uncertainty. Producers who are better informed are more likely to be innovators than producers who are less informed. The two most relevant services accessible to farmers are the Agricultural Extension Service and private agricultural supply firms. Extension services specialize in disseminating information. Private supply firms supply information on how and when to use new technologies.

Wozniak (1986) presumes that the opportunity cost of not adopting an innovation increases with the scale of production. Producers functioning on a larger scale have a greater motive to obtain information about new innovations and production techniques than smaller scale producers. Large scales can supersede less education or experience, but if information is substituted, producers could encounter diminishing returns. This illustrates the importance of staying well-informed.

Lee (1985) modeled a large corporation that adopted the outputs from R&D, in addition to performing its own R&D to improve its products and processes. An example is the research on the adoption for use of optical fiber by ITT Incorporated, a world leader in engineering and manufacturing electronics. His investigations led to development of a model for firms' joint decisions of R&D and technology adoption. First, if there is an increase in the cost of R&D, a firm is less likely to perform R&D procedures. Second, an increase in the cost of technology adoption or an increase in market interest rates tends to make firms hesitant to adopt a new technology.

Feder, Just, and Zilberman (1982) reviewed theoretical and empirical studies on the diffusion of agricultural innovations in under-developed or less-developed countries (LDCs). In the paper, the adoption process is defined as "the mental process an individual passes from initially becoming aware of an innovation to final adoption." However, they believed a distinguishable definition must be declared between individual adoption and aggregate adoption. Adoption at the individual level (farm level) is the implementation of a new technology in long-run equilibrium with the farmer having acquired full disclosure of information about the new technology. Adoption at the aggregate level is now defined as "the process of spreading a new technology throughout a region." It is measured by the utilization of a specific new technology within a particular region or population.

Temporal Adoption

Feder, Just, and Zilberman (1982) bestows credit upon Zvi Griliches, a pioneering economist who produced a noteworthy article in 1957, for completing the first econometric study of aggregate adoption over time. He estimated the fraction of land used for hybrid corn as a function of time for 132 corn- producing regions. Griliches discovered variation in the diffusion curve parameters among regions. Further investigation confirmed that considerable variation in the rate of adoption of hybrid corn could be explained by differences in profitability of the new technology across different regions.

According to Hall and Densten (2002), "followership in technology has little value." In a temporal sense of the matter, most firms are destined to be followers when it comes to new technology adoption. It is perfectly logical because everyone cannot enter the market at the same time. The timing of market entry is a critical decision, weighing the risk of premature entry with the problems of lost opportunities as a result of late entry. Time of entry has distinctive factors that influence it.

Giovannetti (2000) performed an empirical study on technological adoption. It focused on the sequential patterns of diffusion for given technologies. His study highlighted that adoption of a new technology resembles an S-shaped time path and the diffusion rate varies across industries, as previously shown by Griliches (1957). There are two noted facts in the empirical literature on technology adoption: 1) There are highly diversified geographical patterns of adoption for new technologies and 2) Temporal technological adoption is constrained to a subset of firms in a given industry.

New technology adopters often bear some types of sunk costs. Sunk cost is an outlay or loss already incurred which cannot be recovered regardless of future events. Riordan and Salant (1994) proclaim a firm should weigh the sunk cost of each investment against the benefits from the lowered cost of production. Furthermore, the benefits a firm gains from new technology adoption are reduced when a competing firm adopts an even newer technology. They developed a formula to explain this mathematically: If v_i is the period of firm *i*'s technology, then the profit flow of firm 1 is $\pi_1(v_1, v_2)$. The profit flow of firm 2 is supposedly symmetric, $\pi_2(v_2, v_1)$ If firm 1 adopts a new technology at date *t*, and firm 2 does not follow, the respective profit flows are $\pi_1(t, v_2)$ and $\pi_2(v_2, t)$. This is interpreted as the profit firm 2 may not realize given their late adoption into the market, resulting in firm 1 attaining a profit surplus because of early adoption. Thus, the period of a firm's technology corresponds to its last adoption date. Firms begin symmetrically with technologies $v_i = 0$. They assume $\pi(v_1, v_2)$ is increasing in v_1 and decreasing in v_2. In other words, firms initially have the same opportunity to adopt new technologies; however, some choose to postpone adoption while others opt for early entrance. The time difference determines the possible profits to be attained by any given firm.

Lane (1991) uses the coal mining industry as a case study to show how technology adoption, if used correctly, can improve an industry as a whole. She states new technologies displace older methods and lead to advancements in productivity. Since the cost-benefit tradeoff directly affects the decision to invest in a new technology, the use of new technologies will not be uniform across adopters or time. Also, structure of the market plays a significant role, such as vertical integration. It may either expedite or hinder technology adoption. Underground mining traditionally had procedures that were carried out in separate, sequential operations. After World War II, more recent innovations, such as continuous mining machines, integrated the separate steps, enabling coal mining to be more efficient and profitable.

Barriers to Adoption

A study conducted by Sinha and Noble (2005) gives information on the development of what once was a new technology, automated teller machines (ATM), and how the banking industry adapted to its implementation. Consumers generally handled financial transactions through personal interactions between themselves and a bank teller inside of the establishment. Beginning in the early 1970's, ATMs offered an alternative way of doing business. Like any new technology, there were some issues that needed to be resolved. One example was the business-to-business challenge of formulating the division of usage fees among ATM network participants. Most convenience-based technologies have costs and benefits associated with them. For instance, a bank's adoption of the ATM resulted in a reduction in teller labor expense and a net reduction in costs per transaction from $1.20 to under $0.60 (Sinha and Noble, 2005). The model in which they based their study identifies three key reasons that influence the market entry decision: (1) sources of market opportunities, (2) firm characteristics, and (3) market characteristics.

The barriers to technology adoption and development were discussed by Parente and Prescott (1994). They proclaim the size of the barriers differs across time and regions. The larger these barriers, the greater the financial commitment a firm must make to espouse a more advanced technology. A model was constructed assuming a firm must make an investment to advance its technology level. The amount of investment required by a firm to progress from one technology level to a higher one depends upon two factors: the level of general and scientific knowledge in the world and the size of the barriers in the region. General and scientific knowledge is assumed to be available to all and expand exogenously. With growth in these types of knowledge, the amount of investment a firm must undergo to move from one technology level to a higher level should decrease.

Ex-Ante Adoption Studies

Thus far, most of the literature concerning the acquisition of a new technological process presented in this paper relates to ex-post technology adoption, which is relatively extensive in the field of agricultural economics. Studies pertaining to ex-ante technology adoption are less extensive. However, some researchers have published work regarding these unique provisions. Contingent valuation methods to determine non-adopter willingness to pay were the main focus for the majority of research readily available. The contingent valuation, which is used to elicit a consumer's willingness to pay for a specific good or service, is often used to evaluate the worth of non-priced environmental services. However, it could also be used to determine the demand for a good when a market does not exist or when a test market would become too costly or difficult to define.

Qiam and Janvry (2003) conducted research on Bt cotton, a genetically-modified (GM) crop, which contains a gene of the bacterium *Bacillus thuringiensis*, allowing it to be resistant to major insect pests. It was one of the first commercially available GM crops offered in the mid 1990s, developed by Monsanto. Based on data results from a survey on Argentina cotton producers by Qiam and Janvry (2003), it is shown that the seed technology significantly reduces insecticide applications and increase yields due to a lack of crops destroyed by insect damage. However, the advantages are outweighed by the high price charged for seeds that have been genetically modified. They used contingent valuation to show that farmers' average willingness to pay is less than half the actual technology price. Farmers had to pay $103 per hectare for the use of Bt cotton seeds (GAO, 2000), yet the mean willingness to pay was $48.

Farmers' decisions whether to use Bt cotton is modeled in a random utility framework, that is, he/she will not adopt unless utility associated with the technology is at least equal to or greater than without it. Argentina has a significant high dropout rate of Bt cotton users, unlike other countries where grower satisfaction is high. In their sample population (Qiam and Janvry, 2003), they observed about half the farmers who used the technology in the previous three years discontinued use in the following year. Bear in mind it is difficult to make practical conclusions based on the data available. There have been farmers who stopped using Bt in one season, but resumed again after a short period.

Hudson and Hite (2002) focused on the willingness to pay for a site-specific management system (SSM), which refers to a management technique that allows for the collection of spatially referenced in-field data. The system includes the most modern technological change in precision applications such as global positioning systems (GMS), in conjunction with older technology such as soil sampling and pest scouting. Like other ex-ante studies, contingent valuation was used to analyze (WTP) for SSM technology under the hypothesis that a higher willingness to pay coincides with higher adoption rates. However, unlike previous studies, a large, initial fixed investment cost must be endured to adopt the technology. It is common for producers to seek technological advances that reduce cost and/or increase profits.

A mail-in questionnaire was designed to obtain relevant information about various demographic statistics with a series of contingent valuation questions. Respondents were told that the price of a SSM package was $16,500 (Hudson and Hite, 2002). They were able to calculate a producer's WTP for a technological change by using the profit function, $\pi(p,z)$. Given the explicit profit function, the shadow price for the technology change is as follows;

$$s = \pi(\mathbf{p},z_1) - \pi(\mathbf{p},z_0) \tag{3}$$

The shadow price represents a producer's maximum WTP for a progress from standard to SSM technology. Price is denoted by **p** in the profit function while z_0 and z_1 are the initial technology and the SSM technology, respectively. Based on Hudson and Hite (2002), estimates for producer WTP is $3,316, which is 20% of the total cost to acquire the technology. This suggests either producers would be willing to pay $3,316 for the SSM package or they would expect the government to subsidize the package by 80% for the average producer to adopt it. Overall, this study implies SSM adoption is low and will not increase until effects on profits become more definite.

As mentioned above, Bt cotton was one of the most recent technological advances in the agricultural field. Hubbell, Marra, and Carlson (2000) commenced a study on the potential demand for Bt cotton in the southeastern states of the U.S. They used the information gathered within the first year of commercialization. A major problem at the time was the cost to other growers in close proximity to producers that used Bt cotton. Growers of other crops, including conventional cotton, may experience decreases in the effectiveness of sprayable Bt because insect resistance to the Bt toxin builds up over time. To estimate demand, they combined revealed preferences (RP) on Bt cotton varieties with the stated preferences (SP) data on willingness to adopt.

Since Bt cotton was already on the market, it had a price. Farmers either chose to adopt at the market price or not. Thus, farmers revealed their preferences for Bt cotton at the market price, which was a $32/acre technology fee (Hubbell, Marra, and Carlson, 2000). Some of the adopters stated they would be willing to pay more than the market price while the non-adopters stated they would adopt at a lower price. Combining the revealed choices for adopters with the revealed and stated choices for non-adopters allows for an estimation of willingness to pay (WTP). They believe this methodology to estimate WTP for a new technology where little information is available about price sensitivity could be very helpful in formulating policy responses. However, the full sample model that combined RP/SP tends to produce a higher adoption rate at any given price level relative to the sub-sample of non-adopters alone.

Direct input prices are known to have a significant effect on the price of commodities, but external factors also influence cost. Kenkel and Norris (1995) provided evidence that an external factor such as weather conditions directly affects producer incomes and profitability. A mesoscale weather network could provide improved weather information to agricultural producers because it would supply more accurate and timely data by using a denser network of observation points. The development of such a technology would require a substantial investment. There is also cost associated with machine maintenance and information distribution. Researchers in Oklahoma began work on a mesoscale network called “Mesonet,” costing $2.7 million in 1990. The estimated annual cost for maintenance and operating the system ranged from $500,000 to

$700,000 (Kenkel and Norris, 1995). Unlike a crawfish peeling machine, the Mesonet system offered data for public use; thus it was expected that public sources would assist with financial support. This study used contingent valuation (CV) to determine the willingness of Oklahoma producers to pay for the adoption of a mesoscale weather system.

Identifying a group of interested subscribers to the mesoscale service was crucial to the success of the Oklahoma program. The basis of Kenkel and Norris (1995) research stemmed from a Texas study performed by Vining, Pope, and Dugas (1984). Although the Texas survey did not use CV, their study mended the disparity since none have used contingent valuation to conclude a farmers' willingness to pay for improved weather information. The authors described their measurement of willingness to pay in the Texas study as "a pragmatic attempt to evaluate perceptions of the usefulness of weather information provided to Texas farmers." They found, on average, Texas producers were willing to pay $40/month for current weather information and as much as $118/month for perfect weather information, depending on the advanced time forecast (Kenkel and Norris, 1995).

Kinnucan, Molnar, and Venkateswaran (1990) analyzed the injectable protein bovine somatotropin (BST), which is capable of enhancing a cow's ability of producing 7% - 23% more milk. The demand for dairy products is price inelastic, meaning the BST-induced declines in price will have little effect on consumption. The main objective reported in this paper was the determination of bias in the scale neutrality of BST. For instance, technical innovations involving a large capital investment for fixed-inputs is disadvantageous for smaller farmers because per-unit cost of the new technology is higher. This issue was never explicitly addressed in previous studies.

Theory and related empirical work suggests an inverse relationship between risk aversion and wealth (Kinnucan, Molnar, and Venkateswaran, 1990), indicating the larger farmer, because of his greater wealth and diverse portfolio, will be more willing to accept the risk associated with the early adoption of a new technology and will adopt sooner than his counterpart, the smaller farmer. In addition, the larger farmer can spread search cost over a larger volume of production; the motivation to become more informed is greater for a larger farmer. The linkage between farm size and early adoption was tested using a logit model. Results indicate farmers with 1) large herd sizes, 2) higher levels of education and 3) readily available access to substantial capital are positively related to the adoption of BST technology. Surprisingly, farmers with more productive herds are slower to adopt BST, *ceteris paribus*. The negative sign associated with productivity and early adoption contradicts assumptions made in preceding studies that more productive farmers would be more willing to adopt BST (Kinnucan, Molnar, and Venkateswaran, 1990).

Economics of Crawfish Processing

An analysis of the Louisiana crawfish processing industry was conducted by Dellenbarger et al. (1986). Farmers had faced many hardships at that time. Crawfish production began to increase and spread in popularity to maintain income levels. The growth in plant capacities were a direct result of the increased production. At the time, the market demand was very limited to Louisiana and its immediate neighboring states. Processing plant expansions were governed by anticipated and actual demand for crawfish. In order to gain better insight of the industry, two surveys were formed to: 1) determine the operating characteristics of Louisiana crawfish processing plants and 2) establish product characteristics that would influence product marketability to wholesalers outside of Louisiana. Of the 81 processors in business, 38 were surveyed to determine the amount of crawfish being handled, types of products offered, and destination of the processed products. Size, price, payment methods and product transportation were also items of concern in the survey.

Crawfish harvesting and processing are both seasonal in nature as indicated by Dellenbarger et al. (1986). The actual harvesting begins in October and periodically continues until August. Therefore, processors diversify their production by marketing other species of seafood to minimize downtime. Twenty-one of the 38 processed other products on the property. Plant managers stressed the high dependence on manual labor for processing and peeling the finished product. From the earliest days of processing crawfish to today, the peeling of cooked crawfish has been unchanged. Thus, labor is a significant input in the industry. The crawfish processing plants averaged 5.4 full-time annual employees, 4.4 other wage-type seasonal employees, and 27.6 peelers per plant. They (peelers) were compensated on a "piece-rate" basis.

Crawfish processors sold multiple variations of crawfish products (Dellenbarger et al., 1986). Unpurged crawfish, which differ from purged crawfish because they possess the black vein (since they are not held in water for the 24-36 hour period) was responsible for 56% of the crawfish liveweight equivalent handled by processors. Sales of fresh tailmeat in conjunction with unpurged crawfish accounted for 67% of total revenues. Other products accounted for 15% while frozen tailmeat accounted for 10% of sales. The crawfish industry contributed $47 million to the Louisiana economy during the 1983-84 crawfish season. Total cost of crawfish production was close to $16.5 million. Operating costs associated with the operation varied with the size of the facility, volume carried and the types of products produced. A major finding was the cost of the actual crawfish, the raw material, was the largest expense, responsible for 68% of the cost associated with processing. It was estimated that the processing plants were fully depreciated, which reduced fixed cost relative to other costs (Dellenbarger et al., 1986).

Gillespie and Capdeboscq (1996) conducted a survey to become knowledgeable of the factors that needed to be considered when developing a crawfish peeling machine. Their research is the framework for the present study conducted. They gathered information on crawfish peeling labor cost, crawfish labor availability, crawfish processors' acceptance of hypothetical crawfish peeling machines, factors that would influence potential machine developers' decisions, and monetary expenditures on acquiring such a machine. A partial budgeting structure was created in order for the potential investors to be well informed about the type of machine to develop, if any.

Harrison, Özayan, and Meyers (1998) analyzed new food products processed from small crawfish, such as crawfish base and seafood stuffing. They believed the Louisiana crawfish industry did not maximize the use of smaller graded crawfish. The main products the industry generates are live crawfish and peeled tailmeat. Most of the crawfish comes from the Atchafalaya Basin. After fisherman harvest the crawfish, they are sorted into three or four grades. The larger grades are sold abroad to European markets or kept in the domestic market for live sales, which would be set at a premium price. The smaller grades, which can account for as much as 20% of the yield, are the by-products of the peeling process and are generally not suitable for sale in the live markets. Thus, they are priced well below the market price. More importantly, the crawfish industry produces about 80 million pounds of small crawfish during peeling recovery, where only 15% is edible tailmeat (Harrison et al., 1998). It was reported by earlier researchers that on-farm area dedicated crawfish production decreased by 5,000 acres in 1990. They concluded the decrease was a direct result from a decline in the demand for domestic crawfish caused by lower priced substitute products. Harrison, Stringer, and Prinyawiwatkul (2002) later conducted conjoint analysis on the attributes of additional value-added products that could be derived from crawfish, such as sausage.

Chapter 3

Methods and Analytical Techniques

This chapter is comprised of three sections. The first gives a description of the data collection process. The second discusses the conjoint method, with a sub-section describing a cluster analysis. The final section explains the exogenous criteria to be analyzed for the adoption of a new technology.

Data Collection

A survey was formulated to collect data for this research. The survey followed the outline of a survey conducted by Gillespie and Capdeboscq (1996) with additional questions included. The researchers decided personal interviews, as opposed to mail surveys, would be more suitable, considering the intricate nature of the questions being asked, such as conjoint and technology adoption questions. According to Dillman (1991), mail surveys are more frequently used for social research than any other survey method due to the much lower cost for completion. However, they usually yield response rates of 70 percent to 75 percent in large general population samples. Person-to-person interviews are more costly but have higher response rates.

Since there is a small sample size in the present study, the researchers chose the personal interview method to encourage as many respondents as possible to participate for greater accuracy. Calls were made to determine who and how many processors were still involved in the crawfish peeling business. All active processors who were identified by the Louisiana Department of Agriculture and Forestry personnel as potential processors were sent a letter requesting a visit to their plant with the expectation of completing an interview. Then processors received follow-up phone calls and thirty (30) gave their consent for the survey. Dates and times were confirmed for the interviews, leading the researchers to travel to the plants and conduct the surveys.

The researchers originally sent letters to fifty-three (53) firms requesting interviews. Ten were no longer in business, five were returned as non-deliverable, three did not agree to participate in a survey, one was not in the peeling business and seven were either never reached after frequent attempts or a time could not be agreed upon to take the survey. Even though three firms that were interviewed were not peeling anymore, they were formerly active peelers but presently only dealt with live crawfish. They were still included in the study because they expressed interest in a crawfish peeling machine if it were to be developed. This resulted in the 30 surveyed processors.

Upon arrival to each firm, the researchers reassured the processors any information gathered during the interview would remain confidential, as had been approved by the Internal Review Board of the LSU AgCenter, Human Subjects Committee. In most cases, the interview was conducted in a private setting, usually the main office of the processing plant. The researchers then asked the questions from the survey (Appendix A).

The survey was developed with 6 sections. The first section dealt with information on the volume of crawfish that was presently being processed. Processing months and labor availability were the main focus of this section. The second section determined the equipment currently owned by the processing plant, such as crawfish graders and cooking systems. The third section asked respondents to provide information on crawfish peeling labor and associated costs. Determination of crawfish peeling machine acceptability was the main objective in Section Four. This was one of the most important sub-sections because the answers revealed preferences for specific attributes of the machines. The fifth section contained the conjoint analysis questions. The sixth and final section included valuation questions where 3 specific machines (medium, large, and small) were made available. This was carried out to gain information on technology adoption.

Conjoint Analysis

Conjoint Analysis (CA) was introduced in the 1970's to quantify consumer tradeoffs (Cattin and Wittink 1982). Conjoint Analysis uses a survey-based approach to determine the importance of attributes in determining preferences for products or services. The conceptual model for conjoint analysis follows the theory that consumers generally choose products according to the attributes linked to the product.

Using conjoint analysis, the preferences of Louisiana crawfish processors in adopting crawfish peeling machines are analyzed. Utility is the numerical score representing the satisfaction a consumer gains from acquiring a product. For instance, if buying one pair of shoes provides more satisfaction than buying one shirt, the shoes provide more utility than the shirt. Utility is the dependent variable in the conjoint model. A processor's utility could be defined as:

$$U_Y = f(\text{devein, retain fat, retain backstrap, handling, own})$$

where U_Y is, in this case, the processor's utility associated with machine Y. U_Y is dependent on levels of combinations of attributes, such as whether the machine deveins, retains the backstrap, whether individual handling of each crawfish is required, and whether it is owned or leased. Thus, utility is assumed to be based on the value placed on each of the levels of the attributes.

The attributes were initially selected from a discussion with a local crawfish processor who informed the researchers the important qualities his colleagues deemed to be of importance in a machine that would replace their current peeling labor. A meeting was arranged between the researchers and Laitram Inc., a potential developer of a crawfish peeling machine that is involved seafood processing equipment manufacturing and distribution. It was confirmed the attributes stated by the processor were of importance to the success of a crawfish peeling machine. These interviews provided insight over and above experience held by Gillespie from a previous study (Gillespie and Capdeboscq, 1996). Unlike some other conjoint analyses, price was not included in the equation. Price was excluded because it would be dependent on the size of the machine and the attributes of the machine. More important, there was no previous knowledge of machine costs so there was little basis to affix a price.

As stated earlier, data were collected to elicit preferences via conjoint analysis through survey questions. Respondents were initially asked the following questions: "Would you prefer a machine that deveins or does not devein the crawfish?;" "Would you prefer a machine that retains the fat or does not retain the fat of the crawfish?;" "Would you prefer a machine that retains the backstrap or does not retain the backstrap of the crawfish?;" "Would you prefer a machine in which an individual must handle each crawfish or one in which an individual need not handle each crawfish?;" "If you were to adopt a crawfish peeling machine, would you prefer to own or lease it on an annual basis assuming necessary maintenance services were included in the price?" Answers to these five questions provided the framework for determining a "most desired machine" and a "least desired machine" for each respondent. These two machines were then described to the respondent with the information gathered and assigned ratings of 10 and 0, respectively. This would anchor the most and least preferred machines at the extreme values such that all others would be rated accordingly.

One of the main goals of this research was to gather useful information about a processor's rating of a particular crawfish peeling machine. A full factorial design, which includes all combinations of attributes and their associated levels, requires a respondent to analyze each profile individually. This study had five attributes at two levels each, resulting in 32 profiles (2x2x2x2x2 = 32) in the full factorial design. This proved to be an excessive amount of information for any respondent to functionally analyze; therefore other designs were examined to reduce the number of profiles for evaluation.

A fractional factorial design was considered to minimize ambiguity and maximize selected choice validity. It is a sample of attribute levels from the full factorial design without losing valuable information, so it effectively measures the effects of the attributes on the preference of the producer. Fractional factorial designs provide an orthogonal collection of profiles for analysis by each respondent (Green and Srinivasan, 1990). With this approach, only the main effects are estimated, reducing the number of profiles to an ideal level.

Conjoint Designer software was used to determine the fractional factorial design. There were five attributes at two levels each entered in the program. It reduced the number of profiles from 32 to 8. Two additional hold-out machines were introduced for processors to evaluate. They were included to assess the internal validity of the model. The two hold-out machine options would be used to determine whether the firms' predicted ratings would differ significantly from their actual ratings in the aggregate models.

Formally stated, the five major attributes processors deemed most valuable in a potential crawfish peeling machine were: (1) whether or not the machine would be able to devein the crawfish, (2) whether or not the machine would retain the fat, (3) whether or not the machine would retain the backstrap, (4) whether or not the machine would require individual handling of each crawfish, and (5) whether the machine would be owned or leased.

It was assumed all other machines with differing levels of the above 5 attributes would be positioned between the most and least desired machines, and accordingly range between 10 and 0. The ten alternative machines were then presented to the processors on a corresponding sheet. The processor was asked to examine each of these machines and rate them on a scale from 0 to 10, where 0 represented the least favored machine and 10 represented the most favored machine. Given that the "0" and "10" ratings had already been established for the least and most favored machines, respectively, other ratings of 0 and 10 were not expected. Each machine had a description of its capabilities and limitations accompanied alongside. They are described in Table 3.1.

A two-limit tobit model was used to determine the importance of specific attributes. A two-limit tobit (TLT) is the preferred method as opposed to the Ordered Probit (OP) model because when degrees of freedom are limited, such as the case with individual-level conjoint models, the OP cannot be estimated. Harrison, Gillespie, and Fields (2005) showed that there were no significant differences in part-worths estimated by OP and TLT using three datasets. Since individual level models would be run for this study, the TLT is used here.

Table 3.1: Hypothetical Crawfish Peeling Machine Descriptions

Machine 1	**Machine 6**
Devein	No Devein
Keep Fat	No Fat
Handling	Handling
Backstrap	Backstrap
Own	Lease
Machine 2	**Machine 7**
No Devein	Devein
Keep Fat	No Fat
Handling	No Handling
No Backstrap	Backstrap
Lease	Lease
Machine 3	**Machine 8**
Devein	No Devein
Keep Fat	No Fat
No Handling	No Handling
No Backstrap	No Backstrap
Lease	Lease
Machine 4	**Machine 9**
No Devein	Devein
Keep Fat	Keep Fat
No Handling	No Handling
Backstrap	Backstrap
Own	Lease
Machine 5	**Machine 10**
Devein	No Devein
No Fat	No Fat
Handling	Handling
No Backstrap	No Backstrap
Own	Own

Description of Independent Variables

In the present study, the independent variables are presented as follows: DEVEIN, FAT, NOHANDLI, BACKSTRA, and OWN. These variables were used in a two-limit tobit model to attain part-worth estimates for the aggregate and individual firm models. The model can be written as follows (Verbeek, p. 198):

$$(4) \qquad \begin{aligned} y_i^* &= x_i'\beta + \varepsilon_i, \quad i = 1,2,\ldots,N, \\ y_i &= L_{1i} \text{ if } y_i \leq L_{1i} \\ &= y_i^* \text{ if } L_{1i} < y_i^* < L_{2i} \\ &= L_{2i} \text{ if } y_i^* \geq L_{2i} \end{aligned}$$

where ε_i is assumed to be $(0,\sigma^2)$ and independent of x_i. This means the error terms ε_i are independent drawings from a normal distribution (NID) with mean 0 and variance σ^2. The latent variable is y_i^* and the dependent variable (machine rating) is y_i. In this model, L_{1i} and L_{2i} represent the lower and upper limits, respectively. The marginal effects for the two-limit tobit could be written as (Greene, p. 766):

$$(5) \qquad \frac{\partial E[y_i \mid x_i]}{\partial x_i} = \beta[\Phi(L_{2i} - x_i'\beta/\sigma) - \Phi(L_{1i} - x_i'\beta/\sigma)]$$

The change in x_i affects the conditional mean of y_i^* in the distribution, also influencing which part of the distribution the observation will be a part of. In addition, each variable was considered to contribute to the importance of the prospective peeling machine; therefore part-worths were tabulated for the entire industry and at the firm level. Definitions of the variables used in the analysis are as follows:

DEVEIN represents the process in which a machine would remove the black vein found on top of the crawfish tailmeat, underneath the hard exterior shell. It generally encases the sand and waste the crawfish passes through its body, emitting off-odors and a fishy taste. Consumers are assumed to generally prefer the vein not to be present in the end product. DEVEIN is a dummy variable that takes the value of 1 if the machine performs this task or a 0 if it does not.

FAT is the yellow-orange substance, also known as hepatopancreas, found around the crawfish tailmeat. Processors deem this important because it adds richness and flavor to the product. Most consumers of the popular Cajun cuisines have become accustomed to purchasing crawfish tailmeat with the fat surrounding it (crawdads.net, 1990). FAT is a dummy variable that takes the value of 1 if the machine retains the fat or a 0 if it does not.

NOHANDLI represents the absence of manual labor required to handle each individual crawfish when using a hypothetical peeling machine. Individual handling of each crawfish would generally require more labor. If the machine did not require any individual handling of each crawfish, it received a value of 1; 0 otherwise.

BACKSTRA is a dummy variable indicating the presence of the meat covering the black vein on top of the crawfish tailmeat. It accounts for roughly 15% of the total body weight of the peeled crawfish tailmeat. This is why processors are expected to prefer a machine that would retain the backstrap; they would lose considerable volume if the backstrap were lost in the deveining process. BACKSTRA is dummy variable that takes the value of 1 if the hypothetical machine could preserve it without harm or a 0 if it could not.

OWN represents whether processors would own or lease the machine. If owned, they would purchase it. If leased, they would pay a specified amount per period, without accruing equity in the machine. OWN is a dummy variable that takes the value of 1 if the processor prefers to own the machine or 0 if they prefer to lease it.

The data elicited from the conjoint analysis were tested for multicollinearity. Ramanathan (2002, pp. 319-316) states, in controlled experiments, that the right-hand side variables in a statistical model may have been designated with specific values in a way that their individual effects can be identified with precision. In an uncontrolled experiment, many of the economic variables move together in a systematic pattern. When this occurs, the variables are said to be collinear. Multicollinearity is the result when several variables are involved. A commonly used rule is that the absolute value of a correlation coefficient between two descriptive variables greater than 0.8 suggests a strong linear association and a potentially hurtful collinear relationship. To determine multicollinearity, the variation inflation factors (VIF) in conjunction with the condition index (CI) values will be used for analysis (Ramanathan, pp. 318-319). Multicollinearity would not be expected to be problematic in a conjoint model using a fractional factorial design due to orthogonality, but it is tested for in this study.

Another problem that may arise but can be detected and resolved is heteroskedasticity. Heteroskedasticity exists when the variances of the errors is not the same (Ramanathan, p. 415). One method of identifying heteroskedasticity is to estimate the model using least squares and to plot the least squares residuals. If the errors are heteroskedastic, they may demonstrate greater variation in a systematic way. White's LM Test will be the method of analysis for determining heteroskedasticity. This method of investigating heteroskedasticity can be used for any simple regression (Greene, p.

222). As with multicollinearity, heteroskedasticity would not generally be expected in conjoint models, but it is tested for in this case.

Cluster Analysis

Among the most valuable information a possible investor of a crawfish peeling machine can have is the knowledge of what types of processors prefer specific types of machines. A method known as cluster analysis may help in providing such information. Cluster analysis is a multivariate statistical technique which assesses the similarities between units in order to create homogeneous groups of cases or variables (Hair et al. 1998, p. 473). Clusters are formed using distance functions. The objective is to maximize the homogeneity within the clusters and maximize the heterogeneity between the clusters. The elements in a cluster have moderately small distances from each other and relatively larger distances from factors outside of a cluster. It is the expectation of the researcher to separate the 30 crawfish processors interviewed in the study into two or three clusters (groups) with similar demographics or resources.

Once the processors are distinguished by their cluster, developers of the potential crawfish peeling machine would be able to manufacture various versions of the machine by including or excluding machine capabilities, depending on the type of customer requesting the order. This would also enable vendors to make the machine more appealing in terms of product acceptability.

With respect to this study, the SPSS statistical software is used to execute a cluster analysis program based on the part-worth estimates reported in the conjoint analysis. To identify the clusters, Ward's method is used. Ward's method is an agglomerative clustering method in which the similarity used to link clusters is calculated as the sum of squares between the two clusters computed for all variables. This method usually produces clusters of approximately equal size because of its minimization of within-group variation (Hair et al. 1998, p. 473).

The most common types of algorithmic procedures using Ward's method are hierarchical and nonhierarchical procedures. A hierarchical procedure involves a stepwise clustering procedure consisting of a combination, or division, of the objects into clusters. For example, if the procedure starts with five objects in separate clusters, it will explain the reduction of the separate clusters into finally one cluster. Instead of a treelike construction process expressed in the hierarchical procedure, the nonhierarchical procedure produces only a single cluster solution for a set of cluster seeds based on the number of clusters specified (Hair et al. 1998, p. 496). For example, if only two cluster seeds are specified, only two clusters are formed. For this study, the nonhierarchical procedure was chosen due to the limited number of observations.

To determine the preference structure for individuals within the cluster, two-limit tobit models were generated on the data for each cluster. The model for each cluster was evaluated with the same methodology as the aggregate model for all respondents. The part-worth estimates and relative importance values for the attributes was evaluated to determine producer preference in each cluster. Lastly, the part-worth estimates induced by the two-limit tobit models for each cluster were compared to the other cluster to establish the difference in cluster affinities to various elements.

In order to determine differences in processor characteristics among the clusters, the clusters were evaluated based upon the characteristics of each crawfish processor using a logit model. The model can be written as follows (Verbeek, p. 179):

(6) $F(w) = L(w) = e^{w}/1+ e^{w}$

The essential characteristics that were considered in the logit were: pounds (in thousands) of tailmeat peeled (Meat1000); production of value added products (Valueadd); whether other seafood species are also processed (Diverse); the percentage of purchased crawfish that are peeled (Pctpeel2); whether enough labor is available during the peeling season (Labor3); cooker capacity (Lbcook13); presence of a continuous cooker (Contco12); whether alteration of facilities would be required to adopt a large machine (Alter15); wage per pound peeled paid to workers (Wage20); years the processor is expected to remain in the crawfish peeling business (Years43); and whether the processor anticipates a close family member to take over the business (Family44).

Technology Adoption

The processors were asked to respond to what degree of certainty they would or would not purchase the offered machine. They were then asked to determine the degree of certainty or uncertainty of adoption if the machine were offered as a lease option at a comparable rate on an annual basis. The three different machines are as follows:

- **Medium Peeling Machine**

1. Peels 1000 lbs of shell-on, cooked crawfish per hour (8000 lbs per 8-hour day, 40,000 per 40-hour week, 168,000 lbs per 21-day month, or 504,000 lbs for 3 months).
2. Allows an individual to pour 500-lb totes of shell-on, cooked crawfish into a hopper at a time, and at the end of an assembly line, peeled crawfish is delivered.
3. Crawfish are deveined, the backstrap is saved, and the fat is recovered.
4. Wastewater is filtered and recirculated, reducing water consumption. With this system, water usage is 28 gal/min (1,680 gal/hr, 13,440 gal/day, 67,200 gal/wk, 282,240 gal/mo, or 846,720 gal/3 months).
5. The machine may be purchased for $250,000.
6. Electrical usage is based on 22 hp of use. As the machines are running, the charge is $1.00/hr ($8.00/day, $40.00/wk, $168.00/mo, or $504.00/3 months).
7. 5 workers are required to run this system. These include persons familiar with the machinery, as well as those who can inspect the product upon peeling. At a rate of

$10.00/hr, this would cost $400.00/day ($2000.00/week, $8400.00/mo, or $25,200/3 months).
8. Assume the useful life of this machine is 10 years. Maintenance cost would be approximately $60,000/year.

- **Large Peeling Machine**

1. Peels 2000 lbs of shell-on, cooked crawfish per hour (16,000 lbs per 8-hour day, 80,000 per 40-hour week, 336,000 lbs per 21-day month, or 1,008,000 lbs for 3 months).
2. Allows an individual to pour 500-lb totes of shell-on, cooked crawfish into a hopper at a time, and at the end of an assembly line, peeled crawfish is delivered.
3. Crawfish are deveined, the backstrap is saved, and the fat is recovered.
4. Wastewater is filtered and recirculated, reducing water consumption. Thus, water usage is 46 gal/min (2,760 gal/hr, 22,080 gal/day, 110,400 gal/wk, 463,680 gal/mo, or 1,391,040 gal/3 months).
5. The machines may be purchased for $370,000.
6. Electrical usage is based on 29 hp of use. As the machines are running, the charge is $1.40/hr ($11.00/day, $56.00/wk, $235.00/mo, or $705.00/3 months).
7. 5 workers are required to run this system. These include persons familiar with the machinery, as well as those who can inspect the product upon peeling. At a rate of $10.00/hr, this would cost $400.00/day ($2000.00/week, $8400.00/mo, or $25,200/3 months).
8. Assume the useful life of this machine is 10 years. Maintenance cost would be approximately $90,000/year.

- **Small Crawfish Peeling Machine**

1. The machine can sit on a table top. Its dimensions are 1ft X 2ft.
2. Two people are needed to operate the machine, one to feed the individual crawfish into the machine and one to visually inspect them when they are peeled.
3. Crawfish are peeled and deveined. The backstrap is saved.
4. Crawfish fat may be recovered.
5. The machine can process 45 crawfish per minute.
6. The machine is electric.
7. The machine costs $2,000.
8. Assume the useful life of this machine is 10 years.

Processors were asked whether they would adopt particular hypothetically developed crawfish peeling machines if they were the only machines in existence for peeling crawfish with seven different degrees of certainty. They were provided with sheets containing all of the information about each machine as shown above. They were not provided with a pre-determined cost per pound associated with each machine because they were advised to consider this for their personal situations. The different levels of certainty were asked for the 1,000 pound per hour peeling machine, 2,000 pound per hour peeling machine and the small, individually fed machine. The respondents were to indicate one of the following seven options:

- **Would you purchase this machine?**

1. I am 100 percent certain I would purchase this machine.
2. I am almost certain I would purchase this machine (with 81-99 percent certainty).
3. I would more than likely purchase this machine (with 61-80 percent certainty).
4. I am not at all certain whether or not I would purchase this machine (with 41-60 percent certainty).
5. I would more than likely not purchase this machine (with 61-80 percent certainty).
6. I am almost certain I would not purchase this machine (with 81-99 percent certainty).
7. I am 100 percent certain I would not purchase this machine.

The following question was then asked of respondents concerning leasing the machine.

- **Would you lease this machine at a comparable rate on an annual basis?**

1. I am 100 percent certain I would lease this machine.
2. I am almost certain I would lease this machine (with 81-99 percent certainty).
3. I would more than likely lease this machine (with 61-80 percent certainty).
4. I am not at all certain whether or not I would lease this machine (with 41-60 percent certainty).
5. I would more than likely not lease this machine (with 61-80 percent certainty).
6. I am almost certain I would not lease this machine (with 81-99 percent certainty).
7. I am 100 percent certain I would not lease this machine.

Ordered probit programs were written to assess the technological adoption process. The first was to analyze the firms' acceptance of the three hypothetical machines with seven degrees of certainty ranging from 100% certainty of purchase or lease to 100% certainty of not purchasing or leasing the machine. To extend upon this analysis, programs were run to model the certainty of purchasing and leasing the hypothetical small, medium, or large machines without taking the other two machines into consideration. This was of interest to explore whether the size of the machine had an effect on the variables being analyzed. For the single machine models, several responses were never or rarely (once or twice) selected. For instance, only two processors indicated they were 81% - 99% certain they would not purchase or lease the medium machine. In these cases, these responses were combined with an adjacent response for estimation. Tests for multicollinearity and heteroskedasticity were conducted for the variables used in the ordered probit model in the same manner as discussed earlier.

In statistics, a probit model is a popular specification of a generalized linear model, using the probit link function. The probit function is the inverse cumulative distribution function of the normal distribution. Ordered probit is suitable when the dependent variable is naturally ordered and assumes more than two values. In this study, seven potential responses were provided, ordered from 0 (100% certainty the processor would not purchase or lease the machine) to 6 (100% certainty the processor would purchase or lease the machine). Probabilities in the ordered probit are estimated as follows (Verbeek, p. 190):

$$
\begin{aligned}
(7) \qquad & \Pr(y = 0) = \Phi(-\beta'\chi), \\
& \Pr(y = 1) = \Phi(\mu_1 - \beta'\chi) - \Phi(-\beta'\chi), \\
& \Pr(y = 2) = \Phi(\mu_2 - \beta'\chi) - \Phi(\mu_1 - \beta'\chi), \\
& . \\
& . \\
& \Pr(y = J) = 1 - \Phi(\mu_{j-1} - \beta'\chi)
\end{aligned}
$$

where Pr(.) represents probability, the function $\Phi(.)$ is a commonly used notation for the standard normal distribution, β represents the estimated parameters, μ are threshold levels and x are the independent variables in the model.

Processors are assumed to maximize profits subject to a budget constraint. An ordered probit analysis was considered to be the best model for implementation in the study due to the ordered nature of response options. The 30 processors were asked to indicate their certainty in response for the medium and large hypothetical machines given seven levels of uncertainty for the lease and purchase options. Only the purchase option was elicited for the small machine with the same levels of uncertainty. Respondents were only given the purchasing option for the small, individually fed machine since it was assumed a machine at this price level {$2,000} would not likely be offered for lease. This resulted in 150 observations considered for the combined ordered probit model.

Uncertainty is incorporated into the model because a crawfish peeling machine has never been made commercially available. Polychotomous choice questions that requested the level of certainty of adoption were asked, acknowledging that there would be significant uncertainty in a respondent's answer regarding the adoption of a technology that had not yet been developed. According to Kenkel and Norris (1995), the contingent valuation method that includes uncertainty responses can be used to determine the extent to which individual buyers could be expected to purchase a non-existent good. Though the current study is not technically a contingent valuation study, eliciting willingness to adopt in this manner avoids the nonresponse problem which has been found in an open-ended format.

Model Specification

The adoption of technology is influenced by distinct variables. With regards to the present research, important independent variables are: meat peeled annually, whether value added products are produced, diversification, percentage of purchased crawfish that are peeled, labor availability, whether a grader is owned or leased, crawfish cooker capacity, whether a continuous cooker is present, whether altering of facilities would be required for a large machine, piece rate currently paid to labor per pound, whether a machine would be purchased or leased, dummy variables for machine size, years expected to remain in crawfish processing, and having a family member expected to take over the operation upon the operator's retirement.

Four different models (aggregate, large, medium, and small) were developed to gain information on the adoption of the hypothetical crawfish peeling machines. The aggregate model considered all of the independent variables listed below since it encompassed all of the machines offered. The large and medium models contained the same variables but differed from the aggregate model because they excluded the large and small machine dummy variables. The small machine model included all of the independent variables of the large and medium models except for altering the facilities (Alter15) and purchasing the machine (Purchase). The independent variable indicating the alterations to the current facility was not included in the small model because it was assumed a small-sized peeling machine would not require processors to make modifications for adoption. The purchase variable was not included in the small model because it was the only option in adopting this size machine. A formal listing of the independent variables included in the models is as follows:

Meat 1000 is the total annual amount of peeled crawfish tailmeat in thousands of pounds produced by the firm. Larger producers tend to be greater adopters of technology (Kinnucan et al., 1990).

Valueadd is a dummy variable indicating that value-added products are produced at the processor's facility. This variable is included to explore how value-added products would affect adoption.

Diverse is a dummy variable indicating that other species of seafood besides crawfish are processed. Processors that sell other species that require extensive labor but are processed in a different season, such as crabs, would be less likely to adopt a machine. This would be due to the need to fully employ labor year-round.

Pctpeel2 indicates the percentage of all purchased crawfish peeled. The percentage peeled might bear significance in the adoption of a crawfish peeling machine because a processor may have most of its sales coming from live sales. An increase in the percentage of crawfish peeled is expected to have a positive effect on the adoption of a crawfish peeling machine.

Labor3 is an independent variable denoting sufficient labor availability throughout the peeling season for peeling crawfish. A crawfish peeling machine would be the substitute for peeling labor so it is of great interest whether or not enough labor is available. Processors who believe there is not enough labor available are expected to assume the adoption of a peeling machine would be beneficial and more favorable. On the other hand, if there is not a real or perceived threat of a limited supply of labor, then the need for the peeling machine may not be as great.

Grader8 represents whether the processor stated they owned or leased a crawfish grader. There are generally four grades (sizes) of crawfish; (1) Jumbo 15 (count/lb) and under, (2) Large 16-20, (3) Medium 21-24, and (4) Peeler 25 and over. Most processors grade two to three sizes of crawfish, rarely all four. The possession of a grader should be complimentary to the adoption of a crawfish peeling machine since only the small crawfish (Medium and Peeler) are likely to be peeled.

Lbcook13 is the approximate poundage of live crawfish a processor's cooking facility can handle during one working day. Some producers reported their cooked crawfish in terms of hourly production. In order to get an accurate account of daily production potential, this number was converted into eight hour work day units. More extensive cooking capacity would be complimentary with peeling machine adoption, especially for larger peeling machines.

Contco12 is a dummy variable indicating the processor owns or leases a continuous cooker. A continuous cooker is used to cook larger amounts of crawfish, perhaps more consistently. It is possible that the presence of a continuous cooker would be of importance in the incorporation of a crawfish peeling machine. Consistency may be of importance in the adoption of a crawfish peeling machine.

Alter15 is a dummy variable indicating a significant alteration of a processor's current facility would be required if a peeling machine were to be adopted. It is assumed the machine would replace their current peeling labor. The large machine is assumed to require 900 square feet or a space of 35ft x 50ft. However, this would not include the space for cooking or packaging the crawfish. The need to alter facilities to accommodate new technology would serve as a disincentive to adopt.

Wage20 is the piece-rate at which processors compensate their workers for peeling crawfish. A high percentage of crawfish processors pay the peelers on a "per pound of peeled tailmeat" basis. The depreciated cost of the machine would be compared to the cost of paying wages for the peelers plus other factors to determine if it would be economically profitable. It is expected that as wages increase, the probability of processors adopting a crawfish peeling machine also increases.

Purchase (not used in the Small model) is a dummy variable denoting the purchase (vs. lease) of a hypothetical crawfish peeling machine. Some producers may be unwilling to purchase a machine due to a lack of capital or being risk-averse. These producers are expected to be more likely to lease than purchase a machine.

Large and **Small** (used only in the aggregate model) indicate the size of the crawfish peeling machines considered for adoption. Large refers to the large capacity peeling machine while Small refers to the small, table-top machine. Both are independent variables regarded as significant factors when opting to purchase or lease a peeling machine because size would affect acceptability.

Sizelarg and **Sizesmal** (used only in the aggregate model) are dummy variables created to account for the interaction between operation size and preference for a machine. Sizelarg represents the *pounds of meat peeled* x *large-sized machine* and Sizesmal represents the *pounds of meat peeled* x *small-sized machine*.

Years43 is an approximation of the expected years a processor plans to continue peeling crawfish if the market remains viable for crawfish peeling. In other words, if there were a steady or increasing demand for crawfish and its by-products, Years43 would be an indicator of the time the processor would plan to continue actively processing. A production quandary frequently occurs in industries where a forecast of future demand must be made and production is based from the forecast (Smith and Zhang, 1998). Future demand forecasts are costly and difficult to validate, and those with longer planning horizons are more likely to invest in assets that are specific to the operation, especially if there is a slim market for that asset is sold used. It is expected that this independent variable is highly significant based on the principle that a processor who no longer has an interest in the business of crawfish peeling would not invest in adopting technology.

Family44 is an independent variable representing the expectation of a family member whom the processor would assume to accept the responsibilities of managing the daily operations of the business upon the processor's retirement. According to Smith and Zhang (1998), having a family member to take over the operation can effectively extend the processor's planning horizon, especially if the peeling machine has a relatively low salvage value.

Chapter 4

Descriptive Statistics and Empirical Results

Conjoint Analysis

Descriptive Statistics for Conjoint Analysis

In 1995, Gillespie and Capdeboscq identified 80 processors to survey for determination of the costs associated with crawfish peeling labor. By 2004, when the present study was begun, less than half those numbers of processors were found to be peeling crawfish. For the actively producing crawfish processors of Louisiana, 30 were surveyed for the current research. Due to missing data, two observations were omitted from the conjoint analysis; thus the analysis consisted of 28 firms in the Louisiana crawfish industry. Firms 15 and 25 did not provide sufficient information to be included in the conjoint analysis.

The aggregate (industry) statistics are the industry averages of the five variables included in the study. The coefficient values show whether there was an increase or decrease in a hypothetical crawfish peeling machine's rating. The figures in table 4.1 located under the column labeled **Coefficient** denote the increase or decrease in the crawfish peeling machine rating associated with that variable. These are the marginal effects. Other numbers also of particular importance are the values under the column labeled P[|Z|], which are the probabilities. If the numbers are less than 0.10, this denotes that particular variable being significant at the 90% probability level. Furthermore, if the number is 0.05 or lower, the variable is considered to be highly significant, with 95% probability or better. For the industry, a machine that deveins crawfish increases the rating of that machine by 3.89 on the 0-10 scale. Retaining the fat of the crawfish increases the machine's rating by 2.27. With regards to an individual not being required to handle each crawfish, retaining the backstrap, and owning the machine, these increased the ratings of the machine by 2.13, 2.20, and 0.24, respectively. All but one of the variables was significant at the 0.01 alpha levels. Owning the machine received a P[|Z|] score of 0.943, which means it is non-significant at the 90% level of significance. Individual firm results are also included in Table 4.1.

Table 4.1: Marginal Effects for Conjoint Estimates, Aggregate / Individual Firm Results

LIMDEP Output

Aggregate	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-2.068	0.370	-5.591	0.000	
	DEVEIN	3.891	0.336	11.566	0.000	0.500
	FAT	2.269	0.336	6.743	0.000	0.500
	NOHANDLI	2.127	0.337	6.320	0.000	0.500
	BACKSTRA	2.197	0.337	6.523	0.000	0.500
	OWN	0.237	0.330	0.072	0.943	0.496
Firm 1	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	0.589	0.519	1.135	0.257	
	DEVEIN	4.412	0.428	10.315	0.000	0.500
	FAT	-0.349	0.431	-0.809	0.418	0.500
	NOHANDLI	5.412	0.428	12.654	0.000	0.500
	BACKSTRA	-0.273	0.418	-0.652	0.514	0.500
	OWN	-1.227	0.418	-2.935	0.003	0.500
Firm 2	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	1.686	0.865	1.950	0.051	
	DEVEIN	3.149	0.917	3.435	0.001	0.500
	FAT	4.640	0.913	5.084	0.000	0.500
	NOHANDLI	-2.005	1.015	-1.975	0.048	0.500
	BACKSTRA	2.652	0.918	2.888	0.004	0.500
	OWN	2.155	0.920	2.343	0.019	0.500
Firm 3	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-1.114	68.681	-0.016	0.987	
	DEVEIN	0.173	12.633	0.014	0.989	0.500
	FAT	1.543	100.034	0.015	0.988	0.500
	NOHANDLI	0.173	12.633	0.014	0.989	0.500
	BACKSTRA	1.197	74.771	0.016	0.987	0.500
	OWN	-1.197	74.771	-0.016	0.987	0.500

(table continued)

Firm 4	Variable	Coefficient	Standard Error	b/St. Error	P[|Z|>z	Mean of X
	CONSTANT	1.166	0.844	1.381	0.167	
	DEVEIN	4.064	0.727	5.590	0.000	0.500
	FAT	2.565	0.727	3.527	0.000	0.500
	NOHANDLI	2.565	0.727	3.527	0.000	0.500
	BACKSTRA	1.065	0.727	1.465	0.143	0.500
	OWN	0.434	0.728	0.596	0.551	0.500
Firm 5	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-1.549	0.649	-2.388	0.017	
	DEVEIN	2.891	0.581	4.972	0.000	0.500
	FAT	2.391	0.581	4.112	0.000	0.500
	NOHANDLI	1.391	0.581	2.393	0.017	0.500
	BACKSTRA	2.891	0.581	4.972	0.000	0.500
	OWN	0.891	0.581	1.533	0.125	0.500
Firm 6	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	0.032	0.664	0.048	0.962	
	DEVEIN	3.336	0.626	5.328	0.000	0.500
	FAT	2.336	0.626	3.731	0.000	0.500
	NOHANDLI	1.336	0.626	2.134	0.033	0.500
	BACKSTRA	1.836	0.626	2.932	0.003	0.500
	OWN	-0.953	0.614	-1.553	0.121	0.400
Firm 7	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-0.001	0.000	-144.479	0.000	
	DEVEIN	0.001	0.000	217.033	0.000	0.500
	FAT	0.000	0.000	-226.503	0.000	0.500
	NOHANDLI	0.001	0.000	232.195	0.000	0.500
	BACKSTRA	0.000	0.000	-226.503	0.000	0.500
	OWN	0.000	0.000	116.219	0.000	0.500
Firm 8	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	0.974	0.765	1.274	0.203	
	DEVEIN	1.310	0.779	1.681	0.093	0.500
	FAT	-0.190	0.779	-0.243	0.808	0.500
	NOHANDLI	3.310	0.779	4.248	0.000	0.500
	BACKSTRA	2.810	0.779	3.606	0.000	0.500
	OWN	0.810	0.779	1.040	0.299	0.500

(table continued)

Firm 9	Variable	Coefficient	Standard Error	b/St. Error	P[|Z|>z	Mean of X
	CONSTANT	-1.377	1.346	-1.023	0.307	
	DEVEIN	2.478	1.101	2.250	0.024	0.500
	FAT	-1.460	1.209	-1.207	0.227	0.500
	NOHANDLI	4.945	1.091	4.533	0.000	0.500
	BACKSTRA	2.478	1.101	2.250	0.024	0.500
	OWN	0.998	1.109	0.900	0.368	0.500
Firm 10	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-0.001	0.000	-149.617	0.000	
	DEVEIN	0.001	0.000	165.843	0.000	0.500
	FAT	0.000	0.000	-377.405	0.000	0.500
	NOHANDLI	0.001	0.000	248.608	0.000	0.500
	BACKSTRA	0.000	0.000	377.407	0.000	0.500
	OWN	0.000	0.000	110.627	0.000	0.500
Firm 11	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	0.258	0.539	0.478	0.633	
	DEVEIN	4.425	0.458	9.662	0.000	0.500
	FAT	3.925	0.458	8.571	0.000	0.500
	NOHANDLI	0.675	0.458	1.474	0.141	0.500
	BACKSTRA	0.175	0.458	0.382	0.703	0.500
	OWN	0.075	0.458	0.164	0.870	0.500
Firm 12	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-7.014	0.050	-139.473	0.000	
	DEVEIN	10.009	0.033	304.759	0.000	0.500
	FAT	4.000	0.001	2972.345	0.000	0.500
	NOHANDLI	1.005	0.022	45.572	0.000	0.500
	BACKSTRA	4.000	0.001	2972.345	0.000	0.500
	OWN	-1.995	0.022	-90.514	0.000	0.500
Firm 13	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-6.170	35.549	-0.174	0.862	
	DEVEIN	1.000	0.356	2.807	0.005	0.500
	FAT	7.670	35.484	0.216	0.829	0.500
	NOHANDLI	1.000	0.356	2.807	0.005	0.500
	BACKSTRA	8.669	35.440	0.245	0.807	0.500
	OWN	-3.171	35.679	-0.089	0.929	0.500

(table continued)

Firm 14	Variable	Coefficient	Standard Error	b/St. Error	P[|Z|>z	Mean of X
	CONSTANT	-0.001	0.000	-84.306	0.000	
	DEVEIN	0.001	0.000	111.984	0.000	0.500
	FAT	0.000	0.000	17.213	0.000	0.500
	NOHANDLI	0.000	0.000	26.737	0.000	0.500
	BACKSTRA	0.001	0.000	99.506	0.000	0.500
	OWN	0.000	0.000	30.113	0.000	0.500
Firm 16	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-0.775	0.536	-1.446	0.148	
	DEVEIN	1.364	0.490	2.713	0.005	0.500
	FAT	3.864	0.490	7.882	0.000	0.500
	NOHANDLI	2.364	0.490	4.823	0.000	0.500
	BACKSTRA	2.364	0.490	4.823	0.000	0.500
	OWN	1.364	0.490	2.783	0.005	0.500
Firm 17	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	0.098	0.565	0.173	0.863	
	DEVEIN	2.361	0.558	4.229	0.000	0.500
	FAT	2.361	0.558	4.229	0.000	0.500
	NOHANDLI	3.361	0.558	6.021	0.000	0.500
	BACKSTRA	1.361	0.558	2.438	0.015	0.500
	OWN	0.361	0.558	0.646	0.518	0.500
Firm 18	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	0.477	0.817	0.584	0.559	
	DEVEIN	4.224	0.820	5.514	0.000	0.500
	FAT	2.225	0.820	2.714	0.007	0.500
	NOHANDLI	0.725	0.820	0.884	0.377	0.500
	BACKSTRA	0.725	0.820	0.884	0.377	0.500
	OWN	0.725	0.820	0.884	0.377	0.500
Firm 19	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-2.969	0.954	-3.113	0.002	
	DEVEIN	3.161	1.296	2.439	0.015	0.500
	FAT	2.358	1.239	1.904	0.057	0.500
	NOHANDLI	-2.560	1.237	-2.070	0.039	0.500
	BACKSTRA	2.232	1.252	2.582	0.010	0.500
	OWN	0.352	1.370	0.257	0.797	0.500

(table continued)

Firm 20	Variable	Coefficient	Standard Error	b/St. Error	P[|Z|>z	Mean of X
	CONSTANT	-2.596	1.161	-2.237	0.025	
	DEVEIN	4.484	0.929	4.824	0.000	0.500
	FAT	1.136	0.994	1.143	0.253	0.500
	NOHANDLI	2.518	0.937	2.687	0.007	0.500
	BACKSTRA	2.026	0.935	2.157	0.031	0.500
	OWN	0.552	0.949	0.582	0.561	0.500
Firm 21	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	0.461	0.943	0.488	0.625	
	DEVEIN	3.272	0.798	4.101	0.000	0.500
	FAT	1.772	0.798	2.221	0.026	0.500
	NOHANDLI	0.272	0.798	0.341	0.733	0.500
	BACKSTRA	2.772	0.798	3.475	0.001	0.500
	OWN	-0.272	0.798	-0.341	0.733	0.500
Firm 22	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-0.243	0.740	-0.330	0.741	
	DEVEIN	1.681	0.615	2.735	0.006	0.500
	FAT	3.681	0.615	5.989	0.000	0.500
	NOHANDLI	2.181	0.615	3.549	0.000	0.500
	BACKSTRA	1.681	0.615	2.735	0.006	0.500
	OWN	-0.681	0.615	-1.109	0.268	0.500
Firm 23	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-8.843	71.608	-0.123	0.902	
	DEVEIN	7.671	35.791	0.214	0.830	0.500
	FAT	0.500	0.354	1.414	0.157	0.500
	NOHANDLI	6.671	35.795	0.186	0.852	0.500
	BACKSTRA	1.500	0.354	4.242	0.000	0.500
	OWN	4.672	35.804	0.130	0.896	0.500
Firm 24	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	0.662	0.650	1.019	0.308	
	DEVEIN	2.679	0.554	4.831	0.000	0.500
	FAT	2.679	0.554	4.831	0.000	0.500
	NOHANDLI	2.679	0.554	4.831	0.000	0.500
	BACKSTRA	2.679	0.554	4.831	0.000	0.500
	OWN	-0.679	0.554	-1.224	0.221	0.500

(table continued)

Firm 26	Variable	Coefficient	Standard Error	b/St. Error	P[|Z|>z	Mean of X
	CONSTANT	-4.922	35.830	-0.137	0.891	
	DEVEIN	8.836	17.915	0.493	0.622	0.500
	FAT	0.750	0.177	4.243	0.000	0.500
	NOHANDLI	3.336	17.915	0.186	0.852	0.500
	BACKSTRA	-0.250	0.177	-1.414	0.157	0.500
	OWN	3.336	17.915	0.186	0.852	0.500
Firm 27	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-0.058	8.904	-0.006	0.995	
	DEVEIN	0.069	9.085	0.007	0.995	0.500
	FAT	0.066	9.376	0.006	0.995	0.500
	NOHANDLI	-0.027	3.765	-0.007	0.994	0.500
	BACKSTRA	0.061	9.421	0.006	0.995	0.500
	OWN	-0.079	11.699	-0.007	0.995	0.500
Firm 28	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-1.744	1.108	-1.575	0.115	
	DEVEIN	3.288	1.088	3.022	0.003	0.500
	FAT	1.409	1.080	1.305	0.192	0.500
	NOHANDLI	1.879	1.081	1.739	0.082	0.500
	BACKSTRA	1.879	1.081	1.739	0.082	0.500
	OWN	-0.001	1.083	-0.001	0.999	0.500
Firm 29	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-0.001	0.000	-32.599	0.000	
	DEVEIN	0.000	0.000	25.343	0.000	0.500
	FAT	0.001	0.000	99.527	0.000	0.500
	NOHANDLI	0.000	0.000	25.343	0.000	0.500
	BACKSTRA	0.001	0.000	99.527	0.000	0.500
	OWN	-0.001	0.000	-67.657	0.000	0.500
Firm 30	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-1.646	1.044	-1.578	0.115	
	DEVEIN	3.493	0.880	3.971	0.000	0.500
	FAT	3.493	0.880	3.971	0.000	0.500
	NOHANDLI	0.529	0.875	0.604	0.546	0.500
	BACKSTRA	3.493	0.880	3.971	0.000	0.500
	OWN	0.971	0.875	1.110	0.267	0.500

Multicollinearity

Multicollinearity between the regressors is tested to observe any linear relationships between or among two or more independent variables. The presence of multicollinearity in the model will contradict the assumption that the least squares estimators have the smallest variance. Though this does not cause severe disruption in terms of theoretical properties of the statistical tests (Ramanathan, 2002, p. 309), it increases the variance and may give insignificant probability values for the *t*-statistics.

To test for multicollinearity, a VIF (Variation Inflation Factor) option was applied using SAS. The VIF option estimates all VIFs. The VIF is calculated as $1/(1-R_k^2)$, where R^2 is the goodness of fit and *k* are the dependent variables. A value of 5 or greater under the Variation Inflation column is used as an indication of linear dependence (Ramanathan, 2002, p. 318). To further validate the absence of multicollinearity, the Collin option index, which is the most commonly used, was employed. Values of 20 or higher under the Condition Index column are used as an indication of linear dependence (Greene, 2003, p. 258). Based on the outcomes of the values reported, it is concluded the variables in the model do not show signs of multicollinearity.

Heteroskedasticity

To test for heteroskedasticity, the case where the residuals of the random variables in the sequence may have different variances, White's LM test was employed using SAS. The White test is equivalent to obtaining the error sum of squares for the regression of the squared residuals on a constant with respect to the estimated parameters. The null hypothesis that the variances of the residuals are constant is accepted if the probability value for the White test is less than 0.05 (Ramanathan, p. 423). Results indicate a p-value of 1 as shown in table B.2 under Appendix B; therefore we accept the null hypothesis and conclude that the data is homoskedastic.

Part-Worths for Crawfish Peeling Machine Attributes

Ratings for the hypothetical crawfish peeling machine could be determined by summing the part-worths. Once the coefficients (β) were estimated, the relative importance of each attribute to the various producers could be determined (Gillespie and Lewis, 2005). The formula for calculating the part-worths is:

$$RI_i = \frac{|\beta_i|}{\sum_{k=1}^{5} |\beta_k|} \tag{8}$$

RI_i is defined as the relative importance of each attribute (i). The β in the numerator signifies the β estimate in the conjoint analysis and the Σ in the denominator refers to the summation of the β of the 5 attributes. In other words, the importance of each attribute is calculated once the value of the attribute for the individual firm is divided by the total value of all the attributes. Table 4.2 provides the relative importance of each attribute for the aggregate and individual models, where the coefficients reported are the absolute values of the coefficients reported in Table 4.1. This is because the absolute value, in this case, provides the basis for calculating the relative importance.

Table 4.2: Part-Worth Estimates for the Louisiana Crawfish Industry

		Part-Worths		
Aggregate	**Variable**	**Coefficient**	**Importance**	**Percentage**
	DEVEIN	3.891	0.362932562	30.6%
	FAT	2.269	0.211640705	20.0%
	NOHANDLI	2.127	0.198395672	19.5%
	BACKSTRA	2.197	0.204924914	18.4%
	OWN	0.237	0.022106147	11.5%
	Total	10.721	1	100.0%

(table continued)

Firm 1	Variable	Coefficient	Importance	Percentage
	DEVEIN	4.412	0.377966247	37.8%
	FAT	0.349	0.029898055	3.0%
	NOHANDLI	5.412	0.463634027	46.4%
	BACKSTRA	0.273	0.023387304	2.3%
	OWN	1.227	0.105114366	10.5%
	Total	11.673	1	100.0%

Firm 2	Variable	Coefficient	Importance	Percentage
	DEVEIN	3.149	0.21567016	21.6%
	FAT	4.640	0.317786453	31.8%
	NOHANDLI	2.005	0.137319362	13.7%
	BACKSTRA	2.652	0.181631395	18.2%
	OWN	2.155	0.147592631	14.8%
	Total	14.601	1	100.0%

Firm 3	Variable	Coefficient	Importance	Percentage
	DEVEIN	0.173	0.040392248	4.0%
	FAT	1.543	0.360261499	36.0%
	NOHANDLI	0.173	0.040392248	4.0%
	BACKSTRA	1.197	0.279477002	27.9%
	OWN	1.197	0.279477002	27.9%
	Total	4.283	1	100.0%

Firm 4	Variable	Coefficient	Importance	Percentage
	DEVEIN	4.064	0.380061723	38.0%
	FAT	2.565	0.239876555	24.0%
	NOHANDLI	2.565	0.239876555	24.0%
	BACKSTRA	1.065	0.099597868	10.0%
	OWN	0.434	0.0405873	4.1%
	Total	10.693	1	100.0%

Firm 5	Variable	Coefficient	Importance	Percentage
	DEVEIN	2.891	0.276518412	27.7%
	FAT	2.391	0.228694405	22.9%
	NOHANDLI	1.391	0.133046389	13.3%
	BACKSTRA	2.891	0.276518412	27.7%
	OWN	0.891	0.085222382	8.5%
	Total	10.455	1	100.0%

Firm 6	Variable	Coefficient	Importance	Percentage
	DEVEIN	3.336	0.340512402	34.1%
	FAT	2.336	0.238440339	23.8%
	NOHANDLI	1.336	0.136368276	13.6%
	BACKSTRA	1.836	0.187404307	18.7%
	OWN	0.953	0.097274676	9.7%
	Total	9.797	1	100.0%

(table continued)

Firm 7	Variable	Coefficient	Importance	Percentage
	DEVEIN	0.001	0.464684015	46.5%
	FAT	0.000	0.023234201	2.3%
	NOHANDLI	0.001	0.325743494	32.6%
	BACKSTRA	0.000	0.023234201	2.3%
	OWN	0.000	0.163104089	16.3%
	Total	0.002	1	100.0%

Firm 8	Variable	Coefficient	Importance	Percentage
	DEVEIN	1.310	0.15539739	15.5%
	FAT	0.190	0.022538553	2.3%
	NOHANDLI	3.310	0.392645314	39.3%
	BACKSTRA	2.810	0.333333333	33.3%
	OWN	0.810	0.096085409	9.6%
	Total	8.430	1	100.0%

Firm 9	Variable	Coefficient	Importance	Percentage
	DEVEIN	2.478	0.200501659	20.1%
	FAT	1.460	0.118132535	11.8%
	NOHANDLI	4.945	0.400113278	40.0%
	BACKSTRA	2.478	0.200501659	20.1%
	OWN	0.998	0.08075087	8.1%
	Total	12.359	1	100.0%

Firm 10	Variable	Coefficient	Importance	Percentage
	DEVEIN	0.001	0.399681853	40.0%
	FAT	0.000	0.039964189	4.0%
	NOHANDLI	0.001	0.36011335	36.0%
	BACKSTRA	0.000	0.039968185	4.0%
	OWN	0.000	0.160272423	16.0%
	Total	0.003	1	100.0%

Firm 11	Variable	Coefficient	Importance	Percentage
	DEVEIN	4.425	0.47710753	47.7%
	FAT	3.925	0.423193419	42.3%
	NOHANDLI	0.675	0.072751701	7.3%
	BACKSTRA	0.175	0.01883759	1.9%
	OWN	0.075	0.008109761	0.8%
	Total	9.274	1	100.0%

(table continued)

Firm 12	Variable	Coefficient	Importance	Percentage
	DEVEIN	10.009	0.476429149	47.6%
	FAT	4.000	0.190389833	19.0%
	NOHANDLI	1.005	0.047817602	4.8%
	BACKSTRA	4.000	0.190389833	19.0%
	OWN	1.995	0.094973583	9.5%
	Total	21.009	1	100.0%

Firm 13	Variable	Coefficient	Importance	Percentage
	DEVEIN	1.000	0.046477354	4.6%
	FAT	7.670	0.356574335	35.7%
	NOHANDLI	1.000	0.046477354	4.6%
	BACKSTRA	8.669	0.403051689	40.3%
	OWN	3.171	0.147419268	14.7%
	Total	21.509	1	100.0%

Firm 14	Variable	Coefficient	Importance	Percentage
	DEVEIN	0.001	0.439396597	43.9%
	FAT	0.000	0.054814945	5.5%
	NOHANDLI	0.000	0.066260305	6.6%
	BACKSTRA	0.001	0.318452903	31.8%
	OWN	0.000	0.12107525	12.1%
	Total	0.002	1	100.0%

Firm 16	Variable	Coefficient	Importance	Percentage
	DEVEIN	1.364	0.120477671	12.0%
	FAT	3.864	0.341329847	34.1%
	NOHANDLI	2.364	0.20883974	20.9%
	BACKSTRA	2.364	0.20883974	20.9%
	OWN	1.364	0.120513002	12.1%
	Total	11.322	1	100.0%

Firm 17	Variable	Coefficient	Importance	Percentage
	DEVEIN	2.361	0.240799674	24.1%
	FAT	2.361	0.240799674	24.1%
	NOHANDLI	3.361	0.342798858	34.3%
	BACKSTRA	1.361	0.13880049	13.9%
	OWN	0.361	0.036801306	3.7%
	Total	9.804	1	100.0%

(table continued)

Firm 18	Variable	Coefficient	Importance	Percentage
	DEVEIN	4.224	0.489916152	49.0%
	FAT	2.225	0.257981839	25.8%
	NOHANDLI	0.725	0.084034003	8.4%
	BACKSTRA	0.725	0.084034003	8.4%
	OWN	0.725	0.084034003	8.4%
	Total	8.623	1	100.0%

Firm 19	Variable	Coefficient	Importance	Percentage
	DEVEIN	3.161	0.296472045	29.6%
	FAT	2.358	0.221148977	22.1%
	NOHANDLI	2.560	0.240045389	24.0%
	BACKSTRA	2.232	0.209332858	20.9%
	OWN	0.352	0.033000731	3.3%
	Total	10.663	1	100.0%

Firm 20	Variable	Coefficient	Importance	Percentage
	DEVEIN	4.484	0.418418007	41.8%
	FAT	1.136	0.106041659	10.6%
	NOHANDLI	2.518	0.234956512	23.5%
	BACKSTRA	2.026	0.189088805	18.9%
	OWN	0.552	0.051495017	5.1%
	Total	10.716	1	100.0%

Firm 21	Variable	Coefficient	Importance	Percentage
	DEVEIN	3.272	0.391368834	39.1%
	FAT	1.772	0.211963542	21.2%
	NOHANDLI	0.272	0.032534329	3.3%
	BACKSTRA	2.772	0.331563083	33.2%
	OWN	0.272	0.032570212	3.3%
	Total	8.360	1	100.0%

Firm 22	Variable	Coefficient	Importance	Percentage
	DEVEIN	1.681	0.169718381	17.0%
	FAT	3.681	0.371595841	37.2%
	NOHANDLI	2.181	0.220187746	22.0%
	BACKSTRA	1.681	0.169718381	17.0%
	OWN	0.681	0.068779651	6.9%
	Total	9.907	1	100.0%

(table continued)

Firm 23	Variable	Coefficient	Importance	Percentage
	DEVEIN	7.671	0.36505965	36.5%
	FAT	0.500	0.023788789	2.4%
	NOHANDLI	6.671	0.317472554	31.7%
	BACKSTRA	1.500	0.071375886	7.1%
	OWN	4.672	0.22230312	22.2%
	Total	21.014	1	100.0%

Firm 24	Variable	Coefficient	Importance	Percentage
	DEVEIN	2.679	0.235109278	23.5%
	FAT	2.679	0.235109278	23.5%
	NOHANDLI	2.679	0.235109278	23.5%
	BACKSTRA	2.679	0.235109278	23.5%
	OWN	0.679	0.059562889	6.0%
	Total	11.393	1	100.0%

Firm 26	Variable	Coefficient	Importance	Percentage
	DEVEIN	8.836	0.535269886	53.5%
	FAT	0.750	0.04543527	4.5%
	NOHANDLI	3.336	0.202077906	20.2%
	BACKSTRA	0.250	0.015139032	1.5%
	OWN	3.336	0.202077906	20.2%
	Total	16.507	1	100.0%

Firm 27	Variable	Coefficient	Importance	Percentage
	DEVEIN	0.069	0.229156348	22.9%
	FAT	0.066	0.218590061	21.9%
	NOHANDLI	0.027	0.089351164	8.9%
	BACKSTRA	0.061	0.201122668	20.1%
	OWN	0.079	0.261779759	26.2%
	Total	0.303	1	100.0%

Firm 28	Variable	Coefficient	Importance	Percentage
	DEVEIN	3.288	0.388858357	38.9%
	FAT	1.409	0.166613033	16.7%
	NOHANDLI	1.879	0.222198017	22.2%
	BACKSTRA	1.879	0.222	22.2%
	OWN	0.001	0.000132576	0.0%
	Total	8.456	1	100.0%

(table continued)

Firm 29	Variable	Coefficient	Importance	Percentage
	DEVEIN	0.000	0.111140678	11.1%
	FAT	0.001	0.222192656	22.2%
	NOHANDLI	0.000	0.111140678	11.1%
	BACKSTRA	0.001	0.222192656	22.2%
	OWN	0.001	0.333333333	33.3%
	Total	0.002	1	100.0%

Firm 30	Variable	Coefficient	Importance	Percentage
	DEVEIN	3.493	0.291607884	29.2%
	FAT	3.493	0.291607884	29.2%
	NOHANDLI	0.529	0.044126854	4.4%
	BACKSTRA	3.493	0.291607884	29.2%
	OWN	0.971	0.081049495	8.1%
	Total	11.979	1	100.0%

For the aggregate model, whether the crawfish peeling machine deveins is viewed as being most important; devein constitutes 30.6% of the total importance. This was calculated by taking the average for that particular attribute from each individual firm. This is why the aggregate percentages reported in Table 4.2 are not consistent with the "importance" numbers. Devein is the highest rated variable in terms of processor importance. The second most important variable to the producers was the retention of fat, at 20.0% significance. No handling and retaining the backstrap were the third and fourth variables of importance, separated by relatively slim margins of 1.1%, worth 19.5% and 18.4%, respectively. Own was considered the least important attribute, receiving 11.5% of the processors' measure of importance when adopting a crawfish peeling machine.

In terms of individual firms, the calculations of the part-worths were derived in the same manner as the aggregate model. For instance, firm 1 reported a machine possessing the variable Devein having a beta coefficient of 4.412. The summation for all the variables given by firm 1 equals 11.673. Dividing the beta coefficient by the total of the absolute values of the five attributes suggests firm 1 views the Devein property in a crawfish peeling machine as being 37.8% important. Unlike the aggregate, firm 1 believes No Handling was the most important attribute, with 46.4% importance, which was calculated in the same manner as for Devein. The same process was performed for all the individual firms and can be observed in table 4.2. An illustrated pictorial estimation of the importance of the aggregate part-worths can be seen in Figure 1.

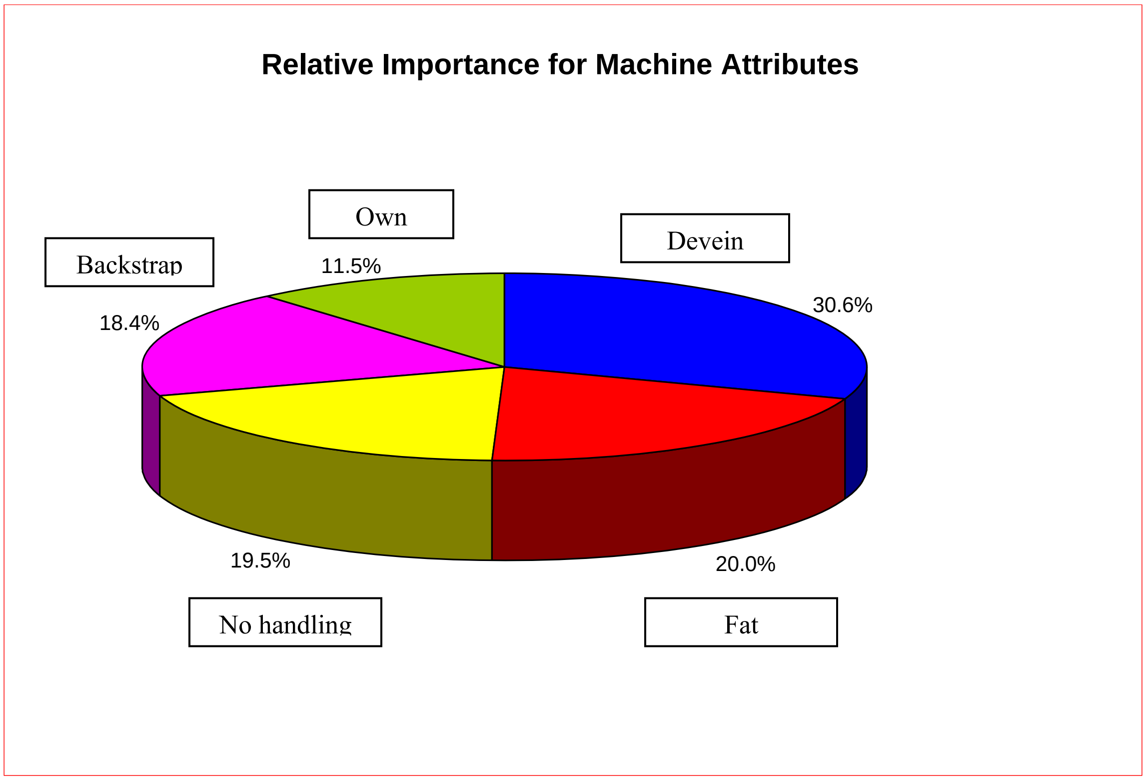

Figure 1: Depiction of Percent Importance Estimates

Actual and Predicted Values

Another area of interest concerning Conjoint Analysis is the predicted values being in close proximity to the actual values reported for the two hold-out machines. The two machines were described as:

(1) Hold-Out Machine 1 would devein the crawfish, retain the fat, require handling of crawfish, would not retain the backstrap, and would be available for leasing.

(2) Hold-Out Machine 2 would not devein the crawfish, nor retain the fat, would not require handling of the product, yet retain the backstrap, and be available for ownership.

Table 4.3 gives an account of each firm's actual and predicted values given for each hypothetical machine.

Table 4.3: Actual and Predicted Values for Hold-Out Machines

	Hold-Out	*Machine 1*		*Hold-Out*	*Machine 2*
	Actual	**Predicted**		**Actual**	**Predicted**
Firm 1	5	4.65		5	4.50
Firm 2	7	9.48		3	4.49
Firm 3	0	0.60		0	-0.94
Firm 4	7	7.79		0	5.24
Firm 5	6	3.73		6	3.62
Firm 6	6	5.71		2	2.26
Firm 7	6	0.00		0	0.00
Firm 8	5	2.09		7	7.90
Firm 9	4	-0.36		6	7.04
Firm 10	3	0.00		0	0.00
Firm 11	3	8.60		3.5	1.85
Firm 12	1	7.00		0	-4.01
Firm 13	5	2.50		5	0.33
Firm 14	0	0.00		0	1.03
Firm 16	6	4.45		3	5.31
Firm 17	5	4.82		5	5.18
Firm 18	8	6.92		3	2.64
Firm 19	0	2.55		1	-1.95
Firm 20	2	3.02		2	2.50
Firm 21	5	5.50		4	3.23
Firm 22	5	5.12		3	2.94
Firm 23	6	-0.67		3	4.00
Firm 24	7	6.02		6	5.34
Firm 26	7	4.67		2	1.51
Firm 27	5	0.06		0	-0.10
Firm 28	4	2.96		1	2.02
Firm 29	0	0.00		0	0.00
Firm 30	3	5.33		1	3.35

The predicted values were calculated by dissecting the hold-out machine attributes and summing the coefficients reported from the Conjoint Analysis output using the two-limit tobit model including the variable CONSTANT. Firm 1 assigned hold-out machine 1 a rating of 5. However, when summing the variables CONSTANT, DEVEIN and FAT with the values of 0.589, 4.412, and -0.349 respectively, the predicted value of that particular machine was 4.65. The processor's predicted rating was within 0.35 of an exact estimation of his recorded rating.

Pearson Correlation

The Pearson's Correlation coefficients for the actual Hold-Out Machine 1 ratings with the predicted ratings are positively correlated (0.39715), with a p-value of 0.0364. Since the p-value is less than 0.05, we conclude that the actual and predicted values have significant correlation. This implies the predicted values are relatively close to the actual values and are statistically significant, which the researcher anticipated. The Pearson's Correlation coefficients for the actual Hold-Out Machine 2 ratings with the predicted ratings are positively correlated (0.70823), with a p-value less than 0.0001. Since the p-value is less than 0.05, we conclude that the actual and predicted values have significant correlation, like that of Hold-Out Machine 1. This implies the predicted values are relatively close to the actual values and are statistically significant, which also satisfies the researcher's expectations. The relative position of every potential machine is displayed in Table A.1 in Appendix A.

Cluster Analysis

One of the supplementary objectives of this study using the information gathered from the conjoint analysis was to identify the types of crawfish processors who prefer certain attributes at different levels in a crawfish peeling machine. For this study, cluster analysis was used to categorize processors into homogenous groups compliant with their individual part-worth values for the machine attributes. The purpose of the cluster analysis is to bring together crawfish processors with a relatively high similarity in machine type preferences while separating them from another group with comparatively different preferences for machine functions.

In order to obtain reputable results, the β coefficients reported in the conjoint analysis for the individual firms were transposed into columns with their corresponding firm numbers. The end result was 6 columns (Constant, Devein, Fat, Nohandling, Backstrap, Own) and 28 rows (Firms 1-30). Firms 15 and 25 were excluded from the analysis because they did not provide the sufficient information needed to obtain results. Appendix Table C.1 provides the analogous coefficients used to draw inferences on. The part-worth estimates for the 28 firms were used as the variables in the cluster analysis. The data were evaluated in SPSS using Ward's Method, which is a hierarchical agglomerative procedure. Ward's method is often chosen to minimize the within-cluster differences and to avoid problems with "chaining" of the observations found in the single linkage method (Hair et. al, 1998, pp. 493-494). Appendix D.2 shows the results of Ward's method for grouping processors into clusters based on their part-worth estimates.

Once the firms were separated into two distinct clusters, Cluster 1 and Cluster 2, aggregate models could be run for each. Cluster 1 included 15 firms while Cluster 2 included 13 firms. The results are presented for each cluster in Tables 4.4 and 4.5. The aggregate (entire cluster) statistics were created using the same procedures as performed in the conjoint analysis using a two-limit tobit in LIMDEP. The coefficient values explain the increase or decrease in a hypothetical crawfish peeling machine's rating. These are the marginal effects. For Cluster 1, a machine that deveins crawfish increases the rating of that machine by 4.39. A machine that retains the fat of the crawfish increases its rating by 1.24. With regards to not handling crawfish, retaining the backstrap, and owning the machine, these increased the ratings of the machine by 2.45, 2.09, and 0.70, respectively. All but one of the variables is significant at the 0.10 alpha levels or better. Owning the machine received a P[|Z|] score of 0.117.

Table 4.4: Marginal Effects for Cluster 1

Cluster 1						
Aggregate	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-2.886	0.484	-5.960	0.000	
	DEVEIN	4.386	0.450	9.740	0.000	0.500
	FAT	1.243	0.454	2.736	0.006	0.500
	NOHANDLI	2.452	0.449	5.467	0.000	0.500
	BACKSTRA	2.092	0.452	4.629	0.000	0.500
	OWN	0.697	0.445	1.567	0.117	0.500

Table 4.5: Marginal Effects for Cluster 2

Cluster 2						
Aggregate	**Variable**	**Coefficient**	**Standard Error**	**b/St. Error**	**P[|Z|>z**	**Mean of X**
	CONSTANT	-1.005	0.529	-1.902	0.057	
	DEVEIN	3.272	0.463	7.068	0.000	0.500
	FAT	3.309	0.461	7.184	0.000	0.500
	NOHANDLI	1.728	0.464	3.725	0.002	0.500
	BACKSTRA	2.263	0.462	4.902	0.000	0.500
	OWN	-0.620	0.455	-1.361	0.173	0.492

For Cluster 2, a machine that deveins crawfish increases the rating by 3.27. A machine that retains the fat of the crawfish increases its rating by 3.31. With regards to not handling crawfish and retaining the backstrap, these increased the ratings of the machine by 1.73 and 2.26, respectively. Owning decreased the rating of a crawfish peeling machine in cluster 2 by 0.62. All but one of the variables is significant at the 0.10 alpha levels or better. Owning the machine received a P[|Z|] score of 0.173, which means it is not significant at the 90% level.

Part-Worths for Cluster Members

The relative importance of the machine attributes for the cluster aggregates was estimated in the same manner as the overall aggregate model. To determine the relative importance of the individual attributes, the coefficient values for each attribute were divided by the summation of the total values. Figures 2 and 3 illustrate the relative importance of the five attributes considered to be the most significant in the adoption of a crawfish peeling machine in the two separate clusters. Each cluster contained the same number of firms aforementioned. Table C.1 in Appendix C gives the specific value for the coefficient values for each attribute indicated by the individual firms.

According to Figure 2, Cluster 1 values the deveining aspect of a crawfish peeling machine with over 35 percent of importance. No handling and backstrap retention were rated second and third in order of importance, respectively, with a margin of difference of about 9 percent. The processors in this cluster considers a machine that does not need an individual to handle each crawfish being 25.9 percent important while a machine that is able to retain the backstrap being 17 percent important. Cluster 1 regarded the inclusion of a machine keeping the fat when separating the head from the tail with 12 percent of importance. Whether the firms in this cluster owned or leased the machine was valued at only 10.2 percent importance. Tables C.4 and C.5 in Appendix C give the precise variable estimates used in calculating the relative importance of each variable.

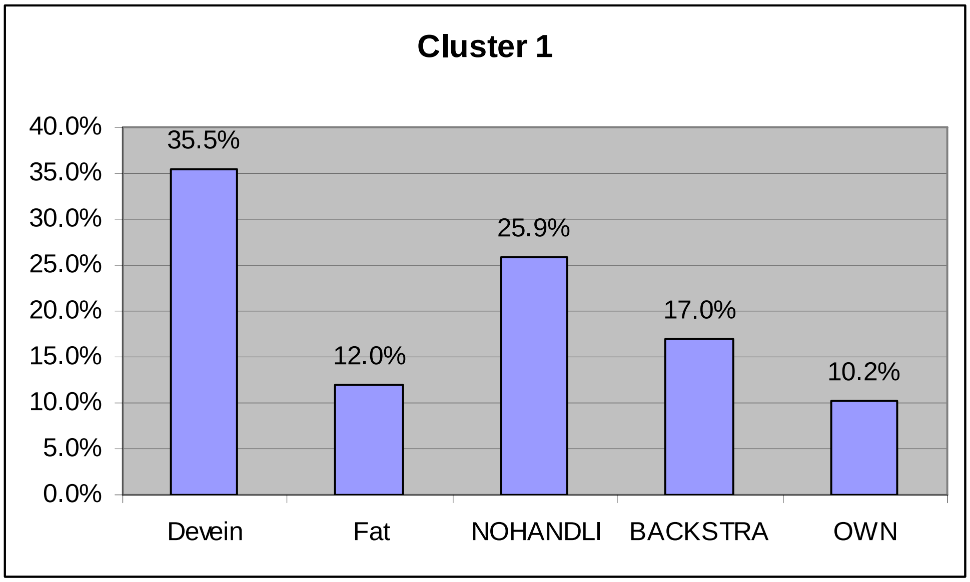

Figure 2: Relative Importance of Machine Attributes for Cluster 1

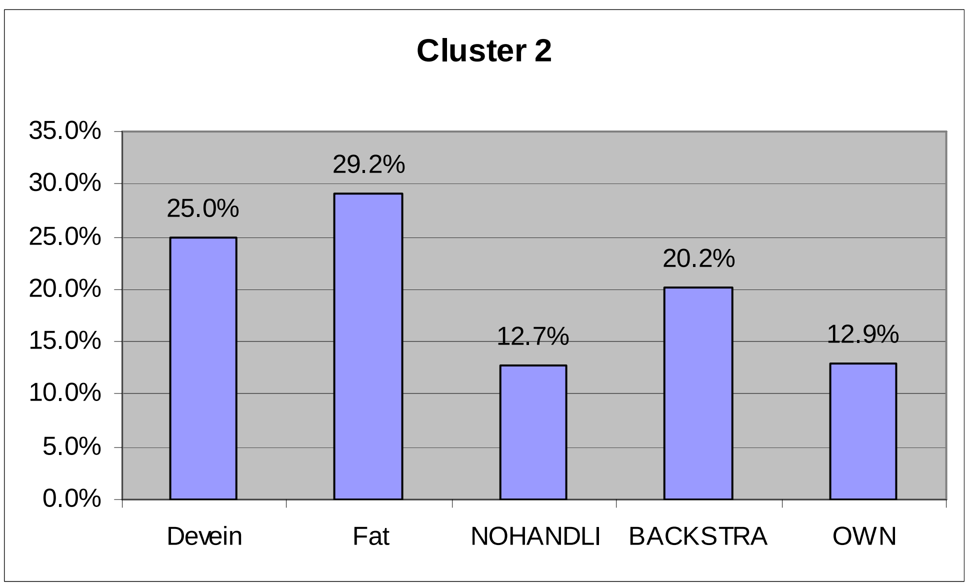

Figure 3: Relative Importance of Machine Attributes for Cluster 2

According to Figure 3, Cluster 2 values the fat attribute highest in a crawfish peeling machine with almost 30 percent of importance, unlike the devein attribute being regarded as most important in cluster 1. These individuals considered deveining to be the second most important attribute, at 25 percent. Backstrap retention was the third most important attribute, like in cluster 1, at 20.2 percent. Owning the machine was rated fourth in terms of importance at 12.9 percent and no handling demonstrated the lowest percentage of importance, at 12.7 percent. This was the smallest difference between two attributes in this cluster. The biggest difference between the clusters appears to be the importance placed on retention of the fat.

A logit model was utilized to further examine the difference between the two clusters. Processors in the first cluster were coded "0" while processors in the second cluster were coded "1". The independent variables included for the analysis were; meat1000, valueadd, diverse, pctpeel2, labor3, lbcook13, contco12, alter15, wage20, years43, and family44, each defined in Chapter 3. The dependent variable was cluster.

When all of the independent variables were included in the model, none showed significance. However, when the independent variables were run individually, only one showed significance. The model including only pctpeel2 was positively significant when it was run by itself. It had a coefficient value of 2.512 and a probability value of 0.012. This suggests processors peeling a higher percentage of crawfish tailmeat tended to be grouped into cluster 2. The overall lack of significance may be due to the relative homogeneity of preferences across attributes. The clusters differed in direction of preference for only one attribute, OWN, which was not significant in any of the runs.

Technology Adoption

The adoption of a relatively new technology such as a crawfish peeling machine is likely to be heavily dependent upon the characteristics of the crawfish processor. An ordered probit was administered using LIMDEP to draw inferences on the adoption of a crawfish peeling machine by the Louisiana crawfish industry. Three different sizes (small, medium, large) of the machine were evaluated on seven different levels of certainty.

Upon the collection of willingness to adopt responses for all 30 individuals, the expected number of machines to be purchased was estimated as:

$$(9) \qquad \text{Expected Number Adopted} = \sum_{i=1}^{7} n_i p_i$$

where n_i indicates the number of respondents indicating response i (how certain the individual is of adopting or not adopting) a machine, and p_i indicates the probability of purchasing (or leasing) the machine, determined as the midpoint in the range of certainty for each response level. Likewise, the expected adoption rate was estimated as:

$$(10) \qquad \text{Expected Adoption Rate} = \frac{\sum_{i=1}^{7} n_i p_i}{R} \times 100$$

where R is the number of respondents answering the question.

Adoption rates among machines, from highest to lowest, are (1) lease the medium-sized machine, (2) purchase the small-sized machine, (3) purchase the medium-sized machine, (4) lease the large-sized machine, and (5) purchase the large-sized machine. Of interest is that, assuming a machine would to be purchased, the small-sized machine would be the most extensively adopted. This is due in large part to adoption not only by large processors, but also by the smallest processors. If a small-sized machine were to be offered for lease, results from the other machines suggest its adoption rate would exceed that for purchasing the small-sized machine and, perhaps, leasing the medium-sized machine. Table 4.6 shows results of response frequencies for the seven certainty levels of the purchase/lease option for all the crawfish peeling machines.

Table 4.6: Frequency of Responses and Expected Adoption Rates, Crawfish Peeling Machines

Response	All Responses	Purchase Large	Lease Large	Purchase Medium	Lease Medium	Purchase Small
I am 100% certain I would purchase (lease) this machine.	24	1	3	3	7	10
I am almost certain I would purchase (lease) this machine (with 81 to 99 percent certainty).	19	2	6	2	6	3
I would more than likely purchase (lease) this machine (with 61 to 80 percent certainty).	30	4	3	8	9	6
I am not at all certain whether I would purchase (lease) this machine (with 41 to 60 percent certainty).	10	0	3	6	1	0
I would more than likely not purchase (lease) this machine (with 61 to 80 percent certainty).	10	4	2	3	1	0
I am almost certain I would not purchase (lease) this machine (with 81 to 99 percent certainty).	4	0	0	1	1	2
I am 100 percent certain I would not purchase (lease) this machine.	49	18	12	7	3	9
Total Responses	146	29	29	30	28	30
Expected Number of Firms Adopting	n/a	7	13	14	20	17
Expected Adoption Rate, Percentage	n/a	23	43	48	70	57

The information from all 30 processors surveyed was interpreted for assessment of the machines. Table 4.7 highlights the descriptive statistics of the variables included in the study given by the surveyed processors.

Table 4.7: Descriptive Statistics of Ordered Probit Variables

Variable Name	Units	Mean	Standard Dev.	Minimum	Maximum
MEAT1000	lbs/1000	59.233	43.794	0.000	200.000
VALUEADD	0/1	0.100	0.301	0.000	1.000
DIVERSE	0/1	0.533	0.501	0.000	1.000
PCTPEEL2	Percent	43.833	35.726	0.000	100.000
LABOR3	0/1	0.400	0.492	0.000	1.000
LBCOOK13	Pounds	14,358	133	1,200	40,000
CONTCO12	0/1	0.233	0.424	0.000	1.000
ALTER15	0/1	0.448	0.499	0.000	1.000
WAGE20	Dollars	1.540	0.162	1.300	2.000
YEARS43	Number	15.033	10.977	1.000	50.000
FAMILY44	0/1	0.600	0.492	0.000	1.000

There were 116 observations reported in the combined model with 28 iterations completed. The dependent variable for the function is PURLEASE, which represents both purchase/lease options for all three machines of acquiring a hypothetical crawfish peeling machine. In other words, this variable includes processors' adoption responses to all of these machines and purchase/lease scenarios: (1) purchase large, (2) purchase medium, (3) purchase small, (4) lease large, and (5) lease medium, for 5 x 30 = 150 observations, less 34 observations considering missing data.

The log likelihood and restricted log likelihood functions are -173.0818 and -199.7235, respectively. This ordered probability model has a Pseudo R^2 of 0.1334 with 16 degrees of freedom. Mu (μ) represents the distance between thresholds parameters. If they are significant, and in this case all are significant because the probabilities are less than 0.10, it is indicative there is a significant difference between the thresholds (Greene, 2003, pp. 35-39). Table 4.8 shows the aggregate ordered probit results.

Aggregate Model

Table 4.8: Ordered Probit Results of the Crawfish Peeling Machine Adoption Model-All Sizes Combined

Variable	Coefficient	Standard Error	B/St.Er.	P[|Z|>]	Mean of X
Index function for probability					
Constant	1.14212	1.25183	0.912	0.3616	
MEAT1000	0.00339	0.00429	0.790	0.4295	70.9810
VALUEADD	0.35824	0.37999	0.943	0.3458	0.1293
DIVERSE	0.69563	0.34719	2.004	0.0451	0.6466
PCTPEEL2	0.00846	0.00383	2.207	0.0273	46.3362
LABOR3	-0.41844	0.25972	-1.611	0.1072	0.4397
LBCOOK13	0.00002	0.00001	1.797	0.0724	15193.9660
CONTCO12	-0.33407	0.38845	-0.860	0.3898	0.2155
ALTER15	-0.52617	0.27350	-1.924	0.0544	0.4397
WAGE20	-0.94169	0.70884	-1.328	0.1840	1.5418
PURCHASE	-0.57781	0.23507	-2.458	0.0140	0.6121
LARGE	-1.31410	0.50167	-2.619	0.0088	0.3966
SMALL	1.40350	0.60981	2.302	0.0214	0.2069
SIZELARG	0.00763	0.00600	1.217	0.2037	28.2372
SIZESMAL	-0.18700	0.00795	-2.352	0.0187	14.4634
YEARS43	0.02996	0.01121	2.673	0.0075	14.3534
FAMILY44	0.17635	0.31800	0.555	0.5792	0.5948
Threshold parameters for index					
Mu (1)	0.09583	0.05280	1.815	0.0695	
Mu (2)	0.39500	0.09214	4.287	0.0000	
Mu (3)	0.57036	0.10342	5.515	0.0000	
Mu (4)	1.26435	0.12980	9.741	0.0000	
Mu (5)	1.83200	0.15859	11.552	0.0000	

According to Table 4.8, of the 17 variables listed, 2 were significant at the 0.10 significance level, 7 were significant at the 0.05 significance level, and the remaining 8 were not significant. In terms of the variables with 90% probability, pounds cooked (LBCOOK13) had a positive impact on adoption while altering the facility (ALTER15) had a negative impact on adoption. This coincides with the researcher's expectations since an operation that produces more cooked crawfish would find a peeling machine beneficial. If a processor would be required to alter the facility to adopt the crawfish peeling machine, adoption would be more costly, reducing his or her willingness to adopt.

With respect to the variables at the 95% probability, as expected diversification (DIVERSE), percentage of crawfish peeled (PCTPEEL2), the small machine (SMALL), and the expected number of years to remain peeling crawfish (YEARS43) had positive impacts on the adoption of a crawfish peeling machine. In contrast, but also as expected, the purchase of a machine (PURCHASE), the large machine (LARGE), and the interaction term for firm size with the small-sized machine operation (SIZESMAL) had negative impacts on the adoption of a crawfish peeling machine.

Table 4.9 presents the marginal effects for the ordered probability with the seven levels of acceptability. These are the statistics reported at the aggregate level pertaining to the purchase and lease options combined.

Table 4.9: Summary of Marginal Effects for Aggregate with Ordered Probability Model

Variable	Y=00	Y=01	Y=02	Y=03	Y=04	Y=05	Y=06
ONE	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MEAT1000	-0.0012	-0.0001	-0.0001	0.0000	0.0003	0.0005	0.0006
VALUEADD	-0.1116**	-0.0071	-0.0171	-0.0052	0.0196	0.0460	0.0753**
DIVERSE	-0.2453**	-0.0096	-0.0165	0.0008	0.0705	0.0893	0.1107**
PCTPEEL2	-0.0029**	-0.0001**	-0.0003	0.0000	0.0007	0.0011	0.0015
LABOR3	0.1453**	0.0068	0.0137*	0.0017	-0.0376	-0.0552	-0.0729
LBCOOK13	0.0000*	0.0000*	0.0000	0.0000	0.0000	0.0000	0.0000
CONTCO1	0.1188**	0.0049	0.0086	-0.0003	-0.0349	-0.0441	-0.0530
ALTER15	0.1805**	0.0084	0.0167**	0.0018	-0.0474	-0.0688	-0.0911
WAGE20	0.3201	0.0163	0.0339	0.0055	-0.0813	-0.1258	-0.1686
PURCHASE	0.1873**	0.0105	0.0235	0.0057	-0.0399	-0.0743	-0.1127
LARGE	0.4513**	0.0145	0.0228	-0.0039	-0.1230	-0.1533	-0.2085
SMALL	-0.3448**	-0.0271	-0.0760	-0.0342	-0.0173	0.1200	0.3795**
SIZELARG	-0.0026	-0.0001	-0.0003	0.0000	0.0007	0.0010	0.0014
SIZESMAL	0.0064**	0.0003**	0.0007	0.0000	-0.0016	-0.0025	-0.0033
YEARS43	-0.0102**	-0.0005**	-0.0011	-0.0002	0.0026	0.0040	0.0054
FAMILY44	-0.0604	-0.0030	-0.0060	-0.0008	0.0158	0.0235	0.0309

* = significant at 0.10 alpha level
** = significant at 0.05 alpha level

Since there was a sufficient amount of adequate data, none of the seven levels of certainty had to be combined as was done in the individual level models. Each column represents a different level as coded by the researcher. A breakdown of the different levels is as follows:

- Y=00 represents a respondent indicating with 100% certainty he or she would not purchase/lease a crawfish peeling machine.
- Y=01 represents a respondent indicating, between 81% - 99% certainty, he or she would not purchase/lease a crawfish peeling machine.
- Y=02 represents a respondent indicating, between 61% - 80% certainty, he or she would not purchase/lease a crawfish peeling machine.
- Y=03 represents a respondent indicating, between 41% - 60% not certain whether he or she would or would not purchase/lease a crawfish peeling machine.
- Y=04 represents a respondent indicating, between 61% - 80% certainty, he or she would more than likely purchase/lease a crawfish peeling machine.
- Y=05 represents a respondent indicating, between 81% - 99% certainty, he or she would more than likely purchase/lease a crawfish peeling machine.
- Y=06 represents a respondent indicating with 100% certainty he or she would purchase/lease a crawfish peeling machine.

According to a cross tabulation of predictions table generated by LIMDEP, it has been calculated 41% of the responses were correctly predicted given the data used. With respect to table 4.9, at least 12 of the 16 variables (excluding the constant) showed some type of significance at one or more levels. For instance, VALUEADD revealed significance at the Y=00 level of certainty with -0.1116. This can be interpreted as processors who are involved in value added food manufacturing lower their probabilities by 0.1116 of answering, “With 100% certainty, I would not purchase a crawfish peeling machine." Alternatively, when examining the identical variable at the Y=06 level, these processors increase their probabilities by 0.0753 of answering, "With 100% certainty, I would purchase a crawfish peeling machine."

Processors who (1) are diversified across multiple species in their seafood processing, (2) are offered the adoption of the small machine, and (3) expect to continue peeling crawfish for a substantial amount of time decrease their probabilities by 0.2453, 0.3448, and 0.0102 respectively of selecting the answer choice equivalent to Y=00 in table 4.9. For each percentage increase in the amount of purchased crawfish that is peeled, the probability of answering choice Y=00 decreases by 0.0029. Processors who (1) have enough available labor throughout the peeling season, (2) own or rent a continuous cooker, (3) would have to alter their facilities to accommodate the large machine, (4) were offered the purchase (versus lease) option of a peeling machine, or (5) were offered the large peeling machine, increased their probabilities of responding Y=00 by 0.1453, 0.1188, 0.1805, 0.1873, and 0.4513, respectively, of choosing "With 100% certainty, I would not purchase a crawfish peeling machine." Each additional pound of crawfish cooking capacity would increase the probability of answering Y=00, a result that was not anticipated. The SIZESMAL variable was also significant for Y=00.

The percentage peeled and expected years in the business lessen processors' probability of falling into the Y=01 category. As percentage peeled increases by 1%, probability decreases by 0.0001; and each additional expected year decreases the probability by 0.0005. The cooker capacity and being a small-sized firm increases processors' probability of selecting this response. Only two variables were significant for respondents answering that they were between 61%-80% certain they would not purchase a crawfish peeling machine. Labor sufficiency is significant at the 0.10 alpha level and would increase the processors' probability of choosing that response by 0.0137. The altering of facilities is significant at the 0.05 alpha level and would increase the probability of choosing that level of certainty by 0.0167. Lastly, in terms of being 100% certain to purchase a crawfish peeling machine (Y=06), for processors who manufacture value-added products, were diversified, or were faced with the small machine, the probability of selecting Y=06 increases by 0.0753, 0.1107, and 0.3795 respectively.

The following tables give further details about the adoption of the three individual hypothetical crawfish peeling machines. Tables 4.10 and 4.11 highlight the small machine. Tables 4.12 and 4.13 analyze the medium sized machine, and tables 4.14 and 4.15 analyze the large machine. Ordered Probit results and the marginal effects are given for each machine presented. Some variables were excluded when not needed in the individual machine models, such as machine size. Explanations for the reasoning of the excluded variables are incorporated within the discussions.

Small Machine

Table 4.10: Ordered Probit Results for the Small Machine

Variable	Coefficient	Standard Error	B/St.Er.	P[|Z|>]	Mean of X
Index function for probability					
Constant	-2.78260	2.93233	-0.949	0.3427	
MEAT1000	-0.01205	-0.00850	-1.417	0.1565	67.7104
VALUEADD	1.43025	0.91224	1.568	0.1169	0.1200
DIVERSE	-0.00348	0.71667	-0.005	0.9961	0.6400
PCTPEEL2	-0.00653	0.00841	0.776	0.4378	48.4000
LABOR3	-1.73148	0.70577	-2.453	0.0142	0.4400
LBCOOK13	-0.00004	0.00004	-1.114	0.2653	15076.0000
CONTCO12	-0.54322	0.78636	-0.691	0.4897	0.2400
WAGE20	3.81858	1.81235	2.107	0.0351	1.5320
YEARS43	-0.02213	0.02802	0.790	0.4297	14.4400
FAMILY44	-1.78241	0.80140	-2.224	0.0261	0.5600
Threshold parameters for index					
Mu (1)	0.52110	0.28624	1.821	0.0687	
Mu (2)	1.23923	0.30461	4.068	0.0000	
Mu (3)	1.53487	0.32458	4.729	0.0000	

There were 25 observations reported in the small machine model with 22 iterations completed. The dependent variable for the function is PURLESML, which represents the purchase option of acquiring a hypothetical small crawfish peeling machine. The log likelihood and restricted log likelihood functions are -25.1241 and -35.7436, respectively. This ordered probability model has a Pseudo R^2 of 0.2969 with 10 degrees of freedom. Mu (μ) represents the distance between thresholds parameters; in this case all are significant because the probabilities are less than 0.10, which indicates a significant difference between the thresholds (Greene, 2003, pp. 35-39).

The variables ALTER15, PURCHASE, LARGE, SMALL, SIZELARGE and SIZESMALL were excluded from the analysis, as they were inconsequential to the model. The reasoning behind the extractions was mainly due to the fact that the small crawfish machine would not cause processors to alter their facilities and the only option in terms of adoption was the purchase option. There was not an alternative decision of leasing the small size machines. Also, since only the small machine was being taken into consideration at this point, researchers had to disregard the other size machine (LARGE) in its evaluation. SIZELARGE and SIZESMALL were removed, as they were irrelevant to the model.

According to Table 4.10, of the 11 variables listed, only 3 were regarded as highly significant at the 0.05 significance level, and the remaining 8 were not significant. In terms of the variables with 95% probability, the wage paid to the crawfish peelers (WAGE20) has a positive impact on adoption while the labor availability (LABOR3) and the expectancy of family to take over the operation (FAMILY44) have negative impacts on the adoption of a small crawfish peeling machine. With respect to wage, it most likely has a positive relationship to adopting the small peeling machine because processors paying higher wages would be more prone to substitute machinery for labor. However, when there is enough labor available, processors would not consider a small peeling machine as valuable, which would warrant a negative impact on adoption. Against expectations, the model states the family variable would negatively affect adoption. Table 4.11 shows the marginal effects for the ordered probability model for the small machine with five levels of acceptability.

Table 4.11: Summary of Marginal Effects for Small Machine with Ordered Probability Model

Variable	Y=00	Y=01	Y=02	Y=03	Y=04
ONE	0.0000	0.0000	0.0000	0.0000	0.0000
MEAT1000	0.0041	0.0007	-0.0010	-0.0008	-0.0030
VALUEADD	-0.3174*	-0.1404**	-0.0629	0.0367	0.4841**
DIVERSE	0.0012	0.0002	-0.0003	-0.0002	-0.0009
PCTPEEL2	-0.0022	-0.0004	0.0006	0.0005	0.0016
LABOR3	0.5679**	0.0441	-0.1317	-0.0939	-0.3863
LBCOOK13	0.0000	0.0000	0.0000	0.0000	0.0000
CONTCO1	0.1974**	0.0154	-0.0599	-0.0376	-0.1153
WAGE20	-1.3098*	-0.2130	0.3217	0.2634	0.9376
YEARS43	-0.0076	-0.0012	0.0019	0.0015	0.0054
FAMILY44	0.5319**	0.0909**	-0.0719	-0.0842	-0.4668*

* = significant at 0.10 alpha level
** = significant at 0.05 alpha level

Unlike the aggregate model, there was not a sufficient amount of adequate data per each answer choice, thus some of the seven levels of certainty had to be combined, down to 5 levels. This was due to the fact some respondents chose not to accept any of the answer choices given or not enough processors chose that particular option. For instance, none of the processors chose the response, "I would more than likely not purchase this machine (with 61%-80% certainty), and as a result it was combined with two other levels of certainty. Each column represents a combination of different levels as coded by the researcher. A breakdown of the different levels is as follows:

- Y=00 represents a respondent indicating with 100% certainty he or she would not purchase/lease a crawfish peeling machine.
- Y=01 represents a respondent indicating between 81% - 99% certainty he or she would not purchase/lease a crawfish peeling machine.
- Y=02 represents a respondent indicating between 61% - 80% certainty he or she would not purchase/lease a crawfish peeling machine; a respondent indicating between 41% - 60% not certain whether he or she would or would not purchase/lease a crawfish peeling machine; and a respondent indicating between 61% - 80% certainty he or she would more than likely purchase/lease a crawfish peeling machine.
- Y=03 represents a respondent indicating between 81% - 99% certainty he or she would more than likely purchase/lease a crawfish peeling machine.
- Y=04 represents a respondent indicating with 100% certainty he or she would not purchase/lease a crawfish peeling machine.

According to a cross tabulation of predictions table generated by LIMDEP, it has been calculated that 60% of the responses were correctly predicted given the data used. With respect to table 4.11, 5 of the 11 variables, excluding the constant variable, showed significance at any given level. For example, FAMILY44 revealed significance at the Y=00 level of certainty. This is interpreted as, processors who expect a family member to assume responsibilities of their facilities increase their probabilities by 0.5319 of answering, "With 100% certainty, I would not purchase a small crawfish peeling machine." Alternatively, when examining at the Y=06 level, processors who expect a family member to take over the family business decrease their probabilities by 0.4668 of answering, "With 100% certainty, I would purchase a small crawfish peeling machine."

Processors who participate in value-added production decrease their probability by 0.3174 of selecting the answer choice Y=00. Also, if the wage paid to crawfish peelers increases by $1, it decreases the probability of answering Y=00 by 1.31. Processors who (1) have enough available labor throughout the peeling season or (2) own or rent a continuous cooker increase their probabilities by 0.5679 and 0.1974, respectively of choosing "With 100% certainty, I would not purchase a crawfish peeling machine."

At the Y=01 level of certainty, producing value-added products decreases the probability by 0.1404 of selecting the answer, "I am almost certain I would not purchase this machine (with 81%-99%)". Also, expecting a family member to take over the business increases the probability of selecting this answer by 0.0909. Other than the family variable, another significant variable when considering a 100% certainty of adopting a small crawfish peeling machine was VALUADD. Producing value-added products increases the probability by 0.4841 of selecting the answer Y=06, "I am 100% certain I would purchase this machine."

Medium Machine

Table 4.12: Ordered Probit Results for the Medium Machine

Variable	Coefficient	Standard Error	B/St.Er.	P[|Z|>]	Mean of X
		Index function for probability			
Constant	1.53947	1.93341	0.796	0.4259	
MEAT1000	0.00410	0.00460	0.893	0.3719	71.3156
VALUEADD	0.46113	0.60636	0.760	0.4470	0.1304
DIVERSE	1.00711	0.53938	1.867	0.0619	0.6522
PCTPEEL2	0.00846	0.00631	1.340	0.1802	46.6304
LABOR3	-0.50798	0.39868	-1.274	0.2026	0.4348
LBCOOK13	0.00004	0.00002	1.842	0.0655	15213.0430

(table continued)

CONTCO12	-0.53614	0.63069	-0.850	0.3953	0.2174
ALTER15	-0.56619	0.42499	-1.332	0.1828	0.4348
WAGE20	-1.37737	1.10165	-1.250	0.2112	1.5446
PURCHASE	-0.74326	0.32816	-2.265	0.0235	0.5217
YEARS43	0.02938	0.01759	1.671	0.0948	14.1739
FAMILY44	0.82935	0.48932	1.695	0.0901	0.5870
Threshold parameters for index					
Mu(1)	0.83827	0.21188	3.956	0.0001	
Mu(2)	2.00578	0.23563	8.512	0.0000	
Mu(3)	2.59786	0.27655	9.394	0.0000	

There were 46 observations reported in the medium machine model with 22 iterations completed. The dependent variable for the function is PURLEMED, which represents the purchase/lease options of acquiring a hypothetical medium-sized crawfish peeling machine. Also, the log likelihood and restricted log likelihood functions are -58.3193 and -72.6975, respectively. This ordered probability model has a Pseudo R^2 of 0.1978 with 12 degrees of freedom. Mu (μ) represents the distance between threshold parameters; in this case all are significant because the probabilities are less than 0.10, which indicates a significant difference between the thresholds (Greene, pp. 35-39).

This model had some of the same variables removed relative to the Full Model as did the Small Machine model. For instance, LARGE, SMALL, SIZELARGE and SIZESMALL were taken out of the model. When observing only the medium-sized machine, we eliminated all exogenous variables that dealt with other sized machines. However, ALTER15 remained in the model to determine whether the modification of plant facilities would be significant in the adoption of a medium-sized machine. As opposed to the small-sized machine, the medium-sized machine had the purchase or lease option (PURCHASE). For this reason, it was included in the model.

According to Table 4.12, of the 13 variables listed, only 4 were significant at the 0.10 significance level, 1 was regarded as highly significant at the 0.05 significance level, and the remaining 8 were not significant. The variable with 95% probability, the purchase option (PURCHASE), has a negative impact on adoption. In terms of the variables with 90% probability, processors that are diversified (DIVERSE), pounds cooked (LBCOOK13), years expected to remain in the business (YEARS43), and expected family take over of the operation (FAMILY44) have positive impacts on adopting the medium-sized crawfish peeling machine.

Processors tend to be less willing to purchase a new technology that requires a great monetary investment, though they might be willing to lease the machine. However, if they plan to remain in the crawfish peeling business for a considerable amount of time and expect a relative to assume responsibilities after they retire, adopting the medium size crawfish peeling machine is more attractive. In addition, an increase in the cooker capacity and greater diversification would enhance the incentive to adopt because a machine could possibly handle greater volume than with human peelers. Table 4.13 illustrates the marginal effects for the ordered probability with five levels of acceptability.

Table 4.13: Summary of Marginal Effects for Medium Machine with Ordered Probability Model

Variable	Y=00	Y=01	Y=02	Y=03	Y=04
ONE	0.0000	0.0000	0.0000	0.0000	0.0000
MEAT1000	-0.0007	-0.0008	0.0002	0.0006	0.0007*
VALUEADD	-0.0647	-0.0868*	-0.0054	0.0612	0.0957
DIVERSE	-0.2146**	-0.1562**	0.1001	0.1278	0.1429**
PCTPEEL2	-0.0015	-0.0016	0.0005	0.0012	0.0014
LABOR3	0.0935**	0.0912**	-0.0331	-0.0692	-0.0823
LBCOOK13	0.0000*	0.0000*	0.0000	0.0000	0.0000
CONTCO1	0.1132**	0.0895**	-0.0573	-0.0715	-0.0739
ALTER15	0.1048**	0.1009**	-0.0375	-0.0767	-0.0915
WAGE20	0.2416	0.2564	-0.0751	-0.1917	-0.2312
PURCHASE	0.1296**	0.1324**	-0.0338	-0.0988	-0.1294
YEARS43	-0.0052	-0.0055*	0.0016	0.0041	0.0049
FAMILY44	-0.1611*	-0.1402**	0.0628	0.1090	0.1295**

* = significant at 0.10 alpha level
** = significant at 0.05 alpha level

Similar to the small machine model, there was not a sufficient amount of adequate data per each answer choice; thus the seven levels of certainty had to be combined into five levels. Each column represents a combination of different levels as coded by the researcher. A breakdown of the different levels is as follows:

- Y=00 represents a respondent: 1) indicating with 100% certainty he or she would not purchase/lease a crawfish peeling machine, and 2) indicating between 81% - 99% certainty he or she would not purchase/lease a crawfish peeling machine.
- Y=01 represents a respondent: 1) indicating between 61% - 80% certainty he or she would not purchase/lease a crawfish peeling machine and 2) indicating between 41% - 60% not certain whether he or she would or would not purchase/lease a crawfish peeling machine.
- Y=02 represents a respondent indicating between 61% - 80% certainty he or she would more than likely purchase/lease a crawfish peeling machine.
- Y=03 represents a respondent indicating between 81% - 99% certainty he or she would more than likely purchase/lease a crawfish peeling machine.
- Y=04 represents a respondent indicating with 100% certainty he or she would purchase/lease a crawfish peeling machine.

According to a cross tabulation of predictions table generated by LIMDEP, it is calculated that 46% of the responses were correctly predicted given the data used. With respect to table 4.13, 10 of the 13 variables, excluding the constant variable, showed significance. For example, DIVERSE revealed significance at the Y=00 level of certainty with -0.2146. This is interpreted as, producing various species of seafood decreases the probability by 0.2146 of answering, “With 81%-100% certainty, I would not purchase a medium-sized crawfish peeling machine." Alternatively, when examining this variable at the Y=04 level, producing various species of seafood increases the probability by 0.1429 of answering, "With 100% certainty, I would purchase a medium-sized crawfish peeling machine."

Believing a family member will take over the crawfish peeling business upon retirement decreases the probability by 0.1611 of selecting the answer choice equivalent to Y=00 in table 4.13. Yet, (1) having enough available labor throughout the peeling season, (2) ability to handle an additional pound of crawfish in cooking facilities, (3) owning or renting a continuous cooker, (4) having to alter facilities to accommodate a peeling machine, or (5) being offered to purchase a peeling machine increases probabilities by 0.0935, 0.0000, 0.1132, 0.1048, and 0.1296, respectively of choosing "With 81%-100% certainty, I would not purchase a crawfish peeling machine."

At the Y=01 level of certainty, (1) producing value added products, (2) processing an additional species of seafood, (3) expecting to be in the crawfish peeling industry for an additional year, and (4) believing a family member will gain control of the crawfish peeling business upon retirement decreases probabilities by 0.0868, 0.1562, 0.0055, and 0.1402, respectively, of choosing "With 41%-80% probability, I would or would not purchase a crawfish peeling machine." Yet, (1) having sufficient labor throughout the peeling season, (2) ability to handle more crawfish in cooking facilities, (3) owning or renting a continuous cooker, (4) needing to alter facilities to accommodate a peeling machine, and (5) being offered the purchase of a peeling machine increases probabilities by 0.0912, 0.0000, 0.0895, 0.1009, and 0.1324, respectively of this response.

At the Y=04 level of certainty, (1) producing more peeled tailmeat and (2) expecting a close relative to take over the family business increases the probability of choosing "With 100% certainty, I would purchase a medium-sized crawfish peeling machine."

Large Machine

Table 4.14: Ordered Probit Results for the Large Machine

Variable	Coefficient	Standard Error	B/St.Er.	P[|Z|>]	Mean of X
Index function for probability					
Constant	5.72551	2.76351	2.072	0.0383	
MEAT1000	0.01977	0.00677	2.918	0.0035	71.2069
VALUEADD	-0.31753	0.70799	-0.449	0.6538	0.1304
DIVERSE	2.11668	1.11676	1.895	0.0580	0.6522
PCTPEEL2	0.01285	0.00842	1.525	0.1272	46.0870
LABOR3	-0.41640	0.57358	-0.726	0.4679	0.4348
LBCOOK13	0.00009	0.00004	2.354	0.0186	15256.5220
CONTCO12	-0.91298	1.08593	-0.841	0.4005	0.2174
ALTER15	-1.68971	0.74647	-2.264	0.0236	0.4348
WAGE20	-7.28586	2.26811	-3.212	0.0013	1.5391
PURCHASE	-1.04960	0.40926	-2.565	0.0103	0.5000
YEARS43	0.08483	0.02948	2.879	0.0040	14.3913
FAMILY44	1.85896	1.11958	1.660	0.0968	0.6087
Threshold parameters for index					
Mu(1)	0.66950	0.21378	3.132	0.0017	
Mu(2)	0.76739	0.22003	3.488	0.0005	
Mu(3)	1.44584	0.27030	5.349	0.0000	
Mu(4)	2.93068	0.47431	6.179	0.0000	

There were 46 observations reported in the large machine model with 29 iterations completed. The dependent variable for the function is PURLELGE, which represents the purchase/lease options of acquiring a hypothetical large crawfish peeling machine. Also, the log likelihood and restricted log likelihood functions are -42.9172 and -68.5007, respectively. This ordered probability model has a Pseudo R^2 of 0.3735 with 12 degrees of freedom. Mu (μ) represents the distance between threshold parameters; in this case all are significant because the probabilities are less than 0.10, which indicates a significant difference between the thresholds (Greene, pp. 35-39).

The large machine model is very comparable to the medium machine model since both models make inferences on the same variables. The variables LARGE, SMALL, SIZELARGE and SIZESMALL were not included in the model. Similar to the aggregate and medium models, ALTER15 and PURCHASE are included in the model. These variables are representative of the fact the large crawfish peeling machine has a purchase and lease option and due to its size, processors may have to consider altering their processing plants to implement the machine into the facilities.

According to Table 4.14, of the 13 variables listed, 2 were significant at the 0.10 significance level, 7 were significant at the 0.05 significance level, and the remaining 4 were not significant. In terms of the variables with 95% probability, volume of peeled crawfish production (MEAT1000), cooker capacity (LBCOOK13), and years expected to remain in business (YEARS43) have positive impacts on adoption, while altering the plant (ALTER15), wages paid (WAGE20), and the purchase option (PURCHASE) have negative impacts on adopting the large peeling machine. In terms of the variables with 90% probability, diversification (DIVERSE) and expecting a family member to take over the operation (FAMILY44) have positive impacts on adopting the large sized crawfish peeling machine.

When interviewing the various crawfish processors in Louisiana, many had concerns of adopting the large peeling machine because they had to take into account not only purchasing an expensive machine but also expanding their current peeling facilities, which amounts to added capital investment to house the machine. As expected, these variables reflect the processors' hesitation in incorporating the new technology. If they plan for a relative to continue running their plants after they exit the industry, and have a high volume of crawfish cooking capacity, then adopting the large crawfish machine is more favorable. Table 4.15 illustrates the marginal effects for the ordered probability with six levels of acceptability. These are the statistics reported at the large machine alternative pertaining to the purchase and lease options combined.

Table 4.15: Summary of Marginal Effects for Large Machine with Ordered Probability Model

Variable	Y=00	Y=01	Y=02	Y=03	Y=04	Y=05
ONE	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MEAT1000	-0.0078**	0.0020	0.0005	0.0030	0.0023	0.0001
VALUEADD	0.1228	-0.0386**	-0.0074	-0.0456	-0.0303	-0.0009
DIVERSE	-0.6652**	0.2000	0.0355	0.2268	0.1924**	0.0104
PCTPEEL2	-0.0051	0.0013	0.0003	0.0020	0.0015	0.0000
LABOR3	0.1633	-0.0442**	-0.0095	-0.0621	-0.0459	-0.0016
LBCOOK13	0.0000**	0.0000	0.0000	0.0000	0.0000	0.0000
CONTCO1	0.3297*	-0.1180**	-0.0201	-0.1167	-0.0728	-0.0021
ALTER15	0.5898**	-0.1510	-0.0310	-0.2097	-0.1878	-0.0104
WAGE20	2.8871**	-7523.0000	-0.1675	-1.1091	-0.8302	-0.0280
PURCHASE	0.3978**	-0.0957	-217.0000	-0.1490	-0.1257	-0.0057
YEARS43	-0.0336**	0.0088	0.0019	0.0129	0.0097	0.0003
FAMILY44	-0.6234**	0.1742	0.0332	0.2176	0.1883**	0.0102

*   = significant at 0.10 alpha level
** = significant at 0.05 alpha level

Analogous to the small and medium machine models, there was not a sufficient amount of adequate data per each answer choice; thus two of the seven levels of certainty had to be combined. Each column represents a combination of different levels as coded by the researcher. A breakdown of the different levels is as follows:

- Y=00 represents a respondent indicating with 100% certainty he or she would not purchase/lease a crawfish peeling machine.
- Y=01 represents a respondent: 1) indicating between 81% - 99% certainty he or she would not purchase/lease a crawfish peeling machine, and 2) indicating between 61% - 80% certainty he or she would not purchase/lease a crawfish peeling machine.

- Y=02 represents a respondent indicating between 41% - 60% not certain whether he or she would or would not purchase/lease a crawfish peeling machine.
- Y=03 represents a respondent indicating between 61% - 80% certainty he or she would more than likely purchase/lease a crawfish peeling machine.
- Y=04 represents a respondent indicating between 81% - 99% certainty he or she would more than likely purchase/lease a crawfish peeling machine.
- Y=05 represents a respondent indicating with 100% certainty he or she would purchase/lease a crawfish peeling machine.

Fifty-nine percent of the responses were correctly predicted by the model. With respect to table 4.15, 11 of the 13 variables, excluding the constant variable, showed significance. LABOR3 exhibited significance at the Y=01 level of certainty, at -0.0442. This means having enough labor available throughout the peeling season for peeling crawfish decreases the probability by 0.0442 of answering, "With 61%-99% certainty, I would not purchase a large crawfish peeling machine."

Producing a large volume of peeled tailmeat, being diversified, anticipating being in the crawfish peeling business for longer, and expecting to have a family take over upon retirement decrease the probabilities of choosing the answer, "I am 100% certain I would not purchase this machine." However, handling more peeled crawfish, owning or renting a continuous cooker, having to alter their facilities, paying higher wages to crawfish peelers, and being offered to purchase a peeling machine increase their probabilities of selecting the answer equivalent at the Y=00 certainty level.

At the Y=01 level of certainty, (1) producing value added products and (2) owning or renting a continuous cooker reduce the probabilities of choosing "I will not purchase this crawfish peeling machine with 61%-99% certainty" by 0.0386 and 0.1180, respectively. Lastly, at the Y=04 certainty level, (1) being diversified and (2) expecting a family member to take over upon retirement increase the probability of selecting, "I am almost certain I would purchase this machine (with 81%-99% certainty)" by 0.1924 and 0.1883, respectively.

Multicollinearity

As performed for conjoint analysis, a test for multicollinearity was conducted for the variables used in technology adoption. Table D.1 in Appendix D includes the VIF and Condition Index values, which are determinants of whether the independent variables have a relationship with one another. According to Ramanathan (2002, pp. 318-319), since none of the VIF values are greater than 5, there is no indication of linear dependence. For further verification, Greene (2003, p. 58) states values in excess of 20 for the Condition Index provides evidence of linear dependence. None of the variables except for the purchase option possess a value greater than 20 which would suggest a potential multicollinearity problem with that variable. This is deemed a key variable, so it remains in the models.

Heteroskedasticity

Lastly, the variables used in the ordered probit program were tested for heteroskedasticity using a White's LM test. The residuals should be random in order for heteroskedasticity to not be present. The null hypothesis that the data is homoskedastic if the probability value is less than 0.05 is accepted (Ramanathan, p. 423). Results indicate a p-value of 1 as shown in table D.2 in Appendix D; therefore we accept the null hypothesis and conclude that the data is homoskedastic.

Chapter 5

Conclusions

This research provides information on the type of crawfish peeling machine that would likely be acceptable to Louisiana crawfish processors. There has been considerable interest expressed by crawfish processors in a machine for over a decade. Prospective machine developers indicated their concerns for the market of a crawfish peeling machine. In order for them to develop an adequate machine, they needed to know the criteria deemed most important to crawfish processors to assure higher adoption rates. According to survey results, if a suitable machine could be produced that reduced the cost of crawfish production, it is expected a substantial number of machines could be sold.

To determine what entails a suitable peeling machine, extensive research and analysis was performed. Using conjoint analysis in conjunction with interviewing various crawfish processors, it was concluded that a machine must devein the product to ensure acceptability. According to the conjoint analysis, the industry viewed deveining as the most important attribute. Processors believe consumers prefer deveined crawfish tailmeat. Furthermore, the cost of manually deveining the crawfish after it has been processed by the peeling machine would be significant since it would require individual handling.

Retaining the fat and backstrap, and not handling individual crawfish were considered to have nearly the same importance. After numerous discussions with processors, it was concluded that the fat is regarded as important because it contributes weight to the final packaging. The inclusion of fat is also preferred by consumers since they believe it provides additional flavor to the product. The backstrap, similar to fat, also supplies yield. Not having crawfish individually handled by workers was considered important because processors believed if a person had to handle it, then the machine would not be as useful since the workers could ultimately peel it, taking into account the speed at which they peel. Purchasing or having a lease option for the machine was the least important attribute. However, most processors prefer to lease the machine rather than purchase it. The attributes proved to be significant but the size of the machine also played an important role in adoption.

The small and medium-sized machines were favored over the large machine that would cause many processors to alter their facilities and expand operations to utilize it fully. Of the five considered hypothetical machine with the purchase/lease combinations, the medium-sized with the leasing option had the highest expected adoption rate, at 70%. Though more respondents stated with 100% certainty they would purchase the small machine than leasing the medium machine, it was not greater than the total expected adoption rate of leasing the medium machine. It is uncertain whether a leased small machine would have been more favorable, though results of the aggregate model predict it would have been.

The small, table-top machine showed the greatest variance in terms of acceptability with 63% of the processors indicating with certainty either they would or would not purchase the machine. Finally, the large-sized machine with respect to the purchase or lease option had the lowest expected rate of adoption. Most processors stated the substantial initial investment required to purchase the large peeling machine deterred them from considering adopting it. Hence, the size of the machine along with initial purchase cost will have a significant impact on the adoption of a machine.

An ordered probit analysis indicated, in general, larger firms that peel a higher percentage of live crawfish, are diversified in the production of other types of seafood, and plan to be actively peeling crawfish for a greater number of years will be the greater adopters. Also, processors who expect to have a family member take over the family businesses, have labor availability problems and have extensive resources are more likely to adopt a crawfish peeling machine. Overall, the type of machine developed and payment agreement will affect the description of firm willing to adopt. For instance, if it were to be leased, processors would less likely be willing to adopt relative to the purchase arrangement. If it were a large machine, it would be less likely to be adopted than a medium-sized machine, and if it were a small machine, it would be more likely to be adopted than a medium-sized machine. However, larger processors with greater resources and who have greater cooker capacity are less likely to adopt a small-sized peeling machine because the volume of crawfish produced exceeds the capabilities a small machine can process. They are more prone to adopt the medium and large-sized machines. Processors with smaller operations prefer to purchase the small machine or lease the medium-sized machine due to their limited resources and limited production capabilities.

Given the relatively small size of the current market (around 40 processors), machine developers need to be well informed of processor criteria for an acceptable machine. Separating processors into clusters was thought to be useful to machine developers in determining which attributes were most important to each group. This should increase marketability because they would know which attributes could be varied for different segments. Therefore, a cluster analysis was used to classify two homogeneous clusters. The only variable that showed significance was the percentage of crawfish peeled. The processors peeling a higher percentage of crawfish were identified as being members of cluster 2. Cluster 2 considered the retention of fat and deveining to be most important in the adoption of a peeling machine with 29.6% and 29.2% importance, respectively. This breakdown, however, does not provide indication that machines with different attributes should be developed for different segments.

The polychotomous choice willingness-to-adopt questions are believed to have encouraged processors to carefully consider their responses. When interviewed, they paid close attention to machine descriptions and thoroughly contemplated the certainty levels of purchasing or leasing the various machines. Yes/No type questions were thought by the researchers to produce more biased responses due to the fact processors would tend to be more receptive of adopting a crawfish peeling machine since they have supported its development for years. On the other hand, the five levels of certainty in the middle made the questions more complex. Whether this caused more confusion or greater contemplation of actual preferences is unknown. This type of comparison would have to be analyzed in a study involving more respondents and additional questioning.

The development of a crawfish peeling machine that produced a similar product as the current hand-peeled product would likely be successfully accepted by the industry. However, this might cause a decrease in the cost of production, leading to an increased supply in the market and, resulting in a lower price for crawfish. Time of market entry has proven to be a critical measure of success for the adoption of new technologies.

Early adopters of the machine would benefit from the reduced cost of production before the market becomes saturated and more processors begin to adopt the machine, thus increasing production. Late adopters would most likely experience lower profits or short-term losses prior to adoption. Lastly, non-adopters would most likely be forced out of business because they would not be able to match the increased production of other processors who adopted the peeling machine and realized a lower cost of production. The U.S. industry might benefit from the development of a crawfish peeling machine if the increased production caused the price of the domestic product to decrease, enabling them to be more competitive with the lower-priced imported tailmeat from China. An increase in domestic crawfish consumption would contribute more revenue to the crawfish industry, which has a major economic impact on Louisiana.

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Appendix A: Crawfish Processor Survey

Crawfish Processor Survey

Information on the Volume of Crawfish Currently Processed

1. Last year, how many pounds of peeled tail meat did your firm peel during the following months?

	Pounds		*Pounds*
November	________	May	_______
December	________	June	_______
January	________	July	_______
February	________	August	_______
March	________	September	_______
April	________	October	_______

2. What percentage of all purchased crawfish do you typically peel during any particular month?

	Percent		*Percent*
November	________	May	_______
December	________	June	_______
January	________	July	_______
February	________	August	_______
March	________	September	_______
April	________	October	_______

3. Do you have enough labor available to you throughout the peeling season for peeling crawfish?

   a. Yes　　　　b. No

4. If you answered "no" to question 3, how many pounds of peeled tail meat would you peel if you had enough labor, given your current facilities?

	Pounds		*Pounds*
November	________	May	_______
December	________	June	_______
January	________	July	_______
February	________	August	_______
March	________	September	_______
April	________	October	_______

5. If a crawfish peeling machine were economically available for your use, would you purchase more crawfish to peel? (Circle One)

a. Yes b. No

6. If you answered "yes" to question 5, approximately how many pounds of crawfish would you purchase for peeling?

	Pounds		*Pounds*
November	________	May	_______
December	________	June	_______
January	________	July	_______
February	________	August	_______
March	________	September	_______
April	________	October	_______

7. What does your firm generally do with the crawfish you peel? Please indicate percentages.

_______% packaged for sale in retail outlets.
_______% used in production of value-added foods prepared by this firm for sale in retail outlets.
_______% used in production of foods prepared by this firm for sale directly to your customers (such as via a restaurant attached to the plant).
_______% other (please specify)_____________________________________
Total = 100%

Equipment Currently Owned by the Processing Plant

8. Do you currently own or lease a crawfish grader?

a. Yes b. No

9. If you answered "yes" to question 8, how many grades can you sort with your grader?______________(Number)

10. If you answered "yes" to question 8, approximately how many pounds of live crawfish can your grader handle during one working day?_______________lbs.

11. If you could increase the number of crawfish you peeled using a mechanical peeler, what size of crawfish would they be? Circle all that apply.

a. Jumbo 15 and under
b. Large 16-20
c. Medium 21-24
d. Peeler 25 and over

12. Do you currently own or rent a continuous cooker?

a. Yes b. No

13. If you answered "yes" to question 12, approximately how many pounds of live crawfish can your cooking facilities handle during one working day?________lbs.

14. Please describe your cooking system.

____
____
____
____

15. Suppose a crawfish peeling machine were made available to you. It is assumed that the machine would replace your current peeling labor. Suppose this peeling machine required a space of 900 ft^2, or a space of 35 ft H 50 ft. This does not include the space for cooking the product or packaging it. Would you have to alter your current facility significantly in order to introduce this machine?

a. Yes b. No

16. If you answered "Yes" to 15, how much do you estimate it would cost you to alter your current facility in order to install a crawfish peeling machine? $__________

Crawfish Peeling Labor Productivity and Costs

17. How many pickers (laborers for peeling) are typically available ***per day*** in the following months? (Please answer for both the beginning and the end of the month *if different*.)

	Beginning of Month	Ending of Month		Beginning of Month	Ending of Month
November	________	________	May	________	________
December	________	________	June	________	________
January	________	________	July	________	________
February	________	________	August	________	________
March	________	________	September	________	________
April	________	________	October	________	________

18. How many pounds of peeled tail meat can a typical picker peel in a day? ____lbs. What is the range from highest to lowest?______lbs to _______lbs.

19. On what basis do you determine a picker's pay for a given day? (Circle One)

a. Pounds of meat peeled
b. Hourly wages
c. Other (Please Specify) _________
____

20. What is the (wage / amount paid per pound peeled) paid to pickers? $__________

21. Do you provide transportation for pickers to and/or from the plant?

a. Yes b. No

22. If you answered “yes” to question 21, how many miles, on average, do you transport each rider per day?_______ Approximately how many riders, on average, do you transport per day during the peeling season?_______

23. Do you provide a meal for the pickers?

a. Yes b. No

24. If you answered “yes” to question 23, what is the cost of the meal per picker per day? $_____________

25. Do you provide any additional benefits to pickers?

a. Yes b. No

26. If you answered “yes” to question 25, please list these benefits and the amount of dollars per picker per year.

____

____$ per worker/per year

27. If there are any additional costs associated with crawfish peeling labor, would you please list them?

____

____

28. What do you estimate your energy costs to be to peel one pound of peeled crawfish? $____

29. Is there any cost expended for any chemical treatment of crawfish, such as phosphate? If so, what do you estimate the cost to be per one pound of peeled crawfish? $____

30. What type of method are you using to package crawfish tailmeat? (Please describe).____

____

____

31. How much do you estimate it costs you to peel one pound of crawfish, not including the cost of crawfish? $____

Determination of Crawfish Peeling Machine Acceptability

32. If a mechanical crawfish peeler, which *deveined, separated the head from the tail, and retained the backstrap* were available from a reputable manufacturer at the same cost as the cost of picking labor, which of the following options would you prefer?

    a. Buy the machine
    b. Rent the machine
    c. Would not be interested in the machine
    d. Other (Please Specify)_______________

33. Would you prefer to have a machine that deveins or does not devein the crawfish?

    a. Devein
    b. Does not devein

34. Would you prefer to have a machine that retains the fat or does not retain the fat of the crawfish?

    a. Retains the fat
    b. Does not retain the fat

35. Would you prefer to have a machine that retains the backstrap or does not retain the backstrap of the crawfish?

    a. Retains the backstrap
    b. Does not retain the backstrap

36. Would you prefer to have a machine in which an individual must handle each crawfish or one in which an individual need not handle each crawfish?

    a. Individual need not handle
    b. Individual must handle

37. If you were to adopt a crawfish peeling machine, would you prefer to own or lease it on an annual basis if the payments were based on a minimum base rent plus a production payment, and basic maintenance services were included in the price?

    a. Own the machine
    b. Lease the machine

38. Conjoint Analysis

Based upon your answers to the above questions, we assume that your most favored crawfish peeling machine would be one that:

____

Let's rate that machine as "10."

And, your least favored crawfish peeling machine would be one that:

____

Let's rate that machine as "0."

We assume that all other machines would fall somewhere in between the most and least favored machines above, and would thus range in rating between 10 and 0. I am going to present you with eight alternatives machines below. I would like for you to examine each of these machines and rate them on a scale from 0 to 10, where 0 represents the least favored machine above and 10 represents the most favored machine above. Here are the machines:

Machine	Attributes	Rating
1	Devein, keep fat, handling, backstrap, own	_______
2	No devein, keep fat, handling, no backstrap, lease	_______
3	Devein, keep fat, no handling, no backstrap, lease	_______
4	No devein, keep fat, no handling, backstrap, own	_______
5	Devein, no fat, handling, no backstrap, own	_______
6	No devein, no fat, handling, backstrap, lease	_______
7	Devein, no fat, no handling, backstrap, lease	_______
8	No devein, no fat, no handling, no backstrap, own	_______
HO1	Devein, keep fat, handling, no backstrap, lease	_______
HO2	No devein, no fat, no handling, backstrap, own	_______

39. Contingent Valuation

1 Large Peeling Machine

(Provide card with description of machine to producer for examination.)

Suppose the following machine were made available to you for peeling crawfish. The machine does the following things:

1. Peels 1000 lbs of shell-on, cooked crawfish per hour (8000 lbs per 8-hour day, 40,000 per 40-hour week, 168,000 lbs per 21-day month, or 504,000 lbs for 3 months).

2. Allows an individual to pour 500-lb totes of shell-on, cooked crawfish into a hopper at a time, and at the end of an "assembly line," peeled crawfish is delivered.
3. Crawfish are deveined, the backstrap is saved, and the fat is recovered.
4. Wastewater is filtered and recirculated, reducing water consumption. With this system, water usage is 28 gal/min (1,680 gal/hr, 13,440 gal/day, 67,200 gal/wk, 282,240 gal/mo, or 846,720 gal/3 mos).
5. The machine may be purchased for $250,000.
6. Electrical usage is based on 22 hp of use. As the machines are running, the charge is $1.00/hr ($8.00/day, $40.00/wk, $168.00/mo, or $504.00/3 mos).
7. 5 workers are required to run this system. These include persons familiar with the machinery, as well as those who can inspect the product upon peeling. At a rate of $10.00/hr, this would cost $400.00/day ($2000.00/week, $8400.00/mo, or $25,200/3 mos).
8. Assume the useful life of this machine is 10 years. Maintenance cost would be approximately $60,000/year.

Would you purchase this machine?

1. I am 100% certain I would purchase this machine.
2. I am almost certain I would purchase this machine (with 81%-99% certainty).
3. I would more than likely purchase this machine (with 61%-80% certainty).
4. I am not at all certain whether or not I would purchase this machine (with 41%-60% certainty).
5. I would more than likely not purchase this machine (with 61%-80% certainty).
6. I am almost certain I would not purchase this machine (with 81%-99 certainty).
7. I am 100% certain I would not purchase this machine.

Alternatively, would you lease this machine at a comparable rate on an annual basis?

1. I am 100% certain I would lease this machine.
2. I am almost certain I would lease this machine (with 81%-99% certainty).
3. I would more than likely lease this machine (with 61%-80% certainty).
4. I am not at all certain whether or not I would lease this machine (with 41%-60% certainty).
5. I would more than likely not lease this machine (with 61%-80% certainty).
6. I am almost certain I would not lease this machine (with 81%-99 certainty).
7. I am 100% certain I would not lease this machine.

2 Large Peeling Machines

(Provide card with description of machine to producer for examination.)

Suppose the following machine were made available to you for peeling crawfish. The machine does the following things:

1. Peels 2000 lbs of shell-on, cooked crawfish per hour (16,000 lbs per 8-hour day, 80,000 per 40-hour week, 336,000 lbs per 21-day month, or 1,008,000 lbs for 3 months).
2. Allows an individual to pour 500-lb totes of shell-on, cooked crawfish into a hopper at a time, and at the end of an "assembly line," peeled crawfish is delivered.
3. Crawfish are deveined, the backstrap is saved, and the fat is recovered.
4. Wastewater is filtered and recirculated, reducing water consumption. Thus, water usage is 46 gal/min (2,760 gal/hr, 22,080 gal/day, 110,400 gal/wk, 463,680 gal/mo, or 1,391,040 gal/3 mos).
5. The machines may be purchased for $370,000.
6. Electrical usage is based on 29 hp of use. As the machines are running, the charge is $1.40/hr ($11.00/day, $56.00/wk, $235.00/mo, or $705.00/3 mos).
7. 5 workers are required to run this system. These include persons familiar with the machinery, as well as those who can inspect the product upon peeling. At a rate of $10.00/hr, this would cost $400.00/day ($2000.00/week, $8400.00/mo, or $25,200/3 mos).
8. Assume the useful life of this machine is 10 years. Maintenance cost would be approximately $90,000/year

Would you purchase these machines?

a. I am 100% certain I would purchase this machine.
b. I am almost certain I would purchase this machine (with 81%-99% certainty).
c. I would more than likely purchase this machine (with 61%-80% certainty).
d. I am not at all certain whether or not I would purchase this machine (with 41%-60% certainty).
e. I would more than likely not purchase this machine (with 61%-80% certainty).
f. I am almost certain I would not purchase this machine (with 81%-99 certainty).
g. I am 100% certain I would not purchase this machine.

Alternatively, would you lease this machine at a comparable rate on an annual basis?

a. I am 100% certain I would lease this machine.
b. I am almost certain I would lease this machine (with 81%-99% certainty).
c. I would more than likely lease this machine (with 61%-80% certainty).
d. I am not at all certain whether or not I would lease this machine (with 41%-60% certainty).
e. I would more than likely not lease this machine (with 61%-80% certainty).
f. I am almost certain I would not lease this machine (with 81%-99 certainty).
g. I am 100% certain I would not lease this machine.

Would you consider purchasing greater capacity with this type of machine?____ If so, please explain ____

____

Small Crawfish Peeling Machine

(Provide card with description of machine to producer for examination.)

Suppose the following machine were made available to you for peeling crawfish. The machine does the following things:

1. The machine can sit on a table top. Its dimensions are 1ft H 2ft.
2. Two people are needed to operate the machine, one to feed the individual crawfish into the machine and one to visually inspect them when they are peeled.
3. Crawfish are peeled and deveined. The backstrap is saved.
4. Crawfish fat may be recovered.
5. The machine can process 45 crawfish per minute.
6. The machine is electric.
7. The machine costs $2,000.
8. Assume the useful life of this machine is 10 years.

Would you purchase this machine?

a. I am 100% certain I would purchase this machine.
b. I am almost certain I would purchase this machine (with 81%-99% certainty).
c. I would more than likely purchase this machine (with 61%-80% certainty).
d. I am not at all certain whether or not I would purchase this machine (with 41%-60% certainty).
e. I would more than likely not purchase this machine (with 61%-80% certainty).
f. I am almost certain I would not purchase this machine (with 81%-99 certainty).
g. I am 100% certain I would not purchase this machine.

If you were to purchase this machine, how many would you purchase?________________

40. If a mechanical crawfish peeler were available which *did not devein the crawfish*, would it be acceptable to your firm if it were available at the same cost that you currently pay picking labor?

    a. Yes   b. No

41. If a mechanical crawfish peeler were available which *did not retain the backstrap*, would it be acceptable to your firm if it were available at the same cost that you currently pay picking labor?

    a. Yes   b. No

42. Would you be open to freezing crawfish prior to peeling if it were needed and would result in a similar quality end product?

a. Yes b. No

43. How many more years do you expect to be peeling crawfish if the market remains favorable for crawfish peeling?__________years

44. Do you have a close family member whom you expect to take over your operation when you retire from the crawfish processing business?

a. Yes b. No

45. Are there additional factors that we have not covered that would affect your decision as to whether to adopt a crawfish processing machine? If so, would you please explain?

____

____

____

THANK YOU FOR PARTICIPATING IN THIS STUDY!

Table A.1: Rankings and Ratings of Machines from the Conjoint Analysis.

Machine Rank		Adjusted Rating
1	Deveins, Retains Fat, No Handling, Retains Backstrap, Own	10.0000
2	Deveins, Retains Fat, No Handling, Retains Backstrap, Lease	9.7560
3	Deveins, Retains Fat, Handling, Retains Backstrap, Own	8.1579
4	Deveins, Retains Fat, No Handling, Does not Retain Backstrap, Own	8.0966
5	Deveins, Does not Retain Fat, No Handling, Retains Backstrap, Own	8.0011
6	Deveins, Retains Fat, Handling, Retains Backstrap, Lease	7.9138
7	Deveins, Retains Fat, No Handling, Does not Retain Backstrap, Lease	7.8525
8	Deveins, Does not Retain Fat, No Handing, Retains Backstrap, Lease	7.7570
9	No Deveins, Retains Fat, No Handling, Retain Backstrap, Own	6.2545
10	No Deveins, Retain Fat, No Handling, Retains Backstrap, Lease	6.1590
11	Deveins, Retain Fat, Handling, Does not Retain Backstrap, Own	6.0977
12	Deveins, Does not Retains Fat, Handling, Retain Backstrap, Own	6.0104
13	Devein, Does not Retains Fat, No Handling, Does not Retain Backstrap, Own	5.9886
14	Deveins, Retain Fat, Handling, Does not Retain Backstrap, Lease	5.9149
15	Deveins, Does not Retain Fat, Handling, Retains Backstrap, Lease	5.8536
16	Deveins, Does not Retain Fat, No Handling, Does not Retain Backstrap, Lease	5.7445
17	No Devein, Retains Fat, Handling, Retains Backstrap, Own	4.2555
18	No Devein, Retains Fat, No Handling, Does not Retain Backstrap, Own	4.1465
19	No Devein, Does not Retain Fat, No Handling, Retains Backstrap, Own	4.0851
20	No Devein, Retains Fat, Handling, Retains Backstrap, Lease	4.0115
21	No Devein, Retains Fat, No Handling, Does not Retain Backstrap, Lease	3.9897
22	No Devein, Does not Retain Fat, No Handling, Retains Backstrap, Lease	3.9024
23	Deveins, Does not Retain Fat, Handling, Does not Retain Backstrap, Own	3.8410
24	Deveins, Does not Retain Fat, Handling, Does not Retain Backstrap, Lease	3.7456
25	No Devein, Retains Fat, Handling, Does not Retain Backstrap, Own	2.2430
26	No Devein, Does not Retain Fat, Handling, Retains Backstrap, Own	2.1476
27	No Devein, Does not Retain Fat, No Handling, Does not Retain Backstrap, Own	2.0862
28	No Devein, Retains Fat, Handling, Does not Retain Backstrap, Lease	1.9989
29	No Devein, Does not Retain Fat, Handling, Retains Backstrap, Lease	1.9035

30	No Devein, Does not Retain Fat, No Handling, Does not Retain Backstrap, Lease	1.8421
31	No Devein, Does not Retain Fat, Handling, Does not Retain Backstrap, Own	0.2441
32	No Devein, Does not Retain Fat, Handling, Does not Retain Backstrap, Lease	0.0000

Appendix B:
Heteroskedasticity Test for Conjoint Analysis

Table B.2: Testing of Heteroskedasticity

Obs	r2	t	m	lm	pval
1	0.6355	280	21	177.94	1

Appendix C:
β Coefficients for Individual Firms
And Cluster Membership

Table C.1: Beta Coefficients for Individual Firms

Cluster Analysis						
Firms	**CONSTANT**	**DEVEIN**	**FAT**	**NOHANDLI**	**BACKSTRA**	**OWN**
Firm 1	0.589	4.412	-0.349	5.412	-0.273	-1.227
Firm 2	1.686	3.149	4.640	-2.005	2.652	2.155
Firm 3	-1.114	0.173	1.543	0.173	1.197	-1.197
Firm 4	1.166	4.064	2.565	2.565	1.065	0.434
Firm 5	-1.549	2.891	2.391	1.391	2.891	0.891
Firm 6	0.032	3.336	2.336	1.336	1.836	-0.953
Firm 7	-0.001	0.001	0.000	0.001	0.000	0.000
Firm 8	0.974	1.310	-0.190	3.310	2.810	0.810
Firm 9	-1.377	2.478	-1.460	4.945	2.478	0.998
Firm 10	-0.001	0.001	0.000	0.001	0.000	0.000
Firm 11	0.258	4.425	3.925	0.675	0.175	0.075
Firm 12	-7.014	10.009	4.000	1.005	4.000	-1.995
Firm 13	-6.170	1.000	7.670	1.000	8.669	-3.171
Firm 14	-0.001	0.001	0.000	0.000	0.001	0.000
Firm 16	-0.775	1.364	3.864	2.364	2.364	1.364
Firm 17	0.098	2.361	2.361	3.361	1.361	0.361
Firm 18	0.477	4.224	2.225	0.725	0.725	0.725
Firm 19	-2.969	3.161	2.358	-2.560	2.232	0.352
Firm 20	-2.596	4.484	1.136	2.518	2.026	0.552
Firm 21	0.461	3.272	1.772	0.272	2.772	-0.272
Firm 22	-0.243	1.681	3.681	2.181	1.681	-0.681
Firm 23	-8.843	7.671	0.500	6.671	1.500	4.672
Firm 24	0.662	2.679	2.679	2.679	2.679	-0.679
Firm 26	-4.922	8.836	0.750	3.336	-0.250	3.336
Firm 27	-0.058	0.069	0.066	-0.027	0.061	-0.079
Firm 28	-1.744	3.288	1.409	1.879	1.879	-0.001
Firm 29	-0.001	0.000	0.001	0.000	0.001	-0.001
Firm 30	-1.646	3.493	3.493	0.529	3.493	0.971

Table C.2: Cluster Membership using Ward's Method

Case	2 Clusters
1	1
2	2
3	2
4	2
5	1
6	2
7	1
8	1
9	1
10	1
11	2
12	1
13	2
14	1
15	2
16	1
17	2
18	1
19	1
20	2
21	2
22	1
23	2
24	1
25	2
26	1
27	2
28	1

Table C.3: Agglomeration Schedule using Ward's Linkage

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	10	22	.498	0	0	2
2	7	10	.989	0	1	10
3	19	26	1.480	0	0	8
4	23	27	1.964	0	0	14
5	3	13	2.447	0	0	17
6	5	28	2.928	0	0	15
7	6	25	3.392	0	0	11
8	12	19	3.856	0	3	12
9	11	17	4.320	0	0	16
10	7	24	4.773	2	0	24
11	6	20	5.218	7	0	21
12	12	14	5.656	8	0	20
13	8	9	6.091	0	0	22
14	21	23	6.525	0	4	19
15	5	18	6.958	6	0	20
16	4	11	7.371	0	9	21
17	3	15	7.773	5	0	19
18	1	16	8.138	0	0	22
19	3	21	8.445	17	14	25
20	5	12	8.736	15	12	24
21	4	6	8.893	16	11	23
22	1	8	9.040	18	13	26
23	2	4	9.115	0	21	25
24	5	7	9.059	20	10	26
25	2	3	8.667	23	19	27
26	1	5	8.100	22	24	27
27	1	2	7.044	26	25	0

Table C.4: Part-Worths and Attribute Importance for Cluster 1

Part-Worths (Cluster 1)				
Aggregate	**Variable**	**Coefficient**	**Importance**	**Percentage**
	DEVEIN	4.386	0.40349586	35.5%
	FAT	1.243	0.114351426	12.0%
	NOHANDLI	2.452	0.225574977	25.9%
	BACKSTRA	2.092	0.192456302	17.0%
	OWN	0.697	0.064121435	10.2%
	Total	10.87	1	100.0%

Table C.5: Part-Worths and Attribute Importance for Cluster 2

Part-Worths (Cluster 2)				
Aggregate	**Variable**	**Coefficient**	**Importance**	**Percentage**
	DEVEIN	3.272	0.29235168	25.0%
	FAT	3.309	0.295657613	29.2%
	NOHANDLI	1.728	0.154395997	12.7%
	BACKSTRA	2.263	0.202197999	20.2%
	OWN	0.620	0.055396712	12.9%
	Total	11.192	1	100.0%

Appendix D:
Multicollinearity Test for Technology Adoption and
Heteroskedasticity Test for Technology Adoption

Table D.1: Testing of Multicollinearity

Number of Observations Read	150
Number of Observations Used	150

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	16	289.91307	18.11957	4.86	<.0001
Error	133	496.24693	3.73118		
Corrected Total	149	786.16000			

Root MSE	1.93163	**R-Square**	0.3688
Dependent Mean	4.16000	**Adj R-Sq**	0.2928
Coeff Var	46.43332		

Parameter Estimates							
Variable	**Label**	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Variance Inflation**
Intercept	Intercept	**1**	4.71763	2.10927	2.24	0.0270	0
meat1000		**1**	-0.00650	0.00622	-1.05	0.2974	3.03645
valueadd	valueadd	**1**	-1.79547	0.65224	-2.75	0.0067	1.53923
diverse	diverse	**1**	-0.19400	0.50965	-0.38	0.7041	2.59889
pctpeel2	pctpeel2	**1**	-0.00430	0.00652	-0.66	0.5112	2.16796
labor3	labor3	**1**	0.77591	0.36264	2.14	0.0342	1.26885
grader8	grader8	**1**	0.19800	0.64577	0.31	0.7596	2.32849
lbcook13	lbcook13	**1**	-0.00003059	0.00002094	-1.46	0.1465	1.42308
contco12	contco12	**1**	0.17890	0.56156	0.32	0.7505	2.26789
alter15	alter15	**1**	0.37673	0.39220	0.96	0.3385	1.51850
wage20	wage20	**1**	1.47895	1.18552	1.25	0.2144	1.38054
sizelarg	sizelarg	**1**	-0.00001163	0.00000798	-1.46	0.1472	4.01315
sizesmal	sizesmal	**1**	0.00003114	0.00000977	3.19	0.0018	3.51315
years43	years43	**1**	-0.06076	0.01897	-3.20	0.0017	1.73181
family44	family44	**1**	0.35649	0.43815	0.81	0.4173	1.85228
purmed	purmed	**1**	-2.11606	0.57708	-3.67	0.0004	3.21315
pursml	pursml	**1**	-3.83227	0.70678	-5.42	<.0001	3.21315

Collinearity Diagnostics		
Number	**Eigen Value**	**Condition Index**
1	9.15688	1.00000
2	1.61900	2.37821
3	1.11304	2.86826
4	0.98986	3.04149
5	0.86134	3.26051
6	0.79764	3.38821
7	0.61825	3.84850
8	0.49416	4.30465
9	0.39780	4.79779
10	0.29041	5.61521
11	0.18059	7.12087
12	0.15062	7.79718
13	0.12453	8.57515
14	0.09394	9.87279
15	0.06273	12.08229
16	0.04592	14.12093
17	0.00328	52.86775

Table D.2: Testing of Heteroskedasticity

Obs	r2	t	m	lm	pval2
1	0.3688	150	136	55.32	1.00000

Vita

Darius J. Lewis was born February 1, 1981, and is a life-long resident of New Orleans, Louisiana. He is the proud son of Deborah and Donald Lee. He was a 2004 graduate of Louisiana State University where he received a Bachelor of Science degree from the Department of Agricultural Economics and Agribusiness with a concentration in business administration.

In 2004, he pursed a master's degree in agribusiness at Louisiana State University. Throughout his academic career, Lewis has served as President of the LSU MANRRS chapter where he revitalized the campus organization and has won awards on campus for his devout service. He has also participated in numerous conferences and workshops in the agricultural arena and has placed nationally in the American Agricultural Economics Association poster exhibition on the topic of Louisiana's crawfish industry. He has also published 3 articles within the realm of his research in the LSU AgCenter Bulletin and the American Journal of Agricultural Economics. After graduation he plans to work for the National Agricultural Statistical Service, a division of the USDA in Lancing, Michigan.

He came,
He saw,
He conquered…