Journal of Agricultural and Applied Economics, 45,1(February 2013):79–94

A Semiparametric Approach to Analyzing Differentiated Agricultural Products

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When consumers have heterogeneous perceptions about product quality, traditional parametric methods may not provide accurate marginal valuation estimates of a product's characteristics. A quantile regression framework can be used to estimate valuations of product characteristics when quality perceptions are not homogeneous. Semiparametric quantile regressions provide identification and quantification of heterogeneous marginal valuation effects across a conditional price distribution. Using purchase price data from a bull auction, we show that there are nonconstant marginal valuations of bull carcass and growth traits. Improved understanding of product characteristic valuations across differentiated market segments can help producers develop more cost-effective management strategies.

Key Words: bull sales, heritable traits, product differentiation, quantile regression

JEL Classifications: Q13, L15, C52, D49

Consumers often differentiate among products by valuing a product's quantifiable characteristics conditional on their quality perceptions about the product. Consequently, the interaction between quantifiable and perceived characteristic valuations affects purchase decisions and prices. Understanding and measuring these interactions can help producers develop better production and marketing strategies by improving characteristics that are most valued in a targeted market segment. However, identifying and explicitly controlling for product differences in empirical analyses are often complicated, because it is difficult to quantify consumers' perceptions and specify how these perceptions interact with quantifiable product characteristics. Moreover, even when perception measures (or appropriate proxies) are available, commonly used empirical methods only estimate average marginal valuations of product characteristics, which may be inappropriate when substantial product and quality perception heterogeneity exists.

We propose using a semiparametric quantile regression (QR) framework for estimating characteristic valuations when product differentiation and heterogeneous quality perceptions exist. Quantile regressions have been used extensively in the labor economics literature to study topics such as the heterogeneity of wage effects, returns to education, and school quality (Buchinsky, 1997; Chamberlain, 1994; Eide and Showalter, 1998; Levin, 2001). We show that quantile regressions can be used to quantify the effects of quality perceptions on purchasing behaviors. That is, when consumers of an agricultural (or other) product perceive the overall quality of that product to be different than that of a close substitute, then these perceptions may affect the consumers' valuations

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of observable product characteristics. Although such quality perceptions are difficult to explicitly measure, quantile regressions provide a mechanism for improving the understanding of these effects by exploiting variation in revealed transaction prices across quality-differentiated products. Therefore, quantile regressions provide an approach for obtaining additional conditional marginal valuation information.

This study uses quantile regressions to evaluate the effects of quality perceptions on consumers' marginal valuations of genetic cattle seedstock. Genetic seedstock represents a classic example of a differentiated agricultural product (Dhuyvetter et al., 1996). Unlike many other, highly concentrated agribusiness genetic industries (for example, crop and nonbeef livestock genetics), the beef seedstock industry consists of many relatively small firms (Brester, 2002). This fragmented structure is primarily the result of differing environmental and topographical production regions. Beef cow–calf operations exist in all 50 states without the confinement used in pork and poultry production. Hence, the characteristics of the breeding herd and calf production vary greatly by region. Production and survival cattle characteristics needed in the southern United States are vastly different from those of the northern United States. Performance needs in the Midwest are markedly different from those of the desert Southwest. Animal survival and productivity are quite different for mountainous regions vs. flatter terrains, timbered areas, sagebrush environments, and drier vs. wetter/humid regions. Animal characteristics must be developed to adapt to drought tolerance, cow size, ranging abilities, heat/cold tolerance, and many other environmental factors.

For these reasons, a large number of relatively small firms develop cattle genetics based on their own competitive advantages and desire to meet specific market niches with many of these being region-specific. Given that over 30 breeds of cattle are commercially produced in the United States, an even larger range of market segments is met through the differentiation of genetics. Even within a single breed, the needs and desires of specific cattle producers caused by environmental conditions create market niches. Thus, specific beef genetic needs are tailored for each market niche (Vanek, Watts, and Brester, 2008). That is, buyers seek bulls whose offspring can be raised to maximize profits conditional on the opportunities of a specific production and marketing region. Purchase decisions, therefore, often require buyers to rely on both quantitative and qualitative information about an animal.

Although the use of bulls is necessary to produce calves, cattle producers also select bulls to improve calf quality and upgrade the genetic composition of cow herds through heifer calf retention. Previous studies show that producers select seedstock based on production needs, environmental conditions, and marketing strategies (Chvosta, Rucker, and Watts, 2001; Vanek, Watts, and Brester, 2008; Walburger, 2002). These studies used parametric empirical techniques to estimate average marginal consumer valuations. Because bull purchase transactions in these studies occurred at relatively homogeneous production sales, the hedonic average marginal effect estimates across all bulls are likely relatively accurate.[1] At auctions offering substantially heterogeneous bulls, however, buyers' perceptions of overall bull quality can substantially differ across the distribution of available animals. That is, because cattle producers typically know the demands and pricing structures of their markets, they can better identify bulls whose offspring would be most valued in those markets. Consequently, knowledge of a bull's measurable characteristics, perceptions about the animal's quality, and a keen understanding of their region's environmental factors and market structures influence buyers' valuations. Estimated average marginal valuations may, therefore, be insufficient for revealing the impacts of differentiated quality considerations. Jones et al. (2008, p. 331) states that such subjective considerations may be "... as important to buyers as genetic information contained in [expected progeny differences] and actual

[1] Jones et al. (2008) and Vanek, Watts, and Brester (2008) provide some evidence that product segmentation exists across seedstock markets.

weights and, at times, are certainly significant in determining value" of auctioned bulls.

We seek to determine whether meaningful interactions exist between a consumer's valuation of products' measurable traits and unquantifiable factors affecting price differences. Moreover, this study determines whether estimated average marginal valuations of measurable product traits appropriately characterize consumers' assessments of these traits across differentiated goods. Specifically, we show that semiparametric empirical methods exploit information implicit in a product's sales price to reveal marginal effects associated with factors that are not directly observable, including consumers' perceptions of quality. For example, if bull buyers more heavily value a marginal increase in the feed-to-gain trait in perceived higher-quality bulls, then these buyers would be willing to pay more for marginal feed-to-gain increases in high-quality bulls than for identical increases in perceived lower-quality bulls. Quantile regressions can exploit heterogeneity in the conditional price distribution to determine whether average partial effects appropriately describe buyers' valuations or if valuations are substantially different.[2]

We show that consumers' valuations of many characteristics differ across a spectrum of heterogeneous bulls. After adjusting for nonnormality in the price distribution and investigating the presence of nonlinear relationships between a bull's sale price and its observable characteristics, quantile regressions reveal nonconstant marginal effects of bull traits across the conditional sale price distribution. The semiparametric empirical approach exploits variations in realized market outcomes to reveal and quantify perception effects that are difficult (or impossible) to model parametrically. When these effects are revealed, producers can use the information to adjust management decisions and tailor products to better capture their target market's increased willingness to pay for particular characteristics. The literature has shown that this information is important for producers and retailers seeking to differentiate their products and capture opportunities in segmented markets (Dickson and Ginter, 1987; Parcell and Schroeder, 2007). Specifically, producers can better determine cost-effective practices to improve product characteristics that are more valued by a set of targeted consumers.

Modeling Differentiated Product Prices

Following Arias, Hallock, and Sosa-Escudero (2001) and Rosen (1974), we specify a hedonic model with perception interaction effects as:

$$(1) \qquad P_i = \sum_j X_{ij}\beta_j + g\left(X_{ij}, q_i\right)\gamma_{ij} + \varepsilon_i.$$

The term P_i represents the price of product i, X_{ij} is the j^{th} measurable product characteristic, q_i is an explicitly unquantifiable product differentiation measure, ε_i is a random disturbance term, and β_{ij} is the marginal price change associated with an additional unit of X_{ij}. We assume that product differentiation is a function of consumers' perceptions of a product's overall quality.[3] An *a priori* unknown relationship between a product's differentiation measure and a trait X_{ij} is characterized by the function $g(X_{ij}, q_i)\gamma_{ij}$, where the term γ_{ij} represents the marginal contribution to price from changes in $g(X_{ij}, q_i)$. For example, γ_{ij} is expected to be positive if consumers value additional units of X_{ij} more in perceived higher-quality products.

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[2] That is, quantile regressions provide a method for parameterizing the relationship between sale prices and observable characteristics, but also flexibly measure potential impacts of perceptions without *a priori* knowledge of how these perceptions interact with consumers' valuation of observable product characteristics. For example, instead of making an assumption about the functional form of consumers' valuations and quality perceptions, quantile regressions are used to allow data to reveal this relationship.

[3] It is generally difficult to characterize factors affecting quality perceptions. Several conceivable examples include consumers' perceptions of a seller's reputation, impressions after visual examination of the product, previous product experiences, and assumptions about the product's overall quality from the interaction of multiple product characteristics. For example, for a product that has five observable characteristics, consumers may explicitly place value on each particular characteristic but evaluate the overall value of the product conditional on one or more of the $\sum_{r=2}^{n} \frac{n!}{(n-r)!r!}$ combinations of product traits.

Parametric regression frameworks are widely used in agricultural economics research to estimate marginal values of characteristics in hedonic models. Estimating equation (1) using these approaches requires that the interaction term, $g(X_{ij}, q_i)$, be parameterized. For example, one common parameterization is the multiplicative form: $g(X_{ij}, q_i) = X_{ij}q_i$. The parameterization requires that the term q_i be explicitly identified by a quantifiable measure describing a product's differentiation or by a closely correlated proxy. However, even if such measures exist, it may still be difficult to quantify marginal effects on price across a spectrum of differentiated product levels. For example, an ordinary least squares (OLS) estimation of equation (1) yields the following marginal effect of X_{ij}:

$$(2) \qquad \frac{\partial E\left[P_i | X_{ij}\right]}{\partial X_{ij}} = ij + \gamma_{ij} \cdot \bar{q}.$$

This implies that the marginal valuation of X_{ij} is altered by an average effect of product differentiation across all products. When products are relatively homogeneous, OLS estimates may accurately describe the marginal effect of quality on the conditional price distribution. However, average marginal effect estimates of product characteristics may be less conclusive when substantial product heterogeneity exists.[4]

When products are heterogeneous, consumers' perceptions of overall quality may be conditional on their perceived product quality differentiation. It is frequently the case that perceived quality and product difference metrics either do not exist or are unmeasurable. In such cases, buyers reveal their perceptions of product differences through willingness-to-pay valuations. For example, auction bidders actively reveal their preferences by contributing to the price determination process, and these contributions can differ based on a bidder's perception of product characteristics. These differences are reflected in the conditional price distribution, because a product's perceived quality can affect the premiums that consumers are willing to pay.

When it is difficult or unfeasible to directly account for unmeasurable quality perception effects, the uncontrolled heterogeneity is incorporated into the regression error term. An alternative interpretation of this situation is the inability to structurally control for omitted information. Barnes and Hughes (2002) and Fitzenberger, Koenker, and Machado (2002) show that quantile regressions are useful in identifying parts of the conditional dependent variable distribution in which omitted information is especially influential. For example, when quality perceptions influence consumers' valuations and willingness to pay for differentiated products, sale prices of those products are likely to be higher (lower) than the expected average price of the product, which is conditional only on the observable product characteristics. Parametrically accounting for the omitted information can be difficult not only because it may be infeasible to identify factors explaining quality perceptions, but also because the manner in which these factors interact with observable product characteristics, $g(X_{ij}, q_i)$, is unknown.

We show that quantile regressions can provide a flexible, semiparametric estimation framework for quantifying conditional marginal impacts of product differentiation across the conditional price distribution. For a sample quantile φ, the conditional quantile marginal effect (regression quantile) is characterized as follows:

$$(3) \qquad \frac{\partial Q(\varphi)\left[P_i | X_{ij}\right]}{\partial X_{ij}} \equiv \hat{\beta}_{ij}(\varphi) = \hat{\beta}_{ij} + \gamma_{ij} \cdot \frac{\partial Q(\varphi)\left[g\left(X_{ij}, q_i\right) | X_{ij}\right]}{\partial X_{ij}}.$$

where $0 < \varphi < 1$ is the proportion of P_i with outcomes below the φ^{th} sample quantile. Unlike conditional marginal effects implied by conditional-mean parametric specifications, the conditional quantile partial effect does not

[4] Other parametric frameworks can be envisioned for estimating product differentiation effects on valuation across a spectrum of products. However, these methods would still require a parameterization of the product differentiation interaction term, $g(X_{ij}; q_i)$, as well as *a priori* knowledge of factors influencing quality perceptions, q_i.

necessitate an explicit parameterization of the product differentiation interaction term $g(X_{ij}, q_i)$. Rather, performing a set of quantile regressions across different values of φ allows the data (instead of a selected parameterization) to identify the impacts of unaccounted perceived product difference effects across heterogeneous products.

It is possible that product differentiation perceptions do not impact valuations of one or more product characteristics in X_{ij}. For example, all products are sold by a single producer (i.e., reputation perceptions are identical) or consumers' quality perceptions are homogeneous. In this case, it is likely that the average consumer's valuation of $\hat{\beta}_{ij}$ appropriately characterizes the marginal value of the product's characteristic in the market. Therefore, studies investigating these types of markets would obtain accurate marginal valuations of product characteristics using empirical methods that estimate average partial effects.

When there is no *a priori* knowledge of whether product differentiation and heterogeneous quality perceptions exist, quantile regressions can be used to empirically test for this information. That is, if perception effects trivially affect the valuation of X_{ij}, then $\frac{\partial Q(\varphi)\left[g\left(X_{ij}, q_i\right)\middle|X_{ij}\right]}{\partial X_{ij}} = 0$.

Estimating Quantile Regressions

Conditional-mean functions are the foundation for a large number of modeling techniques including linear regressions, weighted and nonlinear least squares regression specifications, and maximum likelihood models. Under appropriate statistical conditions, these estimation techniques are relatively simple and empirical results are easily interpreted. However, conditional-mean functions are not easily generalizable to modeling data in noncentral locations of the conditional dependent variable distribution, making analyses of the distribution tails difficult. Furthermore, conditional-mean functions focus primarily on marginal effects of modeled regressors on the central tendency of the conditional distribution. When marginal effects vary across the conditional dependent variable distribution, estimates of these effects at the data's central tendency may substantially distort economic inferences. In these cases, quantile regressions can provide a more robust characterization of data relationships (Koenker and Bassett, 1978).[5]

A linear quantile regression is similar to conditional-mean least squares models in that both minimize weighted sums of residuals. However, they differ in their specification of weighting mechanisms. For a model $y = \boldsymbol{x}'\boldsymbol{\beta} + \varepsilon$, OLS estimate the conditional mean function $E[y|X = x] = \boldsymbol{x}'\boldsymbol{\beta}$ by solving $\hat{\beta} = \min_{\beta\in\mathbb{R}} \sum_i (y_i - x_i'\beta)^2$. Similarly, Koenker and Bassett (1978) show that for the φ^{th} regression quantile, the model $y = \boldsymbol{x}'\boldsymbol{\beta}(\boldsymbol{\varphi}) + \varepsilon(\varphi)$ can be estimated using a linear conditional quantile function, $Q(\varphi)(y|X = x) = \boldsymbol{x}'\boldsymbol{\beta}(\boldsymbol{\varphi})$, solving:

$$\hat{\boldsymbol{\beta}}(\boldsymbol{\varphi}) = \hat{\beta} = \min_{\beta\in\mathbb{R}} \left\{ \sum_{i\in(i:y_i\geq x_i'\beta(\varphi))} \varphi|y_i - x_i'\boldsymbol{\beta}(\boldsymbol{\varphi})| + \sum_{i\in(i:y_i<x_i'\beta(\varphi))} (1-\varphi)|y_i - x_i'\boldsymbol{\beta}(\boldsymbol{\varphi})| \right\}. \tag{4}$$

where $0 < \varphi < 1$ is the proportion of y with outcomes below the φ^{th} sample quantile. The estimation of a linear conditional quantile function is loosely analogous to least squares estimation, in which a Euclidian distance $\|y - \hat{y}\|$ is minimized over all $\hat{y}$ in the column span of X (Koenker, 2005). A quantile regression minimizes a weighted sum of absolute errors with weights φ and $(1 - \varphi)$ assigned to positive and negative residuals, respectively. A different set of weights is assigned and a different associated conditional quantile function is estimated for each φ^{th} sample quantile. Bootstrapping is an effective method for obtaining standard errors, especially if random variables cannot be assumed to be *i.i.d.*

Regression quantiles cannot be obtained by performing least squares estimation on subsamples of the data associated with the φ^{th}

[5] An overview of quantile regression methods and examples of applications in economics is provided by Hao and Naiman (2007) and Koenker (2005).

dependent variable quantile. Subsampling truncates the dependent variable and results in biased and inefficient parameter estimates (Hausman and Wise, 1977; Heckman, 1979). Estimation methods for truncated data exist; however, using these methods on subsamples can omit relevant information present in the excluded sample portions. Furthermore, researchers typically do not have knowledge of demarcation zones in the dependent variable distribution at which subsampling should occur. Truncation and information loss does not occur with quantile regression estimation because each conditional quantile estimation uses the entire sample data set. However, absolute positive and negative residuals are weighted differently depending on the sample quantile value φ, resulting in a unique set of conditional-quantile parameter values for each φ.

It is also inappropriate to assume that differentiated marginal effects across the conditional price distribution can be replicated by simply adding interaction terms or transforming the data. For example, Ladd and Martin (1976) show that in modeling agricultural commodity prices, the marginal effect of changes in a particular product characteristic, x_{ij}, may be nonlinearly related to price. That is, the effect of changes in characteristic x_{ij} is conditional on the level of the characteristic. The authors recommend modeling prices as $P_i = \beta_0 + \beta_1 x_{ij} + \beta_2 x_{ij}^2 + \varepsilon_i$ such that the marginal effect of x_{ij} is $\partial P_i \big/ \partial x_{ij} = \widehat{\beta_1} + 2\widehat{\beta_2} x_{ij}$. However, this marginal effect describes only the average impact on price at different levels of x_{ij}. It does not reveal whether $\partial P_i \big/ \partial x_{ij}$ is different across noncentral portions of the conditional price distribution such as the upper and lower tails. Therefore, altering the functional form using interaction terms is not a substitute for inferences provided by quantile regressions.

Product Differentiation at Bull Auctions

Bull auctions are one example of an agricultural market containing differentiated products, especially when a heterogeneous set of producers sells bulls to a heterogeneous set of buyers. Bull purchasers make bidding decisions conditional on measurable information contained in sale catalogs along with unrecordable visual inspections of a bull's physical characteristics, knowledge of sellers' reputations, a bull's expected length of service, and perceptions about a bull's overall quality. Conditional on purchasers' considerations of measured bull traits, buyers may implicitly value marginal changes in each trait differently depending on perceptions of differences among bulls. For example, it seems likely that the value placed on a particular trait may vary if a consumer perceives improvements in the trait to contribute more to the overall quality of a particular animal than the contribution to the quality of another animal.

Most genetic improvements in the beef industry occur through bull (rather than cow) selection with higher value placed on bulls with better expected progeny differences (EPDs) and simple performance measures (SPMs). EPDs are quantitative predictions of a bull's heritable traits based on genealogical histories. These measures help forecast characteristics of a bull's progeny relative to the progeny of other bulls of the same breed. Examples of EPDs include birth weight, weaning weight, and ribeye area. Vanek, Watts, and Brester (2008) found that buyers pay more for bulls with better EPDs. SPMs refer to actual observed bull measurements occurring during 70- to 120-day performance testing (i.e., feed trials). For example, bull SPMs include the 205-day weight, intramuscular fat, and feed-to-gain ratio. Chvosta, Rucker, and Watts (2001) and Dhuyvetter et al. (1996) show that both EPDs and SPMs affect bull sale prices at auctions.

Midland Bull Test (MBT) measures feed efficiency, weight gain, carcass quality, and fertility characteristics of bulls during the testing period. More than 100 bull producers annually contract with MBT to conduct bull performance tests.[6] At the conclusion of the testing period, MBT publishes test results in sale catalogs and facilitates an open out-cry auction. Using sale catalogs and visual inspections, buyers evaluate bull characteristics and offer bids

[6] MBT is one of only a few venues that facilitate the testing and sale of bulls that are not owned by the auction facilitator. Most bull auctions focus on a single (or only a few) producer's bull offerings.

during a live auction. During the 2008 and 2009 MBT bull auctions, 328 unique producers sold 999 bulls to 514 unique buyers.

Following existing literature on bull auctions (Jones et al., 2008; Schroeder, Espinosa, and Goodwin, 1992), we use a semilog linear hedonic price model to quantify bull characteristic effects on the natural logarithm of bull sale prices. The logarithmic transformation is intended to reduce the high positive skewness of price levels. The bull price model is specified to be:

$$\ln p_i(\varphi) = \beta_{i0}(\varphi) + \sum_j \theta_{ij}(\varphi) \cdot SPM_{ij} + \sum_k \gamma_{ik}(\varphi) \cdot EPD_{ik} + \boldsymbol{\beta}_i X + \varepsilon_i(\varphi), \quad (5)$$

where $\ln p_i(\varphi)$ represents the logged purchase price of bull i, SPM_{ij} is the j^{th} simple performance measure, and EPD_{ik} is the k^{th} expected progeny difference measure. SPM measures include actual birth weight (pounds), weaning weight, 365-day weight, age (in days) at sale, age squared, average daily gain (pounds per day), intramuscular fat (percentage of fat in the ribeye area), ribeye area (square inches), and residual feed intake. RFI is a measure of the difference between an animal's actual feed intake and its expected feed intake and may provide a means for selecting bulls with higher feed efficiency characteristics without negatively impacting cattle growth and carcass traits because it is uncorrelated with average daily weight gain (Koch et al., 1963). Ribeye area and intramuscular fat (marbling) are bull carcass characteristics that improve perceived product quality and are, therefore, valued by end-users. Expected progeny differences include birth weight EPD, birth-to-yearling weight gain EPD, ribeye area EPD, intramuscular fat EPD, and milk EPD. EPDs are measured using the same units as simple performance measures. The term $\boldsymbol{X}$ represents a vector of other variables included in the model, including indicators of whether a bull was sold at 67% or 75% fractional interest, the sale order (i.e., the order in which bulls are presented for sale at the auction), and a year fixed effect. Lastly, $\varepsilon_i(\varphi)$ is an error term and $\beta_{i0}(\varphi)$, $\theta_{ij}(\varphi)$, and $\gamma_{ij}(\varphi)$ are estimable parameters for the φ^{th} sample quantile.

High correlations between birth weight and yearling weight EPD measures reduce our ability to uniquely identify marginal valuations of these two EPDs. Following Vanek, Watts, and Brester (2008), we instead include indicators of an initial weight EPD (birth weight) and of the capacity to gain weight before sale (i.e., weight gain between birth and 365 days). Therefore, we specify a hedonic bull price model that includes the birth weight EPD and the birth-to-yearling weight gain EPD, which we calculate as the difference between birth weight and yearling weight EPDs.

Information on bulls offered for sale in MBT's 2008 and 2009 auctions was published in a catalog and distributed in advance of the sale. Although 11 different bull breeds were offered at these auctions, only Black Angus and Red Angus bulls were sold in sufficient quantities to allow for meaningful inferences. An indicator variable is included to account for Black Angus bulls. All Angus bulls were sold on the same day in each year and MBT excluded bulls from the sale that ranked in the bottom 30% of all SPM test measures. Although the data include product characteristics of animals that were offered for sale but not purchased (i.e., "no-sale" bulls), we do not have information about the consigner's reservation price, the bidding history, or the highest bid. Therefore, we are unable to identify bidders' willingness to pay for these bulls and, consequently, exclude these observations from the analysis. Finally, some bulls were sold at 67% and 75% fractional interest (i.e., those purchased with 67% or 75% ownership rights). Because we are unable to observe whether fractional interest sales indicate a seller's semen retention rights or some other factor, we assign indicator variables for fractional interest bull sales.[7]

[7] Data identifying information of sellers and buyers were not available. Information about the sellers and buyers can allow explicit control for potential reputation effects, which could represent one of the factors contributing to quality valuation. Although these data contain anonymous seller and buyer identification, assigning indicator variables for 328 unique sellers and 514 unique buyers as controls given 999 total transactions would substantially limit the estimation power.

Table 1 presents summary statistics and shows that the standardized median absolute deviation (MAD) of logged bull prices (0.41) is lower than its standard deviation (0.48). Because MAD is a robust measure of location and scale, the discrepancy is indicative of a long upper tail (Huber 1981). This indicates our use of natural logarithms to transform prices is insufficient to effectively reduce potential biases created by outlier observations. As shown by the histogram and fitted kernel density of the logged price in Figure 1, the logged sale price distribution is also skewed. Because each buyer seeks to purchase bulls for breeding purposes, the substantial price variation and skewness are likely indicative of product differentiation. That is, buyers signal their valuation of bull differences by paying prices that are not equally proportionate to changes in observable bull traits; therefore, quantile regressions are used to semiparametrically estimate this relationship.[8] Lastly, a correlation matrix among the independent variables reveals relatively low relationships, implying that bull producers seeking to improve particular bull traits would not incidentally alter other traits that may adversely impact sale prices.

Least Squares Estimation Results

For comparison purposes, equation (5) is estimated using OLS regression and QR at five sample quantiles.[9] Table 2 presents parameter estimates, R^2 and pseudo-R^2 statistics, and tests for joint significance of parameters. OLS estimates of bull traits represent average marginal effects, which appear to be reasonable relative to previous research and *a priori* expectations (for example, see Chvosta, Rucker, and Watts, 2001; Jones et al., 2008; Vanek, Watts, and Brester, 2008; Walburger, 2002). Parameter estimates associated with all modeled variables except ribeye area EPD, bulls sold at 67% fractional interest, and the year fixed effect were statistically significant at least at the 5% level.

Lower birth weights and birth weight EPDs indicate that a bull's progeny are on average expected to have lower birth weights, contributing to reduced manual labor, veterinary costs, and animal mortality during parturition. A 1-pound decrease in a bull's birth weight or birth weight EPD increases a conditional bull's price by approximately 0.8% and 5.5%, respectively. A 1-pound increase in weaning weight or 365-day weight increases conditional bull prices by 0.08% and 0.06%, because higher bull weaning weights are an indicator of higher weaning weights for its progeny. Older bulls are valued 2.6% more for each day of age, and a 1-pound increase in average daily gain increases bull prices by 20.1%.[10]

Intramuscular fat and ribeye area are end-user carcass quality characteristics. One-unit increases in either measure are expected to increase expected price. A negative parameter estimate indicates that RFI is positively valued, because bulls with lower RFI are able to attain higher growth with less feed. OLS estimates indicate that a 1-pound per day gain in RFI increases the conditional value of a bull by an average of 3.2%. Finally, bulls offered at 67% fractional interest were not statistically different from others, and Black Angus bulls increased the price of an average bull. The latter suggests that some breed considerations are

[8] Quantile regression estimation is semiparametric and inferences do not depend on distributional assumptions of the error structure (Hao and Naiman, 2007). Skewed or other unconventional data can, therefore, be appropriately analyzed using the QR method. Although M and MM estimators (see Huber, 1973; Yohai, 1987) can also be used for robustly estimating nonnormal data, the estimation results do not reveal heterogeneous marginal effects across multiple parts of the conditional dependent variable distribution.

[9] Standard errors are estimated using a 200-resample Markov chain marginal bootstrap procedure (He and Hu, 2002). Without bootstrapping, observations are assumed to be *i.i.d.*, which implies that covariates do not cause scale shifts of the dependent variable's conditional distribution (Hao and Naiman, 2007). Bootstrapping provides appropriate standard error estimates.

[10] A 1-pound increase in average daily gain represents nearly a three-standard deviation change. Attaining such increases is difficult and highly valued by bull buyers, as indicated by the estimated coefficient. A one-standard deviation increase in average daily gain yields a 5.84% average change in a bull's price.

Table 1. Descriptive Statistics of Variables in the Bull Price Model

Variable (units)	Observations	Mean	Median	Standard Deviation	MAD	Maximum	Minimum
Bull sale price (dollars)	999	2,874.92	2,500.00	1,941.42	1,112.00	21,500.00	1,000.00
Logged bull sale price	999	7.83	7.82	0.48	0.41	9.98	6.91
Birth weight (lbs.)	999	82.89	83	7.99	7.41	111	50
Weaning weight (lbs.)	999	722.61	724	78.29	76.35	980	500
365-day weight (lbs.)	999	1,268.83	1,264.00	87.92	84.51	1,639.00	1,050.00
Bull age (days)	999	429.13	431	22.61	23.72	482	351
Average daily gain (lbs./day)	999	3.44	3.43	0.36	0.37	4.71	2.31
Intramuscular fat (percent)	999	3.59	3.53	0.7	0.68	6.54	1.74
Ribeye area (squared inches)	999	12.3	12.3	1.28	1.19	21.7	8.9
Feed-to-gain ratio	999	6.79	6.72	1.09	1.06	12.25	4.06
Residual feed intake (lbs./day)	999	0.00	0.07	1.69	1.46	7.12	–6.48
Birth weight EPD (lbs.)	999	1.6	1.7	1.67	1.63	6.2	–6.7
Birth-to-yearling gain EPD (lbs.)	999	79.19	82.3	18.08	16.31	120.5	2.6
Ribeye area EPD (squared in.)	999	0.18	0.16	0.19	0.19	0.93	–0.32
Milk EPD (lbs.)	999	21.59	22	6.31	5.93	39	–1.00
Sold at 67% fractional interest	999	0.31					
Sold at 75% fractional interest	999	0.05					
Bull breed indicator (1 if Black Angus)	999	0.69					
Year indicator (1 if 2009)	999	0.48					

MAD, standardized median absolute deviation.

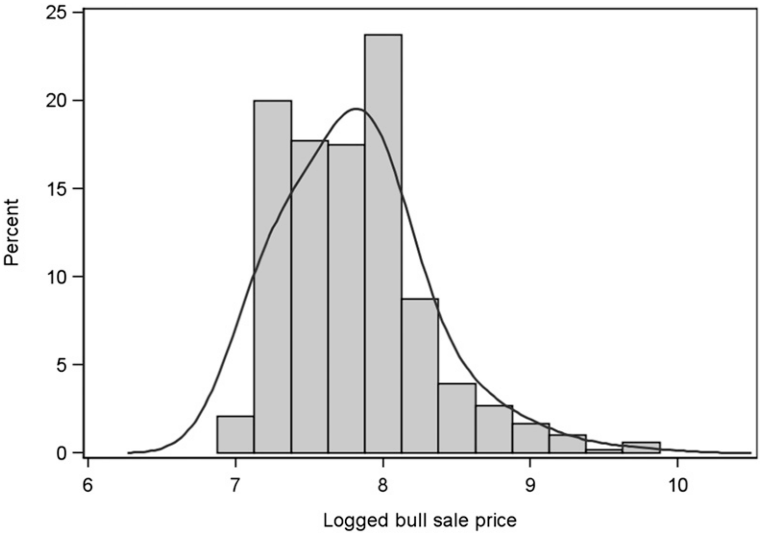

Figure 1. Histogram and Fitted Kernel Density of Logged Bull Sale Prices

controlled for by the bull breed indicator variable.

To evaluate potential nonlinear average partial effects associated with changes in values of explanatory variables, we added squared explanatory variables to the specification. The fit of the model improved with the addition of three squared terms: bull's age, ribeye area, and feed-to-gain ratio. In every case, the estimated coefficients associated with the squared variable indicated an expected outcome. That is, increase in a bull's age, ribeye area, and feed-to-gain ratio is valued by buyers, but these valuations decrease as the value of those characteristics increase.

Quantile Regression Results

The hedonic price function presented in equation (5) structurally controls for consumer considerations using observed bull characteristics. However, unobserved heterogeneity associated with perceived product differences and quality effects may still exist. Such effects would be manifest in the error term and semiparametric quantile regressions are used to quantify this potential heterogeneity. Empirical results of the quantile regressions indicate that different trait valuations across perceived bull quality levels exist. Because a tabular presentation of conditional quantile estimates across the entire spectrum would be voluminous, we only show estimates for the 10th, 25th, 50th, 75th, and 90th conditional quantiles in Table 2 but present the effects across the entire conditional price distribution in Figures 2 and 3. Estimated coefficients in each quantile represent ceteris paribus, the expected location shift in that particular quantile of the conditional bull price distribution.

An interpretation of results in Table 2 is best described with an example. Focusing on the intramuscular fat (IMF) characteristic, we find that a 1% increase in a bull's IMF is expected to increase bull prices by 3.6% at the 50th quantile (median). This conditional-median coefficient estimate is lower than the OLS conditional-mean partial effect estimate of 5.5%, suggesting that the skewed conditional price distribution may inflate expected location shifts of an average bull implied by the OLS model. In addition, parameter estimates across conditional quantiles reveal the effect of the product differentiation interaction term, $g(IMF_i,\ q_i)$. The results indicate that marginal increases in IMF monotonically increase across the conditional price distribution. At the 10th sample quantile of the conditional price distribution, an increase in IMF contributes to a 1.7% increase in sale price, whereas the same increase would raise the value of bulls at the 90th quantile by 12.2%. That is, within a peer group of bulls having a particular set of measurable characteristics, $\bar{X}$, some bulls are perceived to be substantially different than others, because consumers value marginal improvements in the IMF more in those bulls. Buyers in the lower tail of the conditional price distribution (those purchasing perceived lower-quality bulls as revealed by actual winning bid prices) are willing to pay less for improvements in IMF than buyers of perceived higher-quality bulls.

Bull buyers seek animals they believe can produce marketable and profit-maximizing progeny. In the case of IMF, bull buyers are focused on carcass quality characteristics that can contribute to obtaining higher premiums when marketing a bull's offspring. For example, producers marketing cattle using a grid pricing structure receive higher premiums for animals with higher marbling percentages. Consequently, there are incentives to acquire bulls whose progeny have a higher likelihood of having better IMF traits. When purchasing a bull, producers may perceive that animals from a particular seller are of a generally higher quality than bulls from other sellers because of successful past experiences with bulls from that ranch, favorable reputation of the seller, and/or because buyers believe that a combination of the bull's other traits imply that the animal is of higher quality. Consequently, the buyer perceives an improvement in the IMF characteristic of this higher-quality bull would result in offspring with better than average carcass qualities. These above-average qualities would increase the premiums from selling the bull's progeny and, consequently, raise the valuation of the bull's IMF characteristic and the willingness to pay for marbling improvements.

Quantile regression results can also be summarized with plots that help reveal the shape of product differentiation across the conditional price distribution. Figure 2 illustrates regression quantiles for the intramuscular fat covariate.[11] The conditional quantile effect of IMF at different sample price quantiles is represented by the solid line, and a 95% bootstrapped confidence interval is represented by the shaded region around the solid line. The solid line describes the change in a conditional price (within a particular sample quantile) resulting from a 1% change in IMF, holding all other covariates fixed. IMF has a statistically significant effect on conditional bull prices in all regression quantiles, as indicated by the exclusion of zero (shown by the thick black reference line) in the shaded confidence interval region. Moreover, the marginal effect of IMF increases across the entire conditional distribution with a substantial rise at the 75$^{\text{th}}$ sample quantile, suggesting that buyers of higher-quality bulls are willing to pay a higher premium for improvements in IMF. These estimated IMF conditional quantile effects indicate that quality considerations affect both location and scale of the conditional response distribution. For comparison, a pure location shift is depicted by the superimposed horizontal dashed and dotted lines, which represent the OLS estimate and a 95% confidence interval of IMF. The zero-sloped conditional-mean estimate line implies that buyers place the same value on IMF across all conditional bull prices.

Process plots for other bull characteristics of interest are shown in Figure 3. For the birth weight characteristic, quantile partial effects are relatively constant for bulls below the median but display a decrease in the upper sample quantiles. That is, buyers value marginal reductions (improvements) in birth weight greater for perceived higher-quality bulls. Conditional quantile estimates of bull age provide important inferences that were not estimated by the OLS model. Although OLS results suggest that bull age is statistically significant in affecting conditional bull sale prices, quantile regressions indicate that these OLS inferences are not robust across the entire conditional price distribution. Marginal conditional changes in bull age only affect prices of bulls perceived to be in the upper group of their peers (i.e., bulls with the same set of characteristics), increasing the bull's value by 0.05% for 1-day increases in age. Moreover, because the bull age variables

[11] Process plots represent 33 equally spaced conditional-quantile estimates, ranging from the 10$^{\text{th}}$ to the 90$^{\text{th}}$ quantile.

Table 2. Results for OLS and QR Estimation of Bull Sales Prices

		Quantile Regression: Estimated Conditional Quantiles				
Variable	OLS	10%	25%	50%	75%	90%
Intercept	–1.904	2.699	3.857***	2.099	0.717	–5.889***
	(–1.37)	(1.34)	(3.15)	(1.31)	(0.33)	(–2.62)
Birth weight	–0.008***	–0.007***	–0.006***	–0.005***	–0.007***	–0.011***
	(–9.05)	(–10.20)	(–10.70)	(–4.77)	(–5.76)	(–9.12)
Weaning weight	8E–4***	7E–4***	6E–4***	8E–4***	9E–4***	8E–4***
	(8.45)	(5.58)	(8.77)	(6.55)	(5.41)	(4.32)
365-day weight	6E–4***	2.00E–04	3E–4***	6E–4***	6E–4***	0.001***
	(5.26)	(1.62)	(2.95)	(4.15)	(2.73)	(3.47)
Bull age	0.026***	0.013	0.004	0.011	0.012	0.050***
	(4.12)	(1.4)	(0.69)	(1.5)	(1.22)	(5.52)
Bull age, squared	–3E–5***	–2E–05	–2E–05	–2E–05	–2E–05	–1E–4***
	(–3.88)	(–1.28)	(–0.46)	(–1.17)	(–1.09)	(–5.53)
Average daily gain	0.201***	0.182***	0.156***	0.154***	0.262***	0.215***
	(6.83)	(4.5)	(8.01)	(5.19)	(6.42)	(4.86)
Intramuscular fat	0.055***	0.017*	0.022***	0.036***	0.073***	0.122***
	(6.57)	(1.65)	(3.34)	(3.76)	(4.65)	(10.45)
Ribeye area	0.189***	0.016	0.121**	0.129***	0.223***	–0.09
	(6.82)	(0.3)	(2.33)	(4.23)	(8.03)	(–0.52)
Ribeye area, squared	–0.005***	0.002	–0.002	–0.003**	–0.006***	0.008
	(–4.46)	(0.81)	(–1.02)	(–2.36)	(–5.50)	(1.03)
Feed-to-gain ratio	0.117***	0.04	0.102***	0.009	0.099	0.310***
	(2.9)	(0.78)	(3.81)	(0.2)	(1.22)	(4.00)
Feed-to-gain ratio, squared	–0.006**	–8E–04	–0.005***	–1E+05	–0.006	–0.018***
	(–2.28)	(–0.26)	(–2.71)	(–0.02)	(–1.05)	(–3.38)
Residual feed intake	–0.032***	–0.016***	–0.024***	–0.022***	–0.028***	–0.050***
	(–7.22)	(–3.15)	(–7.42)	(–4.16)	(–4.25)	(–7.66)
Birth weight EPD	–0.055***	–0.047***	–0.050***	–0.060***	–0.055***	–0.070***
	(–12.70)	(–10.71)	(–14.88)	(–14.99)	(–9.62)	(–10.41)
Birth-to-yearling gain EPD	0.003***	0.003***	0.002***	0.004***	0.004***	0.008***
	(6.97)	(5.36)	(6.18)	(6.98)	(6.65)	(8.77)
Ribeye area EPD	0.027	–0.092**	–0.039	0.085**	0.065	0.127*
	(0.76	(–2.13)	(–1.19)	(2.34)	(1.21)	(1.88)
Milk EPD	–0.003***	–0.005***	–0.002**	–0.002	–0.002	–0.008***
	(–2.88)	(–5.38)	(–2.06)	(–1.26)	(–1.57)	(–3.30)
67% fractional interest sale	–0.001	–0.01	0.021***	0.015	–0.026*	–0.037*
	(–0.12)	(–0.62)	(2.61)	(1.25)	(–1.94)	(–1.69)
75% fractional interest sale	0.068***	0.043	0.046**	0.072***	–0.044	–0.095
	(2.64)	(1.01)	(2.1)	(2.73)	(–1.20)	(–1.06)
Bull breed indicator	0.033***	0.043***	0.043***	0.026***	0.021***	0.020***
	(12.52)	(16.12)	(22.65)	(11.11)	(6.98)	(4.86)
Year fixed effect	0.013	0.129***	0.052***	0.055***	–0.03	–0.068***
	(0.93)	(8.62)	(5.66)	(3.42)	(–1.49)	(–2.71)
Sale order	–0.001***	–0.001***	–0.001***	–0.001***	–0.001***	–0.001***
	(–17.85)	(–15.64)	(–32.51)	(–21.27)	(–10.76)	(–10.28)

Table 2. Continued

		Quantile Regression: Estimated Conditional Quantiles				
Variable	OLS	10%	25%	50%	75%	90%
R^2	0.53	0.54	0.53	0.49	0.50	0.43
Tests of joint significance						
F-test	193.56***	—	—	—	—	—
Wald test	—	661.19***	1,884.88***	798.63***	429.03***	473.36***
Likelihood ratio test	—	373.75***	763.00***	632.80***	443.16***	323.00***

Pseudo-R^2 is used for quantile regression. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; t-values are in parentheses.
OLS, ordinary least squares; QR, quantile regression; EPD, expected progeny difference.

enter the model nonlinearly, the empirical results indicate that marginal valuations of a bull's age exhibit a reduction in valuations as the bull continues to age.

Valuations of residual feed intake improvements are relatively constant for bulls below the 75th sample quantile but increase for higher-quality bulls. Conversely, improvements in birth weight EPD are relatively constant across the entire conditional logged price distribution, implying that the OLS estimate provides a relatively accurate representation of bull buyers' valuation across all bulls within a peer group. Birth-to-yearling EPD is statistically significant for all conditional quantiles, but changes in the EPD are more highly valued for bulls that are perceived to be of higher quality. Black Angus bulls are valued more highly than Red Angus bulls, but this valuation decreases with the perceived quality of the bull. This relationship is opposite for the year fixed effect parameter. Finally, the results show that the constant OLS estimate of the sale order is supported by the quantile regression results.

Lastly, we evaluate the hypothesis of nonconstant marginal valuations across the conditional price distribution in two ways. First, we use quantile regression process plots to visually assess whether a quantile partial effect estimate is statistically different from an average partial effect by observing whether the confidence intervals around the QR and OLS point estimates intersect. As shown in Figure 2, the confidence intervals for marginal valuations of the IMF trait do not intersect below the 35th

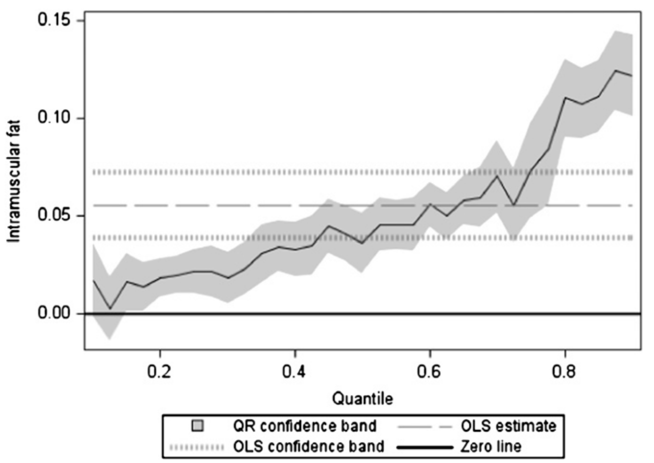

Figure 2. Intramuscular Fat Estimated Parameters in Quantile Regression (QR) and Ordinary Least Squares (OLS) Logged Bull Price Models

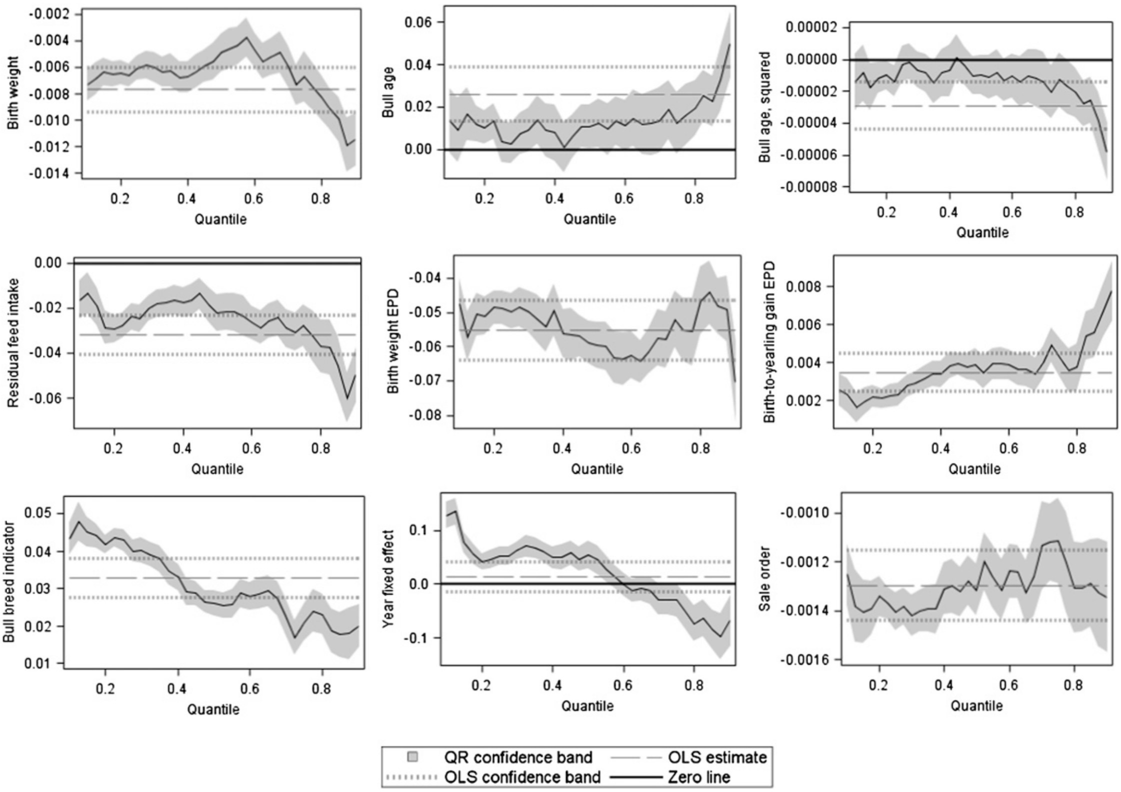

Figure 3. Marginal Effects for Estimated Quantile Regression (QR) and Ordinary Least Squares (OLS) Logged Bull Price Models

and above 75th sample quantiles, indicating that nonconstant marginal valuations are likely. Second, we follow the procedure in Koenker and Machado (1999) to test the hypothesis described previously as well as to determine whether a quantile partial effect in a particular sample quantile is statistically different for a quantile partial effect in another sample quantile. We find that statistically significant differences exist for the following variables: birth weight, average daily gain, intramuscular fat, ribeye area, residual feed intake, feed-to-gain ratio, residual feed intake, birth-to-yearling EPD, and ribeye area EPD for bulls purchased at 67% or 75% fractional interest and for bulls of different breeds.

Conclusions and Implications

This study uses quantile regression estimates of a hedonic model to evaluate marginal implicit values of differentiated agricultural products. Because consumers may value product characteristics differently depending on a set of nonquantifiable product considerations, traditional parametric estimation methods may not reveal these effects on consumer valuations. Furthermore, parameterizing perceived product differences may yield an inaccurate representation of consumer behavior. Quantile regressions provide a semiparametric framework that allows data to flexibly identify and estimate product difference and perception effects across a conditional price distribution.

We use a quantile regression framework to investigate how product difference considerations affect consumers' marginal valuation of bull growth and carcass traits. Auctions that facilitate sales for a heterogeneous set of bull producers offer buyers an opportunity to evaluate and bid on bulls of varying quality. Although not explicitly observable, consumers' considerations of bulls may be affected by seller's reputation, knowledge of bull trait heritability, and visual evaluations. If these characteristics affect a buyer's opinion about the overall quality of the bull and allow for the differentiation among animals, then buyers seeking to purchase lower-quality bulls may value specific bull traits differently than buyers interested in higher-quality animals. Although some quality attributes may be measurable, nonquantifiable traits are revealed by prices bidders actually pay for bulls. A hedonic model of bull sale prices obtained from the 2008 and 2009 MBT auctions is estimated. Regression quantiles show that substantial differences exist among buyer preferences and valuations of bull characteristics. For most bull growth and carcass traits, there exists a significant interaction among perceived differences in overall bull quality and bull traits.

Understanding how consumers value specific characteristics across a spectrum of products is important for making effective production decisions that are conditional on a product's expected quality within a peer group of products. Because there is often little *a priori* information of whether nonconstant valuations exist in agricultural markets, quantile regressions provide foundational knowledge of whether nonconstant marginal valuations of product characteristics exist and which characteristics are affected. If these differences exist, empirical results reveal the value of those valuation differences across market segments (as characterized by prices). More importantly, these inferences can generally not be replicated using traditional OLS estimations.

When producers know the expected segment in which their products are marketed—average prices in the market segment, reputation effects, and other signals are usually common knowledge (although often unquantifiable)—more precise knowledge of consumers' product characteristic valuations within a particular market segment could help them improve the valued characteristics in a particular market segment. For example, improving products by focusing on more highly valued characteristics within a product segment can help reduce production costs. Cost efficiency may be most important to producers of lower-quality products, because simply imitating higher-quality producers and improving all traits may substantially reduce profits. It is necessary to note, however, that quantile regression methods alone cannot predict the market segment in which a producer operates. Developing empirical methods that can accurately reveal this information is an avenue of future research in the quality differentiation literature.

Quality-differentiated products exist in many agricultural markets for which data do not explicitly reveal product differentiation by consumers; potential examples include alfalfa hay, fruit, flour, wine, farmland, and source-verified products. In each case, only limited information exists that clearly distinguishes values of these characteristics across the quality spectrum (e.g., historic land productivity, overall quality of products from the originating region). However, additional unobserved product differences and consumers' quality perceptions may explain price variations in these markets. For differentiated products, quantile regression methods may provide more informative analyses of consumer valuations than traditional parametric, conditional-mean estimation techniques.

[Received August 2011; Accepted July 2012.]

References

Arias, O., K.F. Hallock, and W. Sosa-Escudero. "Individual Heterogeneity in the Returns to Schooling: Instrumental Variables Quantile Regression Using Twins Data." *Empirical Economics* 26(2001):7–40.

Barnes, M.L., and A.W. Hughes. "A Quantile Regression Analysis of the Cross Section of Stock Market Returns." Working paper, Federal Reserve Bank of Boston, 2002.

Brester, G. "Meeting Consumer Demands with Genetics and Market Coordination: The Case of the Leachman Cattle Company." *Review of Agricultural Economics* 24(2002):251–65.

Buchinsky, M. "The Dynamics of Changes in the Female Wage Distribution in the USA: A Quantile Regression Approach." *Journal of Applied Econometrics* 13(1997):1–30.

Chamberlain, G. "Quantile Regression, Censoring and the Structure of Wages." *Advanced in Econometrics*. C. Sims, ed. New York, NY: Elsevier, 1994.

Chvosta, J., R. Rucker, and M. Watts. “Transaction Cost and Cattle Marketing: The Information Content of Seller-provided Presale Data at Bull Auctions.” *American Journal of Agricultural Economics* 83(2001):286–301.

Dhuyvetter, K., T. Schroeder, D. Simms, R. Bolze, and J. Geske. “Determinants of Purebred Beef Bull Price Differentials.” *Journal of Agricultural and Resource Economics* 21(1996):396–410.

Dickson, P., and J. Ginter. “Market Segmentation, Product Differentiation, and Marketing Strategy.” *Journal of Marketing* 51(1987): 1–10.

Eide, E., and M. Showalter. “The Effect of School Quality on Student Performance: A Quantile Regression Approach.” *Economics Letters* 58(1998):345–50.

Fitzenberger, B., R. Koenker, and J. Machado. *Economic Applications of Quantile Regression*. New York, NY: Springer, 2002.

Hao, L., and D. Naiman. *Quantile Regression*. Thousand Oaks, CA: Sage, 2007.

Hausman, J., and D. Wise. “Social Experimentation, Truncated Distributions, and Efficient Estimation.” *Econometrica: Journal of the Econometric Society* 45(1977):319–39.

He, X., and F. Hu. “Markov Chain Marginal Bootstrap.” *Journal of the American Statistical Association* 97(2002):783–95.

Heckman, J. “Sample Selection Bias as a Specification Error.” *Econometrica: Journal of the Econometric Society* 47(1979):153–61.

Huber, P. “Robust Regression: Asymptotics, Conjectures and Monte Carlo.” *Annals of Statistics* 1(1973):799–821.

———. *Robust Statistics*. New York, NY: John Wiley & Sons, 1981.

Jones, R.D., T. Turner, K.C. Dhuyvetter, and T.L. Marsh. “Estimating the Economic Value of Specific Characteristics Associated with Angus Bulls Sold at Auction.” *Journal of Agricultural and Applied Economics* 40(2008): 315–33.

Koch, R., L. Swiger, D. Chambers, and K. Gregory. “Efficiency of Feed Use in Beef Cattle.” *Journal of Animal Science* 22(1963):486–94.

Koenker, R. *Quantile Regression*. New York, NY: Cambridge University Press, 2005.

Koenker, R., and G. Bassett. “Regression Quantiles.” *Econometrica* 46(1978):33–49.

Koenker, R., and A. Machado. “Goodness of Fit and Related Processes for Quantile Regression.” *Journal of the American Statistical Association* 94(1999):1296–310.

Ladd, G., and M. Martin. “Prices and Demands for Input Characteristics.” *American Journal of Agricultural Economics* 58(1976):21–30.

Levin, J. “For Whom the Reductions Count: A Quantile Regression Analysis of Class Size on Scholastic Achievement.” *Empirical Economics* 26(2001):221–46.

Parcell, J.L., and T.C. Schroeder. “Hedonic Retail Beef and Pork Product Prices.” *Journal of Agricultural and Applied Economics* 39(2007):29–46.

Rosen, S. “Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition.” *The Journal of Political Economy* 82(1974): 34–55.

Schroeder, T.C., J.A. Espinosa, and B.K. Goodwin. “The Value of Genetic Traits in Purebred Dairy Bull Services.” *Review of Agricultural Economics* 14(1992):215–26.

Vanek, J., M. Watts, and G. Brester. “Carcass Quality and Genetic Selection in the Beef Industry.” *Journal of Agricultural and Resource Economics* 33(2008):349–63.

Walburger, A.M. “Estimating the Implicit Prices of Beef Cattle Attributes: A Case from Alberta.” *Canadian Journal of Agricultural Economics* 50(2002):135–49.

Yohai, V. “High Breakdown Point and High Efficiency Robust Estimates for Regression.” *Annals of Statistics* 15(1987):642–56.