The Value of Post-Extracted Algae Residue

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Abstract

This paper develops a hedonic pricing model for post-extracted algae residue (PEAR), which can be used for assessing the economic feasibility of an algal production enterprise. Prices and nutritional characteristics of commonly employed livestock feed ingredients are used to estimate the value of PEAR based on its composition. We find that PEAR would have a value lower than that of soybean meal in recent years. The value of PEAR will vary substantially based on its characteristics. PEAR could have generated algal fuel co-product credits that in recent years would have ranged between \$0.95 and \$2.43 per gallon of fuel produced.

Keywords: biodiesel, hedonic pricing, livestock feed, post-extracted algae residue

JEL Codes: Q16, Q41, Q42

1. Introduction

The merits of microalgae as a source of biofuel feedstock have been widely recognized recently [1,2,3,4,5]. Cited benefits, relative to other biofuel feedstocks, include production employing non-arable land and brackish water that are not employed in food production, potential recovery of waste nutrients from water treatment, and greenhouse gas emission reductions. Non-biofuel-related uses of microalgae have been recognized as well, including use as a livestock or aquaculture feed ingredient, production of high-value oils for pharmaceuticals and nutritional supplements for people and animals, biotech applications, agrochemicals, pigments, and cosmetics [6,7,4]. This potential has sparked a frenzy of research, and over 100 commercial start-ups worldwide as of 2009 [8].

However commercial-scale production of biofuels using algal feedstocks is currently economically infeasible [8,9,3,10,4,5]. Essentially all current commercial algae production is motivated by sale of high-value oils for pharmaceutical and nutritional uses [5]. Substantial advances in the underlying biology and algal biomass productivity will be required to achieve economically feasible algal biofuels production, and this achievement is likely 10 to 15 years away [3,5]. It is generally agreed that co-product sales will be critical to achieving economically feasible algal biofuels production [8,9,10,4,5]. Stephens, et al. [4] argue that the market for high-value oil co-products would be rapidly saturated if algal biofuels production increases substantially, and sales of post-extracted algae residue (PEAR) as a livestock feed likely represents the most important long-run component of co-product revenue.

No market for PEAR currently exists, however, and consequently potential prices for PEAR are not currently known with any reasonable certainty. Thus the potential PEAR revenue that a prospective algae producer might enjoy is currently unknown; there thus exists a critical limitation to existing analyses of the economic feasibility of algae production. In short, there is a pressing need to know the likely value of PEAR as a livestock feed ingredient, and how this value varies over time.

Hedonic pricing methods model the interdependence of commodity prices and commodity characteristics to infer the implicit values of the characteristics, which would be difficult to otherwise determine. In simple terms, a hedonic equation is a regression of the market prices of products or commodities on their corresponding characteristics. Three aspects of a hedonic price analysis must be carefully specified to achieve robust results: selecting dependent and independent variables, specifying a functional form, and defining a submarket—a set of goods to include as observations for the regression [11]. Given a well-specified model, the fitted regression coefficients are interpreted as measurements of the values of the products' characteristics in the case of an additive model (wherein the variables have not been transformed) or as elasticities (the percentage change in product value given a one percent increase in a continuously measured attribute or the percentage increase in product value resulting from the inclusion of a discrete feature) in the case where the natural logarithms of continuous variables are employed.[1] While not a common application of hedonic pricing methods, they can also be used to estimate the value of a product that is not currently traded (such as PEAR) based on its characteristics.

The objective of this study is to estimate the value of PEAR using hedonic pricing techniques. Twenty-two commonly used livestock feed ingredients are decomposed into their economically and biologically important constituent nutrients to estimate the market value of each. Calculated prices of these characteristics are then used to estimate the value of PEAR.

[1] In a standard regression model, fitted regression coefficients corresponding to a continuous independent variable are interpreted as the marginal effect on the dependent variable of a unit increase in that independent variable, holding all else constant. This same interpretation applies for a hedonic pricing model with non-transformed variables, but this application admits a more specific interpretation of the fitted coefficients as characteristics' monetary values.

The paper proceeds as follows. In the next section we enumerate the important nutritional characteristics of livestock feed ingredients, which will serve as candidates for explaining observed ingredient prices. We then describe the methodology we employ, and proceed to present our results. We conclude with a discussion of the economic meaning of the results.

2. Common Ration Ingredients and their Constituent Nutrients

We employ in our analysis prices and corresponding nutrient compositions for each of twenty-two common feed ration ingredients. From the pool of oilseed products, animal byproducts, brewers' and distillers' grains, whole and milled grains and other types of feedstuffs, the following ingredients were chosen because they are all commonly employed in cattle rations, and because price observations for these commodities are reliably available: 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, whole corn, sorghum, ground grain screenings, and feed urea.[2]

[2] These ingredients were not selected based on the similarity of their nutrient contents to PEAR. The purpose of the hedonic analysis is to infer how feed commodity value varies as nutrient composition varies. Even if the prices of numerous feed commodities with nutrient contents very similar to PEAR were available, such commodities could not be used by themselves to reliably infer the values of various nutrient characteristics. In any regression model, substantial variability in the independent variables (in our application, nutrient contents of the

Chemical profiles of the feed ration ingredients constitute independent variables in the hedonic regression. The National Research Council [12] reports thirty-six different characteristics for the selected feed meals, which are classified under the categories energy, protein, fiber, minerals and vitamins. Many of the reported components are not expected to substantially influence buying behavior or animal nutritional status. Candidate independent variables for the regression are carefully selected based on the potential importance of each characteristic for the livestock feed ration, as described next.

Total digestible nutrients (TDN), digestible energy (DE), metabolizable energy (ME), net energy for maintenance (NEm) and net energy for growth (NEg) are all measurements of the energy content of feed ingredients. Given that all of these factors are measuring energy, they closely correspond to one another. For example, the relationship between ME and DE is given by:

$$\text{ME (Mcal/kg of DM)} = 0.82 \times \text{DE (Mcal/kg of DM)} \tag{1}$$

where DM represents dry matter and the components of DE and ME are presented on a mega calories per kilogram basis. Since the energy measures are closely related, including more than one of these would likely introduce a multicolinearity problem. The NRC reports TDN as the most frequently used measurement of energy content. Therefore, TDN was selected for inclusion in our list of candidate variables from the pool of available energy measurements.[3]

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feed ingredients in our sample) is absolutely required to reliably infer the influence of those variables on the dependent variable (commodity prices in this application).
[3] While NRC reports that TDN is the most widely used measurement of energy content, Vasconcelos and Galyean [13] report that NEg is most widely used by feedlot nutritionists. However, since NEg is calculated from TDN using the NRC

Protein is a vital nutrient for livestock maintenance, growth and reproduction. Protein is often reported as Crude Protein (CP), which represents total nitrogen content of a sample multiplied by 6.25. Given that protein is universally acknowledged as a critical component of livestock diets, this estimate of the percentage of protein in each ingredient is included in our list of candidate variables.

There are two important characteristics associated with Crude Protein: Degradable Intake Protein (DIP) and Undegradable Intake Protein (UIP). DIP is the portion of CP which can be degraded in the rumen, while UIP represents the portion of CP that is not degraded in the rumen. However, UIP is not an indicator of lost protein, as it may be digested post ruminally and represents a significant source of metabolized protein. Since DIP and UIP sum to 100%, we only include UIP among our candidate variables.

Ether Extract (EE) is an estimate of total fat or oil content, which is a dense source of calories. Fat is a necessary ingredient for livestock body growth as well. It is expected to have a significant influence on the value of the feed and is included in our list of potential explanatory variables.

Fiber is a relatively important component of the livestock diet and can have a significant effect on the buying behavior of feed customers. Acid detergent fiber (ADF) is representative of the fiber content, which is negatively related to digestible energy. Higher ADF concentrations indicate reduced digestibility. Additionally, sufficient intake of effective neutral detergent fiber (eNDF) is required to ensure

model, both of these measures embody the same fundamental information. We employ TDN without loss of generality.

proper rumination, which is essential for long-term animal health and performance. As both of the fiber representatives measure different aspects of the livestock feed ration, ADF and eNDF are both included as possible variables.[4]

Minerals that are important for animals are divided into two groups: macrominerals and trace minerals. Macrominerals are calcium, phosphorus, sodium, chlorine, potassium, magnesium, and sulfur. Trace minerals include cobalt, copper, iodine, iron, manganese, molybdenum, selenium, and zinc. From this pool of minerals, four main macrominerals are identified as most likely to influence feed meal value. The first is calcium (Ca), which is important for bone and teeth formation, cardiac regulation, muscle excitability, and normal growth. The second mineral is phosphorus (P), which is also used for bone growth, enzymatic reactions, and energetic transfers. The third mineral is potassium (K), which is important for blood pressure regulation, oxygen and carbon transport, acid-base balance, and muscle contraction. The fourth mineral is sulfur (S), which is essential for disease resistance, blood sugar regulation, and maintenance of body tissue. Sulfur is of particular interest because of its relation to polioencephalomalacia and its relatively high concentrations in distillers' grains. Any of these four macrominerals may potentially have negative value, as they can be toxic for the livestock if given in high volumes. However, they are not expected to be found in toxic volumes in the feed ingredients listed above or in PEAR.

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[4] The feasibility of including these variables in a final hedonic pricing model for PEAR is limited. Due to PEAR's small particle size, it is impossible to determine ADF by currently available methods, and eNDF is, in part, dependent on particle size. As it happens, the specification search procedure (described later in this paper) did not identify ADF or eNDF as necessary components of our hedonic pricing model, rendering this limitation moot.

Trace minerals are expected to be present in PEAR. Existing data suggests that trace minerals of potential concern, particularly those used in upstream processes, are copper (pond management) and aluminum (flocculation). However, inclusion of PEAR in livestock diets will likely be limited by the high ash content, salt content, and (or) the protein content. Therefore, we do not expect inclusion of PEAR in commercially fed diets to result in complete diets that exceed maximum tolerable concentrations for trace minerals. We also observe that the trace mineral contents of primary feed ration ingredients are clearly not an important determinant of buyer decision-making or those ingredients' market prices.

3. Methodology and Data

3.1 *General Hedonic Pricing Model and Functional Form*

The earliest uses of hedonic pricing were investigations of the influences of vegetable quality attributes on their market prices [14,15]. Hedonic pricing methods gathered momentum beginning with the work of Griliches [16], who analyzed quality-adjusted measures of automobile prices. Lancaster [17] developed underlying theory, arguing that the characteristics of goods are part of the consumers' utility function and preferences depend on the measure of each desired characteristic. Rosen [18] 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.

There have been various applications of hedonic pricing methods to agricultural commodities in recent years. Jordan, Shewfelt, Prussia, and Hurst [19] 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. They found that damage had a significant influence on tomato value, and that the coefficients for quality characteristics that varied from period to period. Hyberg and Uri [20] examined the implicit prices of soybeans exported by the United States to Japan. This study was designed to determine how intrinsic and physical characteristics of soybeans were valued differently for two different markets: soybean meal and soybean oil markets. Ethridge and Davis [21] 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, micronaire reading, 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.

A general hedonic pricing model specifies that the observed market price for commodity n (p_n) is a function of a vector of corresponding quality characteristics for commodity n ($\boldsymbol{x_n}$):

$$p_n = \mathrm{f}(\boldsymbol{x_n}). \qquad (2)$$

There is, however, no specific functional form suggested by theory for such models. Halvorsen and Pollakowski [22] and Cropper, et al. [23] suggest nested non-linear transformations per Box and Cox [24], using a parameter y:

$$\begin{array}{ll} \frac{p_n^{y}-1}{\;} \text{ for y -= 0} & \\ & (3) \\ \ln(\quad) \text{ for y } \; 0 & \end{array}$$

We apply this transformation to p_n creating a transformed variable , and to each of the variables in $\boldsymbol{x_n}$, creating a vector of transformed quality characteristic variables, ……. The transformed variables can be linearly related given a conformable vector of coefficients, p and a stochastic error term u_n:

$$\cdot \mathrm{p} \quad \mathrm{u_n}. \tag{4}$$

For (1, …,)′, (1, …,)′, where each is a row vector of transformed quality characteristics, and u (u1, …, u)r, the relationship across all observations can be written as

$$\mathrm{p} \quad \mathrm{u}. \tag{5}$$

A value of y 1 yields no non-linear transformation, y 0 yields a logarithmic transformation, and y 1 implies a reciprocal transformation. Cropper, et al. [22] suggest that accommodating Box-Cox transformations improves the reliability of hedonic model results. A likelihood ratio test can be used to test the nested alternative transformations (H_0: y 1, H_0: y 0, H_0: y 1)[5]. The likelihood ratio test statistic for a Box-Cox transformation (LR_{BC}), given that L_R is the log-likelihood of a restricted model (i.e., y is restricted to a specific hypothesized value) and L_U is the log-likelihood of the unrestricted model (i.e., the value of y is unrestricted, and is fitted via maximum likelihood) is

$$2(L_R \quad L_U) . \tag{6}$$

LR_{BC} is distributed chi-squared with one degree of freedom corresponding to the single restriction on y [25].

[5] By "nested", we mean that the single model presented as equation (5) can accommodate all of the three data transformations simply through specification of appropriate values of the nesting parameter y.

Malpezzi [11] reviews the theoretical basis of hedonic pricing models and their practical application. He describes how various standard econometric results apply to these models. He identifies 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 (i.e., price observations to employ in the estimation). He observes that sufficient variability is needed in the dependent and independent variables. Also, he shows that coefficient estimates will be biased if important variables are omitted. Malpezzi [11] illustrates that the log-linear form can have several advantages over the linear form, such as heteroscedasticity mitigation and simplification of results interpretation. He also endorses the Box-Cox transformation.

3.2 *Approximate Bayesian Model Specification Search*

Theory also provides little guidance for specifying the specific independent variables to use in a hedonic pricing model. Domain-specific expert knowledge and experience provide some guidance. However such knowledge may not produce a sufficiently small set of commodity characteristics relative to numbers of available price observations. One approach to resolving this issue is a specification search with the objective of finding an individual model (i.e., a model employing a specific subset of available explanatory variables) that is "best" by some measure. Suppose the set of all possible explanatory variables has cardinality K. For our purposes, we define a model M_i as a functional form embodied by equation (5) for some non-empty subset (with cardinality $0 < K_i$ � K) of the set of all possible explanatory variables.

In a Bayesian model averaging framework, a posterior probability is assigned to each model in a set of candidate models. This is an evaluation of how likely a specific model is to appropriately reflect underlying relationships, given the data that are observed. Given data *Y*, if (M_i) is the prior probability assigned to model *i*, and $(Y|M_i)$ is the integrated likelihood for model M_i (see [26] for details), the posterior probability assigned to a specific model M_i given the data is

$$(M_i|Y) \quad \frac{p(M_i)p(Y|M_i)}{\sum_j p(M_j)p(Y|M_j)} \tag{7}$$

This latter value can be quite difficult to evaluate precisely, but Schwarz [27] gives an easily computed approximation. If L_i is the log-likelihood of model *i*, K_i is the number of fitted parameters in model *i*, and *N* is the number of observations, then the approximation is

$$\ln((Y|M_i)) \text{ � } SBC_i \equiv L_i \quad 0.5K_i\ln(N). \tag{8}$$

If the set of considered models are all assigned equal prior probability, then the individual model with the greatest SBC_i will also be assigned the greatest posterior probability $(M_i|Y)$. This motivates *SBC* as a criterion for selecting a specific model from among many possibilities given minimal prior assumptions. Alternatively, a common casual explanation of *SBC* is that it rewards model fit (L_i) while penalizing model complexity ($0.5K_i\ln(N)$), and a desirable model will balance these two considerations.

The space of models that employ all possible subsets of a collection of *K* possible explanatory variables will have dimension 2^K. Rather than exhaustively estimate all of these possible models, a search procedure can be used. We employ a search procedure wherein we start with an empty model (no explanatory variables), compute the *SBC* for all possible models with exactly one explanatory variable, and add the single explanatory variables that results in the greatest increase in *SBC* relative to the empty model. We then repeat these steps for the modified model, adding the variable that next increases *SBC* most, repeating until adding additional variables cannot increase *SBC*. In a second phase, improvements in *SBC* due to removing variables are sought, with single variables providing maximal improvement being removed first. This type of search is known to identify a model at or near the global optimum *SBC* [28].

3.3 *Detection of Influential Observations*

Influential observations are individual data points employed in a regression that have a large influence on the resulting parameter estimates. Such observations may simply be particularly informative, or they may reflect a problem wherein the influential observation inappropriately distorts the regression results to misrepresent the relationships that exist among the remaining data. Cook [29] provides a convenient method for detection of influential observations. Cook's "distance" essentially measures the extent to which removal of an individual datum changes a regression model's predicted values. If K_i is the number of fitted parameters, *MSE* is the mean squared error of the regression residuals when all data are used, *N* is the total number of observations, $\hat{}$ is the predicted value of the dependent variable for observation *n* when all data are used for fitting, and $\hat{}_{,(m)}$ is the predicted value of the dependent variable for observation *n* when the parameters have been fitted without using observation *m*, then Cook's distance is

$$D_m \quad \frac{\sum_{n=1} \left(p_n - p_{n,(m)}\right)^2}{K_i x MSE}. \tag{9}$$

It is generally accepted that observations with $D_m > 1$ merit scrutiny for validity.

3.4 *Data*

Nutrient compositions of the twenty-two feed meals for the ten nutrients described earlier are obtained from Preston [30]. Weekly prices from January 2005 through September 2010 for twenty-two feed meals in Fort Worth, Texas, are obtained from the Miller Publishing Company publication *Feedstuffs* [31]. Fort Worth was chosen due to the consistent availability of prices for a relatively large number of feed ingredients, because the southwest region has favorable conditions for algae growth [10], and because the southwest region has a large number of concentrated animal feeding operations (CAFOs)[6]. The weekly price data are aggregated to a quarterly basis for a total of twenty-three time periods from the first quarter of 2005 through the third quarter of 2010.

The nutrient compositions of various PEAR samples are the authors' original measurements, and are presented in Table 1. The eleven PEAR samples are based on two different algae species grown in open ponds in two separate locations in Texas. PEAR was prepared using various treatments, as indicated in Table 1. TDN values in these data are calculated based on the organic matter content. For instance, suppose a particular sample contains 70% organic matter. We assume

[6] The Texas panhandle and southern plains is the largest cattle feeding area in the world. Texas feedlots marketed 5.8 million fed steers and heifers in 2011, 25.6 percent of fed cattle produced in the U.S. The Texas panhandle and eastern New Mexico are also a growing area for milk production, currently the third largest such area in the country.

that the digestibility of algae will be approximately 80%.[7] Therefore, we multiply 70% by 80% to arrive at a TDN value of 56% of dry matter.

4. Results

The prices of twenty-two feed meals represent the set of dependent variables, while ten selected characteristics of feed ingredients are used as potential independent variables in the model. Our general approach is to specify a final hedonic regression equation by testing restrictions on a preliminary model, and imposing those restrictions that are deemed appropriate. The preliminary, unrestricted hedonic pricing model is given by (5) with all ten possible explanatory variables included: Total Digestible Nutrients (TDN), Ether Extract (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).

We first apply the approximate Bayesian specification search procedure described in the previous section to determine an appropriate subset of explanatory variables. We employ the variables without any Box-Cox transformation for this initial step. Equations representing each quarter of the data sample are stacked to create a single system and therefore a single *SBC* value for each subset of

[7] The small particle size of PEAR compromises our ability to determine digestibility in the laboratory using routine analysis. We assume 80% digestibility based on the small particle size (more specifically, particle size will not limit enzymatic access to nutrients), high protein content, and low levels of structural and chemical limiters of digestions. We expect to refine this number as additional data becomes available for in vivo and in vitro digestibility.

explanatory variables considered.[8] The approximate Bayesian specification search procedure described above in subsection 3.2 suggests a model with the variables *TDN, CP, EE, eNDF, Ca,* and *S* has a higher posterior probability than most or all competing alternatives. Accordingly, we test the null hypothesis that the coefficients on the variables *UIP, ADF, P,* and *K* are all zero. We compute a likelihood ratio test statistic of 3.68 for the joint restriction that these four coefficients are all zero, with an associated p-value 0.451. We therefore do not reject these restrictions, and proceed without the variables *UIP, ADF, P,* and *K* in all analysis that follows.

We next estimate period-wise regressions that accommodate Box-Cox transformations, and test restrictions on y corresponding to specific transformations in each period. We calculate p-values associated with the likelihood ratio tests for each hypothesis for each time period. The arithmetic mean across time periods of the p-values associated with each of the three null hypotheses regarding y, as well as the number of time periods for which we reject each hypothesis, are reported in Table 2. The reciprocal and log transformations are rejected for almost all time periods, and these transformations have very low average p-values. We do not reject the null hypothesis of no transformation for fewer time periods than the log and reciprocal transformations, and the null

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[8] By "stacked", we mean that for a given subset of explanatory variables, the for each of the *T* time periods are vertically concatenated to form a single *NT*-dimensional column vector, the *T* individual p parameter vectors are vertically concatenated to form a single K_iT-dimensional column vector, and the *T* individual are arranged block diagonally in an NT x K_iT matrix. We then use these stacked data and parameters in a single system (across all time periods) analog to equation (5) to estimate a single *SBC* score for the model that employs the given subset of explanatory variables.

hypothesis of no transformation has an average p-value greater than 0.10. We therefore proceed without nonlinear transformations.

A preliminary analysis of the results emanating from the non-transformed data using the six explanatory variables identified above suggests problems caused by influential observations: We therefore calculate Cook's distance measures using this preliminary model for each of our observations for each of our twenty-three time periods. The average (over time periods) Cook's distance measures are presented in Table 3. Poultry byproduct meal, hydrolyzed feather meal, and feed urea all have average Cook's distance measures greater than unity. Further investigation reveals that poultry byproduct meal has a far greater calcium content than any of the other twenty-one feed ingredients included in the analysis, and that its price increased dramatically during our sample period. Observed nutritionist behavior strongly suggests that this ingredient is not valued based on its calcium content, and we therefore conclude that this observation is having a substantial and misleading influence on the implicit calcium values emanating from our hedonic regressions. We identify a similar situation regarding hydrolyzed feather meal and sulfur content. We additionally find that the while we have an appropriate indirect measure of CP content for most feed ingredients, this measure is misleading in the case of feed urea, suggesting that 288% of the dry matter content of feed urea is crude protein.[9] In the analysis that follows, we omit these three feed ingredients, bringing our total number of observations for each time period down to nineteen.

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[9] CP is estimated by quantifying the percent of nitrogen in a sample and multiplying that percentage by 6.25. Urea contains no actual protein, but is nonetheless

We recognize that the three inappropriately influential observations identified above may have influenced the outcome of the approximate Bayesian specification search procedure. We therefore re-apply this procedure using only the remaining nineteen observations. This results in further pruning from our initial set of potential explanatory variables – we now remove the constant, *Ca*, and *S* from the model. The final hedonic pricing model is therefore:

$$f]_1\mathrm{TDN} \qquad f]_2\mathrm{EE} \qquad f]_3\mathrm{CP} \qquad u \tag{10}$$

where we again suppress time subscripts even though we apply the model repeatedly across time periods in our data sample. In the analysis that follows, fitted values for $f]_1$, $f]_2$, and $f]_3$ for each individual time period are employed in calculating corresponding hedonic values.

The evolution of the final values for each of these three characteristics is presented in Figure 1. The fitted values plus and minus one standard error (where standard errors are recovered from each period's hedonic regression) are plotted as dotted lines to give as indication of the uncertainty associated with each value. The monetary values of each percent of dry matter content for EE and CP vary substantially over our sample, and some correspondence between these two monetary values is evident. The monetary value of TDN appears relatively stable from period to period, and its movements exhibit little correspondence with those of EE and CP. Each of these constituent values will be multiplied by the corresponding nutrient contents of feed ingredients, and these nutrient content levels have different average magnitudes in our PEAR samples. Therefore the final

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approximately 46% nitrogen. The available CP measurement therefore misrepresents the actual protein content of feed urea.

contribution of each nutrient's monetary value to overall PEAR monetary value will be modulated by these nutrient content levels. Uncertainty surrounding individual constituent monetary values will also propagate through to final PEAR value uncertainty (as discussed below) based on the relative magnitudes of PEAR nutrient content levels as well.

4.1 *Model Validation Using Soybean Meal*

Before projecting PEAR prices using the final hedonic pricing model, we conduct a simple validation exercise in which we project the in-sample value of high-protein soybean meal. We select soybean meal as it is the commodity with which PEAR will most closely substitute. While the values of two soybean meals (high and low protein) were used in fitting hedonic models for each period, they are only two of nineteen feed ingredients so used. The observations are not weighted in any way. The soybean meal observations therefore should not dominate the results; if the general approach of estimating feed ingredient values using time-varying constituent values has merit, the projected values of soybean meals should not deviate dramatically from their observed market prices.

For each time period in our sample, we multiply the fitted constituent values for that time period for TDN, EE, and CP by the corresponding quantities of those constituents contained in high-protein soybean meal. The sum of these products then constitutes a point estimate of the hedonic value of high-protein soybean meal for each period. We additionally employ two simulation procedures to characterize the uncertainty surrounding these estimates. First, we stochastically simulate the error term (u_n in equation 10), assuming that it is normally distributed with a zero mean and a variance equal to that of the recovered regression residuals in each time period. We employ 1,000 random draws for u_n for each time period, thereby generating 1,000 realizations for the price of high-protein soybean meal (and other feed commodities below). For the second simulation approach, we draw random values for u_n and for f]$_1$, f]$_2$, and f]$_3$. The betas are drawn jointly normal, based on the recovered coefficient covariance matrix from each time period. The error term is assumed to be independent of the betas, and is randomly drawn as before. We employ 1,000 random draws for the four stochastic components in this second simulation approach, again creating 1,000 realizations of the relevant feed ingredient price.

The projected hedonic values for high protein soybean meal, and two sets of 50% confidence intervals for these values corresponding to our two simulation procedures, are plotted against the observed market price for high-protein soybean meal in Figure 2. The average value of the actual price less the projected hedonic price over all time periods is $8.23 per ton. That is, the model tends to slightly undervalue high protein soybean meal, and analyses that follow for PEAR may be somewhat conservative. However as Figure 2 shows, there is a high degree of correspondence between the actual and projected prices. The correlation between the two series is 0.986.

The actual observed high-protein soybean prices fall within the 50% confidence interval for our first simulation approach (stochastic u_n only) for 19 out of 23 time periods. For the second simulation approach, all actual price observations are inside of the 50% confidence interval. For well-calibrated probabilistic forecasts, we would expect observed prices to fall outside of the 50% confidence interval for approximately half of all observations. We hypothesized that the soybean meal results indicate that there is some heteroskedasticity in the data, and that soybean meal and corn prices are more reliably projected by our approach than the prices of other, less popular feed ingredients. To test this hypothesis, we randomly selected three non-soybean and non-corn feed ingredients (suncured pellets, rice hulls, and rice bran), computed the two forms of 50% confidence intervals for price projections for those commodities, and tallied the occurrences of actual observations falling outside those intervals. This occurred 23, 11, and 19 times for the confidence intervals that do not reflect beta uncertainty, and 16, 8, and 12 times for the confidence intervals that do reflect beta uncertainty. Given these results, we accept that the simulation procedure accommodating beta uncertainty produces reasonable confidence intervals for non-staple feed ingredients. Given our very limited number of observations in each time period (prices of only nineteen feed ingredients), and given that we apply to the model to a currently unpopular feed ingredient below, we do not pursue a more complex econometric specification to accommodate heteroskedacticity. Below, we simply report PEAR value uncertainty based on the simulation procedure accommodating parametric uncertainty.

Given the high degree of correspondence and minimal differences between projected point values and observed prices for soybean meal, we are very comfortable applying the overall hedonic approach to valuing PEAR. Since PEAR is a protein-rich meal that will be more similar to soybean meal than most of the other feed ingredients in our data sample, we acknowledge, based on the performance of the high-protein soybean meal confidence intervals, that our PEAR value analysis below may reflect overly wide (i.e., conservative) confidence intervals.

4.2 *Hedonic Value of PEAR*

For each time period in our sample, we multiply the fitted constituent values for that time period for TDN, EE, and CP by the corresponding quantities of those constituents contained in each of our eleven PEAR samples (see Table 1). For brevity, we present the hedonic values of the PEAR samples in two groups based on their observed qualitative differences. A high-protein group consists of the first three samples of *nannochloris oculata*, while the second group consists of all other PEAR samples. All samples in the first group have crude protein content that is greater than 34 percent of dry matter, while all samples in the second group are less than 24 percent crude protein. The average characteristics of high-protein soybean meal and the two PEAR groups are presented in Table 4.

The evolution of the average hedonic values for the two PEAR groups is depicted in Figure 3. Both PEAR groups are valued below the soybean meal price for all dates in our sample. The high-protein PEAR group is almost always valued higher than the corn price, while the other PEAR group is valued similarly to or lower than corn. PEAR is valued lower than soybean meal due to generally lower nutrient content. Relative to soybean meal, PEAR samples have less CP, lower TDN, and similar or lower EE (Table 4). The values of the two PEAR groups relative to soybean meal and relative to one another are commensurate with the varying protein and ash content. Due to the higher protein content of the first PEAR group, these varieties are more valuable than those of the other PEAR group. There is a very high correspondence between PEAR value changes and soybean meal price changes, and noticeably less correspondence with corn price changes.

There is no obvious correspondence between algae harvesting method and meal extraction method, and resulting meal protein content and value. However there are relatively few samples compared to the number of possible combinations of species, harvesting methods, and extraction methods, so these data do not allow conclusions in this regard. While none of the *chlorella sp* samples had a higher protein content, the available observations do not include identically treated algae samples for the two different species, so the effect of species on PEAR value also is unclear from these data. The general impression is that PEAR protein content and value will vary substantially due to algae harvesting method, meal extraction method, and perhaps due to species, and the interactions among these factors.

Uncertainty surrounding hedonic PEAR values for two individual PEAR samples is depicted in Figure 4. One high-protein PEAR variety and one other PEAR variety are presented (*Nannochlor oculata* flakes, drum-dried, hexane-extracted meal and *chlorella sp*, flocculated, spray-dried, pentane extracted meal, respectively). Confidence intervals are calculated using the simulation procedure that incorporates parametric uncertainty as described in subsection 4.1. The average magnitude of the 50% confidence interval for each PEAR variety is slightly greater than $50 per ton. The confidence intervals for the two PEAR samples presented in Figure 4 overlap for most of the earlier time periods. In the later periods, however, the higher protein values (Figure 1) result in higher values for the higher-protein PEAR, and the confidence intervals do not overlap for many of these periods. We do not, however, assert any statistical differences in these values or formally test for any such differences.

The volumes of algal oil generated per unit of volume of PEAR generated for our samples were not available. We therefore use assumptions in this regard to calculate approximate co-product credits that might be generated per gallon of diesel-like, algae-based fuel produced. Specifically, we use the relative volumes of oil and PEAR jointly produced in the open-pond model of [10]. That work assumed that algae was harvested by centrifuge, and the oil and meal separated using the proprietary solvent process of Solution Recovery Services. This process is reported to yield from total biomass approximately 28% oil (by weight) and 72% meal. We assume that algae oil is used to produce either fatty acid methyl ester (FAME) biodiesel produced by trans-esterification of algal oil, or non-esterified renewable diesel (NERD) produced by hydrotreating algal oil. We assume 7.4 pounds of oil are needed to produce one gallon of FAME biodiesel and 8.4 pounds are needed to produce one gallon of NERD.[10] Using all of these assumptions, and high and low values of PEAR of $100 and $225 per ton (based on the hedonic PEAR values for 2008 onward presented in Figure 3), we calculate that PEAR should generate co-product credits in the ranges of $0.95 to $2.14 (FAME) and $1.08 to $2.43 (NERD) per gallon of diesel-like fuel.[11]

[10] These values are inferred from Marker, et al. [32].
[11] The co-product credit calculations presented here assume that the algae producer chooses to market PEAR as a livestock feed ingredient. We acknowledge that the producer could instead choose to recover nutrients from the algae residue and reuse them in the algal production process. However, the market value of PEAR as a

5. Conclusions

We used the prices of common livestock feed ration ingredients to infer the values of constituent nutrients: total digestible nutrients, crude protein, and ether extract (a measure of approximate fat content). We then used the values of these nutrients in conjunction with the nutrient content of various PEAR samples to infer the potential value that PEAR would have had as a livestock ration ingredient from 2005 through 2010.

We found that PEAR would have had considerable value as a feed ration ingredient, although it is less valuable than soybean meal owing to lower protein content and higher ash content. Changes in PEAR value would correspond closely, but not perfectly, to changes in soybean meal value. We found that for most of the 2006 through 2010 period, PEAR would have been valued between $100 and $225 per ton. Using some assumptions about relative yields of oil and meal extracted from algae, we calculated that PEAR sales could have yielded co-product credits ranging between $0.95 and $2.43 per gallon of diesel-type fuel produced for most of this period.

Relative to the size of livestock feed markets, quantities of PEAR produced would likely be fairly small even if large quantities of algae-based fuel were

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livestock feed ingredient would not be determined by its cost of production, or by the value of recovering nutrients from algal residue for further algae production, but rather by PEAR's potential contribution to the production of livestock or dairy commodities (in economic terminology, the value of the marginal product of PEAR). The market value of PEAR as a livestock feed ingredient may be below its cost of production, and may be below the value of using recovered nutrients in further algae production. Optimal management of an algae production enterprise is beyond the scope of this paper.

produced. In the U.S. alone, the estimated combined feed use of only corn and soybean meal in the 2011/12 marketing year is about 158 million short tons. Using the average of the FAME and NERD fuel yields from above, and the assumed proportions of oil and meal yield from algae from above, we calculate that approximately 20.3 pounds of PEAR would be produced per gallon of algae-based, diesel-type fuel. Production of one billion gallons of algae-based fuel (which would fully satisfy the annual requirement for biodiesel use under the U.S. Renewable Fuel Standard) would result in production of approximately 10.1 million short tons of PEAR, which is slightly more than 6% of U.S. feed use of corn and soybean meal in the 2011/12 marketing year.

As with any research, various caveats apply. We used the prices of feed ingredients observed at a single geographic location (Fort Worth, Texas) in inferring the values of constituent nutrients. We ignored the possibility that PEAR may yet be discovered to contain substances toxic to livestock, and that such toxic content may obviously vary by algae processing methods. For some PEAR samples, calcium and sulfur contents are fairly high, which may limit the proportion of a total livestock ration that can consist of PEAR. Our results should be interpreted with these limitations in mind.

This information should prove useful in evaluating the economic feasibility of different algal production systems. While a formal, complete analysis would obviously be required to draw definitive conclusions, our results imply that systems which do not generate a PEAR co-product (e.g., where algae is anaerobically digested to generate fuel) may be less economically attractive than systems that do generate a PEAR co-product. Among systems that do generate PEAR, the algal species, harvesting and extraction details and their simultaneous effects on both PEAR value and oil value will need to be carefully considered.

References

1. Chisti, Y. 2008. “Biodiesel from microalgae beats bioethanol.” School of Engineering, Massey University, Private Bag 11 222, Palmerston North, New Zealand.

2. Brune, D.E., T.J. Lundquist, and J.R. Benemann. 2009. “Microalgal Biomass for Greenhouse Gas Reductions; Potential for Replacement of Fossil-Fuels and Animal Feeds.” *Journal of Environmental Engineering,* 135:1136-1144.

3. Lundquist, T.J., I.C. Woertz, N.W.T. Quinn, and J.R. Benjamin. 2010. “A Realistic Techonlogy and Engineering Assessment of Algae Biofuel Production.” Technical report from the Energy Biosciences Institute, University of California, Berkeley.

4. Stephens, E., I.I Ross, Z. King, J.H. Mussgnug, O. Kruse, C. Posten, M.A. Borowitzka, and B. Hankamer. 2010. “An Economic and Technical Evaluation of Microalgal Biofuels.” *Nature Biotechnology*, 28(2):126-128.

5. Wijffels, R.H. and M.J. Barbosa. 2010. “An Outlook on Microalgal Biofuels.” *Science*, 329(August 2010):796-799.

6. Becker, E.W. 2007. “Micro-algae as a Source of Protein.” *Biotechnology Advances*, 25:207-210.

7. Spolaore, P., C. Joannis-Cassan, E. Duran, and A. Isambert. 2006. “Commercial Applications of Microalgae.” *Journal of Bioscience and Bioengineering,* 101(2):87–96.

8. Waltz, E. 2009. “Biotech’s Green Gold?” *Nature Biotechnology*, 27(1):15-18.

9. Williams, P.J.B., and L.M.L. Laurens. 2010. “Microalgae as Biodiesel & Biomass Feedstocks: Review & Analysis of the Biochemistry, Energetics & Economics.” *Energy & Environmental Science,* 3:554–590.

10. Richardson J.W., J.L. Outlaw, and M. Allison. 2010. "The Economics of Microalgae Oil." *AgBioForum,* 13(2):119-130.

11. Malpezzi, S. 2002. "Hedonic Pricing Models: A Selective and Applied Review." In K. Gibb and A. O'Sillivan (Eds.) *Housing Economics: Essays in Honor of Duncan Maclennan.* Madison, WI: The Center for Urban Land Economics Research, pp. 1-43.

12. National Research Council. 2001. *Nutrient Requirements of Dairy Cattle*, 7th ed. National Academy Press.

13. Vasconcelos, J. T., and M. L. Galyean. 2007. "Nutritional Recommendations of Feedlot Consulting Nutritionists: The 2007 Texas Tech University survey." *Journal of Animal Science*. 85:2772-2781.

14. Waugh, F.V. 1929. *Quality as a Determinant of Vegetable Prices.* New York: Columbia University Press.

15. Vail, E.E. 1932. "Retail Prices of Fertilizer Materials and Mixed Fertilizers." AEA Bulletin 545, Cornell University, Ithaca, New York.

16. Griliches, Z. 1961. "Hedonic Price Indexes for Automobiles: An Econometric Analysis of Quality Change." *The Price Statistics of the Federal Government,* 73:173-196.

17. Lancaster, K., 1966. "A New Approach to Consumer Theory." *Journal of Political Economy,* 74:132-57.

18. Rosen, S. 1974. "Hedonic Price and Implicit Markets: Product Differentiation in Pure Competition." *Journal of Political Economy,* 82(1):34-55.

19. Jordan, J. L., R. L. Shewfelt, S. E. Prussia and W. C. Hurst. 1985. "Estimating the Price of Characteristics for Tomatoes: Quality Aiding the Evaluation of the Postharvest System." *Horticultural Science*, 20.

20. Hyberg, B., N.D. Uri, and V. Oliveira. 1996. "The Quality Characteristics of Japanese Soybean Imports." *Japan and the World Economy*, 8(1):81-98.

21. Ethridge, D.E. and B. Davis. 1982. "Hedonic Price Estimation for Commodities: An Application to Cotton." *Western Journal of Agricultural Economics*, 7:293-300.

22. Halvorsen, R., and H.O. Pollakowski. 1981. "Choice of Functional Form for Hedonic Price Equations." *Journal of Urban Economics,* 10:37-49.

23. Cropper, M.L., L.B. Deck, and K.E. McConnell. 1988. "On the Choice of Functional Form for Hedonic Price Functions." *The Review of Economics and Statistics,* 70:668-675.

24. Box, G., and D. Cox. 1964. "An Analysis of Transformations." *Journal of the Royal Statistical Society,* 26:211-252.

25. Wooldridge, J.M. 2001. *Econometric Analysis of Cross Section and Panel Data.* Cambridge, Massachusetts: The MIT Press.

26. Hoeting, J.A., D. Madigan, A. Raferty, and C. Volinsky. 1999. "Bayesian Model Averaging: a Tutorial." *Statistical Science*, 14:230-242.

27. Schwarz, G. 1978. "Estimating the Dimensions of a Model." *Annals of Statistics*, 6:461-464.

28. Chickering, D.M. 2002. "Optimal Structure Identification with Greedy Search." *Journal of Machine Learning Research*. 3:507-554.

29. Cook, R.D. 1979. "Influential Observations in Linear Regression." *Journal of the American Statistical Association,* 74(365): 169-174.

30. Preston, R.L. 2010. "2010 Feed Composition Tables." *Beef Magazine,* November.

31. Feedstuffs, Miller Publishing Company. 2005-2010. "Ingredient Market Prices." *Weekly Newspaper for Agribusiness.*

32. Marker, T., J. Petri, T. Kalnes, M. McCall, D. Mackowiak, B. Jerosky, B. Reagan, L. Nemeth, M, Krawczyk, S. Czernik, D. Elliot, D. Shonnard. 2005. "Opportunities for Biorenewables in Oil Refineries." Technical report submitted to U.S. Department of Energy by UOP, LLC; DOE award number DE-FG36-05GO15085.

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Table 1: Composition of PEAR Samples (selected characteristics)*

			As a Percent of Dry Matter:				
Species and Sample	Treatment	% Dry Matter	Organic Matter	Ash	TDN	CP	EE
Chlorella sp 1	Flocculated, spray dried, pentane-extracted meal	93.78	58.99	41.01	47.19	21.33	0.76
Chlorella sp 2	Flocculated, spray dried, pentane-extracted meal	95.78	56.79	43.21	45.43	20.16	1.56
Chlorella sp 3	Flocculated, spray dried, pentane-extracted meal	91.40	51.47	48.53	41.18	19.8	2.37
Chlorella sp 4	Flocculated, spray dried, pentane-extracted meal	91.64	48.70	51.3	38.96	20.40	1.93
Nannochloris oculata 1	Flakes drum-dried, ethanol-extracted meal	90.13	75.76	24.24	60.61	34.20	<0.20
Nannochloris oculata 2	Flakes drum-dried, hexane-extracted meal	88.82	50.34	49.66	40.27	35.50	0.66
Nannochloris oculata 3	Flocculated expanded collets, hexane-extracted meal	92.82	52.16	47.84	41.73	38.06	1.90
Nannochloris oculata 4	Spray dried-expanded collets, ethanol-extracted meal	90.08	56.06	43.94	44.85	23.58	2.96
Nannochloris oculata 5	Spray dried-expanded collets, hexane-extracted meal	90.81	53.32	46.68	42.66	23.24	2.93
Nannochloris oculata 6	Flocculated, ethanol-extracted meal	94.29	50.96	49.04	40.77	21.90	0.31
Nannochloris oculata 7	Flocculated, hexane-extracted meal	92.66	42.41	57.59	33.93	18.76	0.68

* PEAR sample quantities varied, but were each greater than 5kg. In the context of animal feed processing, a "collet" is a nozzle through which a meal is extruded, or

the product that results from this process. We use this latter usage here. TDN = total digestible nutrients, CP = crude protein, EE = ether extract.

Table 2: Average P-values for Period-wise Box-Cox Parameter Restrictions

Null Hypothesis	Transformation	Average p-value	Number of Rejections (alpha = 0.10)
H_0: y 1	Reciprocal	0.036	20
H_0: y 0	Log	0.000	23
H_0: y 1	None	0.120	15

Table 3: Average Cook's Distance for Period-wise Hedonic Regressions

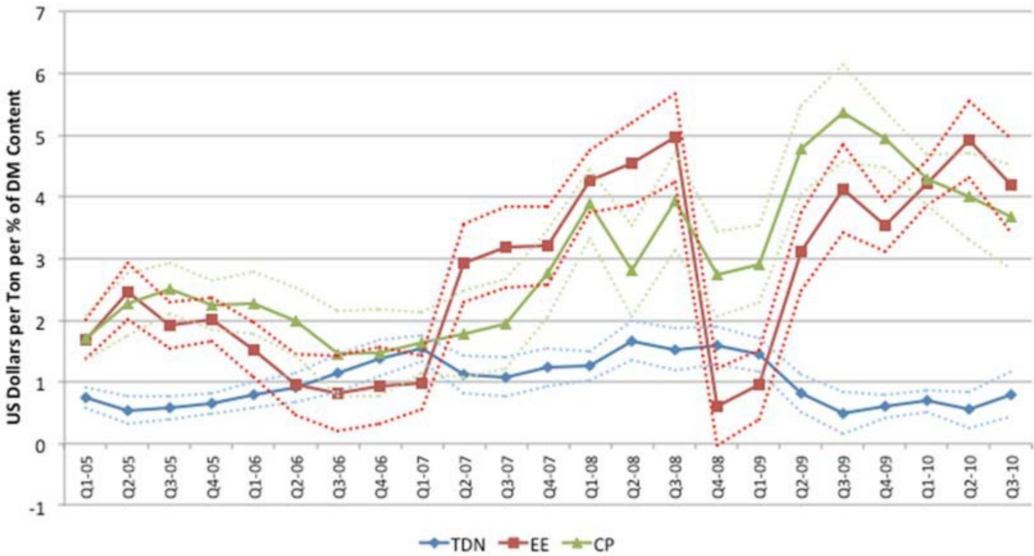
Price Observation	**Cook's Distance**
Soybean meal (high protein)	0.044
Soybean meal (low protein)	0.037
Soybean hulls	0.031
Whole Cottonseed	0.227
Cottonseed meal	0.005
Linseed meal	0.007
Poultry byproduct meal	3.224
Hydrolized feather meal	1.378
Prime tallow	0.009
Yellow grease	0.051
Bleachable fancy tallow	0.073
Vegetable-animal blend	0.007
Suncured pellets (dehydrated 17%)	0.057
Middlings	0.016
Rice bran	0.021
Rice millfeeds	0.010
Rice hulls	0.152
Corn	0.015
Milo	0.009
Ground grain screenings	0.020
Feed urea	41.060

Table 4: Average Composition of PEAR Samples and High-Protein Soybean Meal*

	Percent of Dry Matter		
	TDN	CP	EE
High-protein soybean meal	87	54	1.1
High–protein PEAR**	47.5	35.9	0.9
Other PEAR***	41.9	21.1	1.7

* PEAR = post extraction algae residue, TDN = total digestible nutrients, CP = crude protein, EE = ether extract.
** Average characteristics of *Nannochloris oculata*, flakes, drum-dried, ethanol-extracted meal; *Nannochloris oculata*, flakes, drum-dried, hexane-extracted meal and *Nannochloris oculata,* flocculated expanded collets.
*** Average characteristics of all other PEAR samples, consisting of two different species and various harvesting and extraction methods.

Figure 1: Evolution of the Values of Feed Meal Characteristics*



* Dotted lines represent values plus or minus one standard error.

Figure 2: Projected versus Actual High-protein Soybean Meal Values

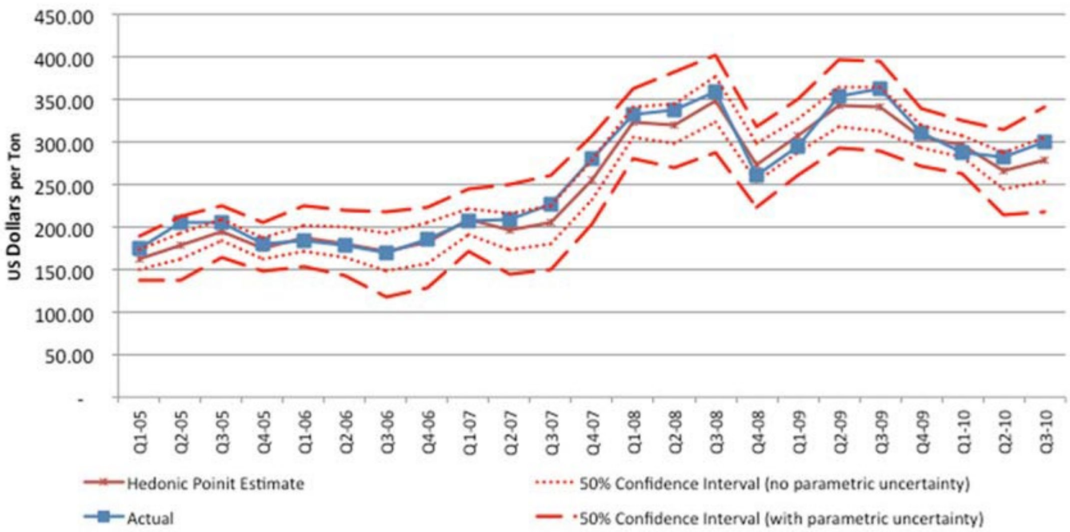


Figure 3: Hedonic PEAR Values

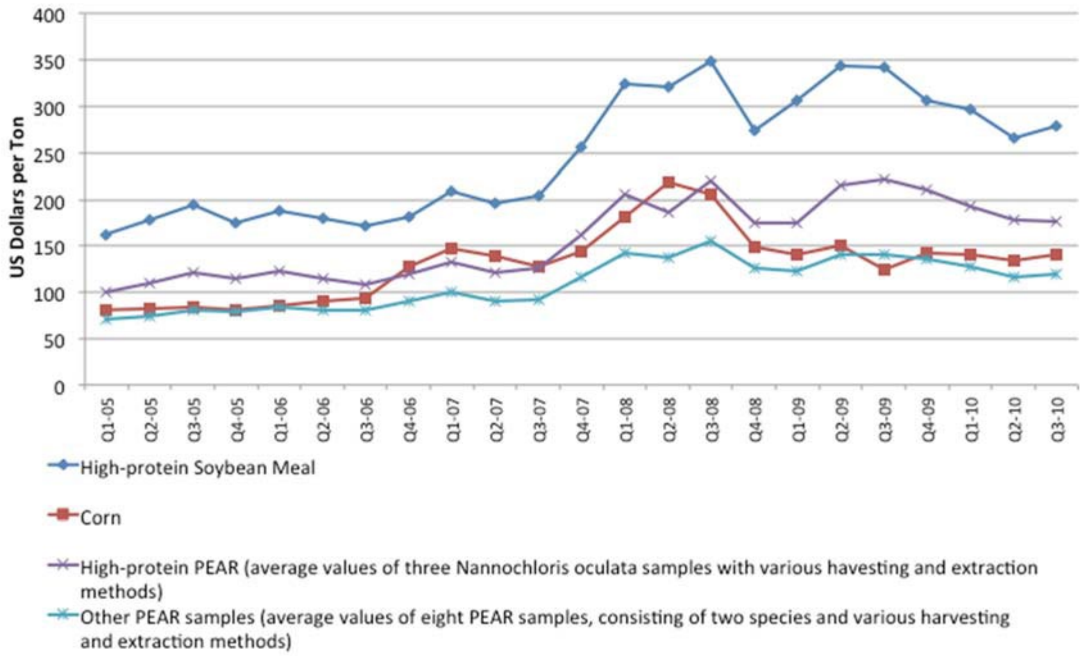


Figure 4: Hedonic Values of Specific PEAR Samples with Confidence Intervals