APPLICATION OF HEDONIC PRICE MODELING TO ESTIMATE THE VALUE OF ALGAE MEAL

A Thesis

by

ILIA GOGICHAISHVILI

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

MASTER OF SCIENCE

August 2011

Major Subject: Agricultural Economics

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Approved by:

Co-Chairs of Committee,	James W. Richardson
	Henry L. Bryant
Committee Members,	David P. Anderson
	Jason E. Sawyer
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ABSTRACT

Application of Hedonic Price Modeling to Estimate
the Value of Algae Meal. (August 2011)

Ilia Gogichaishvili, B.S., Georgian State Agrarian University

Co-Chairs of Advisory Committee: Dr. James W. Richardson
Dr. Henry L. Bryant

High productivity rates, usage of nonproductive land, renewability and recovery of waste nutrients and potential for CO_2 emission reduction represent some of the advantages that selected algae species might have over competing products. Many research studies have investigated potential usage of algae for different purposes, such as cosmetics or aquaculture; however most of the research studies have focused on the feasibility of algae as a source of second generation biodiesel and feed meal. Because of its high costs of production, using algae only for the purpose of biodiesel production might not be profitable. Thus, for global scale algae commercialization it is important that it be used as a feed meal along with being marketed to the biodiesel industry.

One of the major problems faced by economists when attempting to analyze the feasibility of algae is the absence of a market for algae-based fuel and meal. Given that no market exists, prices for algae cannot be observed and realistic investment analysis becomes difficult to perform in this sector.

The objective of this study is to estimate a potential price of algae meal using hedonic pricing techniques. For that purpose, twenty two different feed meals commonly having the same usage as Post Extracted Algae Residue (PEAR) are decomposed into their chemical constituents in order to calculate the market value of each characteristic. Calculated prices of these characteristics are then used to estimate the price of algae meal and compare it to different feed meals.

Results suggest that algae prices are strictly variable to its chemical components across different algae types. Besides, PEAR represents a sustainable source of financial value and might be considered one of the cornerstones in making algae commercialization a feasible and profitable option.

DEDICATION

ეს თეზისი ეძღვნება ჩემს ახალშობილ ძმისწულს ილია გოგიჩაიშვილს და ჩემს დიდ და ლამაზ ოჯახს მათი სიყვარულისა და თანადგომისთვის. თითოეულმა ჩემმა ოჯახის წევრმა ფასდაუდებელი წვლილი შეიტანა ჩემს საგანმანათლებლო მიღწევებში მათი უანგარო სიყვარულითა და მხარდაჭერით.

This thesis is dedicated to my newborn nephew Ilia Gogichaishvili and to my entire family for their love, support and encouragement. Each of my family members has provided an invaluable input to my educational accomplishments with their selfless love and support.

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I would also like to thank and express my deepest respect to my former professor Dr. Daniel J. Dunn for his support before and during my graduate studies in the U.S.

Finally, thanks to my family for their encouragement and love.

TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

CHAPTER I

INTRODUCTION

1.1 General Overview

Algae is one of the fastest growing plants in the world and its importance for energy security could be important. Algae transfers energy from the sun and absorbs nutrients from water, making it a very efficient and sustainable source of energy. It contains a high percentage of lipids, which can be used as a replacement for oil-based fuels. Per unit yield of oil from algae is 7 to 31 times greater than the next best crop, palm oil (Demirbas and Demirbas 2010).

At the same time, algae are rich in protein and carbohydrates, which are necessary components in human and animal diets. As long as the production and processing requires less energy than algae actually produces and it is easily adaptable to the desired environments, algae has potential as an energy source on a global scale. Moreover, production of algae has the potential for reducing Greenhouse Gas emissions, which attracts the interest of both the private and public sector.

Along with all the direct effects that algae may have on the world economy, certain potential indirect economic effects must be considered. One case in point is that if algae production becomes large, quantities of post-extracted algal residue (PEAR or algae meal) will increase which will reduce the prices of other feed meals such as soybean meal and fish meal and will reduce the production costs in agribusiness.

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

1.2 Statement of the Problem

Considerable research has been conducted to investigate the potential of algae as a source of energy (Laws and Berning 1990; Spolaore, Joannis-Cassan, Duran, and Isambert 2006; Subhadra 2010), however few studies have addressed the economics of algae production (Richardson, Outlaw, and Allison 2010; Williams and Laurens 2010). One of the major problems faced by economists when attempting to analyze the feasibility of algae is the absence of a market of algae based fuel and meal. Given that no market exists, prices for algae cannot be observed and realistic investment analyses become difficult to perform in this sector.

1.3 Objective

The objective of this study is to estimate the likely price of algae meal using hedonic pricing techniques. For that purpose, twenty two different feed meals commonly having the same usage as PEAR – for example, soybean meal, cottonseed meal, linseed meal – will be decomposed into their constituent values to calculate the market value of each characteristic – for example, crude protein, either extract, acid detergent fiber. The calculated values of these characteristics will then be used to estimate the price of algae meal according to its content percentage obtained from chemical analyses.

CHAPTER II

BACKGROUND

2.1 Algae Overview

Considerable research has addressed the diverse usage of algae and its advantages compared to the competing products. Brune, Lundquist, and Benemann (2009) listed a number of advantages microalgal production can offer compared to conventional biomass production. High productivity rates for some of the algae species, usage of nonproductive land, renewability and recovery of waste nutrients and potential for CO_2 emission reduction were among those advantages. The authors analyzed the potential of microalgae for replacement of fossil-fuels and animal feed. Spolaore et al. (2006) described different commercial applications of microalgae. The authors illustrated the crucial role algae might play in aquaculture and the ability algae might possess to be incorporated for cosmetics production or to be used as a source of highly valuable molecules.

Biodiesel and bioethanol produced from agricultural crops cannot be considered as a substitute of a substantial portion of fossil fuels. However, biodiesel from microalgae has the availability to replace the fossil-based fuels. Chisti (2008) compared biodiesel from microalgae to bioethanol. The research study showed that crop-derived biodiesel does not present a sustainable source of energy as it adversely affects the supply of food. Chmapisti concluded that the productivity of microalgae strictly outperforms the productivity of bioethanol from sugarcane or from any other oil crops.

Richardson et al. (2010) analyzed the economics of microalgae oil for a commercial-scale farm in the Southwest United States. The simulation model developed in the research analyzed the potential costs associated with microalgae production and suggested that algae oil production is highly sensitive to different farming systems. Results from this study show that microalgae oil production could be feasible if high profile small-scale experimental algae are scalable to a commercial size farm. Improvements in algae strain, feeding, CO_2 efficiency and harvesting were selected as the main driving factors for the improved cost efficiency of the hypothetical algae farm.

Williams and Laurens (2010) analyzed the economics of microalgae as biodiesel and biomass feedstock. The study considered potential yields of algae production through photosynthesis and concluded that increased lipid contents reduced other valuable components in algae. This raised the question of whether there exists a tradeoff between lipid content and other valuable contents of algae such as protein. Moreover, the study concluded that using microalgae for only biofuel production would not likely be economically viable.

Becker (2006) analyzed microalgae as a source of protein. He considered the protein content of algae for human and animal feed. Nutritional and toxicological assessments demonstrated that microalgae is a valuable feed supplement and presents a substitute for conventional protein sources such as soybean meal.

In view of the literature of algae feasibility studies, investigating the potential price of algae meal will represent a valuable addition to the current research studies and can be used as an input for algae profitability analysis.

CHAPTER III

LITERATURE REVIEW

The roots of hedonic pricing date back to Fred Waugh's Columbia thesis in 1929, which analyzed the impact of vegetable quality attributes on its market price. The study focused on the price variations of selected vegetables and referred to quality characteristics as a determining factor for price difference. Vail (1932) analyzed the relationship between fertilizer prices and its intrinsic content, and found a high correlation among the variables. More in depth and applied analyses on hedonic pricing were done on automobile price indexes by Griliches (1961). He analyzed quality-adjusted measures of automobile prices across time. Further theoretical development of hedonic pricing techniques was accomplished by Lancaster (1966) and Rosen (1974). Lancaster argued that the characteristics of goods are part of the consumers' utility function and preferences depend on the measure of each desired characteristic. Rosen applied Lancaster's preference theory to the broader concept of supply and demand analysis based on product characteristics, which then became the foundation of many further studies.

Malpezzi (2002) reviewed the theoretical basis of hedonic price theory and its practical application to the housing market. He noted that the variation of prices within a sample and the variation of the sample characteristics were the necessary features of the data to be employed in hedonic analysis. Once the inverse demand relation was assumed, the elasticities of individual coefficients could be estimated. The author identified the three most important components of the hedonic price equation: choice of dependent and independent variables, specification of the functional form and the definition of the market or submarket. In the case of the housing market, Malpezzi noted that the choice of dependent variable was usually made between the value of the house and the rental price. Also, the author showed that the model could be biased if the independent variables were not properly selected - if some important variables were omitted or if the variables having no effect on the price were included in the equation. With regards to functional form specification, Malpezzi illustrated that the log-linear form had several advantages over the linear form, such as the ability to better mitigate the heteroscedasticity problem and the simplicity of results interpretation. Furthermore, the author showed that the hedonic equation with a Box-Cox transformation was a more flexible functional form than others, where the linear, logarithmic and translog functions were subsumed. Finally, Malpezzi emphasized the importance of market selection in hedonic analysis and classified the assumption of market identification in three main categories: entire nations, regions or states.

Many studies have been conducted to estimate the price of different products in agriculture using hedonic techniques. The method of choosing the components of the equation variables varied according to each specific case. Jordan, Shewfelt, Prussia, and Hurst (1985) studied the effects of quality characteristics on the prices of fresh tomatoes and the economic feasibility of different tomato handling techniques by using hedonic price analysis. Cross sectional data from three states (Florida, Georgia, North Carolina) for three different time periods (April, August, and September) were employed in the model. Three different regressions, rather than one overall, were used in the model, and

Ordinary Least Squares (OLS) was applied for parameter estimation. Among many other characteristics such as soluble solids, moisture and vitamin C, four main criteria were identified as determining factors for fresh tomato prices, which affected the consumer's decisions: size, damage, color and firmness. Slope and intercept estimates were compared across three time periods using the Chow-Fisher error test. Estimated slope coefficient for firmness and size across the periods showed statistically significant differences. Also, a likelihood ratio test was used to test the difference between Box-Cox estimator and standard functional forms, which were found to be significantly different at 0.01 confidence level. The coefficients for quality characteristics varied from period to period indicating the difference of consumer preferences among seasonality and relative importance across time. The estimated coefficient for damage was found to be significant; a one percent reduction in damage would increase the price from \$0.60 to \$0.10.

Hyberg and Uri (1996) examined the implicit prices of soybeans exported by the United States to Japan. This study was designed to identify intrinsic and physical characteristics of soybeans, which were valued differently for two different markets: soybean meal and soybean oil markets. The data used in the analysis were collected by the Federal Grain Inspection Service (FGIS) and represented the actual transaction prices for different shipments, which correspond to different values according to soybean grades and standards. First order serial correlation was found in the data and was corrected using the Cochrane-Orcutt procedure. Linear-in-logarithm specification proved to be the most appropriate model. Mean and variance comparisons of price, quantity, oil, protein and other characteristics showed that a $60 higher price per metric ton was going to the crushing market instead of the food market. Oil and protein content comparisons showed that soybeans for the food sector had a higher protein and lower oil content. However, there was no significant difference in the test weights and moisture content between the two markets. Soybeans processed for the food market were found to have a significantly lower foreign material, damage, and split. It was concluded that food processors had higher requirements for clean, undamaged products. After testing content variables, meal and oil values were found to be positive and significant at 1% confidence level. Also, coefficients for foreign material and damaged kernels were found to be negative and statistically significant at 5% and 10% confidence levels respectively. These statistically significant coefficients were robust having little or no effects in either sign or magnitude contrasted to other variables entering or leaving the model. While comparing the results of different geographic locations, observing Japan and the rest of the world, the results suggested that there is no significant difference between the prices paid for soybeans by different countries after adjusting for the quality characteristics.

Ethridge and Davis (1982) described the application of hedonic pricing techniques to estimate the quality characteristics of semi-processed cotton lint. A hedonic price model for cotton was specified as a function of trash content, color characteristics of the lint, staple length code as the length of cotton fiber, micronaire reading, variations of each of the above characteristics, and lot size in number of bales. The model was designed for the period of 1976-77 and 1977-78. The prices were estimated separately for these years and then combined since cotton quality appeared to be different in each year. Multicollinearity problems were found by the authors in quality variability after examining the data. It was suggested to leave only the variation of micronaire and remove the rest of the quality variations from the model. Moreover, the Durbin-Watson statistic showed a considerable degree of autocorrelation in the data. Autocorrelation problems were expected to be in the model as cotton tended to display a seasonal pattern over time. Both, a Feasible Generalized Least Squares (FGLS) model and an Ordinary Least Squares (OLS) model, were used. The value of cotton tended to decrease as micronaire deviated from the range of desired levels for textile manufacturing. For that reason, the relationship between price and micronaire was expected to be curvilinear and was formulated as quadratic, while the rest of the variables were specified as linear. Regression coefficients for different years were compared by F statistics. Results from this study showed a significant difference in prices among years. The authors suggested that it might not be practical to use only one equation to attempt to analyze the effects of quality on prices in different years. Thus, separate equations for each year were suggested as a solution. Estimated results showed that two variables, lot size and variation of micronaire, on which the producers had the most substantial influence, had the least impact on cotton price.

Several studies have addressed the problem of functional form specification for the hedonic price equation. Halvorsen and Pollakowski (1981) analyzed the appropriateness of functional forms by using goodness of fit criterion in hedonic pricing. A Box-Cox transformation was combined with a flexible functional form approach to avoid theoretically unwarranted restrictions in the hedonic equation. All potential functional forms were obtained as special cases of the general form, making it possible to use a likelihood ratio approach in the functional form valuation. The general functional form provided flexibility to obtain different functional forms by changing parameters. For instance, the quadratic Box-Cox was a functional form obtained from the general form, which was then used to obtain the translog form. The latter was used to get the log-linear form and all potential forms were obtained with a similar procedure. The disturbance term for the true functional form was assumed to be normally and independently distributed with zero mean and constant variance. Each particular functional form was tested to evaluate if the parameters of the hedonic equation satisfied relevant restrictions. This analysis was applied to the housing market using a survey of 29,000 households. According to the test statistics, linear, log-linear and semilog functional forms, which were most frequently used in the hedonic equations, were strongly rejected at a 1% confidence level.

Cropper, Deck and McConnell (1988) examined various functional forms for the hedonic price equation. Simulation based on equilibrium house prices and house attributes was used in the hedonic price function to estimate errors in marginal attribute prices. The errors were calculated as the difference between the derivative of the price function and the true marginal bid. Six functional forms were analyzed: linear, semi-log, double-log, quadratic, and linear and quadratic Box-Cox transformed variables. The linear and quadratic Box-Cox functions performed the best among all functional forms, as they produced the lowest ratio of mean error to true mean bid. The linear Box-Cox function had the lowest error variance, while the quadratic Box-Cox had the lowest normalized error. Many of the attributes were found highly correlated, raising concerns of collinearity. Since Box-Cox and quadratic functions depend on several coefficients instead of only one, these functions appeared to handle collinearity problems better than linear, semi-log and double-log functions. Also, two different approaches were analyzed depending on whether the researcher was assumed to be capable of observing all product attributes without error or not. The results showed that when attribute variables were omitted, the linear Box-Cox function did the best in producing the lowest error. When all attributes were observed, linear and quadratic Box-Cox functions outperformed the rest. The authors concluded that linear Box-Cox provided reliable results in both cases and it was suggested to be the choice for the functional form.

Despite the fact that hedonic pricing techniques have been applied to many products and industries, there has been no attempt in the literature to price algae meal using hedonics or any other method.

CHAPTER IV

THEORY

4.1 Price Theory

A market economy works based on the signals generated by the decisions of economic agents in the market, which reflects and influences the prices of goods. A market is a complex system, which along with many other factors involves economic agents, products and services, and the determinants of the demand and supply factors. These aspects have an impact on price determination of a particular product or service.

Price theory is one of the underlying principles in economics, which attempts to explain economic activity of transferring value while trading goods and services. The price theory starts with Adam Smith (1776) who discussed the paradox of a diamond having a higher price than water as a life essential product. He stated that the value of the product could be derived from the value in use or the value in exchange. He observed that the diamond price was higher than water price due to their relative scarcity and labor intensity associated with the diamond extraction. Later developments of the price theory involved the explanation of the dynamics of pricing based on the marginal utility and rational preferences (Walras 1874).

Given that products are traded in the market, prices depend on the demand and supply factors. There are different theories that describe the price determination process, which takes place in different ways depending on the type of product, type of market and the level of competition in the market. Assuming product homogeneity, prices are achieved differently in different markets. Weber (2010) distinguishes pure exchange, competitive markets, complete and incomplete markets, monopoly and oligopoly pricing as different types of market conditions which affect the price determination process. In empirical studies, price determination and price discovery are frequently differentiated.

4.2 Price Determination versus Price Discovery

Price determination is a process established by the broad supply and demand factors as well as firm or product specific factors. Figure 4.1 illustrates price determination process, where a general price level is achieved.

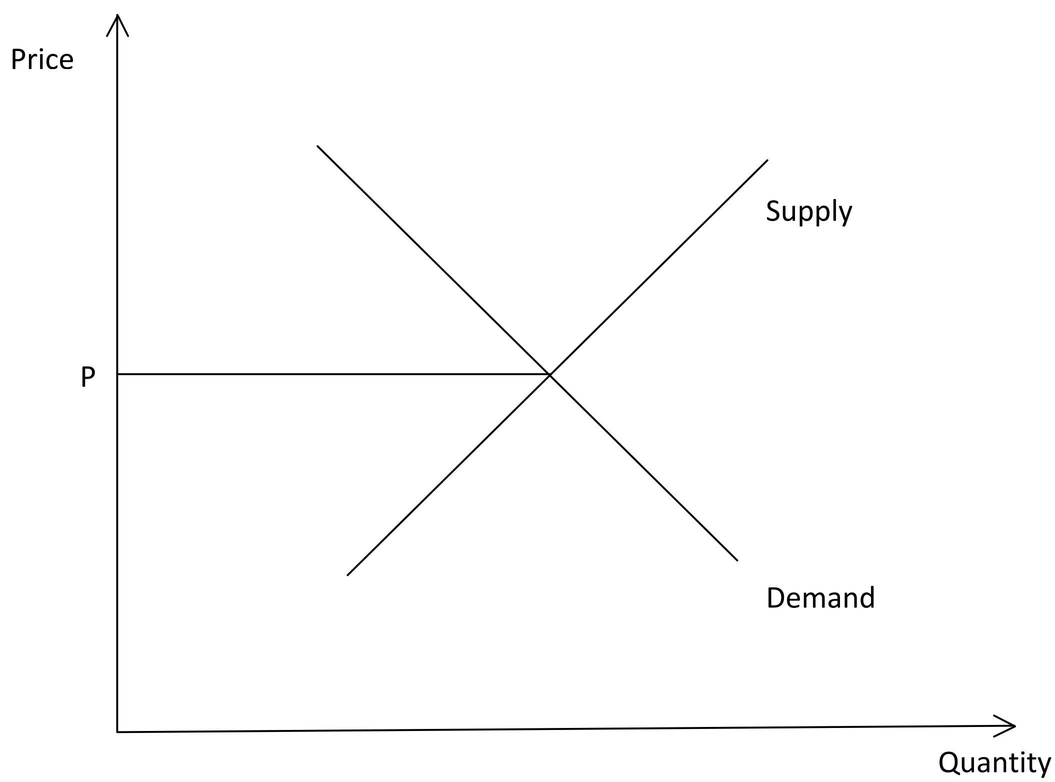

Figure 4.1. Price determination

Supply forces for a given product include but are not limited to the input costs, production technology, producer's expectations, and number of competitors in the market. Demand forces can refer to the price of the goods, the price of competing products, customer disposable income, and consumer tastes and preferences.

Price discovery is a process of arriving at an equilibrium price, which satisfies both producers and consumers given a particular level of demand and supply. Price discovery is established by different factors among which are market structure, market behavior, market information and risk management alternatives (Ward et al. 1996). Price discovery process is shown in Figure 4.2.

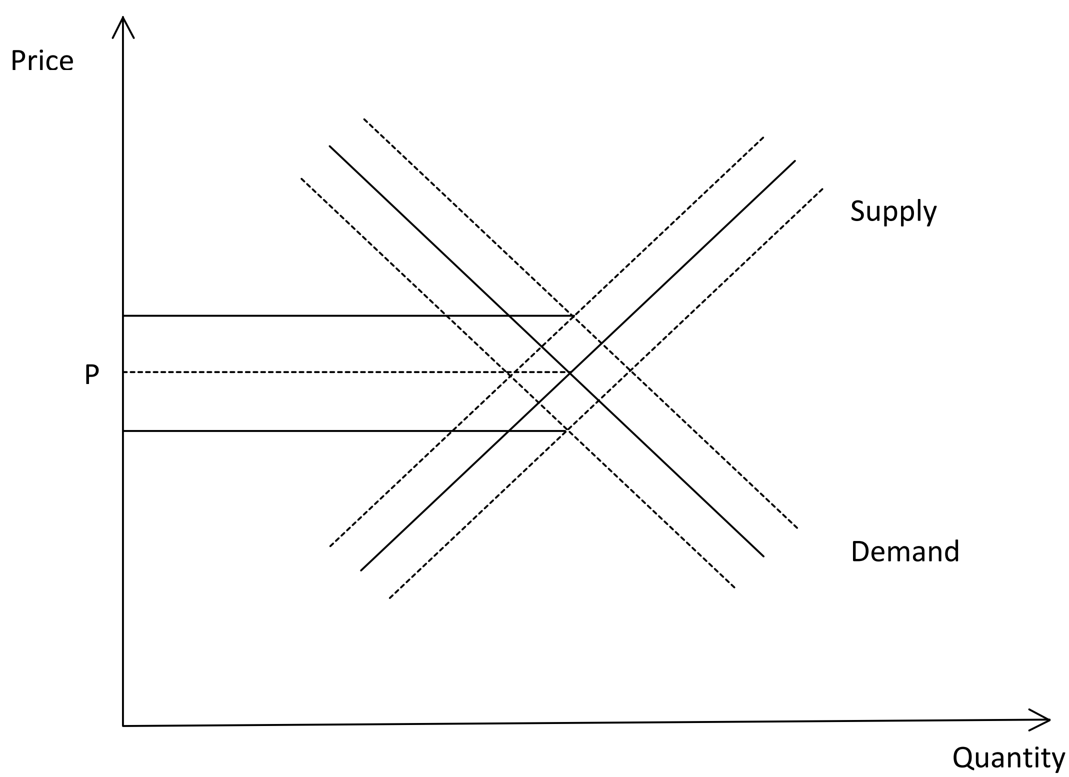

Figure 4.2. Price discovery

4.3 Pricing Methods and its Applications

Pricing methods vary based on the market structure (i.e. monopoly, perfect competition, oligopoly, monopolistic competition). Using actual market prices to forecast the price of the product of interest is applicable when a market exists for the given goods. Forecasting algae meal prices based on market-based models is not applicable since a market for algae meal does not yet exist. Among the options of pricing techniques, hedonic pricing method may generate a better forecasting ability and give more accurate and robust results compared to the alternative methods.

4.4 Repeat Sale Price Index

Repeat sales price index is sometimes used to estimate the price of a product of interest. The necessary condition for this index is to have the data range of all unites sold at least twice. These series will represent the annualized percentage growth in sales and will not process any information about the individual characteristics of the product. The advantage of this model is that it is based on actual transaction prices and is not subject to omitted variable bias (Malpezzi 2002). This method has application to certain problems and is best for estimation of price changes. However, this index does not estimate the price level itself, which limits its application.

4.5 Hybrid Indexes

Hedonic pricing techniques discussed in Chapter V represent the alternative to Repeat Sales Price Index. The usage of these pricing techniques or the selection among them is based on the convenience and availability of the data. A wide range of data can be used for the Repeat Sales Price Index while data are not always readily available for hedonic pricing models.

In case the data are available, Hybrid Indexes are preferred by the practitioners, which contain both Repeat Sales Price Index and Hedonic Pricing Index. Usage of both of the methods limits the disadvantages each of the model possesses and gives more robust results. Nonetheless, research studies that use Hybrid Index for price estimation are limited.

4.6 Other Approaches of Pricing in the Industry

There are some practical ways of price estimation used in the industry. One of them is referred to as Bottom-up pricing. The model first estimates the direct and indirect costs of production along with other costs associated with the product and then adds the required rate of return as a profit margin. This is a practical way to set a price in the market. This method usually applies to the initial pricing and after its application economic factors such as demand and supply interact to achieve the equilibrium price. In contrast to the Bottom-up pricing, Top-down pricing starts from the macro level, monitors the industry prices and comes down to the price of the product of interest.

Within the limited choice of techniques for estimating the algae meal price, hedonic pricing presents the most realistic approach of price assessment.

CHAPTER V

METHODOLOGY

5.1 Hedonic Pricing Overview

Hedonic pricing models observe the price and quality variation across time to identify the interdependence among variables and find implicit values of the characteristics which would be difficult to measure otherwise. The ability to observe product heterogeneity and corresponding price variability makes it possible to estimate a product value based on its content. Hedonic pricing techniques are widely applied to the housing industry to quantify environmental factors, such as air pollution or aesthetic views. In simple terms, a hedonic equation is a regression between market prices of the product and its corresponding characteristics. The regression decomposes the total product value into content coefficients, which could be an equivalent measurement of the value of product characteristics. Hedonic equations observe customer buying patterns and identify the relative importance of independent variables on the dependent variable to find the "share" of each characteristic in the given pattern of price variability. Hedonic pricing techniques can be used to estimate the value of a product which is not marketed yet based on the hedonic regression of the complement products to identify the common characteristics among known and unknown goods.

There are several aspects of hedonic price analysis which need to be carefully reviewed to achieve robustness of the results. Malpezzi (2002) reported three main parts of hedonic pricing techniques: selecting dependent and independent variables, specifying a functional form, and defining a submarket. The correct selection of these three parts is a determining factor in the success of hedonic analysis and needs to be well thought out and justified.

5.2 Data

Weekly prices of the twenty-two feed meals for the hedonic price equation were obtained from the Miller Publishing Company publication, *Feedstuffs 2010*. Nutrient requirement reports were obtained from the National Research Council (1984) as well as from the cattle publication *Beef Magazine*, which were used to input the content information of each feed meal as independent variables in the model.

5.3 Defining a Submarket

Defining a submarket is an important component of hedonic price analysis. Feed meal markets are very diverse, and it is necessary that the selection of the data is consistent with the purpose of the hedonic equation. In designing the hedonic pricing model for algae meal, Fort Worth was selected as the market in which to observe the prices of different existing feed meals. The choice of geographic location was mainly stipulated by the availability of the data and by the fact that the Southwest region has favorable conditions to grow algae (Richardson et al. 2010) and will therefore be more relevant for use in the analysis.

5.4 Choice of Variables in the Equation

Prices of twenty-two different feed meals are used as a vector of independent variables. From the pool of oilseed products, animal byproducts, brewers and distillers grains, wheat millfeeds, oats and rice products, grains and other types of feedstuffs, the following variables were chosen because they are all substitutes for post extracted algal residue: soybean meal (high protein), soybean meal (low protein), soybean hulls, whole cottonseed, cottonseed meal, cottonseed hulls, linseed meal, poultry byproduct meal, hydrolyzed feather meal, prime tallow, yellow grease, bleachable fancy tallow, vegetable-animal blend, suncured pellets (dehydrated 17%), wheat middlings, rice bran, rice millfeeds, rice hulls, corn, sorghum, ground grain screenings and feed urea. Weekly prices from January 2005 to the third quarter of 2010 were used in the analysis.

The chemical profile of each feed meal represents the independent variable in the hedonic regression. The National Research Council (NRC) reported thirty-six different characteristics for the selected feed meals, which primarily were classified under the subset of energy, protein, fiber, minerals and vitamins. Many of the reported components are not expected to have an effect on customer buying behavior or the value of animal nutrition. Thus, independent variables for the regression were carefully selected based on the relative importance of each characteristic for the livestock feed ration.

Total digestible nutrients (TDN), digestible energy (DE), metabolizable energy (ME), net energy for maintenance (NEM) and net energy for growth (NEG) are the major measurements used for energy requirements for livestock. Given that all of these factors are measuring energy requirements, they are strictly related to each other. The NRC reports the conversion formulas from one type of energy measurement to the other. For example, the following formula is used to convert ME to DE:

$$ME\ (Mcal/kg\ of\ DM) = -0.45 + 1.01\ DE\ (Mcal/kg\ of\ DM)$$

where DM represents dry matter and the components of DE and ME are presented on a mega calories per kilogram basis. Since the energy measurements are equivalently proportional, including more than one energy value in the equation would induce multicollinearity, which negatively affects the standard errors of the estimates and hypothesis testing of the model. The NRC reports TDN as the most frequently used measurement of energy content. For example, a 600-kg cow requires 17.09 kg of TDN for maintenance and milk production (NRC 1984). Therefore, TDN was selected to be included in the equation from the pool of energy measurements discussed above.

Protein is a vital nutrient for the maintenance, growth and reproduction of livestock. Protein in many cases is reported as Crude Protein (CP), which represents total nitrogen in the diet. After the nitrogen content is identified, it is multiplied by a standard number of 6.25 to obtain the total protein content in the sample (NRC 1988). Since crude protein is a true estimate of the percentage of protein in the sample, it is included in the hedonic equation.

There are two important characteristics associated with Crude Protein: Degradable Intake Protein (DIP) and Undegradable Intake Protein (UIP). DIP is a percent of CP, which can be digested in the rumen, while UIP represents the percent of the CP that is not degraded in the rumen. However, UIP is not an indicator of lost protein, as it is digestible in the abomasums and represents an important part of livestock nutrition. If DIP and UIP sum to 100%, we only include UIP in the equation to avoid problems with perfect multicollinearity in the model.

Ether Extract (EE) is equivalent to lipids and represents an estimate of total fat or oil content, which is a rich source of energy. EE represents the major determining factor for the value of input used for biodiesel production; however limited content of EE (fat) is a necessary ingredient for livestock body growth as well. As it is expected to have a significant influence on the value of the feed meal, it is included in the hedonic regression equation for algae meal value estimation.

Fiber content in the feed meal is a relatively important component in the livestock diet and can have a significant effect on the buying behavior of feed meal customers. Acid detergent fiber (ADF) is representative of the fiber content, which is negatively related to digestible energy. The higher the ADF content, less energy is digested by livestock. On the contrary, effective fiber such as effective neutral detergent fiber (ENDF) can be digested and can have a relatively important nutritive value in the livestock feed ration. As both of the fiber representatives measure different aspects of the livestock feed ration, ADF and ENDF are both included in the hedonic equation.

Minerals that are important for animals are divided into two groups: macrominerals and trace minerals. Macrominerals are represented by the following group of minerals: calcium, phosphorus, sodium, chlorine, potassium, magnesium, and sulfur. Trace minerals include cobalt, copper, iodine, iron, manganese, molybdenum, selenium, and zinc (NRC 1984). From this pool of minerals, four main macrominerals were selected because they potentially influence feed meal value. The first mineral in the equation is calcium, which is important for bone and teeth formation, cardiac regulation and muscle excitability. Calcium deficiency prevents an animal from growing normally.

The second mineral is phosphorus, which is an important dietary component for dairy cattle and other livestock. Phosphorus determines how the animal stores and uses energy. The third mineral in the equation is potassium, which is important in pressure regulation, oxygen and carbon transport, acid-base balance and muscle contraction. A lack of potassium will reduce the weight of the animal and decrease milk yield. The forth mineral in the equation is sulfur, which is essential for disease resistance and blood sugar regulation and is necessary for maintaining body tissue. All four of the minerals may have strictly negative values, as they can be toxic for the livestock if given in high volumes; however, they are not expected to be found in toxic volumes for the feed meals used in this research.

5.5 Algorithms of Inductive Causation

An Algorithm of Inductive Causation (AIC), which represents an effective tool to identify the causal effects among variables, was used in this research to discover the feed meal characteristics (independent variables) which have a causal relationship with the price of feed meal (dependent variable) in the model. There are three main assumptions that need to hold to obtain unbiased results: Causal Sufficiency, the Markov Condition, and the Faithfulness Condition. Causal Sufficiency implies that there are no omitted variables that cause two or more of the included variables. Since we included all 10 variables from the total pool of 36 chemical characteristics, which have a significant nutritive value for the livestock feed ration, Causal Sufficiency is a proper assumption in this case. The Markov Condition assumes that we can write probabilities of variables by conditioning only on each variable's "parents." The Faithfulness Condition implies that if we see zero correlation between two variables, the reason is that they are unrelated (Bessler 2010). The two most frequently used algorithms for inductive causation are: the Constraint-Based Algorithm (CBA) and the Scoring Metric Algorithm (SMA). CBA searches for correlations and conditional correlations, which are set equal to zero to remove edges between variables, while SMA uses Observationally Equivalent Graphs (OBG) to identify causation among variables. According to the method of OBG, the graphs are equivalent if the joint distribution of the data from one graph has the same probability distribution as the second graph.

Fast Causal Inference (FCI) and Partial Correlation-Based (PC) algorithms belong to the Constraint-Based Algorithms class of inductive causation. In spite of the wide application of CBAs, the common obstacle in this approach is that it is difficult to find a strong theoretical basis to specify the significance level (α-alpha) in the model, and in many cases, the researchers use a subjective approach for its specification.

A Scoring Metric Algorithm such as Greedy Equivalent Search (GES) however does not require the significance level to be specified in the model and accordingly is easier to calculate. It uses OBG that can be uniquely identified from the data and have the capability to imply causation among variables. GES searches over equivalence classes scoring each graph to find the best model, according to different criterion (e.g. Schwartz, Hannan and Quinn's Phi, Akaike's Information Criterion), that measures forecast and fit of the model. GES starts with all variables having the set condition that they are unrelated and no edges exist among them. Afterward, it adds an edge among variables and scores it according to a loss function. A Loss function such as Schwartz Loss (SL) is given as:

$$SL = \log | \sum | + k \log (T) / T \tag{5.1}$$

where $\sum$ represents an error covariance matrix estimated with k regressors in each equation, log is natural logarithm, | | denotes the determinant operator, k is the number of endogenous variables in the system and T is the total number of observations on each series.

Both the CBA and SMA types of inductive causation are effective tools and are used by many researchers to identify causal inference among variables. Bryant, Bessler, and Haigh (2009) use the FCI algorithm to identify causality between alcohol consumption and traffic fatalities. Mjelde and Bessler (2009) use the PC algorithm and find that energy price discovery originates from electricity markets. Wang and Bessler (2006) use the GES algorithm to test causation among meat prices, quantities and expenditures.

The GES algorithm is used in this research to identify which feed meal chemical contents cause price (dependent variable) to change over time. GES was preferred over PC or FCI algorithm based on the fact that it enables us to avoid bias of specifying alpha. The quarterly data starting from the first quarter of 2005 until the third quarter of 2010 were pooled together to identify the variables affecting the price as a whole in integrated system Variables suggested by the GES algorithm will be included in the hedonic regression equation and will represent the restricted model. As a final point, the reduced form model and the full model will be compared using a likelihood ratio test.

The one having the better goodness-of-fit will be selected for the final hedonic regression.

5.6 Likelihood Ratio Test

The GES algorithm selects the feed meal characteristics that are in a causal relationship with price. The restricted model only includes suggested variables and is then compared with the unrestricted model, where all of the variables before GES was applied are included. A likelihood ratio test is used to compare the goodness-of-fit of the restricted and unrestricted models, where the null is a restricted model as a special case of an alternative (unrestricted) model.

If the log-likelihood function is

$$\Phi(\mathrm{R}) = \sum_{i=1}^{N} l_i\,(R) \tag{5.2}$$

then the likelihood ratio statistic (LR) is equal to

$$\mathrm{LR} = 2\{\Phi(\text{null model}) - \Phi(\text{alternative model})\} \tag{5.3}$$

where LR is distributed Chi-Squared (Wooldridge 2001).

The likelihood ratio test measures the performance of the two models based on goodness-of-fit. The one with the highest performance is selected for the final regression in this research.

5.7 Functional Form Specification

Hedonic regression results strongly depend on the choice of functional form, and there is no specific functional form suggested by theory for hedonic pricing models. Halvorsen and Pollakowski (1981) used a methodology based on the goodness of fit of alternative forms developed by Box and Cox (1964) and applied it to hedonic modeling to determine a more general functional form specification. The suggested form is flexible and takes on different functional forms as the parameters change in the following equation:

$$R^{\theta} = B_0 + \sum_m B_m X_m^{\gamma} + \frac{1}{2} \sum_m \sum_n \gamma_{mn} X_m^{\gamma} X_n^{\gamma} \qquad (5.4)$$

If θ and γ are both equal to 1 and γ_{mn} is equal to zero, equation (5.3) will be referred to as a simple linear functional form, but when θ and γ are both zero, the model becomes a logarithmic model (Halvorsen and Pollakowski 1981). The rest of the functional forms are similarly obtained by changing the parameters in the equation (5.3).

Cropper et al. (1988) suggested that the linear Box-Cox model provided the most reliable results among many other functional forms. The linear Box-Cox transformation converts the parameters that result in the functional form with a linear specification. The linear Box-Cox transformation was used in this research to find out whether any type of transformation was necessary for the given data. The null hypotheses for the Box-Cox parameters were as follows:

1) Ho: θ = -1, which corresponds to the logarithmic transformation
2) Ho: θ = 0, which corresponds to the reciprocal transformation
3) Ho: θ = 1, which corresponds to no transformation needed.

Alternative hypotheses were specified as $\theta \neq$ -1, 0 or 1 respectively. The likelihood ratio test was used to compare the goodness of fit of the restricted and unrestricted models, where the null is a special case of an alternative model. The results will validate whether or not the transformation is needed and, if needed, which functional form will best fit the data.

5.8 Hedonic Regression Equation

Ordinary Least Squares (OLS) is used to estimate the unknown coefficients in the hedonic pricing model. OLS identifies the parameters based on the minimization of the Sum of Squared Errors (SSE) in the model. There are two main assumptions in the OLS model. First assumption is population orthogonality condition, which indicates that the regressors are exogenous and are not correlated with the error term. Second assumption is that the matrix of independent variables has the full rank, which means that the regressors are not linearly related to each other. Thus, the selection of variables in the model is crucial to get consistent parameter estimates for the regression (Wooldridge 2001).

Standard percentage chemical contents of feed meals as independent variables in the full model are selected from the full set of chemical composition tables reported by NRC and Beef Magazine. There is minor variability of reported percentage contents among reporting agencies due to the different methods of treatments (such as reporting on different percent of dry matter basis); however the overall content of the feed meals is consistent. The variables in the model are carefully chosen based on their significance in the feed ration. Accordingly, we do not suspect that omitted variable bias exists in the model. Furthermore, we use Algorithms of Inductive Causation to identify the content of feed meals among all included independent variables which directly affect price. Likelihood ratio tests will yield the model that gives better goodness of fit: restricted or unrestricted. The model with better performance will be chosen and corresponding variables will be included in the equation. Therefore, the OLS will present consistent parameter estimate for the hedonic regression in this research.

The final hedonic regression equation is selected between unrestricted and restricted models. The unrestricted hedonic pricing model is as follows:

$$Price_{FM} = B_0 + B_1 TDN + B_2 EE + B_3 CP + B_4 UIP + B_5 ADF + B_6 ENDF + B_7 Ca + B_8 P + B_9 K + B_{10} S + \mathrm{e} \quad (5.5)$$

where price of the feedmeal is determined by the content of Total Digestible Nutrients (TDN), Either Extract/Fat (EE), Crude Protein (CP), Undegradable Intake Protein (UIP), Acid Detergent Fiber (ADF), Effective Neutral Detergent Fiber (ENDF), calcium (Ca), phosphorus (P), potassium K), sulfur (S). An error term is represented by the symbol e in the equation.

The restricted model will exclude the independent variables having no causal relationship with the price as suggested by the GES algorithm. The restricted model will be compared to unrestricted model based on the likelihood ratio test and the model having better goodness of fit will be the final form of the hedonic regression equation.

5.9 Model Development

The prices of twenty-two feed meals represent the set of dependent variables for the model, while ten selected contents of feed meals are used as independent variables in the full model. The weekly data is aggregated and transformed to a quarterly basis to avoid affects of seasonality in the data and to display a more general picture of algae meal price movement. The aggregated data cover a total of twenty-three time periods from the first quarter of 2005 to the third quarter of 2010. The GES algorithm is used to identify the causal effects among variables in the model. The suggested variables having a causal relationship with the price of the feed meal are included in the restricted model, which is then compared with the unrestricted model based on the likelihood ratio test. The variables in the model having better goodness of fit according to the likelihood ratio test will be selected for the final regression equation.

As the proper variables are selected in the model, the linear Box-Cox transformation is run to identify the functional form specification for the hedonic equation. The Box-Cox transformation is run 23 times along the timeline and the results are reported. As we get different likelihood ratios and theta coefficients at each time period, the results are reported on two different bases. In the first case, we calculate the number of times the specific transformation is suggested as a percent of the total number of regression equations. In the second case, we average the P-values of the theta coefficients to identify the overall probability for the given coefficient. The mixture of both of the cases is used to identify the appropriate model specification at the 95% confidence level.

After determining whether the transformation is needed, an OLS regression is run 23 times along the timeline and the coefficients for each of the independent variables are reported. The same procedures as for the functional form specification are used for parameter estimation; both the number of times the coefficients were significant and the average P-value for the overall significance are used to identify the significant variables in the model. As the feed meal characteristics that have a significant impact on the feed meal prices are identified, the coefficients are plugged into the corresponding percentage content of algae meal to determine the value of algae meal. The price of algae meal is calculated at each time interval and is displayed from the first quarter of 2005 through the third quarter of 2010.

CHAPTER VI

RESULTS

6.1 Results Overview

The results present the parameter estimates for each independent variable, which then are aggregated to project the price of algae meal given alternative chemical profiles. Each parameter included in the model is reported over time. However, only the parameters that are significant at the 95% confidence level are included in the algae meal price determination formula. Estimated algae meal price will be obtained by multiplying the significant parameters in the model by the percentage content of a given algae meal. Since the value of algae meal is predicted based on various existing feed meals, the expected results will reflect the market forces affecting the prices of each particular feed meal and therefore will provide reliable results for further price analysis.

6.2 GES Algorithm Results

The GES algorithm is used to identify which feed meal characteristics (independent variables) have a causal relationship with feed meal prices (dependent variables). The GES algorithm identified six of the ten characteristics which have a causal relationship with feed meal price: Total Digestible Nutrient, Crude Protein, Ether Extract, Effective Neutral Detergent Fiber, calcium and sulfur. The GES algorithm results are given in Figure 6.1, which provides an efficient representation of the causal relationship among variables based on the variance-covariance matrix.

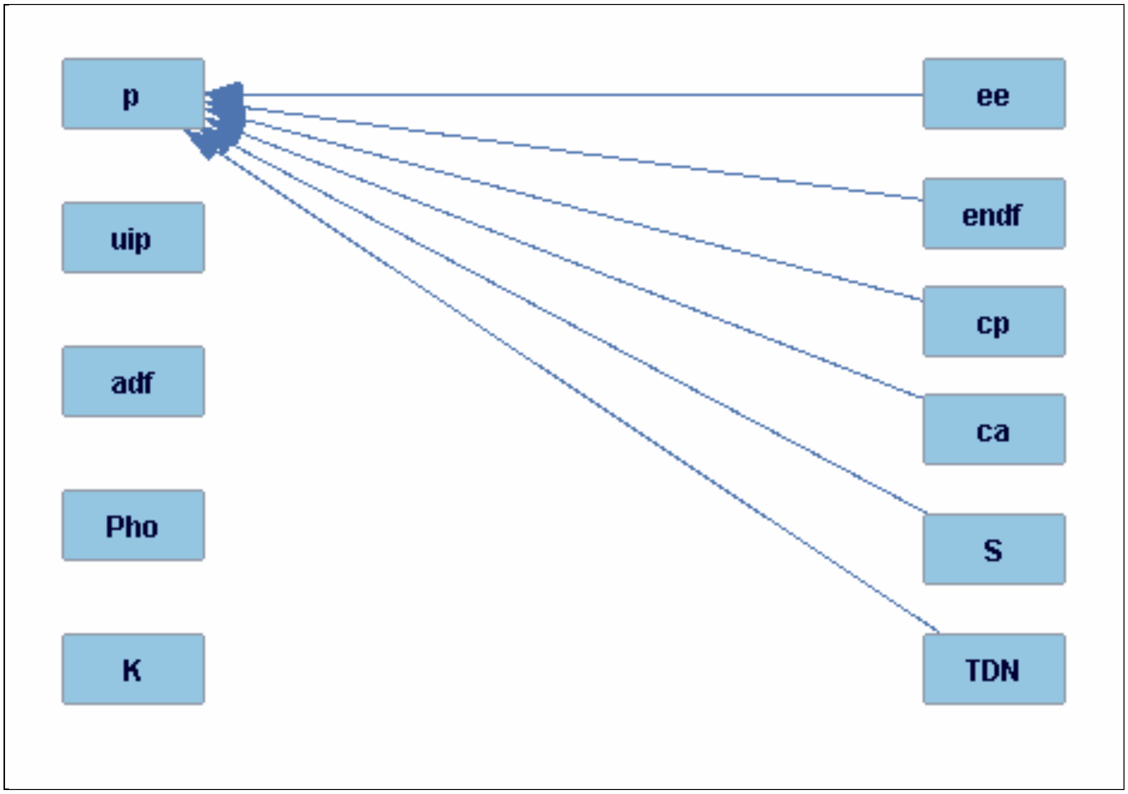

Figure 6.1. GES algorithm results

GES results given in Figure 6.2 represents an efficient means of finding a set of data supported conditional inference relations that can usefully guide the specification of the hedonic model. It can be inferred from the graph that price is influenced by the six variables TDN, EE, ENDF, CP, Ca, S. The rest of the variables, ADF, UIP, K and Pho might affect the price of feed meal through these six variables; however inclusion of TDN, EE, ENDF, CP, Ca and S will nullify this impact.

Therefore, the restricted model will be the following:

$$Price_{FM} = B_0 + B_1 TDN + B_2 EE + B_3 CP + B_6 Endf + B_7 Ca + B_{10} S + \mathrm{e} \qquad (6.1)$$

6.3 Likelihood Ratio Results

The GES algorithm selected the feed meal characteristics that are causally related to price. Thus, only these variables were included in the restricted model, which is then compared with the unrestricted model. The pooled quarterly data starting from the first quarter of 2005 until the third quarter of 2010 were used to obtain a single measure of goodness of fit. The likelihood ratio test is used to compare the goodness of fit of the restricted and unrestricted models, where the null is a restricted model as a special case of the alternative (unrestricted) model.

Null hypothesis was specified as follows:

$$H_0: Price_{FM} = B_0 + B_1TDN + B_2EE + B_3CP + B_6Endf + B_7Ca + B_{10}S + \mathrm{e}$$

where four variables (UIP, ADF, P, K) were restricted from the model based on the results given from GES algorithm.

Alternative hypothesis was specified as follows:

$$H_A: Price_{FM} = B_0 + B_1TDN + B_2EE + B_3CP + B_4UIP + B_5ADF + B_6Endf + B_7Ca + B_8P + B_9K + B_{10}S + \mathrm{e}$$

where the variables excluded based on the GES algorithm is included in the model.

The results of the Likelihood Ratio Test (assumption: the restricted model nested in the unrestricted model) are as follows:

LR $\mathrm{chi}^2 = 3.68$ Prob > $\mathrm{chi}^2 = 0.4506$

The results show that null hypothesis holds and we fail to reject that the coefficients of UIP, ADF, P, K are equal to zero. Therefore, the restricted model is preferred for the final regression analysis.

6.4 Box-Cox Transformation Results

A linear Box-Cox transformation was used to identify the appropriate functional form for the hedonic pricing model. The null hypotheses for the Box-Cox parameters were as follows:

1) Ho: θ = -1, which corresponds to the logarithmic transformation
2) Ho: θ = 0, which corresponds to the reciprocal transformation
3) Ho: θ = 1, which corresponds to no transformation needed.

The results were reported over twenty-three time periods starting from quarter 1 of 2005 through quarter 3 of 2010. Results for the last quarter of the data can be observed in Table 6.1.

Table 6.1. Box-Cox Transformation Results for the Quarter 3, 2010 (full model)

Test H_0	Restricted Log Likelihood	LR Statistic Chi^2	P-value Prob > Chi^2
theta = -1	-79.91	51.12	0.000
theta = 0	-60.67	12.64	0.000
theta = 1	-54.86	1.03	0.311

The first two hypotheses in Table 6.1 are strictly rejected at the conventional 5 percent level of significance, while the hypothesis that theta =1 cannot be rejected at 95 percent of confidence equivalently. The result suggests that there is no transformation needed for the given data for hedonic regression analysis. However, Table 6.1 only presents the results for the Box-Cox transformation in one time period. The results are subject to change as we run them in different time periods. The Box-Cox regression is run 23 times along the timeline and the results are reported in Table 6.2. There might be two different approaches for the interpretation of the results: In the first case, we calculate the number of times the specific transformation is suggested as a percent of total number of regression equations. In the second case, average P-values of the theta coefficients are computed to identify the overall probability for the given parameter.

Table 6.2. Box-Cox Regression Results Based on the 95% Confidence Interval

% of Times the Model Failed to Reject the Hypothesis		Average P-value of Theta	
Log	0.00%	Log	0
Reciprocal	21.73%	Reciprocal	0.035522
No Transformation	43.47%	No Transformation	0.119739

The mixture of both of the approaches was used to evaluate the regression results and identify the appropriate functional form specification for the hedonic regression model. Based on the average P-value of thetas, there was no transformation needed at the 95% confidence level. Furthermore, no transformation was needed 43.47% of the time, which outperformed the reciprocal transformation in twice as many periods. The logarithmic transformation was strictly rejected at each time period. Thus, the Box-Cox transformation results suggest no evidence of the need to transform the data to any of the linear functional forms. Both of the reporting methods conclude that no transformation is needed for the given data.

6.5 Regression Results Overview

The model was run 23 times along the timeline and the coefficients for each of the independent variables were reported. The same reporting procedures as in the case of functional form specification were used; the number of times the coefficients are significant and the average P-value for the overall significance are used as measurements to identify the significant parameters in the equation. Table 6.3 reports the results of the hedonic regression equation.

Table 6.3. OLS Regression Results for the Period of Q1, 2005 Through Q3, 2010

% of Times the Null Hypothesis of $B_i = 0$ was Rejected		Average P-value of Theta	
Constant	43.48	Constant	0.2985
TDN	100	TDN	0.005
EE	91.30	EE	0.020
CP	100	CP	0.000
ENDF	34.78	ENDF	0.143
Ca	100	Ca	0.001
S	73.91	S	0.142

A confidence level of 95% was used to determine the significance of the variables. Total Digestible Nutrients is significant in all of the cases along the timeline and its average P-value of 0.005 suggests that TDN is significant with 99% confidence. Ether Extract is significant in 91% of cases and its average P-value of 0.02 suggests that Ether Extract has an overall significance with 98% confidence. Crude Protein is significant in all time periods with an average P-value of 0.000, which suggests that CP is significant in the equation with 99% confidence. Effective Neutral Detergent Fiber is significant in 35% of the cases, which is not sufficient to be considered for the algae meal price determination. Moreover, it has an average P-value of 0.152, which is rejected at the 95% confidence level. Calcium is a significant component in the hedonic equation 100% of the time and its average P-value is 0.001. Thus, calcium is a significant feed meal characteristic with 99% confidence. Sulfur is significant 74% of the time and its P-value of 0.142 is rejected at the 95% confidence level.

According to the results, four variables having a significant impact on the feed meal prices based on the 95% confidence level were used to determine the price of algae meal based on its chemical profile. ENDF and S are reported as they might present interesting results for different research purposes; however they do not participate in the algae price determination as they were rejected at the 95% confidence level.

6.6 Total Digestible Nutrients

Total Digestible Nutrients appeared to be a crucial component in the hedonic feed meal price model with the average confidence level of 99%. The TDN price along the timeline ranges from a minimum of \$0.73 to a maximum of \$2.63 per percentage content in the feed meal. This means that if a feed meal contains 50% TDN, the price of TDN equals the product of the above determined price (\$0.73-\$2.63) and 50. The results also show that the average price of TDN over time is $1.52 with a standard deviation of $0.59. Figure 6.2 shows the trend of TDN prices over time.

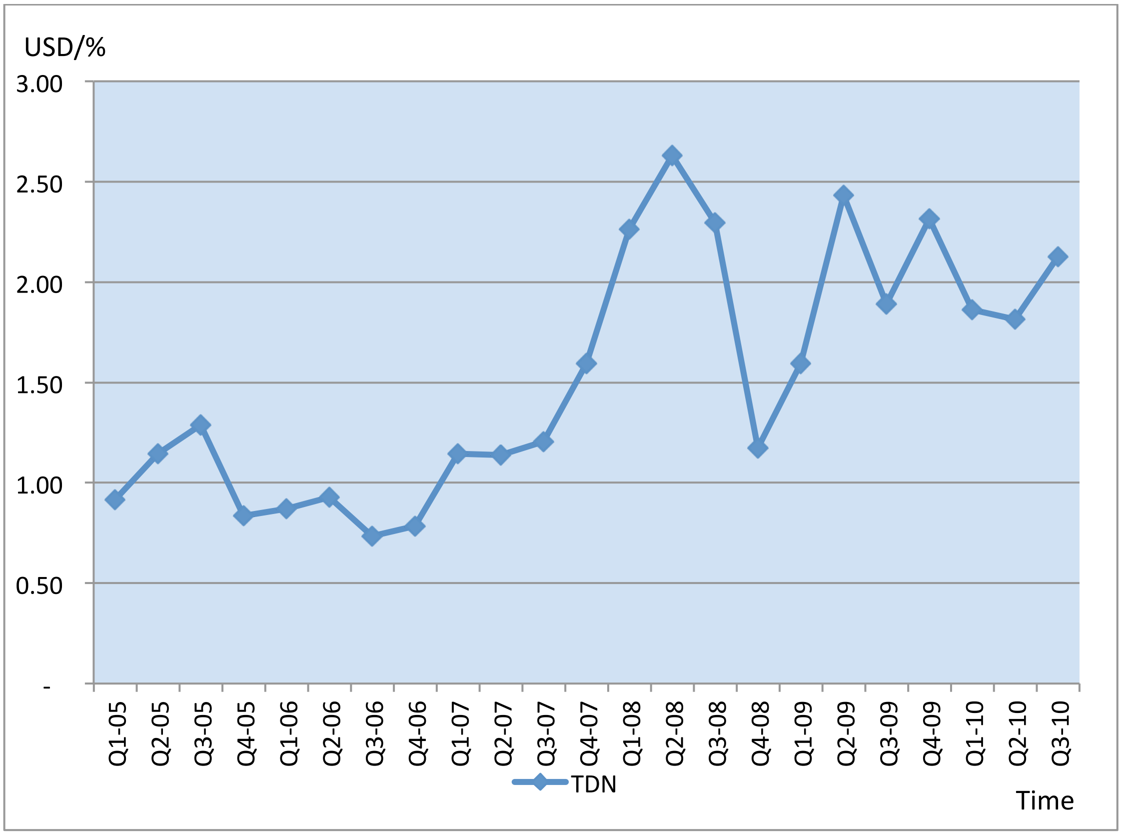

Figure 6.2. Total digestible nutrients prices

6.7 Ether Extract

Ether Extract appeared to be an important characteristic of the feed meal with an average confidence level of 95%. EE price along the timeline ranges from a minimum of $1.01 to a maximum of $4.33 per percentage content in the feed meal. The average price over time is $2.20 with a standard deviation of $0.94. Figure 6.3 shows the trend of EE prices over time.

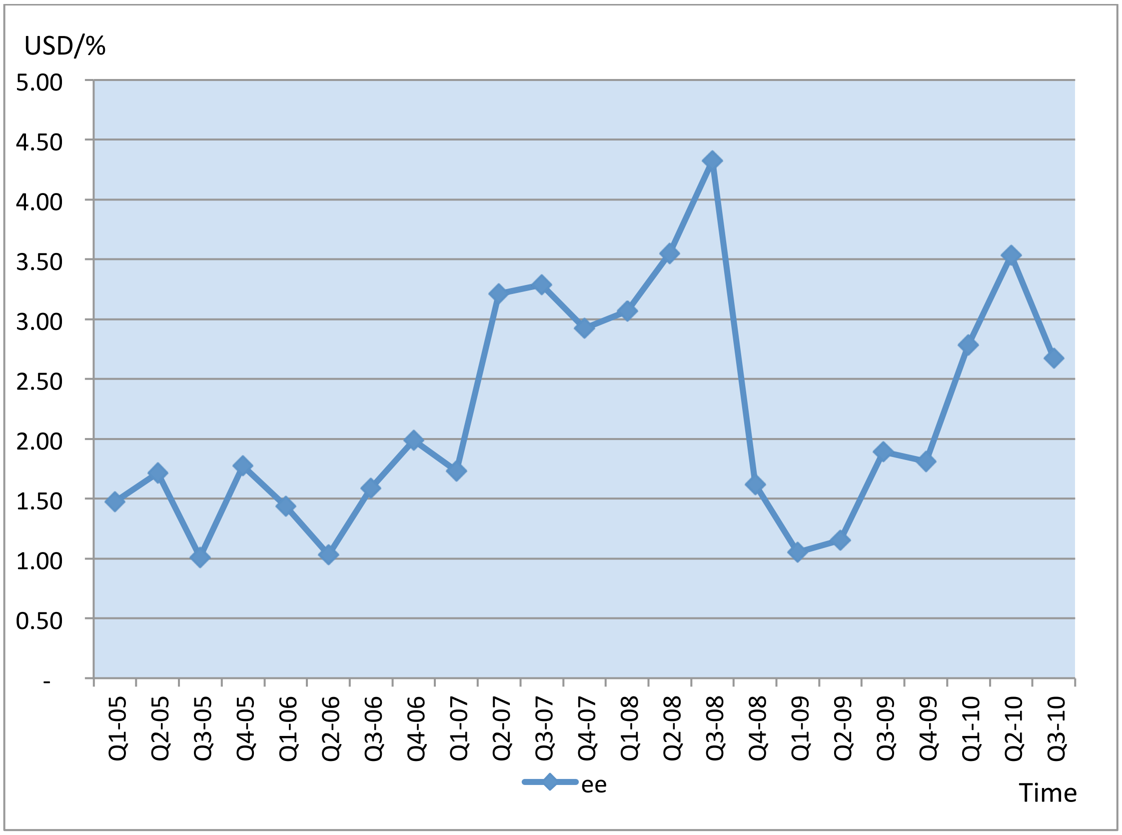

Figure 6.3. Ether extract prices

6.8 Crude Protein

Crude Protein appeared to be a vital component in the hedonic feed meal price determination with an average confidence level of 99%. CP value along the timeline ranges from a minimum of $1.01 to a maximum of $2.92 per percentage content in the feed meal. The average price over time is $1.47 with a standard deviation of 0.41. Figure 6.4 shows the trend of CP prices over time:

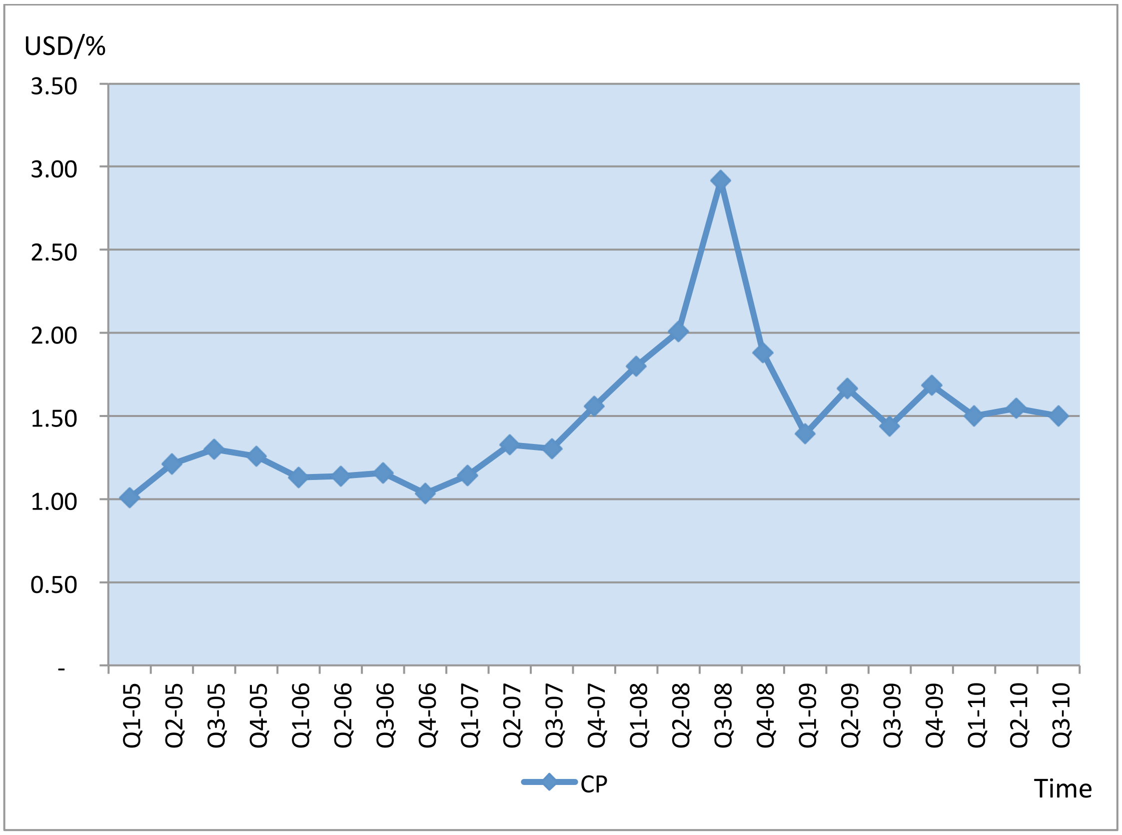

Figure 6.4. Crude protein prices

6.9 Effective Neutral Detergent Fiber

Effective Neutral Detergent Fiber was rejected based on 95% confidence level. Thus, it is not included in the algae meal price determination equation. As ENDF results might present relatively important information for different research purposes, the results are reported (but not included) across time. The minimum value of $0.12 was in the first quarter of 2005. It reached its peak in the third quarter of 2009, with a value of $0.81 per percentage content in the feed meal. The average price over time was $0.44 with a standard deviation of $0.19. Figure 6.5 shows the trend of ENDF values over time.

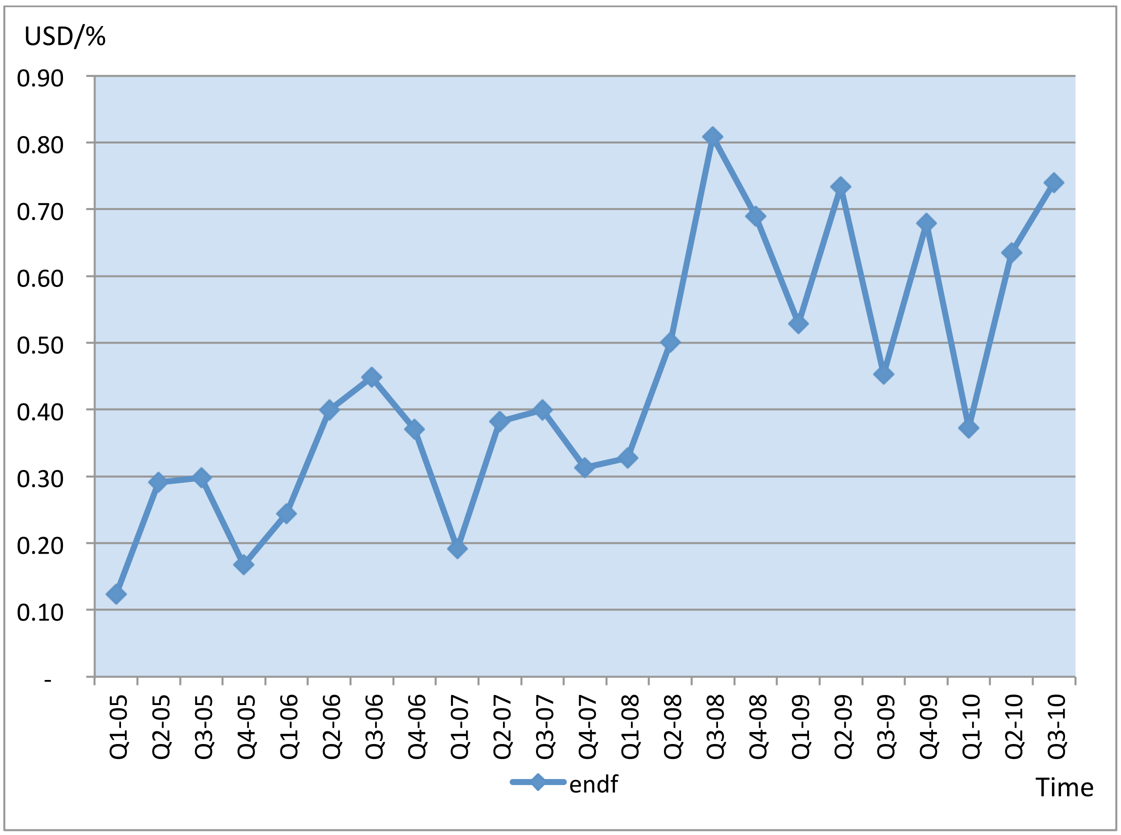

Figure 6.5. Effective neutral detergent fiber prices

6.10 Calcium

Calcium appeared to be an important characteristic for the feed meal with an average confidence level of 95%. Calcium value along the timeline ranges from a minimum of $16.77 to a maximum of $134.48 per unit of percentage content in the feed meal. The average price over time is $73.24 with a standard deviation of 35.92. Figure 6.6 shows the trend of calcium values over time.

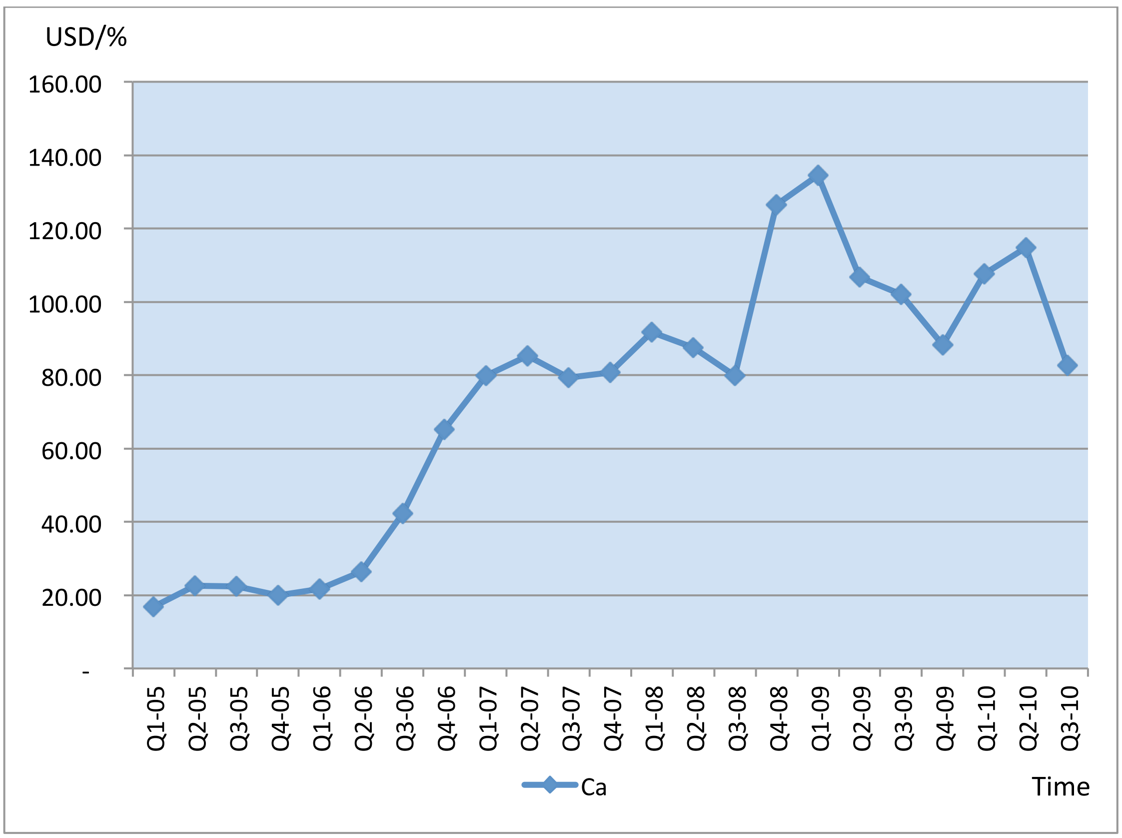

Figure 6.6. Calcium prices

6.11 Sulfur

Sulfur was rejected based on both the average P-value and the number of times it was significant across time. It appeared to be significant in 74% of the time periods and was rejected at the 95% confidence level with a P-value of 0.1429. Thus, it is not included in the algae meal price determination equation. However, sulfur can be relatively significant and its value variation might present useful information for different purposes of the research. Figure 6.7 shows the trend of sulfur values over time.

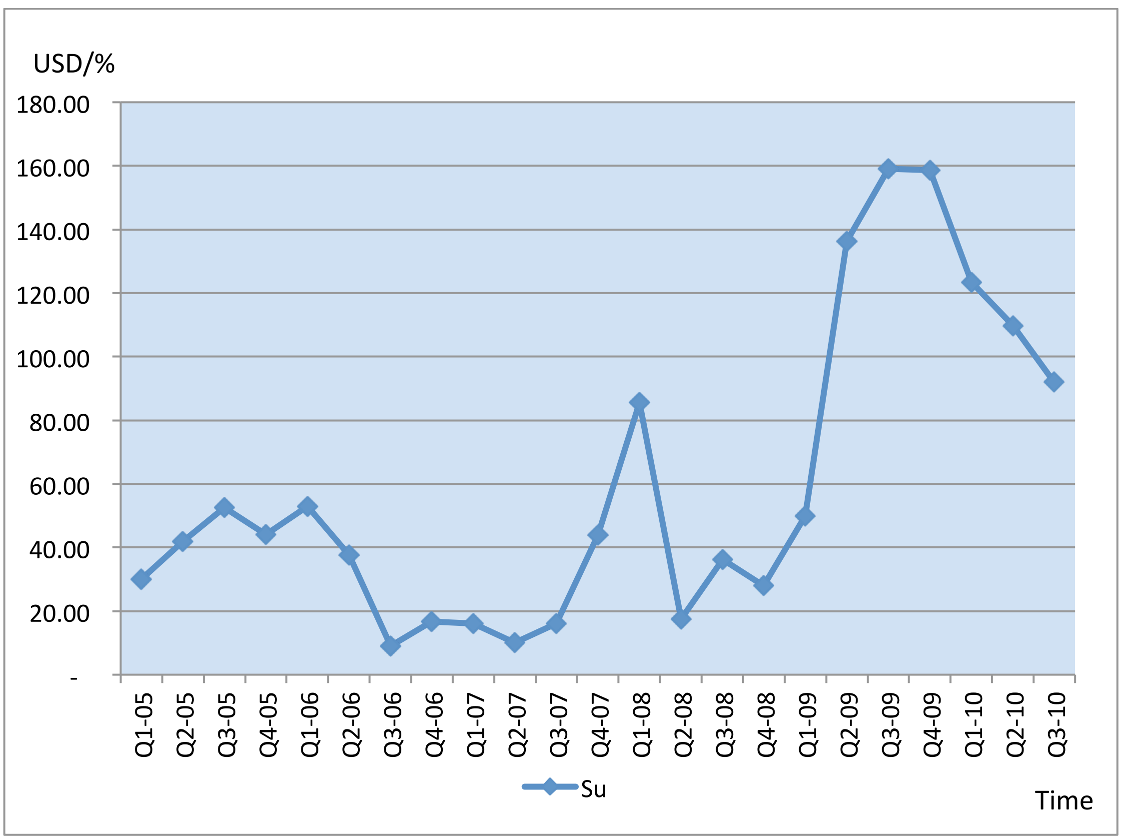

Figure 6.7. Sulfur prices

Sulfur value along the timeline ranges from a minimum of $8.99 to a maximum amount of $159.06 per unit of percentage content in the feed meal. The average value over time is $59.43 with a standard deviation of 46.71. Based on the 95% significance level, TDN, EE, CP and Ca were selected to be determinants of algae meal price. All of the four variables have a significant positive trend across time, which will be symmetrically reflected on the algae meal price as well.

6.12 Algae Meal Price Determination

A hedonic pricing model for feed meal can be used to determine the price of algae meal. The coefficients which appeared to be significant in the hedonic regression can be transferred to algae meal value in the following way:

$$\text{Algae Meal Value} = \text{TDN} * \%\,\text{TDN}_{algae} + \text{EE}*\%\text{EE}_{algae} + \text{CP} * \%\,\text{CP}_{algae} + \text{Ca}*\%\text{Ca}_{algae} \tag{6.2}$$

where estimated parameters of the feed meal characteristics are multiplied by their percentage content in the algae meal respectively. Table 6.4 presents the chemical composition of two different algae samples: wild algae and N. Oleoabundans.

TDN values in the table are hypothetical and calculated based on the ash content. For instance, Wild Algae contains 30% ash, thus 70% (100-30) is organic matter. It is expected that the digestibility of algae will be approximately 80%. Therefore, 0.7 is multiplied by 0.8 and we get the TDN value of 55.58.

Table 6.4. Chemical Composition of Algae Samples

Description	Wild Algae	N. Oleoabundans
TDN	55.58	45.46
EE	9.07	11.84
CP	18.28	21.93
Ca	0.67	1.02
Ash	30.52	21.93
Source: *FeedC. P. Payne, J. E. Sawyer, and T. A. Wickersham, 2010*		

Wild Algae price would have ranged across time from a minimum of $93.92 to a maximum of $273.75 per short ton. The average price would have been $180.53 with a standard deviation of 60.92 across the time period of the first quarter of 2005 to the third quarter of 2010. Figure 6.8 shows that there would have been a positive trend in the value of wild algae across time.

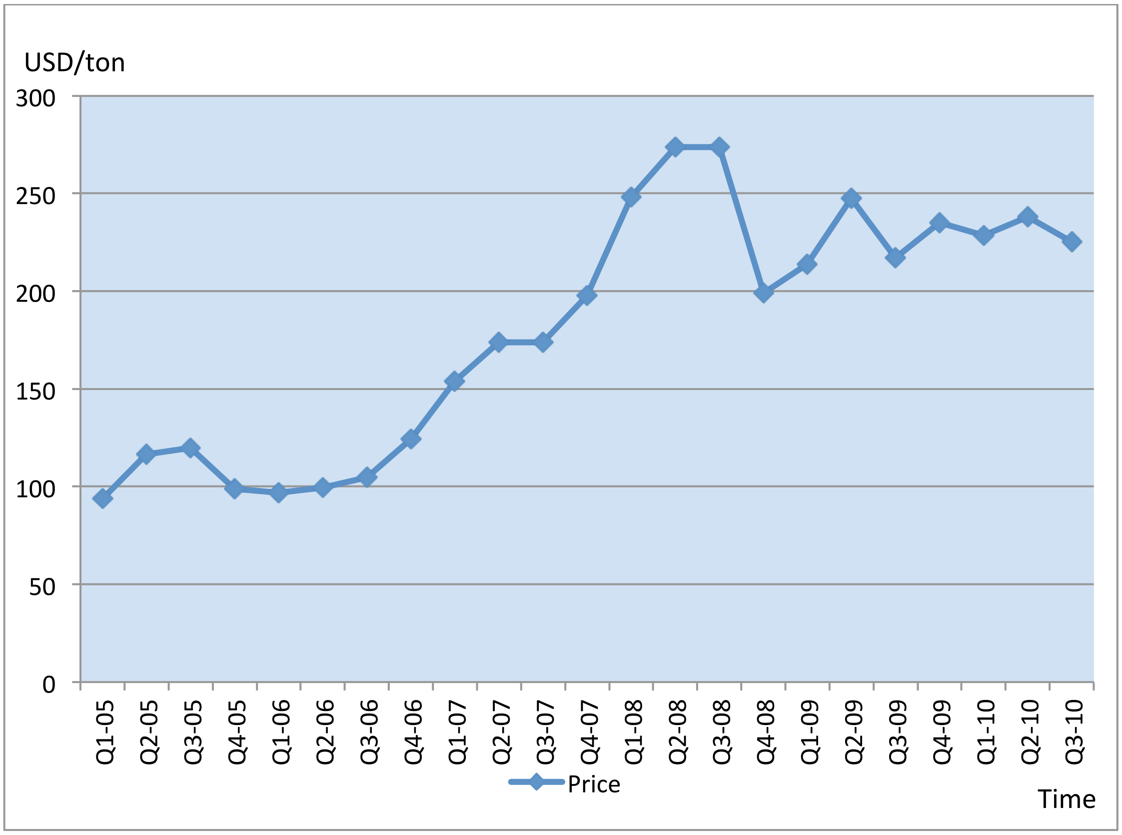

Figure 6.8. Wild algae prices

The price of algae meal changes relative to its characteristics. Thus, different types of algae will have different values. *Neochloris oleoabundans* (*N. oleoabundans*) would have had an average price of $202.25 per short ton over 23 time periods, which is higher than the time-varying average price of wild algae. *N. oleoabundans* price would have ranged from a minimum of $98.28 to a maximum of $301.01 per short ton. It has a standard deviation of 68.90.

Figure 6.9 presents price variation of *N. oleoabundans* algae from the periods of the first quarter of 2005 to the third quarter of 2010.

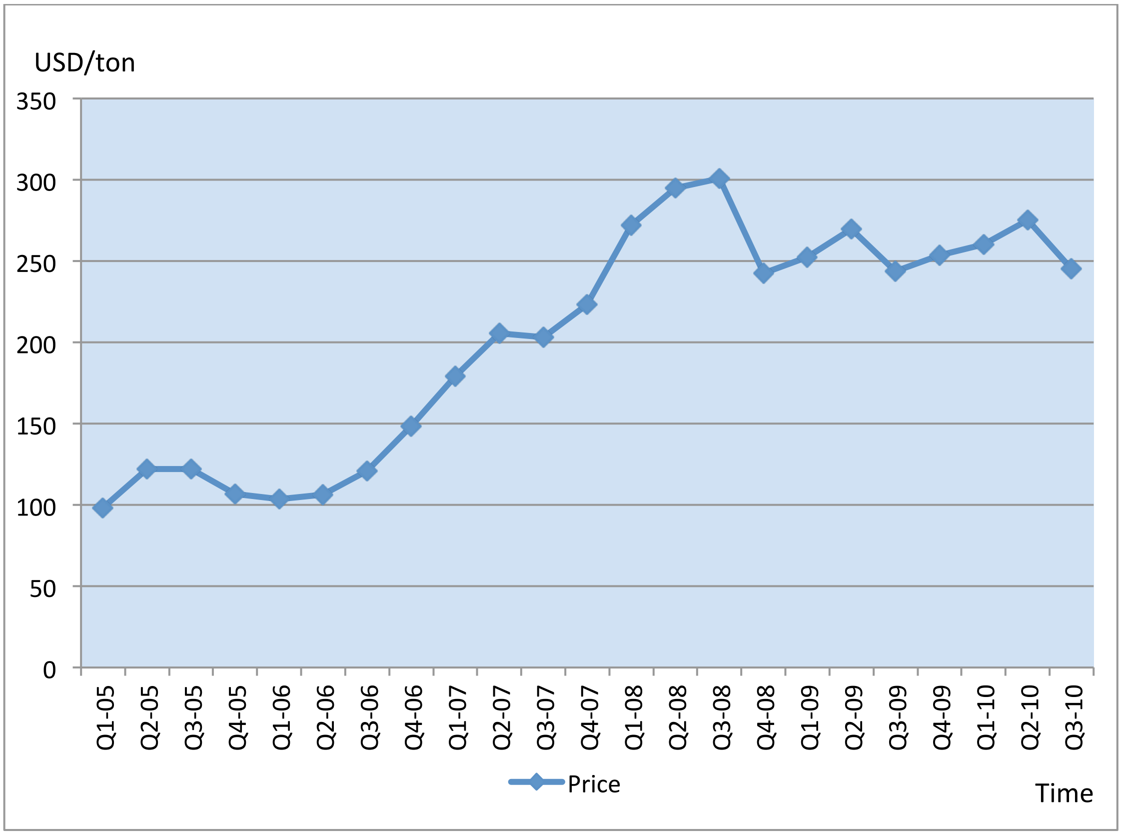

Figure 6.9. ***N. Oleoabundans*** **prices**

6.13 Comparison of Algae Meal to Different Feed Meals

The competitiveness of algae meal depends on its relative performance to competing feed meals in terms of price. The charts below represent a comparison of *N. oleoabundans* algae to the most commonly used feed meals such as corn, soybean meal (high protein), cottonseed meal, rice and sorghum.

Figure 6.10 presents the comparison between *N. oleoabundans* and corn across time.

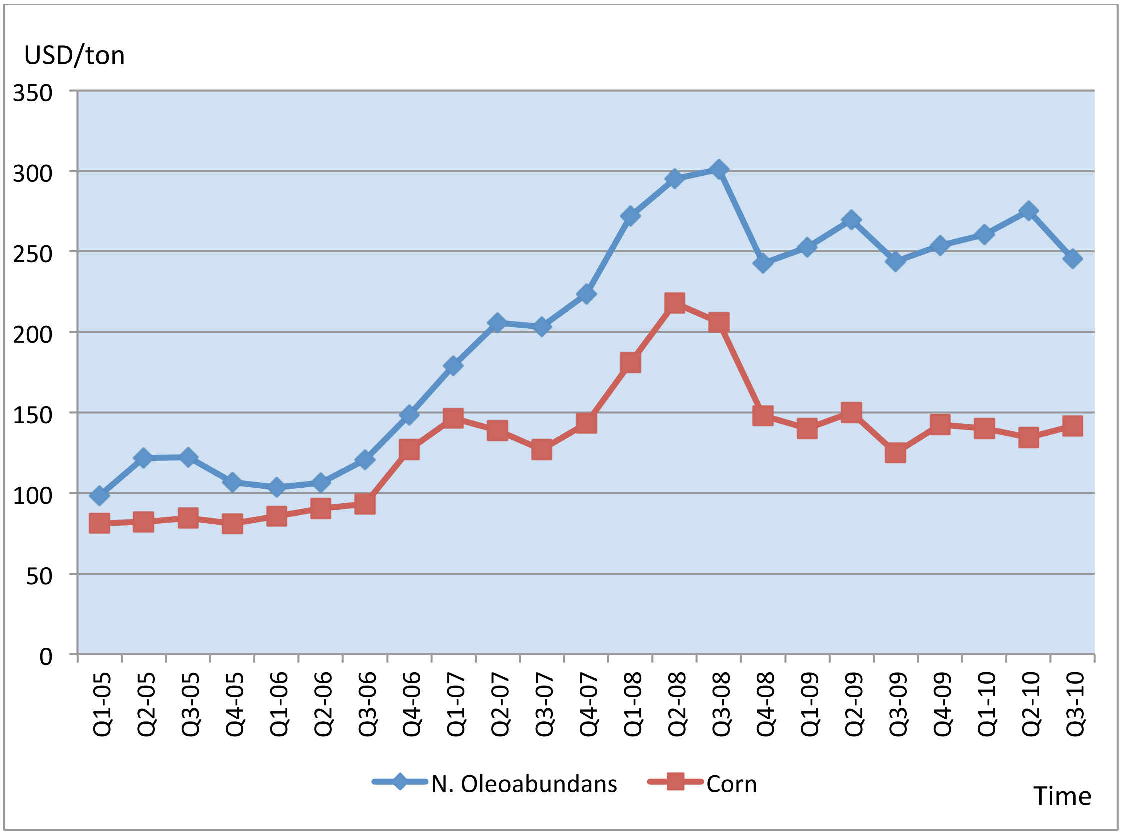

Figure 6.10. Price comparison I

The price of *N. oleoabundans* is higher than corn in all time periods starting from the first quarter of 2005 to the third quarter of 2010. Similar results are obtained in the case of rice and sorghum: algae prices are much higher than both of the crop prices across time.

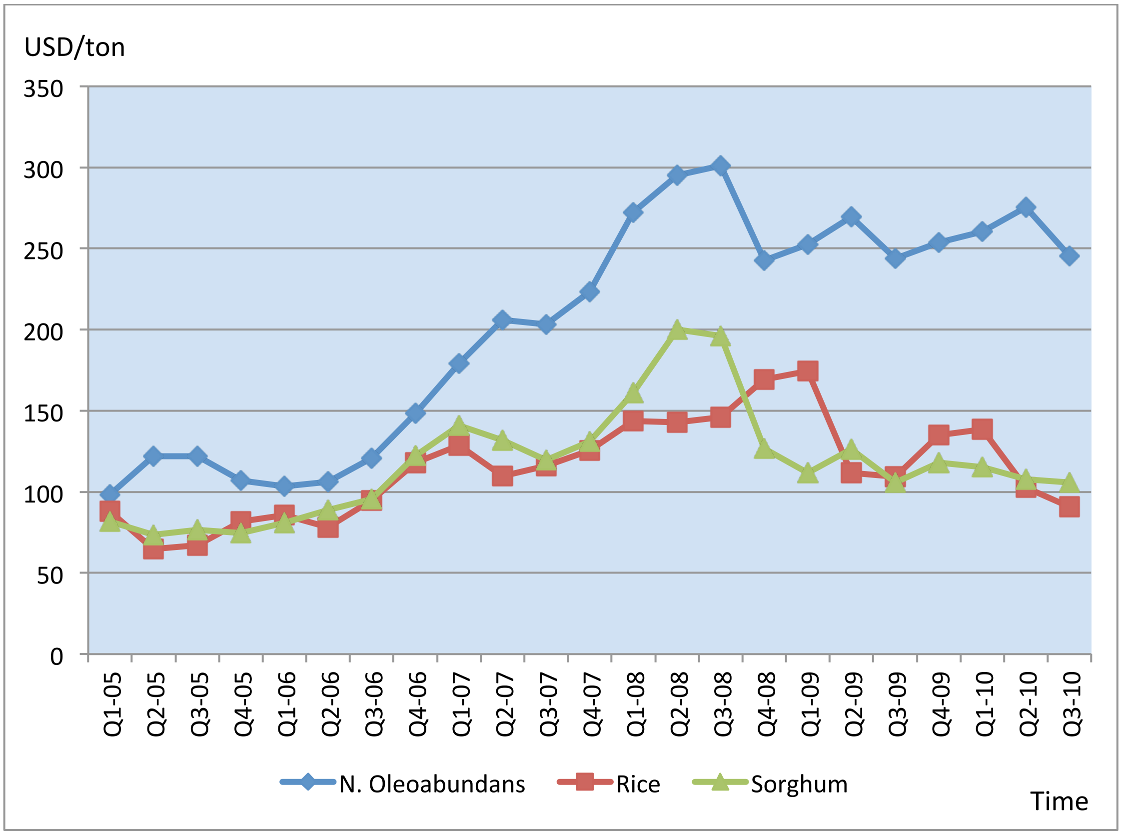

Figure 6.11. Price comparison II

The results are not that obvious in the case of comparing *N. oleoabundans* to cottonseed meal. Figure 6.12 shows that the prices of *N. oleoabundans* and cottonseed meal overlap across time. These prices follow a similar pattern and have about the same magnitude for this length of the period.

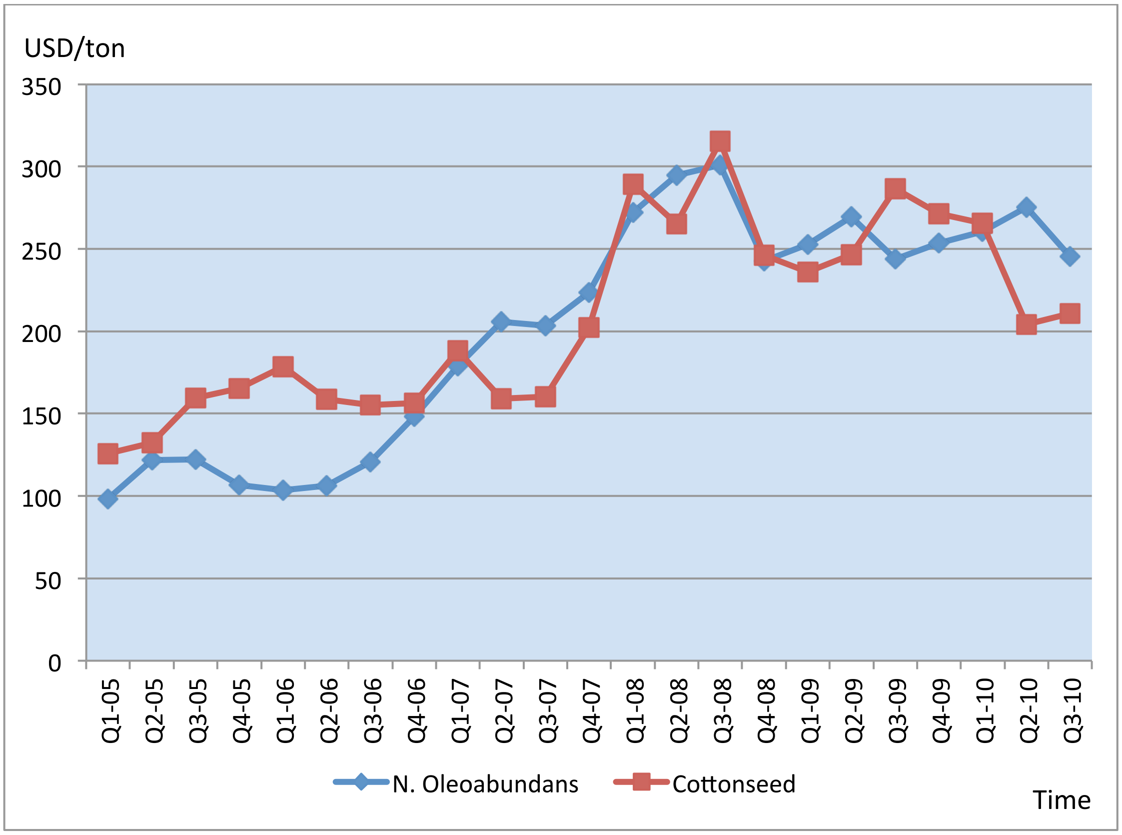

Figure 6.12. Price comparison III

Figure 6.13 shows the price comparison between *N. oleoabundans* and high protein soybean meal where the price of *N. oleoabundans* is relatively lower than that of high protein soybean meal. The true price series follows a similar path that post extracted algae meal price is $100 to $200/ton cheaper than high protein soybean meal.

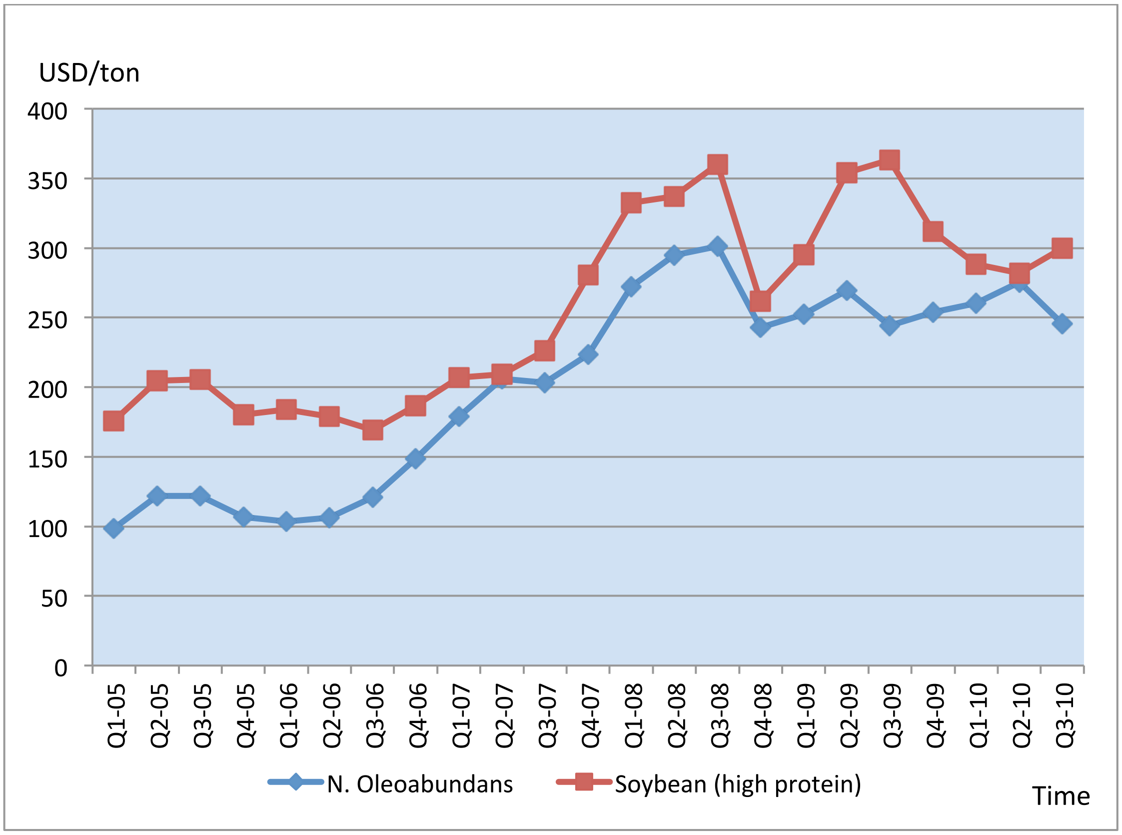

Figure 6.13. Price comparison IV

The price determination for *N. oleoabundans* represents the price for post-extracted algal residue and is based on the chemical profiles of algae from which the lipid content has already been extracted for biodiesel production. Therefore, the total value of algae is deteriorated and is not as high as it can be for the types of algae, which have high content of TDN, EE, CP and Ca. Becker (2007) reports the general composition table of different algae, where many of the reported microalgae have a protein content of more than 50%, while the algae meal we analyzed only had 18.28% and 21.39 % protein content based on the post-extracted values. Thus, algae meal might have much higher value than post-extracted wild algae or *N. oleoabundans* depending on the type of microalgae from which the meal is extracted.

In the algae composition table reported by Becker (2007), the inverse relationship between protein and lipids can be observed - if one of the algae contains high volume of lipids, it is very likely to contain a low amount of protein and vice versa. Since the algae meal we analyzed above is obtained from the microalgae type used for biodiesel production, it was originally supposed to be rich in lipids and could have considerably lower amounts of protein, as the latter is of no benefit for biodiesel production. As long as the lipids were extracted, the amount of protein and lipids therefore were both relatively low for wild algae and *N. oleoabundans*.

Let's now compare the price of algae meal based on the high chemical profile algae to the price of high protein soybean meal. Ortega-Calvo, Mazuelos, Hermosin, and Saiz-Jimenez (1993) reported the chemical composition tables of different types of microalgae, one of which is Spirulina. Three different lots were tested for chemical composition. The chemical profiles were averaged and plugged in the formula to calculate the value of high-protein algae meal. Figure 6.14 compares the price of Spirulina to the price of high-protein soybean meal.

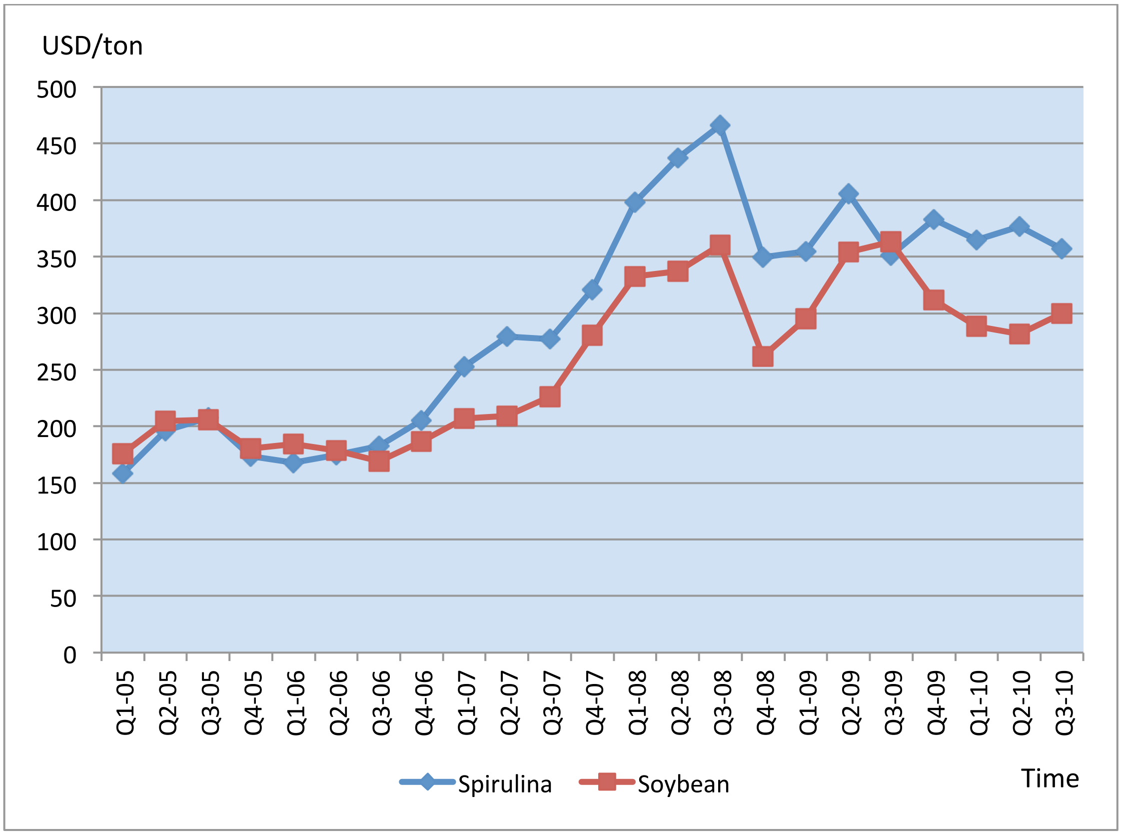

Figure 6.14. Price comparison V

Prices of Spirulina were higher than high-protein soybean meal prices in 74% of the cases across time with an average positive difference of $41. As the results show, the prices of algae meal are highly dependent on what type of algae is used for the analysis. Figure 6.15 shows the difference between the prices of Spirulina and post-extracted *N. oleoabundans*.

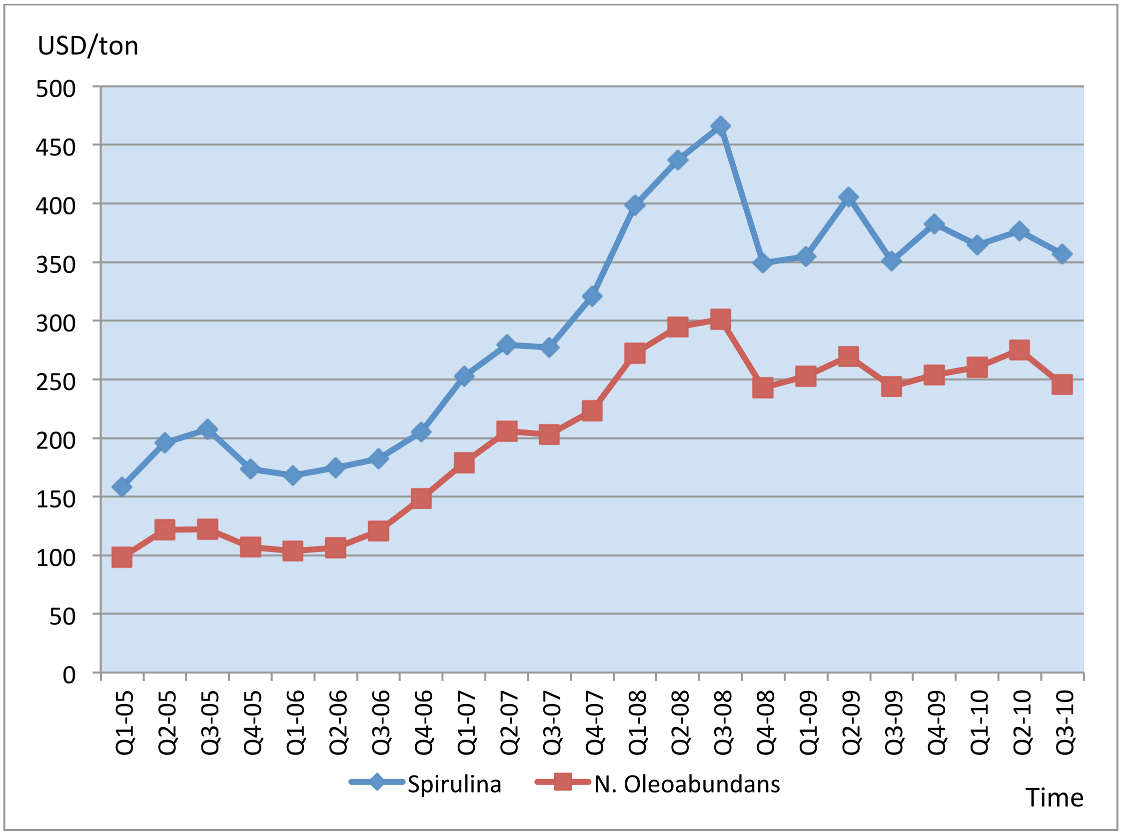

Figure 6.15. Price comparison VI

Therefore, the prices of algae meal calculated by means of hedonic price analysis give researchers insight into the movement of algae meal price and its potential compared to other competing feed meals. The results observed over time show that post-extracted algae meal had a significant value, which could compete with all types of feed meals existing in the market. Since there is a price variation among different types of algae, future research could investigate the optimal types of microalgae according to chemical profile.

6.14 Stochastic Simulation of Feed Meal Chemical Components

The results obtained from the hedonic price analysis show the series of prices for each significant feed meal characteristic from the first quarter of 2005 till the third quarter of 2010. These series can be used to forecast the 2011 prices of the feed meal chemical components. The forecasted values will be used to calculate the prices of algae meal in 2011 that will then be compared to high and low protein soybean meals.

Stochastic simulation techniques are used to incorporate risk in the analysis. TDN, EE, CP and Ca are correlated and made stochastic using Multivariate Empirical Distribution procedures reported by Richardson, Klose, and Gray (2000). Stochastic variables are obtained as follows:

$$\tilde{y}_{it} = \bar{y}_{it} + \sqrt{\Sigma} * W \tag{6.3}$$

where $\bar{y}_{it}$ is the deterministic component, Σ is the variance-covariance matrix, and W is a vector of Independent Standard Normal Deviates (ISND). As trend has been found in each of the variables, deterministic component is obtained through the trend forecast:

$$\bar{y}_t = a + by_{t+1} \tag{6.4}$$

where a is an intercept and b represents the slope coefficient calculated from the OLS regression. Obtained stochastic variables are simulated 500 times and the results are reported in Table 6.5. The mean of the simulated values is used as the average price for each feed meal chemical component.

Table 6.5. The Price of Feed Meal Contents for 2011 USD/%

TDN	EE	CP	Ca
2.48	2.99	1.92	136.67

Forecasted prices for TDN, EE, CP and Ca are multiplied by the corresponding algae chemical composition given in Table 6.6 to obtain the prices of post extracted *N. Oleoabundans* algae.

Table 6.6. Chemical Composition of *N. Oleoabundans* (Transferred from Table 6.4)

TDN %	EE %	CP %	Ca %
45.46	25.37	21.93	1.02

$$\text{Price} = 45.46 * 2.48 + 25.37 * 2.99 + 21.93 * 1.92 + 1.02 * 136.67 = 329.51 \qquad (6.5)$$

Therefore, the average price of *N. Oleoabundans* algae for 2011 is $329.51.

Stochastic simulation techniques similar to those used in the calculation of feed meal chemical components are used to obtain the forecasted price of soybean meal. Soybean meal prices are correlated with the rest of the analyzed feed meals and a stochastic forecast is made for 2011. Stochastic forecasts are simulated and the mean of 500 simulated values are used to calculate the average price of high protein soybean meal for 2011. The price statistics are reported in Table 6.7.

Table 6.7. Soybean Meal Price Statistics for 4 Quarters of 2011

	Q1-2011	Q2-2011	Q3-2011	Q4-2011	Average Price 2011
Mean	360.50	366.36	372.99	383.29	370.78
Standard Dev.	54.43	55.18	55.99	57.89	55.87
CV	15.10	15.06	15.01	15.10	15.07
Min	279.94	286.10	292.26	298.41	289.18
Max	461.52	471.67	481.82	491.97	476.74

Average price of high protein soybean meal for 2011 is calculated by using an arithmetic average and is equal to \$370.78, which is 11% higher than the calculated price of *N. Oleoabundans* (\$329.51).

As discussed in Subsection 6.13, the chemical composition of *N. Oleoabundans* could be relatively low compared to other types of algae. Thus, it is interesting to calculate the level of each chemical component at which post extracted algae meal price is equal to high protein soybean meal price.

Each chemical component changes one at a time while the rest of them stay the same in the breakeven analysis. Optimal Control Theory reported by Richardson, Ray, and Trapp (1979) is used to answer the following questions:

1) What should be the percentage content of crude protein in the *N. Oleoabundans* algae to reach the same price as high protein soybean meal in 2011, while the rest of the components stay the same as in the original chemical composition table?

2) What should be the percentage content of TDN in the *N. Oleoabundans* algae to get the same price as high protein soybean meal in 2011, while the rest of the content stays the same as in the original chemical composition table?
3) What should be the percentage content of calcium in the *N. Oleoabundans* algae to obtain the same price as high protein soybean meal in 2011, while the rest of the content stays the same as in the original chemical composition table?
4) What should be the percentage content of ether extract in the *N. Oleoabundans* algae to get the same price as high protein soybean meal in 2011, while the rest of the content stays the same as in the original chemical composition table?

Each variable is constrained at a time while the rest of the components remain fixed to calculate the level at which the *N. Oleoabundans* price is equal to the price of high protein soybean meal. The results show that crude protein needs to be 43% in *N. Oleoabundans* ceteris paribus to reach the same price as high protein soybean meal in 2011. TDN needs to be 60.81%, Ca needs to be 1.32% and EE needs to be 25.37%.

Becker (2007) reported a composition table of different micro algae, where 11 out of 13 sampled algae had higher protein content than 43%. Therefore, certain types of algae have a potential to present a high intrinsic value and outperform the price of high protein soybean meal.

6.15 Comparison of Spirulina Algae to High Protein Soybean Meal

Forecasted prices for TDN, EE, CP and Ca in Subsection 6.14 are plugged into the Spirulina algae chemical composition reported in Table 6.8 to obtain the prices of high profile algae.

Table 6.8. Chemical Composition of Three Different Spirulina Algae

	Spir. A	Spir. B	Spir. C	Average
TDN*	72.24	68.8	74.16	71.73
EE	6.5	7.5	6.4	6.80
CP	60.9	56.6	68.9	62.13
Ca	0.96	1.541	0.687	1.06
Ash	9.70	14.00	7.30	10.33
*TDN is calculated based on the Ash content				
Source: Ortega-Calvo, J.J. et al, 1993, Journal of Applied Phycology				

$$\text{Price} = 71.73 * 2.48 + 6.80 * 2.99 + 62.13 * 1.92 + 1.06 * 136.67 = 462.50 \qquad (6.6)$$

The calculated price of Spirulina algae in 2011 is $462.50 per short ton. Since the forecasted price of high protein soybean meal is $370.78 per short ton, the ratio of Spirulina to soybean meal is 1.25, which means that average Spirulina price is expected to be 25% higher than the high protein soybean meal price.

6.16 Sensitivity Analysis

Spirulina algae price in Subsection 6.15 is calculated based on the average chemical composition of the three different Spirulina algae samples reported by Ortega-Calvo et al. Calculated values give researchers a general impression about the potential of the high profile algae price; however it is interesting to see how sensitive an algae price is to a change in its chemical composition. For illustration, each of the Spirulina contents is changed based on the worst and best case scenario, while the rest of the determinants stay the same. For instance, protein contents in three different reported samples were 56.60%, 60.90% and 68.90%. The arithmetic average of these three sample contents (62.13%) was used to calculate the average price of Spirulina algae. For sensitivity analysis, the average protein content (62.13%) was changed up to the maximum (68.9%) and minimum (56.6%) protein percentage content ceteris paribus to observe how changing this variable one at a time was affecting the price of Spirulina. Every time each variable changes, it results in a different price. The differences caused by the change in Spirulina chemical composition are reported in Figure 6.16.

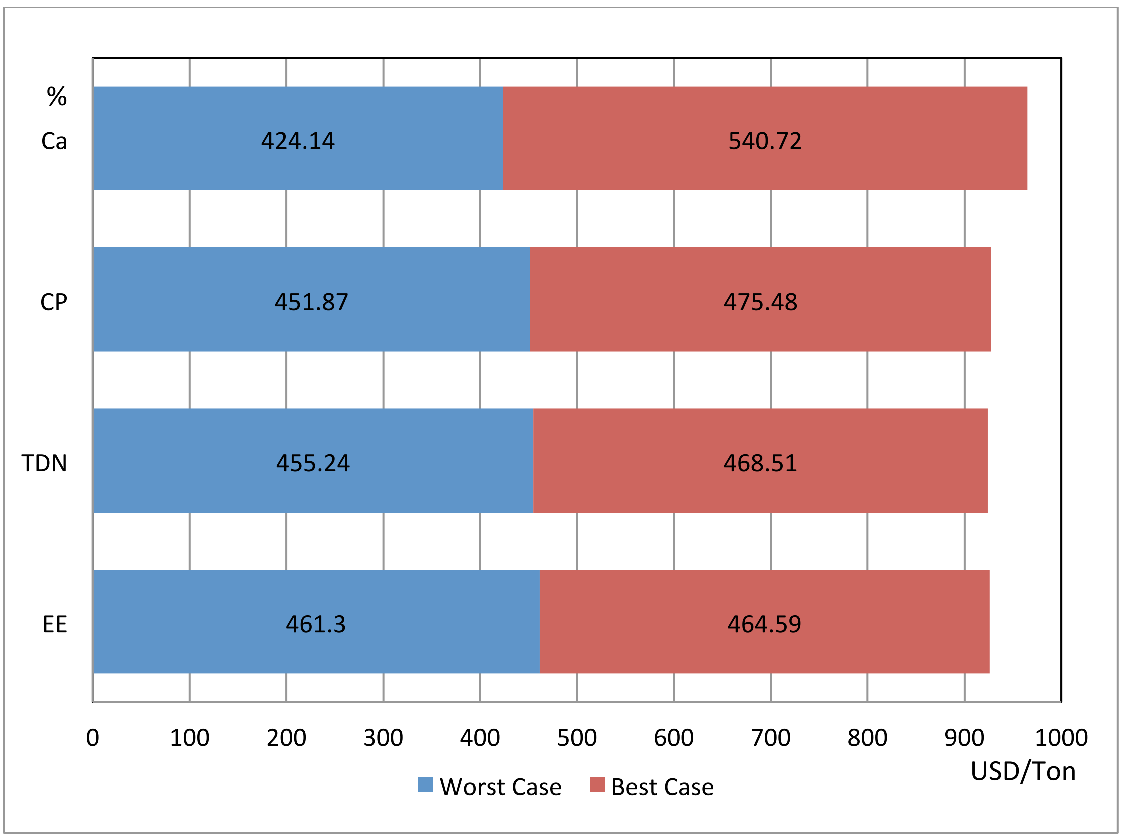

Figure 6.16. Worst vs. best case scenario

The results display the sensitivity of price to a change in the chemical content from average to both lower and upper case scenarios. For instance: price of Spirulina is \$424.14 dropped from \$462.50 if calcium content is decreased from the average of 1.06% to the lowest Ca content of 0.687%.

Calcium appeared to be the most sensitive component followed by CP and TDN. Ether extract appeared to be the lowest sensitive determinant in the equation.

The results of the sensitivity analysis apply only to Spirulina algae given a particular chemical composition samples. The sensitivity to algae price to different chemical components will vary based on the dispersion of its chemical components among samples.

6.17 Comparative Analysis: The Dispersion Between Hedonic and Market Prices of Algae Meal

The intrinsic value of algae calculated using hedonic pricing techniques could present deviation from its actual market price due to the volatility of demand and supply factors. It is of interest to compare intrinsic and actual market prices of algae meal to analyze this divergence. Since we only have intrinsic algae meal prices due to the absence of a market for algae meal, a plausible assumption is that the actual algae meal prices will deviate relatively the same from its intrinsic value as soybean meal. Soybean is an important product in both oil and feed meal industry - 90% of the biodiesel in the United States is produced from soybean oil. At the same time, soybean meal is the dominant component in livestock and poultry feed in the United States. Algae meal is considered as a close substitute for soybean meal among the practitioners. Similar to soybean, algae has a potential to be used for biodiesel and feed meal production and both of the products might have high content of lipids and protein. Thus, it will give a realistic representation to observe the dispersion of actual and hedonic algae meal prices if we use soybean meal in comparison to algae meal.

Soybean meal prices used in the hedonic pricing model represent the historical series of market prices. On the other hand, intrinsic soybean meal prices are calculated based on the prices of calculated feed meal components multiplied by soybean's chemical composition. The chemical composition of high and low protein soybean meal is reported in the Table 6.9.

Table 6.9. Chemical Composition of High and Low Protein Soybean Meal

	TDN	ee	cp	ca
Soybean meal (high protein)	87	1.1	54	0.28
Soybean meal (low protein)	84	1.5	49	0.36

A chemical content of each feed meal is multiplied by the corresponding intrinsic prices of the feed meal characteristics reported in Table 6.5. The historical series of high protein soybean meal hedonic prices are obtained and compared to its historical market prices in Figure 6.17.

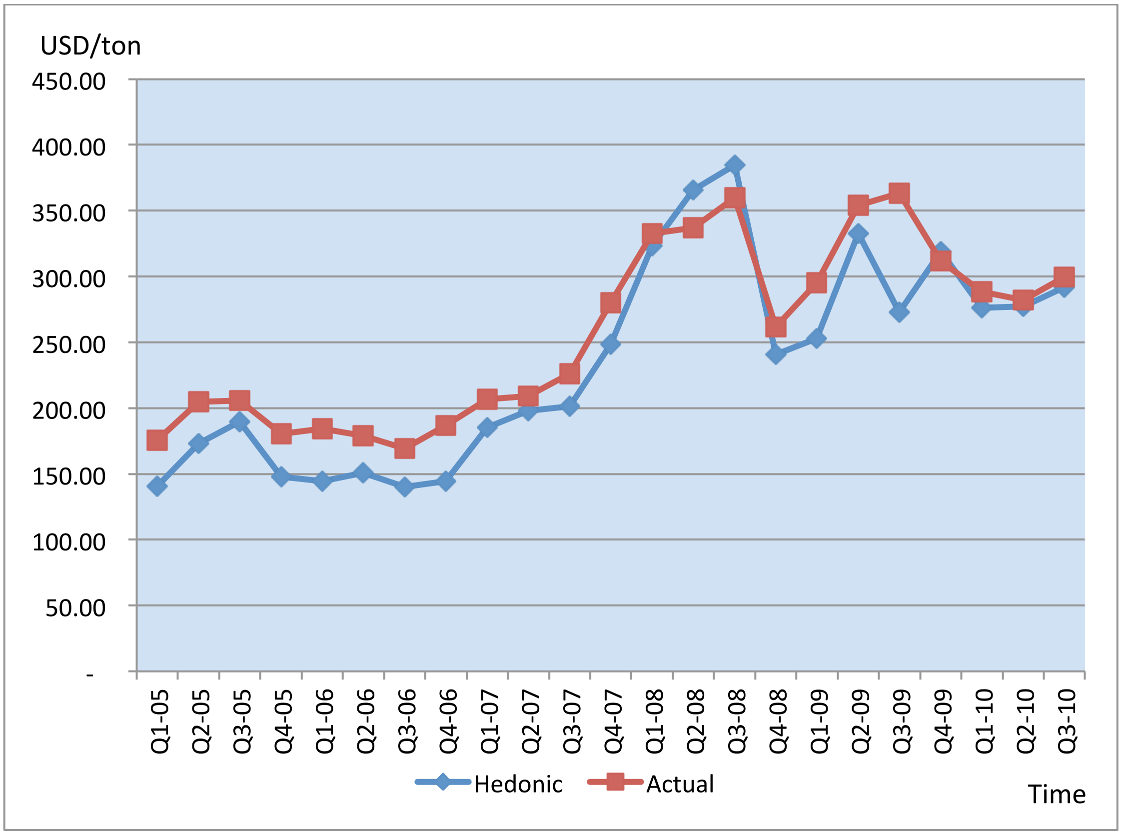

Figure 6.17. High protein soybean meal price analysis

According to the historical performance, the discrepancy between intrinsic value of high protein soybean meal and its market price reached a peak at $90.16 in the third quarter of 2009. The minimum dispersion was $4.50 recorded in the second quarter of 2010. The standard deviation of the actual market prices of high protein soybean meal is $75.80, while the standard deviation of the difference between the actual and hedonic prices is only $17.50, which proves that the model generates robust results.

Actual low protein soybean meal price series is compared to its hedonic prices and the results are reported in Figure 6.18.

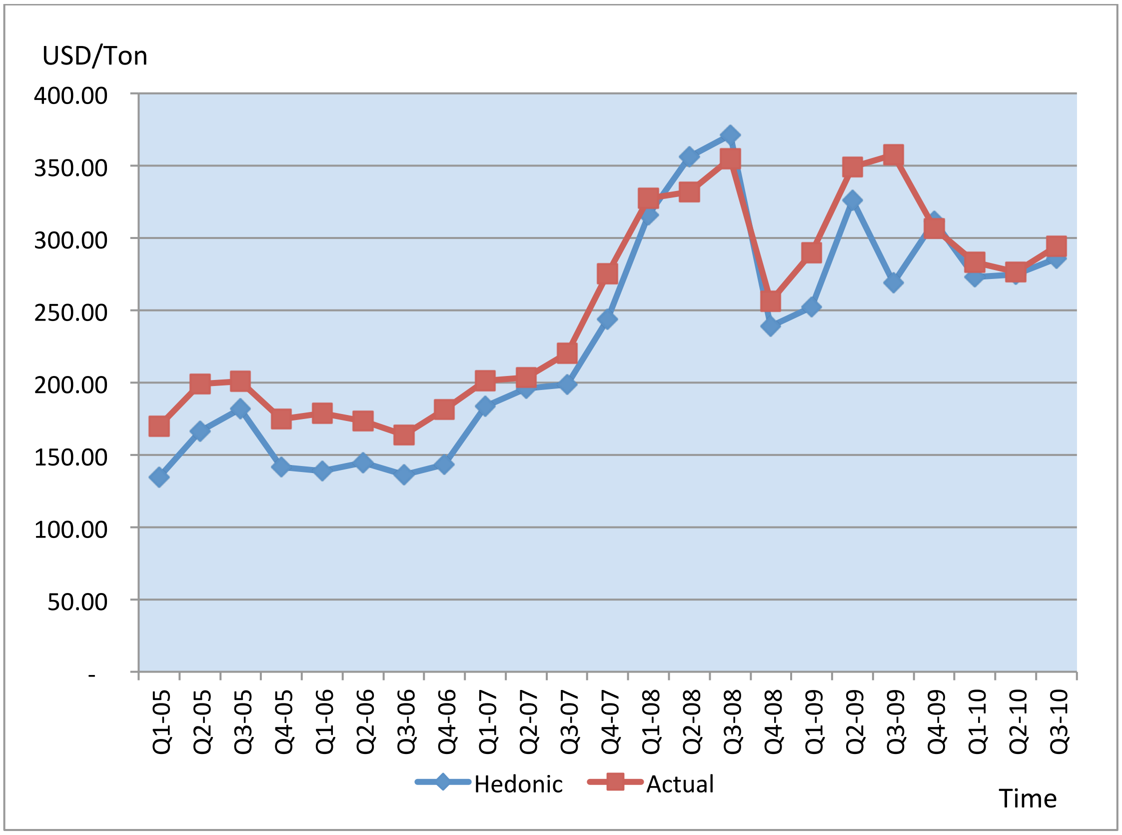

Figure 6.18. Low protein soybean meal price analysis

As the graph shows, hedonic and actual low protein soybean meal price series are very closely related as well. The highest divergence is recorded in the same time period as in case of high protein soybean meal (Q3, 2009) and was $88.60. The minimum dispersion got as close as $1.70 in the second quarter of 2010. Standard deviation of actual market prices of high protein soybean meal across time is $74.60, while the standard deviation of the difference between actual vs. hedonic price is only $17.50, which proves that the model generates robust results in the case of low protein soybean meal as well. The standard deviation of the difference between actual vs. hedonic prices in both low and high protein soybean meal is the same and equals $17.50. Thus, we make the assumption that algae meal market prices might have on average the same standard deviation of $17.50 in the difference between its hedonic and market prices.

CHAPTER VII

APPLICATION

The estimated prices of algae meal projected in this study could become one of the cornerstones of sustainability analysis for algae production. A price of algae meal could aid researchers in deriving realistic measures of the potential of algae and it could help industry leaders to make more sensible investment decisions. The results of this study could be used as an input for feasibility analysis of algae production. Still, there exist different algae types which have not been investigated yet. This research will be one of the foundations of the feasibility studies based on the algae chemical composition and it will provide a base model to plug-in other compositions to obtain a price forecast for algae meal.

Hedonic pricing techniques based on the prices and chemical compositions of the most frequently used feed meals in the industry can be used to calculate the value of a given algae meal according to its chemical composition. For that purpose, each corresponding chemical component of the selected algae is plugged in equation 7.1 to obtain the intrinsic price of algae meal in a per-short ton basis.

$$\text{Algae Meal Value} = \text{TDN} * \%\,\text{TDN}_{algae} + \text{EE}{*}\%\text{EE}_{algae} + \text{CP} * \%\,\text{CP}_{algae} + \text{Ca} * \%\text{Ca}_{algae} \tag{7.1}$$

Based on the hedonic pricing model, corresponding prices of the algae meal chemical components are given in the Table 7.1.

Table 7.1 The Price of Feed Meal Contents for 2011 USD/%

TDN	EE	CP	Ca
2.48	2.99	1.92	136.67

Coefficients given in Table 7.1 are multiplied by the percentage of the corresponding chemical composition to obtain the price of a given algae. The price represents a calculated price based on the intrinsic value of different feed meals. Based on the assumption that algae meal price will have relatively similar standard deviation as soybean meal, algae price is expected to have a standard deviation of $17.50 from its market value across time.

CHAPTER VIII

RECOMMENDATIONS FOR FUTURE RESEARCH

Since the hedonic pricing model developed in this research measures the intrinsic value of feed meal components, price of each feed meal can be derived based on the prices of the calculated chemical components. Due to the market imperfections such as interaction of supply and demand forces, intrinsic value might not always reflect the current market price of the product. However, it is expected that the market price will not be highly deviated from its intrinsic value since the price of a product should be driven by its underlying value. A market can be considered efficient if the price of the product is driven by its value rather than speculative interaction of economic agents. The more diverse is the usage of the product the more agents are involved in the trading process and more forces are interacted to distract the market price from its intrinsic value. If we can assume that the market of a particular feed meal can be efficient, then historical intrinsic prices of a given feed meal calculated based on the methodology developed in this research will present a better forecasting ability than historical market prices. The conclusion is based on the efficient market hypothesis that the price of a given product will be moving around its intrinsic value and its market price will not get widely deviated from its underlying value.

Forecasted intrinsic soybean meal prices for 2011 can be compared to actual soybean meal prices to observe how the forecasting method works. Five series of weekly prices starting from March 2011 till the first week of April 2011 are compared to the average forecasted intrinsic price of soybean meal for 2011. Figure 8.1 shows that in

March 21 and March 28 of 2011, the intrinsic price of high protein soybean meal is about the same as its market price.

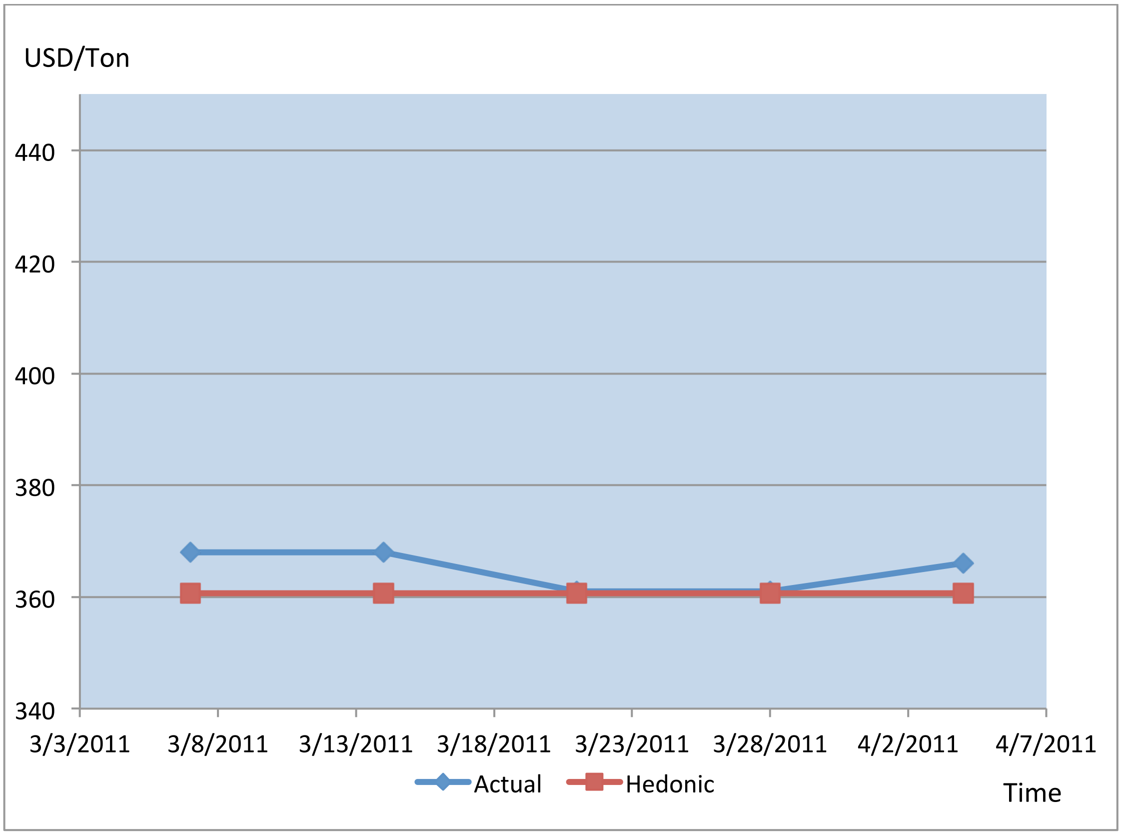

Figure 8.1. High protein soybean meal price forecasts for 2011

Intrinsic and actual prices are not expected to be the same based on the interaction of market forces; however the actual market price is expected to move close to its intrinsic value.

Similar results are obtained when comparing the series of hedonic prices of low protein soybean meal to its market prices. Figure 8.2 shows that in March 21 and March 28 of 2011, intrinsic prices of low protein soybean meal equalized its market price.

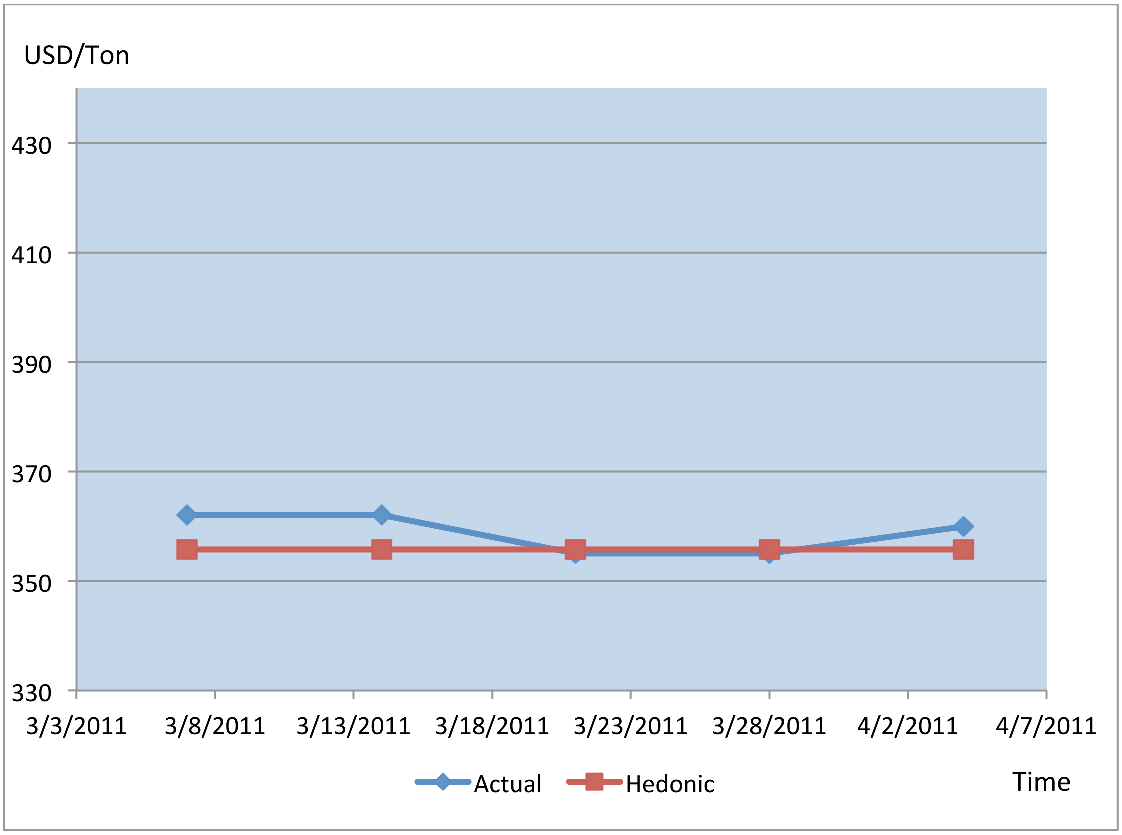

Figure 8.2. Low protein soybean meal price forecasts for 2011

On the other hand, this method is not suggested to be used in forecasting the products with diverse usage and high potential of dispersion from its intrinsic price. For instance, corn is used for ethanol production, as well as for human or animal feed. Along with its intrinsic value, there can be many other factors which determine the price of corn. Thus, a forecasting model based on the intrinsic prices might not present better estimates compared to a model based on the historical prices. Figure 8.3 presents actual and hedonic corn price from the first quarter of 2005 until the third quarter of 2010.

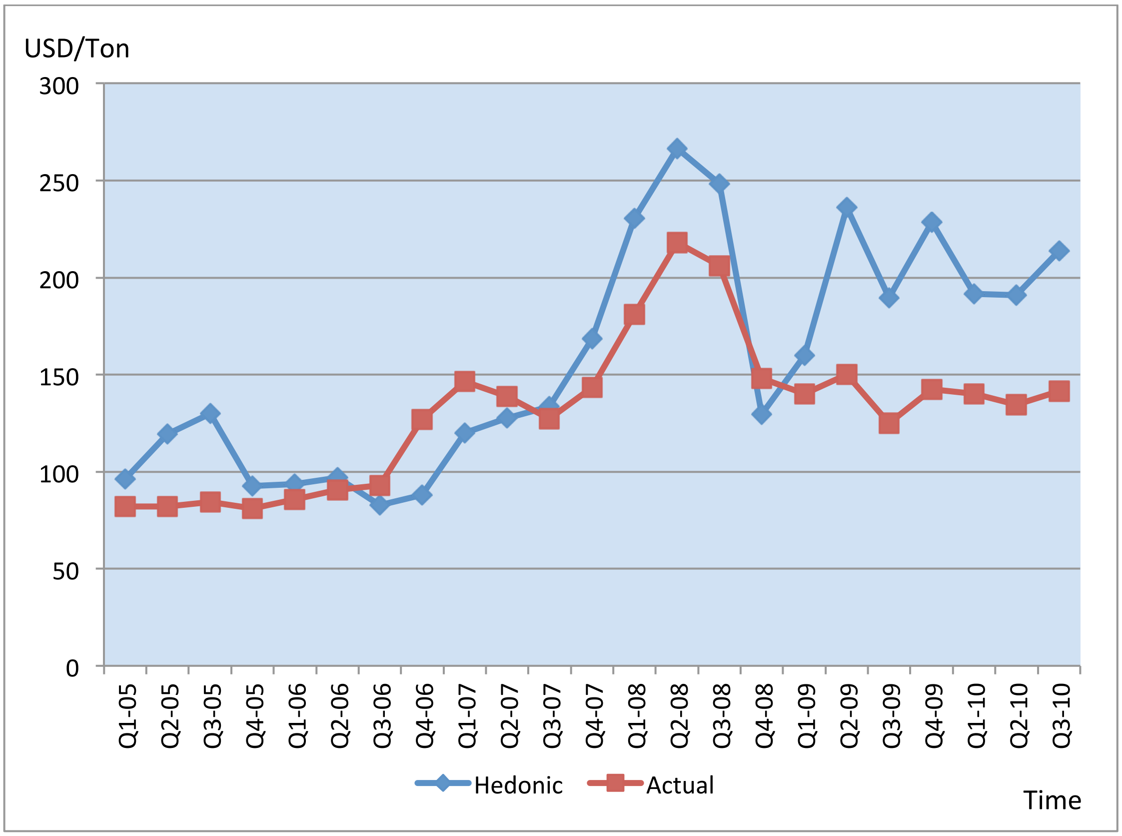

Figure 8.3. Historical series of actual vs. hedonic prices of corn

Based on Figure 8.3, there is a wide dispersion between hedonic (intrinsic) and actual market prices and forecasting model based on the intrinsic value of corn will not give robust estimates.

Similar methodology can also be used to test market efficiency of different feed meals. Moreover, it can be widely applied to different industries in case the data to calculate the intrinsic value of a given product is available.

CHAPTER IX

SUMMARY

Since the importance of finding feasible alternative and renewable energy sources increased dramatically in recent years, many research studies have focused on the investigation of the potential for algae. However, a common barrier for the researchers has been the lack of market prices for algae products. The value of algae represents a sum of the value of two different products it can be used for: production of biodiesel and feed meal. This research utilizes the existing feed meals in the market to calculate the value of algae based on its chemical composition. Estimated prices of algae in this research can be used in feasibility studies to calculate the realistic profitability of algae farms.

Since the hedonic pricing model is calculated based on the feed meals reported in Fort Worth market, the results present the potential algae prices in the same geographic area. However, it is realistic to assume that the ratio of algae to soybean meal prices will be approximately the same from market to market. Also, calculated prices of algae are based on its underlying value and might be subject to the dispersion from it. These assumptions can be adjusted based on the given purpose of different research and does not present an obstacle in the empirical application of the results obtained in this research study.

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VITA

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