8-2012

Three Essays on Contingent Valuation

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THREE ESSAYS ON CONTINGENT VALUATION

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Applied Economics

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by
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August 2012

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ABSTRACT

Contingent valuation (CV), a survey-based method, is widely used by researchers and government agencies to assess the value of those goods or services whose market price is not well defined. This dissertation comprises three essays analyzing and extending the theoretical foundations, estimation methods and empirical applications of the CV method. The first and second essay focuses on producers' willingness to pay for novel inputs or technologies. The first essay analyzes the theoretical underpinnings of producer WTP for new inputs. In addition to conceptualizing the producer WTP function, I derived its comparative statics and show how these properties can be used to recover quantity demanded or supplied and, in some cases, price elasticities. I also discuss the implications of these relationships to specify empirical WTP models and survey design. The WTP model is developed within the context of neoclassical theories of utility and profit maximization. Producers' WTP function for novel inputs or technologies is derived using individual indirect utility function in combination with the firm's profit function. Comparative statics results show that producers' WTP is a decreasing function of the upgraded input price, its initial quality level, and an increasing function of output price and final quality level.

In the second essay, CV methods using online and mail surveys are employed to estimate the economic value that registered producers place on the services received from an Electronic Trade Platform (i.e., MarketMaker). Estimation of the WTP model was carried out using parametric maximum likelihood estimation procedures. Results indicate

that producers, on average, are willing to pay $47.02 annually for the services they receive from MarketMaker and the annual aggregate valuation was calculated to be $361,960. The second essay also presents the effect of producers' characteristics and perceptions on their economic valuation of the site. Specifically, empirical results indicate that registration type, time registered on MarketMaker, time devoted to the website, type of user, the number of marketing contacts received and firm total annual sales have a significant effect on producers' WTP for the serviced provided by MarketMaker.

The third essay proposes alternative distribution-free methods for the estimation of WTP models using nonparametric conditional imputation and local regression procedures. The proposed estimators involve iterated procedures that combine nonparametric kernel density estimation of the errors of the WTP function with parametric linear or nonparametric kernel regression of its conditional mean function. In contrast to other distribution-free procedures (i.e., Turnbull approach), the proposed estimation methodology allows the inclusion of covariates in the modeling of WTP estimates, as well as the thorough recovery of its underlying probability distribution. Monte Carlo simulations are employed to compare the performance of the proposed estimators with that of the Turnbull estimator. Simulation results show that the proposed estimators perform substantially better than the Turnbull approach, and that conditional mean and marginal effect estimates of these models are analogous to the ones obtained using the benchmark correctly specified parametric model. The performance of the procedures is also evaluated using a real data set.

DEDICATION

I dedicated this dissertation to my wife, Cecilia. Her love and support were the source of my inspiration.

ACKNOWLEDGMENTS

First and above all, I thank the Lord for providing me this amazing opportunity and granting me the wisdom and strength to accomplish it.

I am grateful to my major professor, Dr. Carlos E. Carpio, for his constant encouragement, guidance and mentoring throughout these years. Working under his direction, I have acquired not only knowledge and experience, but, also, a professional attitude in terms of academic rigor and career dedication; this will be of benefit throughout my life. Also, I am thankful to the other committee members, Dr. Olga Isengildina-Massa, Dr. Dave Lamie and Dr. Patrick Gerard, for all their support and advice toward the completion of my dissertation.

My most sincere gratitude goes to my wife for her unfailing love, support and for always being by my side. This work would not be possible without her invaluable help. I would, also, like to thank my family for their love, support and encouragement during this time. Finally, I extend my thanks to my fellow graduate students and friends for their kindness and for enhancing my experience at Clemson.

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CHAPTER ONE

GENERAL INTRODUCTION

Contingent valuation (CV), a survey-based method, was initially developed to elicit the value (i.e., willingness to pay, WTP) that people place on non-market goods and services. The CV methodology was first proposed and implemented by Davis (1963) who designed a hypothetical scenario to assess the economic value of recreational possibilities of Maine's forests. Since then, CV methods have been widely used by researchers and government agencies as crucial tools in assessing the value that people place on goods or services whose market price is not well defined. This elicitation method has been used primarily in the assessment of individuals' WTP for environmental services (e.g., Carson et *al*., 1995; Boyle, 2003; Carson and Hanemann, 2005; Zapata et *al*., 2012). More recent applications of CV methods are found in other areas such as health economics (e.g., Diener et *al*., 1998; Krupnick et *al*., 2002), real estate appraising (e.g., Breffle et *al*., 1998; Banfi et *al*., 2008; Lipscomb, 2011), art valuation (e.g., Thompson et *al*., 2002), and agribusiness (e.g., Lusk and Hudson, 2004).

Great progress has also been achieved in the theoretical underpinning of the consumers' WTP measure. More specifically, it has been shown that consumers' WTP is not only a quantity, but is also a function of endogenous variables similar to cost, profit, or demand functions (Hanemann, 1984; Cameron, 1988).

One limitation of theoretical and empirical studies is their predominant focus on the WTP of consumers. Few conceptual and practical studies are found on the literature regarding the use of CV methods for producers. Moreover, applications of CV on agribusiness are mainly related to consumers' WTP for neoteric products, food quality enhancements, or specific attributes (e.g., Lusk, 2003; Carpio and Isengildina-Massa, 2009). Another theoretically valid application of CV is the use of CV to understand and estimate the monetary value that producers and agribusiness place on novel production factors. But, this use of CV has not seen much application to date and is largely ignored in the literature.

1.1. Elicitation Formats and Estimation Methods Employed in the CV Methodology

The standard elicitation format used by CV practitioners is the double-bounded dichotomous choice (DBDC) approach. This elicitation format consists of asking respondents two dichotomous choice questions. First, participants are asked if they are willing to pay a specific bid amount and then face a second question involving another bid, higher or lower depending on the response to the first question. One drawback of the DBCD approach is that it generates interval-censored responses; hence, the estimation of measures of central tendency (e.g., mean WTP) as well as the marginal effects of covariates on the mean WTP requires the use of specialized statistical techniques. Although, the majority of empirical studies using interval-censored responses from CV studies have been analyzed using parametric methods, in which a distribution function for the WTP measure is specified, some authors have advocated the use of distribution-free methods (e.g., Carson et *al*., 1992; Carson et *al*., 1994). With regard to distribution-free methods used to analyze CV interval-censored data, most of the literature is based on the nonparametric maximum likelihood (ML) estimation approach proposed by Turnbull (1974, 1976). The Turnbull approach is not without shortcomings. First, the probability distribution estimated with the procedure is only defined up to a discrete set of observed points. Second, the Turnbull approach does not allow for the inclusion of covariates in the modeling of respondents' WTP. Consequently, the impact of exogenous and endogenous variables on individuals' valuation (i.e., marginal effects) cannot be estimated. Furthermore, the Turnbull approach does not provide a point estimate of the mean WTP, but only upper and lower bound estimates. Hence, it is important to explore alternative distribution-free methods that can be used to analyze DBDC data to produce more refined estimates.

1.2. Dissertation Objectives and Overview

The general objective of this dissertation is to investigate and extend the literature regarding CV theoretical foundations, applications and estimation methods. The specific objectives are:

1. To analyze the theoretical underpinning of the monetary value that agricultural producers place on novel production factors.
2. To estimate the economic value that agricultural producers place on the services provided by an Electronic Trade Platform[1].
3. To develop alternative distribution-free estimation approaches that can be used to analyze interval-censored WTP data obtained using the DBDC elicitation method.

This dissertation comprises three essays. The first essay (Chapter 2) studies the theoretical foundations of producers' WTP for novel inputs. In particular, producers' WTP function is derived as well as its corresponding comparative statics. In the second essay (Chapter 3), I use CV methods to estimate the economic value (i.e., WTP) that producers registered in an Electronic Trade Platform place on the services received from this website. This essay also determines and quantifies the effect of producers' characteristics and perceptions on their

[1] Electronic Trade Platform are electronic systems that support the marketing, selling, buying, and servicing of products by matching vendors and buyers, providing intermediate trading transactions up to contract conclusion, and/or by providing the legal and technical institutional infrastructure and environment that facilitates these interchanges (Fritz et *al*., 2005).

economic valuation of the site. The third essay (Chapter 4) proposes alternative distribution-free methods to analyze DBDC data. The proposed estimators involve iterated procedures that combine nonparametric kernel density estimation of the errors of the WTP function with parametric or nonparametric estimation of its conditional mean function.

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CHAPTER TWO

THE THEORETICAL STRUCTURE OF PRODUCER WILLIGNESS TO PAY ESTIMATES

2.1. Abstract

This paper analyzes the theoretical underpinnings of producers' willingness to pay (WTP) for novel inputs. In addition to conceptualizing the WTP function for producers, I derive its comparative statics and demonstrate the use of these properties to estimate input quantities demanded, outputs supplied, and price elasticities. This study also discusses implications of the comparative statics results for the specification of empirical producer WTP models and survey design.

Key words: Cobb-Douglas production function, contingent valuation, new technologies, price elasticities, survey design.

2.2. Introduction

Producers and agribusinesses are constantly seeking new technologies or inputs with novel attributes that can help them reduce production costs and increase revenues. However, the novel nature of these products also means that prospective suppliers do not have data from actual markets to estimate the potential demand for these new technologies or inputs. To estimate producers' demands, suppliers of these novel factors can rely on stated preference methods such as contingent valuation.

Contingent valuation, a survey-based methodology, was initially developed to elicit the value (i.e., willingness to pay, WTP) that people place on non-market goods and services. This elicitation methodology has been used primarily in the assessment of individuals' WTP for environmental services (e.g., Carson et *al*., 1995; Boyle, 2003; Carson and Hanemann, 2005; Zapata et *al*., 2012). More recent applications of contingent valuation methodologies are found in other areas such as health economics (e.g., Diener et *al*., 1998; Krupnick et *al*., 2002), real estate appraising (e.g., Breffle et *al*., 1998; Banfi et *al*., 2008; Lipscomb, 2011), art valuation (e.g., Thompson et *al*., 2002), and agribusiness (e.g., Lusk and Hudson, 2004).

The majority of empirical and theoretical contingent valuation literature has focused on the consumer side, rather than on the producer side. For example, applications of contingent valuation on agribusiness are mainly related to consumers' WTP for neoteric products, food quality enhancements, or specific attributes (e.g., Lusk, 2003; Carpio and Isengildina-Massa, 2009). However, little conceptual or empirical work has been conducted to understand the monetary value that producers and agribusinesses place on new production factors.

The purpose of this paper is to extend the literature regarding producers' WTP for new technologies or inputs. More specifically, I derive the producers' WTP function (also called variation function) and its corresponding comparative statics, which have implications for the specification of empirical WTP models and survey design. In fact, I demonstrate the use of these properties to estimate the quantity demanded of novel inputs, the quantity supplied of the output and price elasticities. Hence, another contribution of this paper is the establishment of a link between traditional demand analyses (with emphasis on the estimation of price and income elasticities) and contingent valuation studies (with a focus on estimating a mean WTP value). This is important because agribusinesses are mainly interested in estimating market demand for novel products and market reaction measures such as price elasticities.

This paper is laid out as follows: Section 2.3 presents a brief literature review of contingent valuation and its uses in agribusiness. Section 2.4 discusses the theoretical structure of the WTP or variation function and comparative statics. Empirical implications of the theoretical results are presented in Section 2.5. Finally, Section 2.6 provides some brief conclusions. All proofs are presented in the Appendices.

2.3. Literature Review

The contingent valuation methodology was first proposed and implemented by Davis (1963) who designed a hypothetical scenario to assess the economic value of recreational possibilities of Maine’s forests. Since then, great progress has been achieved in empirical procedures and theoretical foundations of the contingent valuation method (Hanemann, 1984; Cameron, 1988). Contingent valuation methods are now widely used by researchers and government agencies as crucial tools in the assessment of environmental benefits (Carson et al., 1995; Boyle, 2003; Carson and Hanemann, 2005).

The theoretical foundations of discrete choice models for contingent valuation were developed by Hanemann (1984) and Cameron (1988). Both authors assumed that individual responses arose from discrete instances of utility maximization, which would imply a consumer WTP function with properties derived from neoclassical utility functions. However, the Cameron approach facilitates the derivation of comparative statics of the WTP function and is consistent with discrete choice and continuous valuation function models (Whitehead, 1995). Consider Whitehead's (1995) definition of consumers WTP for a policy with a goal to change the quality of goods consumed from $\boldsymbol{q}^0$ to $\boldsymbol{q}^1$:

$$WTP = m[\boldsymbol{p}, \boldsymbol{q}^0, v(\boldsymbol{p}, \boldsymbol{q}^1, y)] - m[\boldsymbol{p}, \boldsymbol{q}^0, v(\boldsymbol{p}, \boldsymbol{q}^0, y)] \tag{2.1}$$

$$= m[\boldsymbol{p}, \boldsymbol{q}^0, v(\boldsymbol{p}, \boldsymbol{q}^1, y)] - y,$$

where $m[\cdot]$ and $v(\cdot)$ are the individual's expenditures and indirect utility functions, respectively; $\boldsymbol{p}$ is the vector of good prices; $\boldsymbol{q}$ is a vector of quality of goods consumed; and y is income. Comparative statics of the WTP function can be derived by taking derivatives of equation (2.1) with respect to the variables of interest. For example, Whitehead (1995) shows that the effect of the price of the ith good on consumer WTP is

$$\frac{\partial WTP}{\partial p_i} = x_i^m(\cdot, \boldsymbol{q}^0) - \frac{m_v^0}{m_v^1} x_i^m(\cdot, \boldsymbol{q}^1), \tag{2.2}$$

where $x_i^m(\cdot, \boldsymbol{q}^0)$ and $x_i^m(\cdot, \boldsymbol{q}^1)$ are *Marshallian* demand functions before and after the quality change, respectively, and m_v^ι, $\iota = 0{,}1$, is the partial derivative of the expenditure function with respect to indirect utility ($m_v^\iota = \frac{\partial m}{\partial v}[\cdot, \boldsymbol{q}^\iota]$); $\iota = 0{,}1$, and all arguments other than environment quality level are suppressed for simplicity (Whitehead, 1995).

Comparative statics results, such as those presented in (2.2), can be used to theoretically interpret the results of contingent valuation empirical models or predict the change in demand for goods after quality improvement (McConnell, 1990; and Whitehead, 1995).

One limitation of this theoretical work is its focus on the WTP of consumers[2] Moreover, to the best of my knowledge, the implications of these properties for empirical work have been largely ignored. Similarly, on the empirical side, the vast majority of contingent valuation literature has focused on the consumer side rather than on producers.

Few empirical studies are found on the literature regarding the use of contingent valuation methods for producers. For example, the only studies found in the agribusiness literature related with this subject include the estimation of producers' WTP for information under risk (Roe and Antonovitz, 1985), crop insurance (Patrick, 1988), agricultural extension services (Whitehead et *al*., 2001, Budak et *al*., 2010), and novel technologies or inputs (Kenkel and Norris, 1995; Hudson and Hite, 2003). Overall, as the literature review shows, little conceptual and empirical work has been conducted to understand the monetary value that producers place on new production factors.

2.4. Theoretical Model and Comparative Statics

2.4.1. Theoretical Framework

The derivation of the producer WTP function for novel factors of production is based on the model used by McConnell and Bockstael (2005) to explain the effects of environmental changes in the firm production process. The theoretical model proposed in this paper allows the analysis of producers' WTP for a change in quality of any factor of production and not only a change in the environmental goods or services as in McConnell and Bockstael's model (2005).

[2] McConnell and Bockstael (2005) developed several theoretical models with the aim to conceptualize and measure the economic value that firms place on environmental services. However, the main emphasis of this work has been on elucidating the economic costs and benefits of environmental changes that influence production rather than explaining the economic value producers place on novel factors of production.

Suppose that an individual's utility is given by $U(\boldsymbol{Z})$, where $\boldsymbol{Z}$ is a vector of goods consumed by that individual. The problem faced by the individual consumer can be written as:

(2.3) $$max_{\boldsymbol{z}} U(\boldsymbol{Z}) \text{ subject to } \bar{m} + L = \boldsymbol{P}_{\boldsymbol{z}}^{`}\boldsymbol{Z},$$

where $\bar{m}$ and L are the individual's non-labor and labor income, respectively, and $\boldsymbol{P}_{\boldsymbol{z}}$ is a vector of prices. It is assumed that non-labor income $\bar{m}$ comes from a decision process independent of individual preferences. The indirect utility function is obtained by replacing the optimal quantity demanded of $\boldsymbol{Z} = \boldsymbol{Z}(\bar{m}, L, \boldsymbol{P}_{\boldsymbol{z}})$ into the utility function. Consequently, the indirect utility function is expressed in terms of variables that are assumed exogenous to the individual:

(2.4) $$V(\bar{m}, L, \boldsymbol{P}_{\boldsymbol{z}}) = V_0.$$

It is also assumed that the individual produces a product, Y, to sell it in the market. As a producer, she faces the following problem:

(2.5) $$max_Y \, \Pi = p_y Y - C(Y, \boldsymbol{r}, \boldsymbol{q}),$$

where Π is the profit function, p_y is the price of produced output, and $C(Y, \boldsymbol{r}, \boldsymbol{q})$ is the cost function of the individual's firm. The cost function can be defined as the solution of the following problem:

(2.6) $$min_{\boldsymbol{X}} \, C = \boldsymbol{r}^{`}\boldsymbol{X} \text{ subject to } Y = f(\boldsymbol{X}, \boldsymbol{q}),$$

where $\boldsymbol{r}$ is a vector of input prices, $\boldsymbol{X}$ is a vector of input quantities, $f(\boldsymbol{X}, \boldsymbol{q})$ is the production function of Y, and $\boldsymbol{q}$ is a vector of input quality levels. The level of $\boldsymbol{q}$ is fixed exogenously, thus the profit and cost functions are conditional on $\boldsymbol{q}$. Given p_y, $\boldsymbol{r}$, and $\boldsymbol{q}$, the producer chooses the optimal level of output, $Y(p_y, \boldsymbol{r}, \boldsymbol{q})$, and input, $\boldsymbol{X}(Y, \boldsymbol{r}, \boldsymbol{q})$, which generate the indirect profit function, $\Pi(p_y, \boldsymbol{r}, \boldsymbol{q})$, and cost function $C(Y, \boldsymbol{r}, \boldsymbol{q})$ (see Appendix 2.A).

The link between the consumer and producer problem is given by non-labor income, $\bar{\mathrm{m}}$, which can be assumed to be a function of profits such that $\frac{\partial \bar{\mathrm{m}}}{\partial \Pi} > 0$. Thus, $\bar{m} =$

$\overline{m}(\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}), k)$, where k represents other factors that affect non-labor income; therefore, (2.4) can be rewritten as:

$$(2.7) \qquad V[\overline{m}(\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}), k), L, \boldsymbol{P_z}] = V_0.$$

Then, the compensated variation (CV) and equivalent variation (EV) of a change in the vector of input quality level, $\boldsymbol{q}$, from $\boldsymbol{q}^0$ to $\boldsymbol{q}^1$ are the amounts of money that make the following conditions to hold:

$$(2.8) \quad V[\overline{m}(\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^0), k), L, \boldsymbol{P_z}] = V[\overline{m}(\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^1), k) - CV, L, \boldsymbol{P_z}]$$

$$(2.9) \quad V[\overline{m}(\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^0), k) + EV, L, \boldsymbol{P_z}] = V[\overline{m}(\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^1), k), L, \boldsymbol{P_z}].$$

In this context, CV and EV measures represent the economic value that the producer places on upgrades in input quality levels. Positive CV and EV measures imply a welfare improvement and vice versa. In general, CV and EV measures are not equal except when the variation in welfare comes from a change in exogenous income (e.g., change in the level of non-labor income). Consequently, the CV and EV measures in expressions (2.8) and (2.9) are identical and are given by the variation function (i.e., producer WTP function) d, which can be defined as:

$$(2.10) \qquad d = \overline{m}(\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^1), k) - \overline{m}(\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^0), k).$$

This is a variation function because it represents the CV or EV of the individual, depending on the initial and final levels of non-labor income (McConnell, 1990). If the improvement on a particular input quality level, q_i, results in an increase in profits, such that $d > 0$, then expression (2.10) represents the maximum (minimum) amount of profit that a producer would be willing to forgo (accept) to obtain (give up) the benefits of the new input quality level, q_i^1.

Under the assumption that non-labor income ($\overline{m}$) is a linear function of profit (Π) and k, then the variation on welfare due to a change in $\boldsymbol{q}$ from $\boldsymbol{q}^0$ to $\boldsymbol{q}^1$ is also a linear function of the difference in profits and can be simplified to [3]:

$$d = \Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^1) - \Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^0). \tag{2.11}$$

Consequently, the maximum amount of money a producer is WTP for improvements in input quality levels reduces to the difference between the *ex post* (after adopting the new input) and *ex ante* (before adopting the new input) firm's profit levels.

2.4.2. Comparative Statics of the Variation Function

To derive comparative statics, equation (2.5) can be used to rewrite the variation function (2.11) as[4]:

$$\begin{aligned} d = {} & \left[p_y Y(p_y, \boldsymbol{r}, \boldsymbol{q}^1) - C\left(Y(p_y, \boldsymbol{r}, \boldsymbol{q}^1), \boldsymbol{r}, \boldsymbol{q}^1\right)\right] \\ & -\left[p_y Y(p_y, \boldsymbol{r}, \boldsymbol{q}^0) - C\left(Y(p_y, \boldsymbol{r}, \boldsymbol{q}^0), \boldsymbol{r}, \boldsymbol{q}^0\right)\right]. \end{aligned} \tag{2.12}$$

Without loss of generality, it is assumed that only the quality of one input (i^{th} input) changes, such that $\boldsymbol{q}^1$ contains the same elements as $\boldsymbol{q}^0$ except for the i^{th} element, which is replaced by q_i^1 and the upgraded quality level of the i^{th} input is greater than its previous level

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[3] A general form of a variation function linear in profits is given by $d = b\left[\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^1) - \Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^0)\right]$, where b is a constant and can be thought of as the individual's discount factor of a firm's profits. If $b \neq 1$, then the stated individual producer WTP for novel inputs or technologies is not the value that the firm, as a whole, place on these new factors of production. Therefore, the model presented here only applies to a firm with only one owner. For a firm with multiple owners, the WTP question should be asked in terms of how much the firm is willing to pay for these inputs rather than in terms of the individual WTP value.

[4] The change in profits, due to a change in the vector of input quality levels, can also be derived by adapting the approach proposed by McConnell and Bockstael (2005) to analyze the change in producers' welfare measures of a change in the environmental quality input. Their approach involves the estimation of an essential output supply or input demand function which is later used to recover the change in profits.

$(q_i^1 > q_i^0)$. It is also assumed that the firm operates in a competitive market; thus, the change in quantity demanded of the novel input by the firm does not affect market prices.

To illustrate the theoretical results of the analysis, a Cobb-Douglas production function is used throughout this paper. Specifically, I consider the two inputs case where quality level of input 1 is upgraded and quality level of input 2 remains at its original level. The firm production process is represented by

$$Y = (q_1 x_1)^\alpha (q_2 x_2)^\beta, \tag{2.13}$$

where q_i and x_i, $i = 1,2$, are the levels of quality and quantity of input i, respectively. The product $q_i x_i$ can be seen as the total, or "true," measurement of input i (Griliches, 1957). It is also assumed that the firm has diminishing returns to scale, such that $\alpha + \beta < 1$, and the marginal products of both inputs are positive, therefore $\alpha > 0$ and $\beta > 0$. Furthermore, input quality levels, q_1 and q_2, are positive. Therefore, the variation function (2.11), which corresponds to the two inputs Cobb-Douglas production function in (2.13) is (see Appendix 2.B):

$$\begin{aligned} d &= \Pi\left(p_y, r_1, r_2, q_1^1, q_2^0\right) - \Pi\left(p_y, r_1, r_2, q_1^0, q_2^0\right) \\ &= [1 - (\alpha + \beta)] \left[{q_1^1}^{\frac{\alpha}{1-(\alpha+\beta)}} - {q_1^0}^{\frac{\alpha}{1-(\alpha+\beta)}} \right] \left[\frac{p_y \beta^\beta {q_2^0}^\beta \alpha^\alpha}{r_1^\alpha r_2^\beta} \right]^{\frac{1}{1-(\alpha+\beta)}}. \end{aligned} \tag{2.14}$$

Equation (2.14) clearly illustrates the theoretical structure of the variation or producer WTP function and reveals that WTP is not merely a quantity (i.e., the difference in *ex post* and *ex ante* profits), but is also a function of endogenous variables similar to cost, profit, or demand functions. Moreover, this theoretical structure can be used to derive comparative statics or marginal effects of a change in input and output prices and input quality levels on the variation function using known properties of the profit and cost functions.

2.4.2.1. *<u>Input Price Effects</u>*

The change in the variation function from a change in the input j price is

(2.15) $$\frac{\partial d}{\partial r_j} = \left.\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q}^0)}{\partial r_j}\right|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q}^0)} - \left.\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q}^1)}{\partial r_j}\right|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q}^1)},$$

where $\left.\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q}^\iota)}{\partial r_j}\right|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q}^\iota)}$, ι=0,1, represents the change in production cost due to a change in the input j price. Because $\left.\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial r_j}\right|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})} = x_j\big(Y(p_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q}\big)$, equation (2.15) can be written as (see Appendix 2.C):

(2.16) $$\frac{\partial d}{\partial r_j} = x_j\big(Y(p_y,\boldsymbol{r},\boldsymbol{q}^0),\boldsymbol{r},\boldsymbol{q}^0\big) - x_j\big(Y(p_y,\boldsymbol{r},\boldsymbol{q}^1),\boldsymbol{r},\boldsymbol{q}^1\big) = x_j^0 - x_j^1.$$

Note that the effect of a change in input j price on the variation function is given by the difference between the quantities of the input demanded before and after the change in input i quality level. The variation function "own price effect" $\left(\frac{\partial d}{\partial r_i}\right)$ will be negative if an improvement in the quality level of input i increases the quantity of input i that is demanded, so that $\frac{\partial x_i(Y(p_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}{\partial q_i} > 0$[5]. Similarly, the variation function "cross price effect" $\left(\frac{\partial d}{\partial r_j}\right)$ (for all $j \neq i$) will be negative (positive) if an upgrade in the quality level of input i results in an increase (decrease) in the quantity of input j that is demanded.

In the Cobb-Douglas case, the variation function own price and cross price effects are

(2.17) $$\frac{\partial d}{\partial r_1} = -\frac{\alpha}{1-(\alpha+\beta)}\frac{d}{r_1} < 0$$

and

[5] More precisely, the own price effect will be negative if $\frac{\partial x_i(Y(p_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}{\partial Y}\frac{\partial Y(p_y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i} + \left.\frac{\partial x_i(Y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i}\right|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})} > 0$, where the first term on the left-hand side is expected to be positive and the second term $\left.\frac{\partial x_i(Y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i}\right|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})}$ is expected to be negative.

(2.18) $$\frac{\partial d}{\partial r_2} = -\frac{\beta}{1-(\alpha+\beta)}\frac{d}{r_2} < 0,$$

respectively. For a producer willing to pay for an upgrade in the quality level of input 1 $(d > 0)$, both the variation function own price and cross price effects will be negative. Note from expression (2.14), d will be positive as long as the new quality level of input 1 is higher than its previous level (i.e., $q_1^1 > q_1^0$). Moreover, the general condition to have negative own price and cross price effects, $\frac{\partial x_i(Y(p_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}{\partial q_j} > 0$, $j = 1,2$, is met in the Cobb-Douglas case (i.e., the quantity of x_1 and x_2 demand increase with improvements in the quality level of input 1, where the specific increases are given by $\frac{\partial x_1(Y(p_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}{\partial q_1} = \frac{\alpha}{1-(\alpha+\beta)}\frac{x_1}{q_1} > 0$ and $\frac{\partial x_2(Y(p_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}{\partial q_1} = \frac{\beta}{1-(\alpha+\beta)}\frac{x_2}{q_1} > 0$).

2.4.2.2.<u>*Output Price Effect*</u>

The effect of a change in the output price on the variation function is (see Appendix 2.C):

(2.19) $$\frac{\partial d}{\partial p_y} = Y(p_y, \boldsymbol{r}, \boldsymbol{q}^1) - Y(p_y, \boldsymbol{r}, \boldsymbol{q}^0) = Y^1 - Y^0.$$

Hence, the change in d, due to a change in the output price, is given by the difference between the *ex post* and *ex ante* level of output produced. To sign this effect, additional comparative statics of the firm's profit maximization problem, described in (2.5), need to be derived. At the optimal level of $Y(P_y, \boldsymbol{r}, \boldsymbol{q})$, the following condition holds:

(2.20) $$\frac{\partial Y(p_y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i} = -\frac{C_{Yq_i}}{C_{YY}} = -\left(\frac{\partial \lambda(Y(P_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}{\partial Y}\right)^{-1} \frac{\partial \lambda(Y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i}\bigg|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})},$$

where $C_{YY} = \frac{\partial^2 C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial Y^2}$, $C_{Yq_i} = \frac{\partial^2 C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial Y \partial q_i}\bigg|_{Y=Y(P_y,\boldsymbol{r},\boldsymbol{q})}$ and λ is the Lagrangian multiplier, which represents the firm's marginal cost of production (see Appendix 2.C). Hence, the output price effect is positive if the firm operates where the marginal costs of production increase and an increase in the quality level of input i reduces the marginal cost of production. The two conditions requiring a positive output price effect are likely to occur in practice. First, firms are expected to operate in the "second stage of production" where the marginal product of inputs decreases with each extra unit of input; therefore, the marginal cost to produce each additional unit of output increases. Second, at given input prices and output levels, the use of more efficient inputs (e.g., inputs with higher quality levels) is expected to reduce costs that are incurred in producing each additional unit of output.

In the Cobb-Douglas case, the output price effect is positive and is given by

(2.21) $$\frac{\partial d}{\partial p_y} = \frac{1}{1-(\alpha+\beta)}\frac{d}{p_y} > 0.$$

Once again, the output price effect will be positive if $d > 0$. Additionally, the general properties, identified in expression (2.20), are $\frac{\partial \lambda(Y(P_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}{\partial Y} = \frac{1-(\alpha+\beta)}{(\alpha+\beta)}\frac{\lambda}{Y} > 0$ and $\left.\frac{\partial \lambda(Y,\boldsymbol{r},\boldsymbol{q})}{\partial q_1}\right|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})} = -\frac{\alpha}{(\alpha+\beta)}\frac{\lambda}{q_1} < 0$, where λ is positive because the cost function is non-decreasing in output (see Appendix 2.B).

2.4.2.3. *<u>Input Quality Effects</u>*

The effect of a change in the initial quality level of input i on the variation function is

(2.22) $$\frac{\partial d}{\partial q_i^0} = \left.\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q}^0)}{\partial q_i^0}\right|_{Y=Y(P_y,\boldsymbol{r},\boldsymbol{q}^0)}.$$

Note that expression (2.22) represents the change in the firm's original production cost because of a change in the initial quality level of input i. The firm's cost minimization problem described in (2.6) allows us to rewrite (2.22) as

(2.23) $$\frac{\partial d}{\partial q_i^0} = -\lambda(Y(P_y,\boldsymbol{r},\boldsymbol{q}^0),\boldsymbol{r},\boldsymbol{q}^0) f_{q_i^0}^0 ,$$

where $f^0_{q_i^0} = \left.\frac{\partial f(\boldsymbol{X},\boldsymbol{q}^0)}{\partial q_i^0}\right|_{\boldsymbol{X}=\boldsymbol{X}(Y(P_y,\boldsymbol{r},\boldsymbol{q}^0),\boldsymbol{r},\boldsymbol{q}^0)}$. $f^0_{q_i^0}$ can also be seen as the marginal product of q_i evaluated at the original input quality levels (see Appendix 2.C). Note that the initial input quality effect will be negative if the firm operates where both the marginal costs of production and the marginal product of q_i^o are positive. In general, a firm's marginal cost (λ) is nonnegative because the cost function is non-decreasing in output and improvements in the quality level of inputs are expected to expand the amount of output produced.

Similarly, the final input quality effect can be written as

$$\text{(2.24)} \qquad \frac{\partial d}{\partial q_i^1} = -\left.\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q}^1)}{\partial q_i^1}\right|_{Y=Y(P_y,\boldsymbol{r},\boldsymbol{q}^1)} = \lambda(Y(P_y,\boldsymbol{r},\boldsymbol{q}^1),\boldsymbol{r},\boldsymbol{q}^1)f^1_{q_i^1},$$

where $f^1_{q_i^1} = \left.\frac{\partial f(\boldsymbol{X},\boldsymbol{q}^1)}{\partial q_i^1}\right|_{\boldsymbol{X}=\boldsymbol{X}(Y(P_y,\boldsymbol{r},\boldsymbol{q}^1),\boldsymbol{r},\boldsymbol{q}^1)}$. As in the case of $\frac{\partial d}{\partial q_i^0}$, the final input quality effect is positive if the *ex post* marginal costs of production and marginal product of q_i^1 are both positive.

Finally, the effect on the variation function of a change in the quality level of input *j* (for all $j \neq i$), whose *ex post* and *ex ante* quality level is assumed to be the same, is

$$\text{(2.25)} \qquad \frac{\partial d}{\partial q_j^0} = \left.\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q}^0)}{\partial q_j^0}\right|_{Y=Y(P_y,\boldsymbol{r},\boldsymbol{q}^0)} - \left.\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q}^1)}{\partial q_j^0}\right|_{Y=Y(P_y,\boldsymbol{r},\boldsymbol{q}^1)}$$

$$= \lambda\big(Y\big(P_y,\boldsymbol{r},\boldsymbol{q}^1\big),\boldsymbol{r},\boldsymbol{q}^1\big)f^1_{q_j^0} - \lambda\big(Y\big(P_y,\boldsymbol{r},\boldsymbol{q}^0\big),\boldsymbol{r},\boldsymbol{q}^0\big)f^0_{q_j^0}.$$

Note that the two right-hand side terms in (2.25) differ only in the quality level of input i; therefore, this derivative can be signed by taking the first partial derivate of $\lambda\big(Y\big(P_y,\boldsymbol{r},\boldsymbol{q}\big),\boldsymbol{r},\boldsymbol{q}\big)f_{q_j}$ w.r.t. q_i, where $f_{q_j} = \left.\frac{\partial f(\boldsymbol{X},\boldsymbol{q})}{\partial q_j}\right|_{\boldsymbol{X}=\boldsymbol{X}(Y(P_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}$. Let $A = \lambda\big(Y\big(P_y,\boldsymbol{r},\boldsymbol{q}\big),\boldsymbol{r},\boldsymbol{q}\big)f_{q_j}$ then it is easily verified that $\frac{\partial A}{\partial q_i} = \lambda\big(Y\big(P_y,\boldsymbol{r},\boldsymbol{q}\big),\boldsymbol{r},\boldsymbol{q}\big)f_{q_jq_i}$, where $f_{q_jq_i} = \left.\frac{\partial^2 f(\boldsymbol{X},\boldsymbol{q})}{\partial q_j \partial q_i}\right|_{\boldsymbol{X}=\boldsymbol{X}(Y(P_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}$ (see Appendix 2.C).

Thus, if the marginal costs of production and $f_{q_j q_i}$ are both positive, then the input *j* quality effect is also positive. The term $f_{q_j q_i}$ is expected to be positive because an improvement in the quality of one input is likely to make other quality upgraded inputs even more productive.

The corresponding input quality effects for the Cobb-Douglas case are:

$$\frac{\partial d}{\partial q_1^0} = -\frac{\alpha}{1-(\alpha+\beta)} \frac{\Pi^0}{q_1^0} < 0, \tag{2.26}$$

$$\frac{\partial d}{\partial q_1^1} = \frac{\alpha}{1-(\alpha+\beta)} \frac{\Pi^1}{q_1^1} > 0 \tag{2.27}$$

and

$$\frac{\partial d}{\partial q_2^0} = \frac{\beta}{1-(\alpha+\beta)} \frac{d}{q_2^0} > 0, \tag{2.28}$$

where $\Pi^0 = \Pi(p_y, r_1, r_2, q_1^0, q_2^0) > 0$ and $\Pi^1 = \Pi(p_y, r_1, r_2, q_1^1, q_2^0) > 0$. Note that, in the Cobb-Douglas case, the variation function is decreasing in q_1^0 and increasing in q_1^1 and q_2^0. Moreover, the general properties needed to sign the direction of the different quality effects are given by $f_{q_1^\iota}^\iota = \alpha \frac{Y^\iota}{q_1^\iota} > 0$, $\iota = 1,0$, and $f_{q_2 q_1} = \alpha\beta \frac{Y}{q_1 q_2} > 0$.

2.5. Implications for Current Practice

The derived comparative statics of the variation, or WTP, function have significant implications for current practice. The first concerns the specification of empirical models and the design of surveys. The second implication relates to testing theoretical restrictions.

To clarify the role of the comparative statics results in the specification of empirical models and survey design, consider the simple case that includes only two inputs; the quality level on input 1 is upgraded while the quality level of input 2 remains constant. A linear variation function model including all the explanatory variables identified in the theoretical model (i.e., input prices, output price, and input quality levels) is[6]

$$d = \beta_0 + \beta_1 r_1 + \beta_2 r_2 + \beta_3 p_y + \beta_4 q_1^0 + \beta_5 q_1^1 + \beta_6 q_2^0 + \varepsilon, \quad (2.29)$$

where the $\beta_i's$ are coefficients to be estimated and ε is a zero mean error term. Note that coefficients corresponding to prices or quality levels (β_1 to β_6) can only be estimated if there is variability in the levels of these variables across producers. The variability in the exogenous variables can occur if producers face different prices or use products of different quality levels and can be collected as part of the survey. Alternatively, variability in the explanatory variables can be generated as part of the contingent valuation survey design (i.e., producers are given different hypothetical price and quality levels). After estimation, the marginal effects of the variation function can be recovered using the coefficients in (2.29), so that $\beta_1 = \frac{\partial d}{\partial r_1}$, $\beta_2 = \frac{\partial d}{\partial r_2}$, $\beta_3 = \frac{\partial d}{\partial p_y}$, $\beta_4 = \frac{\partial d}{\partial q_1^0}$, $\beta_5 = \frac{\partial d}{\partial q_1^1}$, and $\beta_6 = \frac{\partial d}{\partial q_2^0}$ and the signs of the coefficients compared to those derived in the theoretical section.

The estimated derived marginal effects from equation (2.29) can also be used to estimate *ex post* input and output quantities. For example, because

$$x_1^1 = x_1^0 - \frac{\partial d}{\partial r_1} \quad (2.30)$$

(from equation (2.16)) and

$$Y^1 = Y^0 + \frac{\partial d}{\partial p_y} \quad (2.31)$$

(from equation (2.19)), estimates of the *ex post* quantity demanded of input 1 (x_1^1) and *ex post* output supply (Y^1) can be calculated combining the estimates of $\frac{\partial d}{\partial r_1}$ and $\frac{\partial d}{\partial p_y}$ from (2.29) (i.e., β_1

[6] The model could also include characteristics of the firm or firm's owner but I exclude these to simplify the analysis.

and β_3) with the current amounts of input demanded (x_1^0) and output supplied (Y^0); these values can also be collected during the survey stage.

One limitation of the linear variation functional form in equation (2.29) is that it does not allow the estimation of marginal effects or elasticities of the new demand and supply functions. Specifically, estimation of marginal effects or elasticities requires the specification of a variation function that allows, at least, second order derivative calculations (e.g., by adding quadratic terms to equation (2.29)). Moreover, as in the case of the *ex post* input and output quantities estimation, the calculation of *ex post* elasticities requires knowledge of *ex ante* elasticity values or marginal effects. For example, the *ex post* input 1 own price marginal effect can be obtained by taking the partial derivate of x_1^1 with respect to r_1 in equation (2.30), which results in

$$\frac{\partial x_1^1}{\partial r_1} = \frac{\partial x_1^0}{\partial r_1} - \frac{\partial^2 d}{\partial {r_1}^2}, \tag{2.32}$$

and the corresponding *ex post* input 1 own price elasticity is given by

$$\varepsilon_{x_1 r_1}^1 = \frac{x_1^0}{x_1^1} \varepsilon_{x_1 r_1}^0 - \frac{\partial^2 d}{\partial {r_1}^2} \frac{r_1}{x_1^1}, \tag{2.33}$$

where $\varepsilon_{x_1 r_1}^0$ is the *ex ante* input 1 own price elasticity. Likewise, the *ex post* output price marginal effect can be estimated by taking the partial derivative of Y^1 with respect to p_y in expression (2.31). Specifically, the *ex post* output price marginal effect and price elasticity of supply are given by

$$\frac{\partial Y^1}{\partial p_y} = \frac{\partial Y^0}{\partial p_y} + \frac{\partial^2 d}{\partial {p_y}^2} \tag{2.34}$$

and

$$\varepsilon_{Y p_y}^1 = \frac{Y^0}{Y^1} \varepsilon_{Y p_y}^0 + \frac{\partial^2 d}{\partial {p_y}^2} \frac{p_y}{Y^1}, \tag{2.35}$$

respectively, where $\varepsilon_{Y p_y}^0$ is the *ex ante* price elasticity of supply.

It is also possible to envision an alternative use of the results obtained by estimating a variation function of the type shown in equation (2.29); specifically, in a case where all parameters of the production function of a firm or industry are known in advance. For example, for the 2 inputs Cobb-Douglas production function introduced earlier, the new input demand and output supply of the firm, derived from a change in the quality level of input 1 from q_1^0 to q_1^1, are given by $x_1^1 = x_1^0 + \frac{\alpha}{1-(\alpha+\beta)}\frac{d}{r_1}$, $x_2^1 = x_2^0 + \frac{\beta}{1-(\alpha+\beta)}\frac{d}{r_2}$, and $Y^1 = Y^0 + \frac{1}{1-(\alpha+\beta)}\frac{d}{p_y}$, respectively. Hence, the new inputs demand and supply values can be calculated using information from the original quantity demanded of inputs and quantity of output supplied the WTP value, and the parameters of the production function.

If the parameters of the production were known, the relevant derivatives of the new demand for input 1 are $\frac{\partial x_1^1}{\partial r_1} = -\frac{1-\beta}{(1-(\alpha+\beta))r_1}\left(x_1^0 - \frac{\partial d}{\partial r_1}\right)$, $\frac{\partial x_1^1}{\partial r_2} = -\frac{\beta}{(1-(\alpha+\beta))r_2}\left(x_1^0 - \frac{\partial d}{\partial r_1}\right)$, $\frac{\partial x_1^1}{\partial p_y} = \frac{1}{(1-(\alpha+\beta))p_y}\left(x_1^0 - \frac{\partial d}{\partial r_1}\right)$, and $\frac{\partial x_1^1}{\partial q_1^1} = \frac{\alpha}{(1-(\alpha+\beta))r_1}\frac{\partial d}{\partial q_1^1}$. Thus, in this case, the calculation of the marginal effects of the new demands only require information on the parameters of the production function, input or output levels, prices, and the marginal effects obtained from (2.29). Similarly, the derivatives of the new output supply, with respect to input prices, output price, and input 1 final quality level are $\frac{\partial Y^1}{\partial r_1} = -\frac{\alpha}{(1-(\alpha+\beta))r_1}\left(Y^0 + \frac{\partial d}{\partial p_y}\right)$, $\frac{\partial Y^1}{\partial r_2} = -\frac{\beta}{(1-(\alpha+\beta))r_2}\left(Y^0 + \frac{\partial d}{\partial p_y}\right)$, $\frac{\partial Y^1}{\partial p_y} = \frac{\alpha+\beta}{(1-(\alpha+\beta))p_y}\left(Y^0 + \frac{\partial d}{\partial p_y}\right)$, and $\frac{\partial Y^1}{\partial q_1^1} = \frac{1}{(1-(\alpha+\beta))p_y}\frac{\partial d}{\partial q_1^1}$, respectively[7]. Moreover, it is easily

[7] These marginal effects are derived using the fact that $\boldsymbol{X}(Y, \boldsymbol{r}, \boldsymbol{q})$ and $Y(p_y, \boldsymbol{r}, \boldsymbol{q})$ come from cost minimization and profit maximization (see Appendix 2.B for specific forms), respectively. Moreover, these derivatives can be signed using the comparative statics results presented in section 2.4. For example, the quantity demanded of the quality upgraded input (input 1) can be shown to decrease with its own and other input prices and increase with output price and its own final quality level.

shown that the *ex post* own input price elasticity of input 1 and price elasticity of supply for the Cobb-Douglas case are given by $\varepsilon^1_{x_1 r_1} = -\frac{1-\beta}{(1-(\alpha+\beta))}$ and $\varepsilon^1_{Y p_y} = \frac{\alpha+\beta}{(1-(\alpha+\beta))}$, respectively.

2.6. Summary and Conclusions

The main objective of this study was to analyze the theoretical underpinnings of producer WTP for new inputs. In addition to conceptualizing the producer WTP function, I derived its comparative statics and showed how these properties can be used to recover the quantity demanded or supplied and, in some cases, price elasticities. I also discussed implications of this relationship to specify empirical WTP models and survey design.

The WTP model presented was developed within the context of neoclassical theories of utility and profit maximization. More specifically, the variation function, or producers' WTP, for novel inputs or technologies is derived using an individual indirect utility function in combination with the firm's profit function. This theoretical model is developed in a context where the production function $f(\cdot)$ has, as arguments, a vector of input quantities $\boldsymbol{X}$ and a vector of input quality levels $\boldsymbol{q}$. The level of $\boldsymbol{q}$ is fixed exogenously, thus the profit and cost functions are also conditional on $\boldsymbol{q}$. The analysis considers an improvement on a particular input quality level, q_i.

The theoretical results imply that the maximum amount of money that a producer is WTP for a new production factor is equal to the difference between the *ex post* and *ex ante* firm's profit levels. Moreover, the results suggest that the producers' WTP is a function of output and input prices and input *ex ante* and *ex post* quality levels. Comparative statics results show that producers' WTP is a decreasing function of upgraded input price, its initial quality level, and an increasing function of output price and final quality level.

Use of the structure required by profit and utility maximization is also helpful in empirical practice. Here, I demonstrated the use of comparative statics results to estimate input demanded, output supplied, and price elasticities after the change in the input quality. However, estimation of these values is dependent upon the empirical model used and data availability. Thus, the results of this study should be of considerable use in specifying empirical WTP models and survey design.

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2.8. Appendices

Appendix 2.A. Cost Minimization and Profit Maximization Problems.

<u>*Cost minimization problem*</u>

The Lagrangian function of the cost minimization problem is given by

(2.A.1) $$\mathcal{L}(\boldsymbol{X}) = \boldsymbol{r}`\boldsymbol{X} + \lambda(Y - f(\boldsymbol{X}, \boldsymbol{q}))$$

and the FOC can be represented by

(2.A.2) $$r_i - \lambda f_{x_i} = 0 \quad \forall\, i$$

and

(2.A.3) $$Y - f(\boldsymbol{X}, \boldsymbol{q}) = 0,$$

where $f_{x_i} = \frac{\partial f(\boldsymbol{X},\boldsymbol{q})}{\partial x_i}$. The FOC imply that

(2.A.4) $$\boldsymbol{X} = \boldsymbol{X}(Y, \boldsymbol{r}, \boldsymbol{q})$$

and

(2.A.5) $$\lambda = \lambda(Y, \boldsymbol{r}, \boldsymbol{q}).$$

The cost function is obtained by replacing (2.A.4) and (2.A.5) into (2.A.1)

(2.A.6) $$C(Y, \boldsymbol{r}, \boldsymbol{q}) = \boldsymbol{r}`\boldsymbol{X}(Y, \boldsymbol{r}, \boldsymbol{q}) + \lambda(Y, \boldsymbol{r}, \boldsymbol{q})[Y - f(\boldsymbol{X}(Y, \boldsymbol{r}, \boldsymbol{q}), \boldsymbol{q})\,].$$

At the optimum, partial derivatives of (2.A.6) w.r.t. Y, r_i and q_i, respectively, are given by

(2.A.7) $$\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial Y} = \lambda(Y, \boldsymbol{r}, \boldsymbol{q}) + \sum_i \frac{\partial x_i}{\partial Y}\left(r_i - \lambda f_{x_i}\right) + \frac{\partial \lambda}{\partial Y}(Y - f(\boldsymbol{X}, \boldsymbol{q})\,)$$

$$= \lambda(Y, \boldsymbol{r}, \boldsymbol{q}),$$

(2.A.8) $$\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial r_i} = x_i(Y, \boldsymbol{r}, \boldsymbol{q}) + \sum_i \frac{\partial x_i}{\partial r_i}\left(r_i - \lambda f_{x_i}\right) + \frac{\partial \lambda}{\partial r_i}(Y - f(\boldsymbol{X}, \boldsymbol{q})\,)$$

$$= x_i(Y, \boldsymbol{r}, \boldsymbol{q})$$

and

(2.A.9) $$\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i} = -\lambda(Y, \boldsymbol{r}, \boldsymbol{q}) f_{q_i} + \sum_i \frac{\partial x_i}{\partial q_i}\left(r_i - \lambda f_{x_i}\right) + \frac{\partial \lambda}{\partial q_i}(Y - f(\boldsymbol{X}, \boldsymbol{q})\,)$$

$$= -\lambda(Y,\boldsymbol{r},\boldsymbol{q})f_{q_i} ,$$

where $f_{q_i} = \frac{\partial f(\boldsymbol{X},\boldsymbol{q})}{\partial q_i}\Big|_{\boldsymbol{X}=\boldsymbol{X}(Y,\boldsymbol{r},\boldsymbol{q})}$.

<u>Profit maximization problem</u>

The producer's cost maximization problem is given by

(2.A.10) $$max_Y \Pi = p_y Y - C(Y,\boldsymbol{r},\boldsymbol{q})$$

and the FOC from (2.A.10) is

(2.A.11) $$p_y - \frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial Y} = 0.$$

From (2.A.11) we obtain that

(2.A.12) $$Y = Y(p_y,\boldsymbol{r},\boldsymbol{q}).$$

The firm's profit function is obtained by replacing (2.A.12) into (2.A.10)

(2.A.13) $$\Pi(p_y,\boldsymbol{r},\boldsymbol{q}) = p_y Y(p_y,\boldsymbol{r},\boldsymbol{q}) - C(Y(p_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q}).$$

The partial derivatives of the profit function w.r.t. p_y, r_i and q_i, respectively, are given by

(2.A.14) $$\frac{\partial \Pi(p_y,\boldsymbol{r},\boldsymbol{q})}{\partial p_y} = Y(p_y,\boldsymbol{r},\boldsymbol{q}) + \frac{\partial Y}{\partial p_y}\left(p_y - \frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial Y}\right)$$

$$= Y(p_y,\boldsymbol{r},\boldsymbol{q}),$$

(2.A.15) $$\frac{\partial \Pi(p_y,\boldsymbol{r},\boldsymbol{q})}{\partial r_i} = -\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial r_i}\Big|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})} + \frac{\partial Y}{\partial r_i}\left(p_y - \frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial Y}\right)$$

$$= -\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial r_i}\Big|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})}$$

and

(2.A.16) $$\frac{\partial \Pi(p_y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i} = -\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i}\Big|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})} + \frac{\partial Y}{\partial q_i}\left(p_y - \frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial Y}\right)$$

$$= -\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i}\Big|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})}.$$

Appendix 2.B. Derivation of the Variation Function under a Cobb-Douglas Two Inputs Production Function.

It is assumed that the production of the output Y is given by

(2.B.1) $$Y = (q_1 x_1)^{\alpha}(q_2 x_2)^{\beta}.$$

Thus, the cost minimization problem of the firm is represented by

(2.B.2) $$min_{x_1,x_2} C = r_1 x_1 + r_2 x_2 \text{ subject to } Y = (q_1 x_1)^{\alpha}(q_2 x_2)^{\beta}$$

and the first order conditions (FOC) are given by

(2.B.3) $$r_1 = \lambda\alpha(q_1 x_1)^{\alpha-1}(q_2 x_2)^{\beta} q_1,$$

(2.B.4) $$r_2 = \lambda\beta(q_1 x_1)^{\alpha}(q_2 x_2)^{\beta-1} q_2$$

and

(2.B.5) $$Y = (q_1 x_1)^{\alpha}(q_2 x_2)^{\beta},$$

where λ is the Lagrangian multiplier.

From the FOC the optimal level of input 1 and 2, respectively, are

(2.B.6) $$x_1 = \left[\frac{Y r_2{}^{\beta} \alpha^{\beta}}{r_1^{\beta} q_1^{\alpha} q_2^{\beta} \beta^{\beta}}\right]^{\frac{1}{(\alpha+\beta)}}$$

and

(2.B.7) $$x_2 = \left[\frac{Y r_1^{\alpha} \beta^{\alpha}}{r_2^{\alpha} q_1^{\alpha} q_2^{\beta} \alpha^{\alpha}}\right]^{\frac{1}{(\alpha+\beta)}}$$

The cost function is obtained by replacing the optimal level of x_1 and x_2 into (2.B.2)

(2.B.8) $$C(Y, \boldsymbol{r}, \boldsymbol{q}) = (\alpha+\beta)\left[\frac{Y r_1^{\alpha} r_2{}^{\beta}}{q_1^{\alpha} q_2^{\beta} \alpha^{\alpha} \beta^{\beta}}\right]^{\frac{1}{(\alpha+\beta)}}.$$

Then, the producer's profit maximization problem is given by

(2.B.9) $$max_Y \Pi = P_y Y - (\alpha+\beta)\left[\frac{Y r_1^{\alpha} r_2{}^{\beta}}{q_1^{\alpha} q_2^{\beta} \alpha^{\alpha} \beta^{\beta}}\right]^{\frac{1}{(\alpha+\beta)}}$$

and the optimal output level from (2.B.9) is

$$(2.B.10) \qquad Y = \left[\frac{P_y^{\alpha+\beta} q_1^{\alpha} q_2^{\beta} \alpha^{\alpha} \beta^{\beta}}{r_1^{\alpha} r_2{}^{\beta}}\right]^{\frac{1}{1-(\alpha+\beta)}}.$$

The profit function is obtained by replacing (2.B.10) into (2.B.9)

$$(2.B.11) \qquad \Pi = [1-(\alpha+\beta)]\left[\frac{P_y q_1^{\alpha} q_2^{\beta} \alpha^{\alpha} \beta^{\beta}}{r_1^{\alpha} r_2{}^{\beta}}\right]^{\frac{1}{1-(\alpha+\beta)}}.$$

Finally, the change in profits or variation function from a change in the quality level of input 1 from q_1^0 to q_1^1 is given by

$$(2.B.12) \qquad d = [1-(\alpha+\beta)]\left[q_1^{1\frac{\alpha}{1-(\alpha+\beta)}} - q_1^{0\frac{\alpha}{1-(\alpha+\beta)}}\right]\left[\frac{p_y \beta^{\beta} q_2^{0\,\beta} \alpha^{\alpha}}{r_1^{\alpha} r_2^{\beta}}\right]^{\frac{1}{1-(\alpha+\beta)}}.$$

Appendix 2.C. Comparative Statics of the Variation Function.

Input price effects

The change in the variation function from a change in the price of input i is

(2.C.1) $$\frac{\partial d}{\partial r_i} = \frac{\partial \Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^1)}{\partial r_i} - \frac{\partial \Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^0)}{\partial r_i}.$$

By replacing the appropriate forms of (2.A.15) into (2.C.1), then expression (2.C.1) can be rewritten as

(2.C.2) $$\frac{\partial d}{\partial r_i} = \left.\frac{\partial C(Y, \boldsymbol{r}, \boldsymbol{q}^0)}{\partial r_i}\right|_{Y=Y(p_y, \boldsymbol{r}, \boldsymbol{q}^0)} - \left.\frac{\partial C(Y, \boldsymbol{r}, \boldsymbol{q}^1)}{\partial r_i}\right|_{Y=Y(p_y, \boldsymbol{r}, \boldsymbol{q}^1)}$$

and by replacing expression (2.A.8) into (2.C.2) we can express $\frac{\partial d}{\partial r_i}$ as

(2.C.3) $$\frac{\partial d}{\partial r_i} = x_i\big(Y(p_y, \boldsymbol{r}, \boldsymbol{q}^0), \boldsymbol{r}, \boldsymbol{q}^0\big) - x_i\big(Y(p_y, \boldsymbol{r}, \boldsymbol{q}^1), \boldsymbol{r}, \boldsymbol{q}^1\big).$$

Output price effect

The effect of a change in the output price on the variation function is given by

(2.C.4) $$\frac{\partial d}{\partial p_y} = \frac{\partial \Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^0)}{\partial p_y} - \frac{\partial \Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^1)}{\partial p_y}.$$

From expression (2.A.14) we can rewrite (2.C.4) as

(2.C.5) $$\frac{\partial d}{\partial p_y} = Y(p_y, \boldsymbol{r}, \boldsymbol{q}^1) - Y(p_y, \boldsymbol{r}, \boldsymbol{q}^0).$$

Moreover, replacing (2.A.12) back into (2.A.11) and taking the partial derivative of (2.A.11) w.r.t. q_i yields

(2.C.6) $$C_{YY}\frac{\partial Y(p_y, \boldsymbol{r}, \boldsymbol{q})}{\partial q_i} = -C_{Yq_i},$$

where $C_{YY} = \frac{\partial^2 C(Y, \boldsymbol{r}, \boldsymbol{q})}{\partial Y^2}$ and $C_{Yq_i} = \left.\frac{\partial^2 C(Y, \boldsymbol{r}, \boldsymbol{q})}{\partial Y \partial q_i}\right|_{Y=Y(p_y, \boldsymbol{r}, \boldsymbol{q})}$. By rearranging terms, at the optimum production level the change in $Y(p_y, \boldsymbol{r}, \boldsymbol{q})$ w.r.t. q_i is equal to

(2.C.7) $$\frac{\partial Y(p_y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i} = -\frac{C_{Yq_i}}{C_{YY}}.$$

By (2.A.7) it is easily verified that expression (2.C.7) can be written as

(2.C.8) $$\frac{\partial Y(p_y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i} = -\left(\frac{\partial \lambda(Y(P_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}{\partial Y}\right)^{-1} \frac{\partial \lambda(Y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i}\bigg|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})}.$$

Input quality effects

The effect of a change in the initial quality level of input i, q_i^0, on the variation function is

(2.C.9) $$\frac{\partial d}{\partial q_i^0} = \frac{\partial \Pi(p_y,\boldsymbol{r},\boldsymbol{q}^0)}{\partial q_i^0}.$$

By replacing (2.A.16) into (2.C.9) we can rewrite expression (2.C.9) as

(2.C.10) $$\frac{\partial d}{\partial q_i^0} = -\frac{\partial C(Y,\boldsymbol{r},\boldsymbol{q}^0)}{\partial q_i}\bigg|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q}^0)}.$$

Finally, replace (2.A.9) into (2.C.10) to obtain

(2.C.11) $$\frac{\partial d}{\partial q_i^0} = -\lambda(Y(P_y,\boldsymbol{r},\boldsymbol{q}^0),\boldsymbol{r},\boldsymbol{q}^0)f^0_{q_i^0}.$$

The same logic can used to derive the marginal effects of a change in the final quality level of input i, $\frac{\partial d}{\partial q_i^1}$, or the marginal effect of a change in the quality level of input j, $\frac{\partial d}{\partial q_j^0}$, on the variation function.

In the case of $\frac{\partial d}{\partial q_j^0}$, let $A = \lambda\big(Y\big(P_y,\boldsymbol{r},\boldsymbol{q}\big),\boldsymbol{r},\boldsymbol{q}\big)f_{q_j}$, then the partial derivative of A w.r.t. q_i is given by

(2.C.12) $$\frac{\partial A}{\partial q_i} = \left[\frac{\partial \lambda\big(Y(P_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q}\big)}{\partial Y}\frac{\partial Y(P_y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i} + \frac{\partial \lambda(Y,\boldsymbol{r},\boldsymbol{q})}{\partial q_i}\bigg|_{Y=Y(p_y,\boldsymbol{r},\boldsymbol{q})}\right]f_{q_j}$$

$$+\lambda\big(Y\big(P_y,\boldsymbol{r},\boldsymbol{q}\big),\boldsymbol{r},\boldsymbol{q}\big)f_{q_jq_i},$$

where $f_{q_jq_i} = \frac{\partial^2 f(\boldsymbol{X},\boldsymbol{q})}{\partial q_j \partial q_i}\Big|_{\boldsymbol{X}=\boldsymbol{X}(Y(P_y,\boldsymbol{r},\boldsymbol{q}),\boldsymbol{r},\boldsymbol{q})}$. Finally, by (2.C.8) expression (2.C.12) can be written as

(2.C.13) $$\frac{\partial A}{\partial q_i} = \lambda\big(Y\big(P_y, \boldsymbol{r}, \boldsymbol{q}\big), \boldsymbol{r}, \boldsymbol{q}\big) f_{q_j q_i}.$$

CHAPTER THREE

THE ECONOMIC IMPACT OF THE SERVICES PROVIDED BY AN ELECTRONIC TRADE PLATFORM: THE CASE OF MARKETMAKER

3.1. Abstract

In spite of the touted potential of E-commerce to improve profits in agriculture, the literature on the economic impact of E-commerce is very limited. This paper assesses the economic impact of an Electronic Trade Platform (i.e., MarketMaker) on agricultural producers. Contingent valuation techniques are employed to estimate the monetary value that registered producers placed on the services provided by MarketMaker. Results indicate that producers, on average, are willing to pay $47.02 annually for the services they receive from MarketMaker. Empirical results indicate that registration type, time registered on MarketMaker, time devoted to the website, type of user, the number of marketing contacts received and firm total annual sales have a significant effect on producers' WTP for the services provided by MarketMaker.

Key words: Contingent valuation, E-commerce, nonparametric methods, willingness to pay.

3.2. Introduction

Agricultural producers' use of computers and the Internet has increased in recent years. In 2011, 62 percent of U.S. farms had Internet access and 65 percent had access to a computer, compared to 29 percent and 47 percent in 1999, respectively (USDA-NASS, 1999, 2011). One of the potential applications of computers and the Internet in agriculture is E-commerce, which refers to the use of the Internet to market, buy and sell goods and services, exchange information, and create and maintain web-based relationships between participant entities (Fruhling and Digman, 2000).

E-commerce has been said to have the potential to both increase sales revenues, as well as to significantly decrease costs through greater efficiencies of operation. Gains in efficiency could result from the reduction of inventory levels, transportation costs, information costs, and order and delivery times (Batte and Ernst, 2007; Montealegre et *al*., 2007).

In spite of the touted potential of E-commerce to improve profits in agriculture, the literature on the economic impact of E-commerce in agribusinesses is very limited. Most of the literature related to the use of computers and the Internet has focused on describing and analyzing the extent of adoption and usage by agribusiness (e.g., USDA-NASS, 2011; Batte, 2004). Moreover, studies evaluating E-commerce websites have focused on assessing users-perceived quality rather than on the economic impacts these sites generate.

The main objective of this study is to extend the E-commerce impact literature by assessing the economic benefits of an Electronic Trade Platform[8] (i.e., MarketMaker) on agricultural producers. Specifically, contingent valuation methods are employed to estimate the economic value (i.e., willingness to pay, WTP) that producers[9] registered in MarketMaker place on the services received from this trade platform. I also evaluate the effect of producers' characteristics and perceptions on producers' economic valuation of the site. In addition, an alternative and practical nonparametric technique is proposed to estimate the means of the variables when their actual values are observed to fall in a certain interval on a continuous scale.

MarketMaker is one of the most extensive collections of electronic searchable food industry related data engines in the country. MarketMaker is a free electronic resource that allows producers to select consumer attributes and receive a geo-coded response that shows the location of consumers with those attributes. A second feature on the web site includes business data that allows producers to identify other potential supply chain partners. For consumers – households, processors, handlers, retail, and wholesale companies – MarketMaker provides useful information to decide where to purchase products and to identify upstream opportunities for adding value before final sale. Therefore, the MarketMaker website can be used by registered producers as a free marketing tool that helps identifying new customers and provides potential clientele with

[8] Electronic Trade Platforms are electronic systems that support the marketing, selling, buying, and servicing of products by matching vendors and buyers, providing intermediate trading transactions up to contract conclusion, and/or by providing the legal and technical institutional infrastructure and environment that facilitates these interchanges (Fritz et *al*., 2005).

[9] Agricultural producers include both farmers and fishermen.

detailed information about farmers' product portfolio, geographic location and contact information. To date, the site is operating in 18 states[10] through the country with over 17,500 profiles – including 7,698 producers – and receives about 1 million hits per month from over 86,000 food industry entrepreneurs.

3.3. Literature Review

The majority of studies evaluating E-Commerce platforms have focused on assessing users-perceived quality of websites based on their design, usability, and performance rather than on the economic impacts that the E-Commerce Platforms generate for their users. For example, Agarwal and Venkatesh (2002) developed a method for measuring and rating specific components of E-commerce website usability from user's perspective such as content quality and design, ease of use and tailoring of a website to fit particular user's needs. Aladwani and Palvia (2001) in addition to website usability also considered the quality of website's technical components including security, availability, interactivity, speed of page loading and customer services. More comprehensive studies have highlighted the importance of other dimensions of perceived web quality beyond those related to the interaction with the E-commerce site. For example, Petre et *al*. (2006) developed an evaluation instrument that measures both purchase and post-purchase web capabilities. Post-purchase components include delivery of products, post-sales support and quality of products and services. The above evaluation

[10] States that have launched MarketMaker sites including Illinois, Iowa, Nebraska, Kentucky, New York, Georgia, Mississippi, Michigan, Ohio, Indiana, South Carolina, Colorado, Arkansas, Florida, Pennsylvania, Louisiana, Alabama and Washington D.C.

methodologies were used to measure the quality of different E-commerce websites including banks, bookstores, car manufactures, electronic retailers and travel-related services.

One of the few studies evaluating economic impacts of E-Commerce platforms was conducted by Ubramaniam and Shaw (2002). The authors estimated the cost savings of a heavy-equipment manufacturer associated to the procurement of indirect inputs through Electronic Trade Platforms. Specifically, the implementation of an electronic business to business collaboration system resulted in procurement cost saving between 33 and 68 percent.

Studies evaluating the effectiveness of specific agricultural E-commerce platforms such as MarketMaker are very limited. In fact, I am only aware of one national and two state level efforts that focused on the impact of MarketMaker for agribusiness operations. At the national level, Zapata et *al*. (2011) estimated the perceived benefits attributed to participation in MarketMaker. Specifically, surveyed producers reported that as a result of their participation with MarketMaker, they have received an average of 2.6 marketing contacts, and have gained an average of 1.5 new customers. Additionally, MarketMaker has assisted registered farmers in increasing their annual sales by an average of $121. This study was based on the evaluation and implementation framework for measuring the impacts of the MarketMaker project developed by Lamie et *al*. (2011). The work of Lamie et *al*. (2011) encompasses the development of a set of tailored evaluation tools including logic models, quantifiable evaluation indicators and survey instruments for the main groups of MarketMaker participants: producers, consumers, retailers, wholesalers, chefs/restaurants and farmers markets.

At the state level, Fox (2009) developed and implemented a survey of various representatives of Ohio's food chain including producers, processors, wineries, farmers' markets and distributors. One of the objectives of the project was to explore changes in marketing practices and market access that resulted from the use of MarketMaker. The survey asked Ohio registered producers if they believed that the MarketMaker site was helping keep more food dollars in the regional economy. Sixty-three percent of producers agreed with the statement. Cho and Tobias (2009) conducted a survey of New York farmers registered on MarketMaker. Survey results indicate that the average increase in annual sales attributed to MarketMaker is between $225 and $790. Additionally, about 12 percent of the respondents reported receiving marketing contacts through MarketMaker and using the MarketMaker directory to contact other food industry business partners.

In short, the evaluation of E-Commerce platforms has mainly focused on human-computer interactions rather than on the economic impacts associated to participation on E-commerce activities. Studies evaluating the economic impact of agricultural E-commerce platforms are very limited.

3.4. Methods and Procedures

Since the main goal of this study is to estimate the economic benefits of MarketMaker for registered producers, I employed contingent valuation methods for the estimation of these benefits. Contingent valuation methods can be used to estimate the economic value of a novel input or a non-market input such as the services provided by MarketMaker because the amount of money a producer is willing to pay for an improvement in the quality of a production factor represents the difference in profits before and after the improvement (see proof below). Moreover, the WTP measure has the potential to incorporate other benefits attributed to the use of MarketMaker beyond the increase in profits such as networking and collaboration between participants.

The use of contingent valuation techniques to estimate the economic value of non-market goods and services is well known. Through the years, contingent valuation has been widely used in the assessment of individuals' WTP for environmental services for which market prices are not well defined (Carson et *al*., 1995; Boyle, 2003; Carson and Hanemann, 2005; Zapata et *al*., 2012). More recently, contingent valuation methods have been used in health economics (Diener et *al*., 1998; Krupnick et *al*., 2002), real estate appraising (Breffle et *al*., 1998; Banfi et al., 2008; Lipscomb, 2011), art valuation (Thompson et *al*., 2002), agricultural extension services (Whitehead et *al*., 2001, Budak et *al*., 2010), and agribusiness (Patrick, 1988; Kenkel and Norris, 1995; Hudson and Hite, 2003).

In the next sections I present the theoretical underpinning of producers' WTP for the services provided by MarketMaker. I also describe the survey instrument used to capture producers' characteristics and perceptions regarding the economic impact of the site on their business performance, as well as the WTP questions and elicitation methodology employed. The econometric methods used to estimate the covariates mean values and to model the producers' WTP measure are presented at the end of this section.

3.4.1. Theoretical Framework

The WTP model presented here is developed within the context of the neoclassical theories of utility maximization and profit maximization as shown in Hanemann et *al*.(1991) and in Chapter Two of this dissertation. More specifically, the variation function or producers' WTP for non-market inputs or technologies is derived using the individual's indirect utility function in combination with the firm's profit function.

In the context of this study, the adoption of MarketMaker can be though as an improvement in the quality of an aggregate marketing input. In fact, a recent study by Zapata et *al*. (2011) found that the majority of producers registered in MarketMaker used the MarketMaker website to reach individual consumers. Other justification to conceive the adoption of MarketMaker as an upgrading in the quality of an aggregate marketing input and not as an additional input is based on the theoretical properties of the production function. Specifically, under the strict essentiality property, production requires the utilization of positive amounts of all inputs (Chambers, 1988 , p.9), thus from the theoretical standpoint the adoption of a novel input (i.e., MarketMaker) cannot be thought as the inclusion of the novel input as a separate input in the production process.

Suppose that the individual maximizes utility $U(\boldsymbol{Z})$, where $\boldsymbol{Z}$ is a vector of goods consumed, subject to income constraint. It is further assumed that part of her income (i.e., non-labor income) comes from the profits she generates in a production process independent of individual preferences. The solution to the problem yields the indirect utility function $V\left[\bar{m}\left(\Pi\left(p_y, \boldsymbol{r}, \boldsymbol{q}\right)\right), L, \boldsymbol{P_z}\right]$, where $\bar{m}$ and L are individual's non-labor and labor income, respectively, $\Pi(\cdot)$ is the profit function, p_y is the price of produced output, $\boldsymbol{r}$ is a vector of input prices, $\boldsymbol{q}$ is a vector of exogenous input quality levels, and $\boldsymbol{P_z}$ is the vector price of the goods or services consumed. Now consider a change in the input quality level $\boldsymbol{q}$ from $\boldsymbol{q}^0$ to $\boldsymbol{q}^1$. In this context, the producers' WTP is the amount of money that makes the following condition to holds: $V\left[\bar{m}\left(\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^0)\right), L, \boldsymbol{P_z}\right] = V\left[\bar{m}\left(\Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^1)\right) - WTP, L, \boldsymbol{P_z}\right]$.

If non-labor income ($\bar{m}$) is a linear function of profits (Π) then the producers' WTP is also a linear function of the difference in profits and can be simplified to:

$$WTP = \Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^1) - \Pi(p_y, \boldsymbol{r}, \boldsymbol{q}^0). \tag{3.1}$$

Consequently, the maximum amount of money a producer is WTP for improvements in the input quality levels reduces to the difference between the *ex post* (after adopting the new input) and *ex ante* (before adopting the new input) firm's profit levels.

3.4.2. Survey Description

Agricultural producers registered in MarketMaker site were surveyed using both online and mail paper instruments during the months of May 2011 and February 2012. The survey was initially distributed by email to 1,446 producers[11] registered on MarketMaker websites in 7 participant states: Arkansas, Florida, Georgia, Indiana, Iowa, Mississippi, and South Carolina. In February 2012, a second round of surveys was mailed

[11] Ninety seven percent of producers registered on the website are farmers, 1 percent are fishermen, and 2 percent are both farmers and fishermen.

to a subsample of 592 producers with the purpose of increasing the number of responses. Traditional mail was used in the final round of surveys to capture the responses of those producers who may be less familiar with using computers and the Internet.

The questionnaire was divided in 4 sections. The first section focused on users' experience with MarketMaker. Section 2 concentrated on participants' perceptions regarding the impact of MarketMaker on their business. The third section asked respondents about their demographic characteristics, as well as business characteristics. Producers' WTP questions were included at the end of this section. Finally, section 4, which was only applied to producers participating in direct marketing channels, focused on the impact of MarketMaker on direct marketing.

An invitation email containing a brief description of the project and the link to the questionnaire was sent to all agricultural producers from the participating states. Two reminder emails (one and two weeks after the initial email) were sent to those individuals who had not responded to the survey. To further encourage participation in the survey, respondents were offered the opportunity to enter a draw to win $100. Typical completion time of the questionnaire was 5-10 minutes.

The overall response rate of the email survey was 8.9 percent and it generated 129 usable observations. As found in Hamilton (2003) meta-study of 199 online surveys, online survey response rates tend to be low (13.4% average response rate in their study). With the aim to increase the number of responses, a mail survey and two reminder letters were sent to a random sample of 45 percent of those producers who did not respond the email survey. The mail survey generated 98 additional responses and had an overall response rate of 16.6%. The aggregated response rate of the study was 15.7 % with 227 usable observations. The sample frame size, number of respondents and response rate by MarketMaker participant state and survey type are shown in Table 3.1. The states with the highest response rate were Arkansas (24.5%) and Florida (21.0%), and those with the lowest response rate were Mississippi (11.8%) and South Carolina (12.5%).

3.4.2.1. *WTP questions*

The producer WTP question was asked using a double-bounded (DB) elicitation format. Using the appropriate elicitation approach has always been a major concern. In recent years, the DB elicitation format has virtually supplanted single-bounded (SB) and open-ended (OE) formats mainly because it reduces the strategic bias present in the OE method (Hanemann, 1994; Boyle, 2003); and it provides more efficient estimates of central tendency compared to the SB format (Hanemann et *al*., 1991) [12]. Two rounds of questions were presented to each participant, the initial bid amount was randomly assigned among respondents and the second bid amount depending on their answers to the first question (higher if participant responded “yes” to the initial bid and lower if participant responded “no” to the initial bid).

The initial bids used were $25, $50, $75, $100, $150, and $200. The corresponding follow-up annual bids were $15, $25, $50, $75, $100, and $150 when the initial response was a “no”, and $50, $75, $100, $150, $200, and $250 when the initial

[12] One limitation of the DB elicitation format is the use of predetermined bids, which could cause anchoring (Boyle, 2003). In addition, a tendency in respondents to answer “yes” to any bid amount presented to them regardless of their true views has been found in some studies (Berrens et *al*., 1997; Blamey et *al*., 1999).

response was a “yes”. The different bids used in the WTP questions were chosen based on the responses to an OE question obtained in a focus group early in November 2010 (producers’ mean WTP value estimated at $65), previous studies evaluating the site and consultation with Market Maker administrators in several states.

The WTP question was preceded by a brief statement that clearly describes the current funding situation of MarketMaker and the possibility that it may become privately funded in the future. An annual participation fee was used as the payment vehicle. The wording and payment vehicle used in the survey were previously tested in a focus group along with two alternative WTP question options. The other two WTP question alternatives involved a more extensive description of the current and future funding situation of MarketMaker. The other payment vehicle considered was an annual voluntary donation. All participants agreed that the scenarios described in the different WTP questions were very realistic and that the WTP question employed in the survey was the easiest to respond. Specific initial and follow-up questions presented to the participants are listed in Appendix 3.A.

3.4.3. Econometric Methods

3.4.3.1.Summary Statistics

In order to simplify the respondent's task and to encourage a response, most of the outcome measures (e.g., number of new contacts found through MarketMaker), as well as demographic and business information, were collected using a discrete number of categories, hence the calculation of the mean value of these variables required the use of special statistical techniques (Bhat, 1994; Carpio et *al*., 2008; Stewart, 1983).

Two alternative approaches were used for the estimation of the mean values of variables with several categories: a parametric and nonparametric approach. The parametric approach was adapted from the literature on the estimation of equations using data in which the dependent variable is only observed to fall in a certain interval (Stewart, 1983; Bhat, 1994). The nonparametric procedure was adapted from the survival statistical literature (Turnbull, 1976) and the contingent valuation literature (Day, 2007).

To estimate the means of the interval-censored variables, denote the true (but unobserved) variable of interest for the i^{th} individual as y_i. The probability that y_i is in the k^{th} interval[13] with boundary values of $A_{(k-1)}$ and A_k is given by:

$$\text{(3.2)} \qquad P\left(A_{(k-1)} \le y_i \le A_k\right) = F(A_k) - F(A_{(k-1)}) \qquad i = 1,2,\dots.N,$$

where $F(\cdot)$is the underlying cumulative density function (CDF) of y.The parametric procedure assumes that y follows a normal distribution with mean μ and variance σ^2 (see Zapata et *al*., 2011). On the other hand, the nonparametric procedure does not impose *ad hoc* assumptions about the probability distribution of the variable of interest *y*. Given that the probability distribution of *y* (*F*) is unknown, Turnbull's procedure considers each $F_k = F(A_k)$ as a parameter to be estimated. Moreover, the maximum likelihood estimation in this case needs to be expressed as a constrained maximization problem of the form:

$$\text{(3.3)} \qquad \text{Max}_F \ \ln L(F|d) = \sum_{i=1}^{N} ln \sum_{k=1}^{K} d_{ik}(F_k - F_{(k-1)})$$

$$\text{subject to: } 0 = F_0 \le F_1 \dots \le F_K = 1,$$

[13] In both parametric and nonparametric procedures, when necessary, the upper bound for the last interval will be set to be equal to twice the value of its lower bound. Overall, the mean estimates were robust to the choice of "reasonable" upper bound values.

where d_{ik} indicates whether the i^th individual chooses the k^th interval among K options.

As shown in the Appendix 3.B, the F_k values can be estimated simply using the raw proportions of observations belonging to each category without having to optimize equation (3.3).The expected value of y can thus be written as (Haab and McConnell 1997):

$$E(y) = \int_0^{A_K} y\, dF(y) = \sum_{k=1}^{K} \int_{A_{k-1}}^{A_k} y dF(y). \tag{3.4}$$

By replacing y by the lower or upper bound of each interval, it can be shown that the lower (LB) and upper bound (UB) estimates of the expected value of y (E(y)) are:

$$E(y_{LB}) = \sum_{k=1}^{K} A_{k-1}(F_k - F_{(k-1)}) \tag{3.5}$$

$$E(y_{UB}) = \sum_{k=1}^{K} A_k\, (F_k - F_{(k-1)}). \tag{3.6}$$

Point estimate of the means of categorical variables were estimated using the parametric approach assuming normal distributions. Formulas (3.5) and (3.6) were used to estimate upper and lower bounds of the means.

3.4.3.2.Estimation of WTP models

The estimation of the producer WTP for the services provided by MarketMaker was based on the methods proposed by Cameron (1988). Let WTP_i be the unobserved true amount that respondent i is willing to pay. In the DB elicitation format every respondent i is presented with an initial bid B_i and asked if she is willing to pay that amount. If the respondent answers "yes" to the first bid, a second WTP question is asked using a higher bid amount B_i^u. If the respondent answers "no" to the first bid, the second WTP question used a lower bid B_i^l. The respondent will answer 'yes" to the initial amount if $WTP_i \geq B_i$, and "no" to the second bid amount if $WTP_i < B_i^u$. Similarly, the respondent will answer 'no" to the initial amount if $WTP_i < B_i$, and "yes" to the second bid amount if $WTP_i \geq B_i^l$. Using the same logic, it is easy to show that the respondent will answer "yes" to both questions if $WTP_i \geq B_i^u$, and "no" to both questions if $WTP_i < B_i^l$. Therefore, the probability that a respondent answers "yes" to both questions (π^{yy}) can be represented by

$$\text{(3.7)} \qquad \pi^{yy}(B_i, B_i^u) = Pr\{WTP_i \geq B_i \; and \; WTP_i \geq B_i^u\} = Pr\{WTP_i \geq B_i^u\}$$
$$= 1 - G(B_i^u; \boldsymbol{\theta})$$

where $G(\cdot; \boldsymbol{\theta})$ is the CDF of some statistical distribution with parameter vector $\boldsymbol{\theta}$. Table 3.2 presents the CDFs of all the distributions considered in this study. The probability that a respondent answers "no" to both questions (π^{nn}) is given by

$$\text{(3.8)} \qquad \pi^{nn}\left(B_i, B_i^l\right) = Pr\left\{WTP_i < B_i \; and \; WTP_i < B_i^l\right\} = Pr\left\{WTP_i < B_i^l\right\}$$
$$= G\left(B_i^l; \boldsymbol{\theta}\right).$$

Similarly, the probability that a respondent answers "yes" to the first question and "no" to the second question (π^{yn}) is given by

$$\text{(3.9)} \qquad \pi^{yn}(B_i, B_i^u) = Pr\{B_i \leq \; WTP_i < B_i^u\} = G(B_i^u; \boldsymbol{\theta}) - G(B_i; \boldsymbol{\theta}).$$

Finally, the probability that a respondent answers "no" to the first question and "yes" to the second question (π^{ny}) is given by

$$\text{(3.10)} \qquad \pi^{ny}\left(B_i, B_i^l\right) = Pr\left\{B_i^l \leq \; WTP_i < B_i\right\} = G(B_i; \boldsymbol{\theta}) - G\left(B_i^l; \boldsymbol{\theta}\right).$$

Given a sample of N individuals, the log-likelihood function can be represented by

$$\text{(3.11)} \qquad \ln L(\boldsymbol{\theta}) = \sum_{i=1}^{N}\{(I_{1i})(I_{2i})\ \ln \pi^{yy}(B_i, B_i^u)$$

$$+ (1 - I_{1i})(1 - I_{2i}) \ln \pi^{nn}\left(B_i, B_i^l\right)$$

$$+ (I_{1i})(1 - I_{2i}) \ln \pi^{yn}(B_i, B_i^u)$$

$$+ (1 - I_{1i})(I_{2i}) \ln \pi^{ny}\left(B_i, B_i^l\right)\},$$

where I_{ji}, j=1,2, are indicator variables such that I_{ji} is equal to 1 if the i^{th} respondent answers "yes" to the j^{th} question and equal to zero otherwise. Explanatory variables can be introduced in the maximum likelihood estimation by modeling some elements of the parameter vector $\boldsymbol{\theta}$ as a function of specific covariates. Table 3.2 shows the parameterizations used in this study. For example, under the log-logistic distribution the parameter μ can be expressed as $\mu = \boldsymbol{X}_{\boldsymbol{i}}^{`}\boldsymbol{\beta}$, where $\boldsymbol{X}_{\boldsymbol{i}}$ is a vector of covariates (including 1 for the intercept) and $\boldsymbol{\beta}$ the corresponding vector of parameters. Moreover, the inclusion of explanatory variables and additional parameters in the modeling process allows the estimation of the conditional mean WTP ($E(WTP|\boldsymbol{X}_{\boldsymbol{i}})$) and the corresponding marginal effects (see Tables 3.2 and 3.3).

The marginal effects for continuous variables are estimated by taking the partial derivative of the conditional mean function w.r.t. the covariate of interest (i.e., $\frac{\partial E(WTP|\boldsymbol{X}_{\boldsymbol{i}})}{\partial x_j}$). For discrete variables (with values of 0 or 1), the marginal effects are given by the change in the conditional mean WTP from a change in the discrete variable form 0 to 1 holding all other variables fixed as suggested by Cameron and Trivedi (2005, p.124) (i.e., $E\left(WTP|\boldsymbol{X}_{\boldsymbol{i}}, x_{ij} = 1\right) - E\left(WTP|\boldsymbol{X}_{\boldsymbol{i}}, x_{ij} = 0\right)$). Table 3.3 shows the specific formulas for the marginal effects of the distributions considered in this study. The marginal effects presented in this paper were calculated as the average marginal effects across the N producers in the sample. The standard errors of the mean WTP, coefficient estimates ($\boldsymbol{\beta}$) and marginal effects were estimated using the bootstrapping procedure outlined by Cameron and Trivedi (2005, p.362). A total of 1000 replications were used to generate the standard errors.

It was assumed that producers' WTP for the services provided by MarketMaker can be explained by producers' characteristics and perceptions. To this end, registration type with MarketMaker, time producers have been registered on the site, time spent on MarketMaker activities, type of user based on usage frequency, number of marketing contacts received due to participation on MarketMaker, total number of new customers gained, increase in annual sales attributed to MarketMaker and size of operation in terms of total annual sales were included in the producers' WTP maximum likelihood modeling process. In particular, variables measuring participation characteristics (i.e., time registered on the site, time spent on MarketMaker activities and type of user) and perceived impacts of MarketMaker (i.e., number of marketing contacts received, new customers gained and increase in annual sales) were considered as covariates in the modeling process because they were identified as quantifiable indicators of an effective participation on MarketMaker based on the producers' logic model developed by Lamie et *al*. (2011). The other variables, registration type and total annual sales, were included in the maximum likelihood estimation to relate the benefits generated by MarketMaker to specific producers' characteristics. An indicator variable (i.e., survey type) was also included in the estimation to control for differences between email and mail surveys' responses. The categorical variables: time registered on MarketMaker, time spent on MarketMaker activities, marketing contacts received, new customers gained, increase in annual sales attributed to MarketMaker, and total annual sales were transformed to "continuous" by using the mid-point of each range. The explanatory variables registration and user type were included as dummy variables. Producers who reported that they frequently or sometimes use at least one feature of MarketMaker were coded as active user of the site and those who rarely or never use any feature of MarketMaker were coded as passive users.

Six statistical distributions were considered in the modeling of the producer WTP for the services provided by MarketMaker including the normal, Weibull, log-normal, exponential, log-logistic and gamma distributions. The model that "best fitted" the data was selected using the Akaike information criterion corrected for finite sample sizes (AICC) (Hurvich and Tsai, 1989). The AICC is a log-likelihood based model selection criterion with degrees of freedom adjustment. Given a data set and several candidate models, the model with the smallest AICC is preferred[14].

3.5. Results

3.5.1. Summary Statistics

Survey results indicate that nearly 97 percent of the respondents were the owners or the managers of the business. This finding gives more credibility to their answers

[14] Even though the Akaike information criterion is not a formal test to discriminate between different models, it is commonly used to compare the type of parametric models employed in this study (e.g., Baghestani et *al*. 2010; Shauly et *al*., 2011; Garcia-Aristizabal et *al*. 2012).

concerning the characteristics of the operation and the impact of MarketMaker on their business performance. Regarding characteristics of the business, survey respondents indicated that their operations generate, on average, about $100,090 in total annual sales (versus $134,806 for the U.S. census). Table 3.4 presents a complete description of the key variables describing respondent and business characteristics.

In terms of MarketMaker registration and use, most of the agricultural producers responding to the survey (75%) indicated they had registered on the site by themselves, 8 percent indicated that were registered by someone else, and 17 percent did not know how they became enrolled in MarketMaker. This finding may be explained by the fact that in some states sometimes producer lists provided by State Departments of Agriculture were used to initially populate the MarketMaker database.

On average, respondents have been registered on the site for 22 months. About 15 percent of respondents have been registered for less than 12 months, 54 percent have been registered between 12 and 24 months, and 31 percent have been registered for more than 24 months (Table 3.4). Producers report various degrees of intensity with respect to the use of MarketMaker features (see Table 3.5). The features that are most commonly used (sometimes and frequently) are the “search for products” (20% of users), “search for buyers and sales opportunities” (19%), and “log on to check or update profile” (18%). Less commonly used features include “search for business partnerships” which was used sometimes or frequently by about 11 percent of users, “find target market for your products (11%), and “use the buy/sell Forum” (13%). Based on reported intensity of use, 33 percent of registered producers were considered active users and 67 percent are passive user of MarketMaker. In relation to the time devoted to the website, producers registered on MarketMaker spend about 22 minutes per month managing their account, with nearly 83 percent of the producers devoting less than 30 minutes per month to MarketMaker related activities (Table 3.4).

Survey questions related to the impact of MarketMaker asked respondents about the perceived impact of MarketMaker on the total number of contacts received due to their participation in the site, total number of new customers gained, and the increase in annual sales since producers became registered in the website. Producers indicated that as a result of their participation with MarketMaker, they have been contacted, on average, about 2.7 times by customers, input suppliers, and other producers. At the same time, nearly 68 percent of producers in the sample have not received any contacts due to MarketMaker. However, the proportion of producers who have received marketing contacts through MarketMaker in the sample (32%) is greater than the 12 percent reported by registered New York producers (Cho and Tobias, 2009).

In terms of the number of new customers gained, respondents indicated that their participation has helped them obtain an average of 1.6 new customers even though 71 percent of the respondents indicated that they have gained no new customers through the site. Lastly, survey respondents perceived average annual increase in sales due to MarketMaker was estimated at about $221, with 77 percent of the participants indicating the increase in annual sales was less than $25. The overall increase in annual sales due to MarketMaker in the sample is lower than that found by Cho and Tobias (2009) where the average increase in annual sales assisted by MarketMaker reported by New York producers was between $225 and $790.

Participants' responses to the initial and follow-up WTP question are presented on Table 3.6. This table suggests that the producer WTP for the services provided by MarketMaker is less than $200 for 96 percent of the respondents. As expected, the share of individual accepting to pay a particular bid amount decreases as the bid asked increases (Table 3.6). For example, as the initial bid amount increases from $25 to $200 the "yes" responses to the first contingent question fall from 28 percent to 6 percent. When a second higher bid is asked, the "yes" responses fall from 7 percent to 0 percent at $250.

3.5.2. WTP Estimation Results

The different statistical distributions considered in this study and their corresponding maximized log-likelihood and AICC are presented in Table 3.7. This table suggests that the preferred distribution is the log-logistic distribution[15]. Therefore, the log-logistic distribution was employed to estimate the mean producer WTP for the services provided by MarketMaker, and the marginal effects of each covariate in the model. The explanatory variables total number of new customers gained and increase in annual sales due to MarketMaker were excluded from the models because they were found to be highly correlated to the total number of contacts received due to MarketMaker and between them. The mean WTP and the marginal effect of each

[15] In general, the mean and marginal effect estimates were robust across the different candidate models considered in this study.

explanatory variable were estimated using the specific formulas presented in Tables 3.2 and 3.3. Maximum likelihood estimation results are reported in Table 3.8.

Registration type, time registered on MarketMaker, time devoted to the website, type of user, the number of marketing contacts received and firm total annual sales were found to have a significant effect on the WTP for the serviced provided by MarketMaker (Table 3.8). The estimated marginal effects of explanatory variables indicate that producers who registered themselves on MarketMaker are willing to pay $26.52 per year less for the services received from MarketMaker than those who were registered by someone else or do not know how they were enrolled in the site. This may reflect the fact that the benefits producers obtain from MarketMaker are the same regardless of how they were registered in the site. Therefore, self-registered producers will have a lower WTP for the services they received from MarketMaker given that they have put more effort registering in the site as compared to those who were registered by someone else or do not know how they were registered in MarketMaker.

Results also suggest that producers' WTP increases by $0.55 for each additional month the producer have been registered on the site. This finding suggests that the benefits associated to participating on MarketMaker are positively related to the time registered to the site. Other variables used to measure MarketMaker usage by participants were also found to be related to producers' valuation of the site. Specifically, each additional minute per month spent on the MarketMaker website increases the annual WTP by $0.10 and active users of the site are willing to pay $24.95 more per year than their passive counterparts.

The number of marketing contacts received due to their participation with MarketMaker, as expected, has a positive effect on producer WTP for the services provided by MarketMaker. Each additional marketing contact received increases the annual WTP by $1.27. Since marketing contacts are potential sales, the more contacts received due to MarketMaker the higher the chance that at least some of them result in actual sales which might be translated into higher WTP.

In terms of the effects of business characteristics on producers' valuation of MarketMaker, results indicate that a $1,000 increase in total annual sales is expected to increase the annual WTP by only $0.02. Thus the difference in annual WTP between a producer who generates $100,000 in total annual sales and one that generates $50,000 in total annual sales is just $1. This suggests that producers' WTP for the services provided by MarketMaker is nearly constant across producers' annual sales levels.

Finally, producers who were surveyed using the online questionnaire are willing to pay $26.33 more than those who responded to the mail survey. This finding could reflect the fact that producers who responded to the email survey are more expose and conscious to electronic technologies such as MarketMaker compared to those who preferred to respond to the traditional survey form.

Results from the unconditional maximum likelihood model (when no regressors are included in the model) in conjunction with the formulas for the unconditional log-logistic mean and median presented in Table 3.2 were used to calculate mean and median annual WTP for the services received from MarketMaker[16]. The average annual producers' WTP for the services provided by MarketMaker was estimated at $47.02 with a standard error of $16.94. The median annual producer WTP for the services provided by MarketMaker is $15.23.

The estimated average annual producer WTP can be used to estimate the aggregate value that registered producers place on the services received from MarketMaker by multiplying the estimated mean annual WTP times the 7,698 producers currently registered at the national level. Thus, the estimated annual aggregate producer' WTP is $361,960 (standard error of $130,404).

3.6. Summary and Conclusions

Despite the touted potential of E-commerce to improve profits in agriculture, the literature on the economic impact of E-commerce in agribusinesses is very limited. The main goal of this study was to assess the economic benefits of an Electronic Trade Platform (i.e., MarketMaker) on registered producers. Contingent valuation methods using online and mail surveys were employed to estimate the economic value that registered producers place on the services received from MarketMaker. Estimation of the WTP model was carried out using parametric maximum likelihood estimation procedures.

[16] The estimated location and scale parameters (standard error) from the unconditional maximum likelihood estimation are $\mu = 2.7231$ (0.1589) and $\sigma = 0.7324$ (0.0844), respectively.

The WTP estimation results indicate that, on average, producers are willing to pay $47.02 annually for the services they receive from MarketMaker. This value is a measure of the increase in annual profits attributed to the use of MarketMaker. The estimated aggregate annual economic value that registered producers place on the services provided by MarketMaker is $361,960. It is important to emphasize that the aggregate estimate of the economic impact of MarketMaker might represent only a portion of the total benefits generated by MarketMaker given that there are other users of the site not considered in the analysis such as consumers, retailers, wholesalers, chefs/restaurants and farmers markets.

Understanding producers' valuation of MarketMaker is necessary for ensuring the efficient allocation of resources dedicated for its support and development. This information could also be useful to government officials and MarketMaker's administrators to justify the expenditure of public funds on the operational and development costs associated with the MarketMaker website. Since its creation in 2000, MarketMaker has offered its electronic infrastructure and resources to registered users at no cost. Currently, the website is entirely funded by federal and state governments. Hence, the estimated WTP function and its features (e.g. mean and median) could also be used as a guide if a participation fee is imposed in the future.

Empirical results indicate that registration type, time registered on MarketMaker, time devoted to the website, type of user, the number of marketing contacts received and firm total annual sales have a significant effect on producers' WTP for the services provided by MarketMaker. In particular, those producers who registered by themselves are willing to pay nearly $26 less per year than their counterparts. This lower WTP could be attributed to the fact that the benefits associated with participation are similar regardless of how producers registered on the site, thus a self-registered producer that have put more time and effort registering in the site is expected to have a lower WTP. Empirical results also show that the effectiveness of MarketMaker is strongly linked with how it is used by producers. For example, a higher WTP is positively related to the time devoted to MarketMaker activities and active users of the site. These findings suggest that MarketMaker leaders should encourage producers to become more active users of the site to achieve the desired benefits from participation. Another interesting result is the positive relation between the time producers have been registered on the site and the stated WTP, implying that the benefits associated with MarketMaker tend to be higher as the users become familiar with the functioning of the site.

Results also indicate that each additional marketing contact received due to their participation with MarketMaker is expected to increase their annual WTP by $1.27. Hence, with the aim to increase the number of marketing contacts received, MarketMaker website development should focus on encouraging producers to frequently update their site profiles, specifically their contact information (phone number, Email, website URL) and products' attributes and availability. Although statistically significant, the benefits generated by MarketMaker are nearly constant across firms of different size as measured by annual sales levels.

Lastly, producers that were surveyed using the mail questionnaire had a lower WTP for the services provided by MarketMaker than those who replied to the email version. This may imply that producers who preferred to respond the mail survey are less aware and familiar with electronic technologies. Hence, MarketMaker administrators should consider devoting additional time and effort not only for site development and maintenance, but also to the delivering of tailored training and promotion.

Table 3.1. Survey Sample Frame Size, Number of Respondents, and Response Rate by State.

State	Sample Frame Size		Number of Respondents			Response Rate		
	Email	Mail	Email	Mail	Total	Email	Mail	Total
Arkansas	45	25	3	8	11	6.67	32.00	24.44
Florida	143	51	27	3	30	18.88	5.88	20.98
Georgia	260	107	18	16	34	6.92	14.95	13.08
Indiana	323	129	34	25	59	10.53	19.38	18.27
Iowa	326	130	27	23	50	8.28	17.69	15.34
Mississippi	93	34	7	4	11	7.53	11.76	11.83
South Carolina	256	116	13	19	32	5.08	16.38	12.50
Total	**1,446**	**592**	**129**	**98**	**227**	**8.92**	**16.55**	**15.70**

Table 3.2. Statistical Distributions Employed and their corresponding CDF, Parameterization, Conditional and Unconditional Mean, and Median.

Distribution	$G(B;\boldsymbol{\theta})$[a]	Parameterization	Mean		Median
			Unconditional: $E(WTP)$	**Conditional:** $E(WTP\|\boldsymbol{X_i})$	
Normal	$\frac{1}{2}\left\{1+erf\left[\frac{B-\mu}{(2\sigma^2)^{1/2}}\right]\right\}$	$\mu=\boldsymbol{X}_i'\boldsymbol{\beta}$	μ	$\boldsymbol{X}_i'\boldsymbol{\beta}$	μ
Weibull	$1-exp\left[-\left(\frac{B}{\sigma}\right)^{\alpha}\right]$	$\sigma=exp(\boldsymbol{X}_i'\boldsymbol{\beta})$	$\sigma\Gamma\left(1+\frac{1}{\alpha}\right)$	$exp(\boldsymbol{X}_i'\boldsymbol{\beta})\Gamma\left(1+\frac{1}{\alpha}\right)$	$\sigma[log(2)]^{-\alpha}$
Log-normal	$\frac{1}{2}\left\{1+erf\left[\frac{log(B)-\mu}{(2\sigma^2)^{1/2}}\right]\right\}$	$\mu=\boldsymbol{X}_i'\boldsymbol{\beta}$	$exp\left(\mu+\frac{\sigma^2}{2}\right)$	$exp\left(\boldsymbol{X}_i'\boldsymbol{\beta}+\frac{\sigma^2}{2}\right)$	$exp(\mu)$
Exponential	$1-exp\left(-\frac{B}{\sigma}\right)$	$\sigma=exp(-\boldsymbol{X}_i'\boldsymbol{\beta})$	σ^{-1}	$exp(\boldsymbol{X}_i'\boldsymbol{\beta})$	$\sigma^{-1}log(2)$
Log-logistic	$\left\{1+exp\left[-\frac{\log(B)-\mu}{\sigma}\right]\right\}^{-1}$	$\mu=\boldsymbol{X}_i'\boldsymbol{\beta}$	$exp(\mu)\Gamma(1+\sigma)\Gamma(1-\sigma)$	$exp(\boldsymbol{X}_i'\boldsymbol{\beta})\Gamma(1+\sigma)\Gamma(1-\sigma)$	$exp(\mu)$
Gamma	$[\sigma^{\alpha}\Gamma(\alpha)]^{-1}\int_0^B WTP^{\alpha-1}exp\left(\frac{-WTP}{\sigma}\right)dWTP$	$\sigma=exp(\boldsymbol{X}_i'\boldsymbol{\beta})$	$\sigma\alpha$	$exp(\boldsymbol{X}_i'\boldsymbol{\beta})\alpha$	

[a] μ, σ and α denote the location, scale and shape parameter, respectively.

Table 3.3. Marginal Effects' Formulas.

Distribution	**Marginal Effects**	
	Continuous: $\frac{\partial E(WTP\|\boldsymbol{X_i})}{\partial x_j}$	**Discrete:** $E\big(WTP\|\boldsymbol{X_i}, x_{ij}=1\big) - E\big(WTP\|\boldsymbol{X_i}, x_{ij}=0\big)$
Normal	β_j	β_j
Weibull	$\beta_j exp(\boldsymbol{X\grave{}_i\beta})\Gamma\left(1+\frac{1}{\alpha}\right)$	$exp(\boldsymbol{X\grave{}_i\beta})\Gamma\left(1+\frac{1}{\alpha}\right)\left[1-exp(-\beta_j)\right]\Big\|_{x_{ij}=1}$
Log-normal	$\beta_j exp\left(\boldsymbol{X\grave{}_i\beta}+\frac{\sigma^2}{2}\right)$	$exp\left(\boldsymbol{X\grave{}_i\beta}+\frac{\sigma^2}{2}\right)\left[1-exp(-\beta_j)\right]\Big\|_{x_{ij}=1}$
Exponential	$\beta_j exp(\boldsymbol{X\grave{}_i\beta})$	$exp(\boldsymbol{X\grave{}_i\beta})\left[1-exp(-\beta_j)\right]\Big\|_{x_{ij}=1}$
Log-logistic	$\beta_j exp(\boldsymbol{X\grave{}_i\beta})\Gamma(1+\sigma)\Gamma(1-\sigma)$	$exp(\boldsymbol{X\grave{}_i\beta})\Gamma(1+\sigma)\Gamma(1-\sigma)\left[1-exp(-\beta_j)\right]\Big\|_{x_{ij}=1}$
Gamma	$\beta_j exp(\boldsymbol{X\grave{}_i\beta})\alpha$	$exp(\boldsymbol{X\grave{}_i\beta})\alpha\left[1-exp(-\beta_j)\right]\Big\|_{x_{ij}=1}$

Table 3.4. Description and Summary Statistics of Respondents Characteristics and Percepions.

Variable Name (Units)	Category	Category Proportion			Mean	
		Email	**Mail**	**Total**	**Nonparametric lower and upper bounds**	**Parametric (Standard Deviation)**
Total annual sales ($1,000)	Less than $10	42.64	40.82	41.85	(72.73, 144.71)	100.09 (217.02)
	$10 to $50	26.36	32.65	29.07		
	$50 to $100	13.95	8.16	11.45		
	$100 to $250	5.43	11.22	7.93		
	$250 to $500	5.43	2.04	3.96		
	$500 to $1,000	0.00	5.10	2.20		
	Over $1,000	6.20	0.00	3.52		
Time registered on MarketMaker (Months)	Less than 1	1.55	0.00	0.88	(16.70, 28.08)	22.02 (11.56)
	1 to 6	10.08	1.02	6.17		
	7 to 12	10.85	4.08	7.93		
	13 to 24	55.81	52.04	54.19		
	25 to 36	13.95	20.41	16.74		
	37 to 48	5.43	16.33	10.13		
	More than 48	2.33	6.12	3.96		
Time spent on MarketMaker activities (Min/month)	Less than 30	79.84	86.73	82.82	(11.02, 46.75)	21.99 (18.39)
	30 to 60	14.73	8.16	11.89		
	61 to 120	2.33	4.08	3.08		
	121 to 300	2.33	0.00	1.32		
	301 to 600	0.00	1.02	0.44		
	More than 600	0.78	0.00	0.44		
Marketing contacts	0	66.38	69.39	67.76	(1.30, 4.00)	2.65 (5.55)
	1 to 9	25.86	24.49	25.23		
	10 to 20	5.17	4.08	4.67		
	21 to 30	2.59	0.00	1.40		
	31 to 40	0.00	2.04	0.93		
New customers	0	69.72	71.43	70.53	(1.04, 2.44)	1.65 (3.47)
	1 to 5	19.27	18.37	18.84		
	6 to 10	9.17	7.14	8.21		
	11 to 20	0.92	2.04	1.45		
	More than 20	0.92	1.02	0.97		

Table 3.4. Description and Summary Statistics of Respondents Characteristics and Percepions (continued).

Variable Name (Units)	Category	Category Proportion			Mean	
		Email	Mail	Total	Nonparametric lower and upper bounds	Parametric (Standard Deviation)
Annual sales	Under $25	73.79	80.61	77.11	(148.05, 393.87)	221.30 (1,076.90)
	$25 to $50	5.83	4.08	4.98		
	$51 to $75	1.94	1.02	1.49		
	$76 to $99	4.85	1.02	2.99		
	$100 to $499	7.77	6.12	6.97		
	$500 to $999	3.88	3.06	3.48		
	$1,000 to $4,999	0.97	3.06	1.99		
	$5,000 to $9,999	0.00	0.00	0.00		
	More than $10,000	0.97	1.02	1.00		

Note: Marketing contacts and new customers refer to the total contacts received and customers gained since the producer became registered on the MarketMaker website.

Table 3.5. MarketMaker Features and their Rate of Use by Producers.

Feature	Never	Rarely	Sometimes	Frequntly
Log on to Check or Update Profile (such as adding new information, photos, social media links, business contacts, alerts, etc.)	0.29	0.53	0.15	0.02
Search for Products	0.46	0.34	0.18	0.03
Search for Business Partnerships (e.g., to find other companies to sell products)	0.60	0.30	0.10	0.01
Search for Buyers and Sales Opportunities	0.49	0.31	0.18	0.02
Find a Target Market for Your Products (e.g., using demographic data, food consumption data)	0.59	0.30	0.10	0.01
Use the Buy/Sell Forum	0.65	0.22	0.11	0.02

Table 3.6. Response Frequency by Initial Bid Amount.

Initial amount	Sample Size	Decision			
		No, No	No, Yes	Yes, No	Yes, Yes
25	46	29	4	10	3
50	34	23	6	4	1
75	43	34	4	5	0
100	46	39	1	5	1
150	24	21	2	0	1
200	34	30	2	2	0

Table 3.7. AICC by Statistical Distribution.

Distribution	Log-Likelihood	AICC
Normal	-166.1	351.6
Weibull	-163.6	345.9
Log-normal	-160.3	339.4
Exponential	-170.1	356.8
Log-logistic	-159.4	337.6
Gamma	-165.2	349.1

Table 3.8. Coefficient and Marginal Effect Estimates.

Variable	Coefficient		Standard Error	Marginal Effect		Standard Error
Constant	2.6964	***[a]	0.3620			
Registration type (Self-registered=1, Otherwise=0)	-0.5872	**	0.2811	-26.5184	**	15.5569
Time registered on MarketMaker (Months)	0.0146	**	0.0084	0.5528	**	0.3183
Time spent on MarketMaker activities (Min/month)	0.0028	**	0.0014	0.1048	**	0.0609
Type of user (Active user =1, Passive user=0)	0.6300	***	0.2531	24.9529	**	11.5420
Marketing contacts	0.0336	**	0.0202	1.2685	*	0.8511
Total annual sales ($1,000)	0.0006	**	0.0003	0.0232	**	0.0129
Survey type (Mail=1, Email=0)	-0.7655	***	0.2671	-26.3297	***	8.5284
σ[b]	0.6020	***	0.0651			

[a] Significance levels of 0.01, 0.05 and 0.10 are indicated by ***, ** and * respectively.
[b] σ corresponds to the shape parameter of the log-logistic model (see Table 3.2).

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3.8. Appendices

Appendix 3.A. Willingness to Pay Questions Used in the Survey.

The initial question presented to the participant, was

"*Since its creation in 2000, MarketMaker has offered its electronic infrastructure and resources to consumers, farmers, processors, retailers, chefs/restaurants, farmer markets, and other users at no cost. Currently, MarketMaker is entirely funded by federal and state government institutions, but may become a privately funded organization in the future. If MarketMaker becomes privately funded, while retaining all the features and services it currently provides, would you be willing to pay an annual participation fee of* $\$B$ *for the services you receive from MarketMaker?*

❒ *Yes* ❒ *No."*

The follow-up question asked them

"Would you be willing to pay an annual participation fee of $\$B^f$ *for the services you receive from MarketMaker?*

❒ *Yes* ❒ *No."*

Appendix 3.B. Nonparametric Probability Distribution Estimation.

When the F_k are parameters, the nonparametric log-likelihood estimation can be written as in expression (3.3), which is reproduced here for convenience

(3.B.1) $$Max_F \ ln\, L(F|d) = \sum_{i=1}^{N} ln \sum_{k=1}^{K} d_{ik}(F_k - F_{(k-1)})$$

Subject to: $0 = F_0 \leq F_1 \ldots \leq F_K = 1.$

The unconstrained version of (3.B.1) can be written as

(3.B.2) $$Max_F \ ln\, L(F|d) = \sum_{k=1}^{K} N_k ln(F_k - F_{(k-1)})$$

where $F_0 = 0$, $F_K = 1$, and N_k are the number of respondents who chose the kth interval. The first order conditions for (3.B.2) are given by

(3.B.3) $$\frac{\partial lnL((F|d))}{\partial F_k} = \frac{N_k}{F_k - F_{(k-1)}} - \frac{N_{k+1}}{F_{(k+1)} - F_k} = 0 \qquad k = 1,2 \ldots K-1.$$

Simultaneously solving (3.B.3) for F_k yields

(3.B.4) $$\hat{F}_k = \frac{\sum_{j=1}^{k} N_j}{\sum_{j=1}^{K} N_j} = \frac{\sum_{j=1}^{k} N_j}{N} \qquad k = 1,2 \ldots K-1.$$

Note that the unconstrained solution to F_k ensures that $0 < \hat{F}_k < 1$ and $\hat{F}_k < \hat{F}_{(k+1)}$, implicitly satisfying the constrain imposed to (3.B.1). There may be the case in which no participant is observed at one or several internals, if this occurs then intervals with no observations needs to be pooled using the following procedure:

(i) For $k = 1 \rightarrow K$, identify intervals with no observations.

(ii) If no participant chose the (k+1)th interval then the kth and (k+1)th intervals need to be merged into one interval containing N_k observations with boundary values of $A_{(k-1)}$ and $A_{(k+1)}$.

(iii) Continue until intervals are pooled sufficiently so that all remaining intervals have observations.

(iv) Estimate the resulting F_k's of the pooled distribution using expression (3.B.4).

CHAPTER FOUR

DISTRIBUTION-FREE METHODS FOR WELFARE ESTIMATES IN DISCRETE CHOICE VALUATION STUDIES

4.1. Abstract

The Turnbull method is the standard distribution-free approach used in contingent valuation studies to model interval-censored willingness to pay (WTP) responses. However, the Turnbull approach has some important limitations. The purpose of this study is to develop alternative distribution-free methods for the estimation of WTP models using nonparametric conditional imputation and local regression procedures. The proposed approach encompasses the recovery of the individuals' WTP using an iterated conditional expectation procedure and subsequent estimation of the mean WTP using linear and nonparametric additive models. In contrast to the Turnbull approach, the proposed estimation method allows the inclusion of covariates in the modeling of WTP estimates, as well as the complete recovery of its underlying probability distribution. Monte Carlo simulations are employed to compare the performance of the proposed estimators with that of the Turnbull estimator. I also illustrate the use of the proposed estimation techniques using a real data set.

Key words: Additive models, double-bounded elicitation, kernel functions, iterated conditional expectation, non-parametric regression, Turnbull.

4.2. Introduction

Contingent valuation (CV) is a survey-based method initially developed to elicit the value (i.e., willingness to pay, WTP) that people place on non-market resources such as environmental preservation (e.g., Carson et *al*., 1992; Hanemann, 1994; Zapata et *al*., 2012). New applications of CV are found in other areas such as health economics (Diener et *al*., 1998; Krupnick et *al*., 2002), real estate appraising (Breffle et *al*., 1998; Banfi et *al*., 2008; Lipscomb, 2011), and agribusiness (Patrick, 1988; Kenkel and Norris, 1995; Hudson and Hite, 2003).

The standard elicitation format used by CV practitioners is the double-bounded dichotomous choice (henceforth DBDC) approach. This elicitation format entails asking survey respondents two dichotomous choice questions. First, participants are asked if they are willing to pay a specific bid amount and then face a second question involving another bid, higher or lower depending on the response to the first question (Hanemann et *al*., 1991). One drawback of the DBDC approach, as well as of other "closed-ended" elicitation formats, is that it generates interval-censored responses; hence, the estimation of measures of central tendency (e.g., mean WTP) as well as the marginal effects of covariates on the mean WTP requires the use of specialized statistical techniques. Although, the majority of empirical studies using interval-censored responses from CV studies have been analyzed using parametric methods, in which a distribution function for the WTP measure is specified, some authors have advocated the use of distribution-free methods (e.g., Carson et *al*., 1992; Carson et *al*., 1994).

With regard to distribution-free methods used to analyze CV interval-censored data, most of the literature is based on the nonparametric maximum likelihood (ML) estimation approach proposed by Turnbull (1974, 1976). However, the Turnbull approach has several important limitations. First, the estimated probability distribution is only defined up to a discrete set of observed points (i.e., it is not a continuous function). Second, the procedure does not allow the inclusion of covariates in the modeling of respondents' WTP. Hence, it is not possible to estimate the impact (i.e., marginal effects) of the respondents' characteristics or attributes of the good under study on the mean WTP value. Finally, the Turnbull approach does not provide a point estimate of the mean WTP, but only upper and lower bounds of its value.

The purpose of this study is to develop alternative distribution-free estimation approaches that can be used to analyze interval-censored WTP data obtained using the DBDC elicitation method. The proposed estimators involve iterated procedures that combine nonparametric kernel density estimation of the errors of the WTP function with parametric linear or nonparametric kernel regression of its conditional mean function.

In contrast to theTurnbull approach, the proposed estimation approach provides a point estimate of the mean WTP, allows the estimation of the marginal effects of covariates on the mean WTP, as well as the estimation of the underlying WTP probability distribution function at any point. Simulation techniques are employed to compare the performance of the proposed estimators with that of the Turnbull approach and the true parametric model. I also illustrate the use of the propose estimation techniques using a real data set.

The remainder of this paper is organized as follows: Section 4.3 provides a brief literature review regarding the theoretical foundations of WTP estimates and the econometric modeling techniques used with data obtained from DBDC questions. Section 4.4 explains the distribution-free methods proposed in this paper and the simulation study design. Simulation results and an illustrative example are presented in Section 4.5. Finally, Section 4.6 provides a summary of the findings and some brief conclusions.

4.3. Literature Review

4.3.1 WTP Theoretical Framework

The theoretical foundations of the WTP concept employed in this paper are based on the consumer utility and producer profit maximization problems described by Hanemann (1991) and in Chapter Two of this dissertation. For consumers, Hanemann (1991) assumes that the consumer objective is to maximize his utility function $u(\boldsymbol{X}, \boldsymbol{q})$, where $\boldsymbol{X}$ and $\boldsymbol{q}$ are the vector quantity and quality of goods or services consumed, subject to a budget constraint. The solution to the problem yields the indirect utility function $v(\boldsymbol{P}, \boldsymbol{q}, y)$, where $\boldsymbol{P}$ is the vector price of the goods or services consumed and y is the consumer income level. Now consider a change in the quality level $\boldsymbol{q}$ from $\boldsymbol{q}^0$ to $\boldsymbol{q}^1$. In this context, the consumers' WTP for the new quality level can be thought as the amount of money that is required for $v(\boldsymbol{P}, \boldsymbol{q}^1, y - WTP) = v(\boldsymbol{P}, \boldsymbol{q}^0, y)$ to hold. Consequently, consumers' WTP can be expressed as function of income, prices and quality levels

(4.1) $$WTP = f(y, \boldsymbol{P}, \boldsymbol{q}^0, \boldsymbol{q}^1),$$

In the case of producers, the WTP function can be derived considering a change in the input quality level (see Chapter Two). The individual producer faces a problem similar to the consumer problem described above; however, part of his income (i.e., non-labor income) comes from the profits generated in a production process Thus, the indirect utility function of a producer is given by $v\left[\bar{m}\left(\Pi(p_z, \boldsymbol{r}, \boldsymbol{q}_i)\right), L, \boldsymbol{P}, \boldsymbol{q}\right]$, where $\bar{m}$ and L are individual's non-labor and labor income, respectively; $\Pi(\cdot)$ is the profit function; p_z is the price of produced output; $\boldsymbol{r}$ is a vector of input prices; and $\boldsymbol{q}_i$ is a vector of input quality levels. Thus, the producers' WTP for a change in the quality level $\boldsymbol{q}$ from $\boldsymbol{q}^0$ to $\boldsymbol{q}^1$is the amount of money required for $v\left[\bar{m}\left(\Pi(p_z, \boldsymbol{r}, \boldsymbol{q}_i^1)\right) - WTP, L, \boldsymbol{P}, \boldsymbol{q}\right] = v\left[\bar{m}\left(\Pi(p_z, \boldsymbol{r}, \boldsymbol{q}_i^0)\right), L, \boldsymbol{P}, \boldsymbol{q}\right]$ to hold. Under the assumption that non-labor income ($\bar{m}$) is a linear function of profits (Π) then the producers' WTP is a linear function of the difference in profits

$$WTP = \Pi(p_z, \boldsymbol{r}, \boldsymbol{q}_i^1) - \Pi(p_z, \boldsymbol{r}, \boldsymbol{q}_i^0). \tag{4.2}$$

Note that for both consumers and producers (equations 4.1 and 4.2), WTP is a function of several variables. Hence, to simplify mathematical notation, for the reminder of the paper I will use Y_i for the WTP value of the i$^{\text{th}}$ individual (consumer or producer) and $\boldsymbol{X}_i$ for the vector of arguments. Moreover, I will assume that Y_i is related to a set of explanatory variables $\boldsymbol{X}_i$ via the following model

$$Y_i = g(\boldsymbol{X}_i) + \epsilon_i \qquad i = 1, \dots, n, \tag{4.3}$$

where the ϵ_i's are independent and identically distributed (i.i.d.) errors, have marginal density f_ε with mean zero and finite variance σ^2. It is also assume that the ϵ_i's are independent of the d-dimensional predictor vector $\boldsymbol{X}_i$. Furthermore, $g(\boldsymbol{X}_i)$ is a function that represents the conditional mean function of Y_i given $\boldsymbol{X}_i$.

4.3.2 DBDC Approach and Estimation

Since its introduction by Hanemann (1985), the DBDC elicitation approach has gradually replaced other elicitation methodologies such as the open-ended and single-bounded dichotomous choice (SBDC) formats (Hanemann and Kanninen, 1999). The main advantages of the DBDC method over the other two formats are that it reduces the strategic bias in respondents compared to the open-ended method (Hanemann, 1994; Boyle, 2003), and provides more efficient estimates of central tendency compared to the SBDC format (Hanemann et *al*., 1991). However, the analysis of the interval-censored responses generated from DBDC CV studies requires the use of special statistical techniques.

DBDC responses have been mainly analyzed using parametric ML estimation methods (Hanemann et *al*., 1991; Chapter Three of this dissertation). The parametric ML method finds the values of a vector of parameters that maximizes the joint probability density function of the data taken as a function of the parameters. One of the main advantages of the parametric ML estimation is that this estimation technique allows the inclusion of covariates in the modeling process, thus marginal effects are usually easy to estimate. On the other hand, the parametric ML method relies on *a priori* assumptions about the underlying distribution function of respondents' WTP. Hence, if the distribution function is misspecified, parameter estimates and any function of them (e.g., welfare estimates and marginal effects) might be inconsistent.

An alternative to parametric ML estimation is the use of distribution-free methods (i.e., without placing any parametric assumptions on the distribution of the error ϵ_i). Distribution-free estimation use in CV studies began with the extension and adaptation of survival analyses models proposed by Ayer et *al*. (1955)**,** Kaplan and Meier (1958) and Turnbull (1974, 1976) (e.g., Kristom, 1990; Carson et *al*., 1992). In the case of DBDC responses, the preferred distribution-free estimation method used by practitioners has been the nonparametric ML estimator proposed by Turnbull (1976) (e.g., Carson et *al*., 1992; Carson et *al*., 1994). Unlike the parametric ML that seeks particular values of the distribution parameters, the Turnbull method directly estimates the underlying cumulative density function of respondents' WTP.

The Turnbull approach is not without shortcomings. First, the estimated cumulative density function is only defined up to a discrete set of observed points given by the bid amounts used in the WTP questions (i.e., the estimated CDF function is a step function). Second, the Turnbull approach does not allow the inclusion of covariates in the modeling of the mean WTP function. The inclusion of explanatory variables in the analysis of individuals' valuation of particular goods and services is very important because in addition to estimating the mean or aggregate WTP values, most CV studies are also interested in estimating the effect of covariates such as individuals' characteristics on WTP (e.g., Carson et *al*., 1994; Chapter Three of this dissertation). Furthermore, the Turnbull approach does not provide a point estimate of the mean WTP, but only upper and lower bound estimates.

More recently, researchers have proposed two types of alternative distribution-free estimation procedures to analyze DBDC responses. The first type includes distribution-free methods that assume a parametric specification for the conditional mean WTP function (i.e., $g(\boldsymbol{X}_i)$ in expression (4.3)) (Watanabe, 2010). The second type of procedures use semiparametric proportional hazard specifications commonly employed in duration models (e.g., An, 1996; Burton, 2000).

In this study I propose two distribution-free methods using kernel based procedures: one that assumes a parametric specifications for the mean WTP function (semiparametric procedure), and another where the mean WTP function is estimated nonparametrically (nonparametric procedure). Hence, to the best of my knowledge this is the first study that uses fully nonparametric methods that allow the inclusion of covariates for the analysis of DBDC data. The semiparametric method can be considered as an alternative to the distribution-free models proposed by Watanabe (2010), An (1996) and Burton (2000). None of the distribution-free estimation methods currently available for the estimation of DBDC data use kernel based procedures. A possible limitation to the lack of adoption of kernel based procedures is the fact that the weighting functions employed by these approaches usually require continuous observations of the dependent variable contrary to the interval-censored observations obtained in DBDC CV studies. However, recently developed algorithms make possible the adaptation of these techniques to interval-censored data (e.g., Kang et *al*., 2011; Braun et *al*., 2005).

4.4. Methodology

In this study, I proposed to estimate the WTP function described in (4.3) by using two novel distribution-free estimation techniques: the Semiparametric Iterated Linear Model (*SPILM*) and Nonparametric Iterated Additive Model (*NIAM*). These models do not impose any arbitrary parametric assumption on the underlying distribution function of the errors $\epsilon_i's$ since its marginal density function (f_ε) is estimated using the nonparametric iterated conditional expectation procedure proposed by Braun et *al*. (2005). In the case of the SPILM, $g(\boldsymbol{X})$ is estimated using linear regression techniques, whereas in *NIAM* it is estimated using nonparametric additive regression methods.

The mathematical relation underlying the proposed procedure is given by:

$$E[Y_i|Y_i \in I_i] = g(\boldsymbol{X}_i) + E\left[\epsilon_i \middle| I_{\varepsilon_i}\right], \quad (4.4)$$

where $E[Y_i|Y_i \in I_i]$ is the conditional expectation of Y_i given $Y_i \in I_i$, I_i is the observed interval of Y_i with boundary values L_i and R_i (i.e., $I_i = [L_i, R_i]$), and $I_{\varepsilon_i} = [L_i - g(\boldsymbol{X}_i), R_i - g(\boldsymbol{X}_i)]$ (Kang et *al*., 2011). It is important to note that equation (4.4) uses $E[Y_i|Y_i \in I_i]$ instead of Y_i since the Y_i's are interval-censored, i.e., observed as I_1, I_2,…,I_n. If the true value of the Y_i's were observed, *SPILM* and *NIAM* are just the standard linear regression and nonparametric additive estimators, respectively.

The proposed procedures involve four major steps which are iterated until convergence: 1) Start with an estimate of $E[Y_i|Y_i \in I_i]$ ($\hat{E}[Y_i|Y_i \in I_i]$); 2) Use the estimates of $E[Y_i|Y_i \in I_i]$ instead of the unobserved Y_i's to estimate $g(\boldsymbol{X}_i)$ using regression procedures (parametric regression in *SPILM* or nonparametric regression in *NIAM*); 3) Use the estimates of $g(\boldsymbol{X}_i)$ to obtain an estimate $E\left[\epsilon_i \middle| I_{\varepsilon_i}\right]$ using nonparametric kernel density estimation procedures; and 4) Use estimates of $g(\boldsymbol{X}_i)$ and $E\left[\epsilon_i \middle| I_{\varepsilon_i}\right]$ obtained in step 2 and 3, respectively, to obtain a new estimate of $E[Y_i|Y_i \in I_i]$.

In the sections below, I first describe in detail all the steps of the proposed nonparametric iterative estimation procedure. For comparison purposes, I also describe the Turnbull's nonparametric ML estimator and the standard parametric approach under a normal distribution. The data generation process and the study design are discussed at the end of the section.

4.4.1. Iterated Conditional Expectation Procedure

The algorithm employed to estimate the conditional expected value of the Y_i's, $\boldsymbol{Y}_{\mathbf{imp}} = \left(\hat{E}[Y_1|Y_1 \in I_1], \dots, \hat{E}[Y_n|Y_n \in I_n]\right)^t$, and subsequently the *SPILM* mean estimator ($\hat{g}(\boldsymbol{X})_{SPILM}$) and *NIAM* mean estimator ($\hat{g}(\boldsymbol{X})_{NIAM}$) works as follows (Kang et *al*., 2011):

i. For all Y_i's compute the interval midpoints: $Y_i^o = \frac{L_i+R_i}{2}$.

ii. Compute the initial mean function estimate: $\hat{g}_0(\boldsymbol{X})_\xi$, $\xi = SPILM, NIAM$, using $\boldsymbol{Y^o} = (Y_1^o, \dots, Y_n^o)^t$.

iii. Estimate the marginal density of the errors f_ε using the iterated conditional expectation procedure developed by Braun et *al*. (2005):

   a) Estimate the interval-censored errors as $I_{\varepsilon_i} = \left[L_i - \hat{g}_0(\boldsymbol{X}_i)_\xi, R_i - \hat{g}_0(\boldsymbol{X}_i)_\xi\right]$.

   b) Compute the error marginal density function using a fixed point estimator where at the jth step:

$$\hat{f}_{\varepsilon;j}(z) = \frac{1}{n}\sum_{i=1}^{n} \frac{\int_{I_{\varepsilon_i}} W_b(z-\omega)\hat{f}_{\varepsilon;j-1}(\omega)d_\omega}{\int_{I_{\varepsilon_i}} \hat{f}_{\varepsilon;j-1}(\omega)d_\omega},$$

the error marginal density at the initial step $\hat{f}_{\varepsilon;0}(\omega)$ is taken as a uniform density[17] on the range $\left[min\left(L_i - \hat{g}_0(\boldsymbol{X}_i)_\xi\right), max\left(R_i - \hat{g}_0(\boldsymbol{X}_i)_\xi\right)\right]$, and $W_b(v) = b^{-1}W(v/b)$, $W(\cdot)$ is a kernel density function with scale parameter b. Here, z is any real number.

iv. Compute the conditional expectation of the ϵ_i's: $\hat{E}\left[\epsilon_i \middle| I_{\varepsilon_i}\right] = \frac{\int_{I_{\varepsilon_i}} z\hat{f}_\varepsilon(z)d_z}{\int_{I_{\varepsilon_i}} \hat{f}_\varepsilon(z)d_z}$.

v. Estimate the conditional expectation of the Y_i's, $\boldsymbol{Y}_{\mathbf{imp}}$, where at the j[th] iteration step its i[th] element is given by: $\hat{E}[Y_i|Y_i \in I_i] = \hat{g}_{j-1}(\boldsymbol{X}_i)_\xi + \hat{E}\left[\epsilon_i \middle| I_{\varepsilon_i}\right]$, where $\hat{g}_{j-1}(\boldsymbol{X}_i)_\xi = \hat{g}_0(\boldsymbol{X}_i)_\xi$ on the first iteration.

vi. Compute $\hat{g}_j(\boldsymbol{X})_\xi$ using the estimate $\boldsymbol{Y}_{\mathbf{imp}}$ from previous step.

vii. Set $\hat{g}_0(\boldsymbol{X})_\xi = \hat{g}_j(\boldsymbol{X})_\xi$ and return to step (iii) or stop if convergence criterion is satisfied[18].

4.4.2. Conditional Mean Function Estimation

4.4.2.1.<u>Linear regression</u>

In the *SPILM* the conditional mean function of Y given $\boldsymbol{X}$, $g(\boldsymbol{X})$, is estimated using the standard linear regression model

(4.5) $$g(\boldsymbol{X}_i) = \beta_0 + \sum_{k=1}^{d} \beta_k x_{ik} \,,$$

[17] Braun et *al.* (2005) show that the final estimate of f_ε does not depend on the density function used on the initial iteration step.

[18] An absolute difference of less than 10^{-5} in successive objective function estimates (e.g., $|\hat{g}_j(\boldsymbol{X})_\xi -$ $g j-1 \boldsymbol{X} \xi$) was used to declare convergence on every iteration procedure employed in this study.

where the estimates of the parameters $\beta_0, \beta_1, \dots, \beta_d$ are obtained by least squares. More specifically, let $\widehat{\boldsymbol{\beta}} = \left(\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_d\ \right)^t$ be a vector of parameter estimates, $\boldsymbol{Y}_{\mathbf{imp}}$ a vector of estimated conditional expected values of Y, and $\mathbf{x} = (\mathbf{1}, \boldsymbol{X}\ )$, where $\mathbf{1} = (1, \dots, 1)^t$. It can be shown that the vector $\widehat{\boldsymbol{\beta}}$ that minimizes the sum of squared error is given by

(4.6) $$\widehat{\boldsymbol{\beta}} = (\mathbf{x}'\mathbf{x})^{-1}\mathbf{x}'\boldsymbol{Y}_{\mathbf{imp}}.$$

The *SPILM* mean estimator $\hat{g}(\boldsymbol{X})_{SPILM}$ is calculated by averaging the estimate of (4.5), $\hat{g}(\boldsymbol{X}_i)_{SPILM}$, for all individuals

(4.7) $$\hat{g}(\boldsymbol{X})_{SPILM} = n^{-1}\sum_{i=1}^{n}\hat{g}(\boldsymbol{X}_i)_{SPILM}.$$

4.4.2.2.<u>Nonparametric Additive Regression</u>

There are several options for the nonparametric estimation of the $g(\boldsymbol{X})$ funtion. In this study, I use a nonparametric additive model instead of a multivariate kernel regression for several reasons. First, additive models are less affected by the curse of dimensionality and multicollinearity. Second, their marginal effects are easier to interpret. Third, additive model estimates possess a faster convergence rate than multivariate kernel estimates (Buja et *al*., 1989; Cameron and Trivedi, 2005, p. 319). Finally, the majority of WTP studies use an additive mean parametric function. The additive model assumes that

(4.8) $$g(\boldsymbol{X}_i) = \mu_0 + \sum_{k=1}^{d}\mu_k(x_{ik})\ ,$$

where the $\mu_k(\cdot)$'s are standardized smooth functions so that $E[\mu_k(\cdot)] = 0$ for every k. These functions are estimated one at a time using a backfitting algorithm as suggested by Hastie and Tibshirani (1986), and Kauermann and Opsomer (2004).

As shown in Kauermann and Opsomer (2004), the $\mu_k(\cdot)$'s can be jointly estimated. First, consider the kth additive function estimator

$$(4.9) \qquad \widehat{\boldsymbol{\mu}}_k = \boldsymbol{S}_k^*\{(\boldsymbol{Y}_{\mathbf{imp}} - \hat{\mu}_0) - \widehat{\boldsymbol{\mu}}_{-k}\}$$

where $\widehat{\boldsymbol{\mu}}_k = \{\hat{\mu}_k(x_{1k}), \dots, \hat{\mu}_k(x_{nk})\}^t$, $\widehat{\boldsymbol{\mu}}_{-k} = \sum_{r\neq k}\widehat{\boldsymbol{\mu}}_r$ is an estimator of the sum of the remaining $d-1$ additive functions, $\hat{\mu}_0 = n^{-1}\sum_{i=1}^{n} Y_i$ and $\boldsymbol{S}_k^* = (\boldsymbol{I}_n - \mathbf{1}\,\mathbf{1}^t/n)\boldsymbol{S}_k$ is a centered smooth matrix to ensure identifiability of the estimators, $\boldsymbol{I}_n$ denotes an identity matrix, and $\boldsymbol{S}_k$is a $n \times n$ smoothing matrix whose ij element is given by

$$(4.10) \qquad \boldsymbol{S}_{k,ij} = K_k(x_{ik}, x_{jk}, h_k)/\textstyle\sum_{j=1}^{n} K_k(x_{ik}, x_{jk}, h_k),$$

where $K_k(\cdot)$ is a kernel density function with scale parameter h_k (i.e., a bandwidth). Joint estimation of the additive functions $\widehat{\boldsymbol{\mu}}_1, \dots, \widehat{\boldsymbol{\mu}}_d$ entails finding the solution to the normal equations

$$(4.11) \qquad M\widehat{\boldsymbol{\mu}} = \boldsymbol{S}^*(\boldsymbol{Y}_{\mathbf{imp}} - \hat{\mu}_0),$$

where $\widehat{\boldsymbol{\mu}} = (\widehat{\boldsymbol{\mu}}_1^t, \dots, \widehat{\boldsymbol{\mu}}_d^t)^t$, $\boldsymbol{S}^* = (\boldsymbol{S}_1^{*\,t}, \dots, \boldsymbol{S}_d^{*\,t})^t$ and

$$M = \begin{pmatrix} \boldsymbol{I}_n & \boldsymbol{S}_1^* & \cdots & \boldsymbol{S}_1^* \\ \boldsymbol{S}_2^* & \boldsymbol{I}_n & \cdots & \boldsymbol{S}_2^* \\ \vdots & & \ddots & \vdots \\ \boldsymbol{S}_d^* & \boldsymbol{S}_d^* & \cdots & \boldsymbol{I}_n \end{pmatrix}.$$

As the *SPILM* estimator, the *NIAM* mean estimator $\hat{g}(\boldsymbol{X})_{NIAM}$ also averages the estimated of expression (4.8), $\hat{g}(\boldsymbol{X}_i)_{NIAM}$, for all individuals

$$(4.12) \qquad \hat{g}(\boldsymbol{X})_{NIAM} = n^{-1}\textstyle\sum_{i=1}^{n} \hat{g}(\boldsymbol{X}_i)_{NIAM}.$$

Whereas in *SPILM* the marginal effects are given by the coefficients $\hat{\beta}_1, \dots, \hat{\beta}_d$, in *NIAM* the relationships between covariates and mean WTP are given by the smooth functions $\mu_k(\cdot)$'s (Buja et *al.*,1989). Therefore, the marginal effect of a covariate on the mean WTP changes from point to point. Consequently, the relationships between explanatory variables and smooth functions in additive models are usually presented in the form of plots (e.g., Opsomer and Ruppert, 1998; Kauermann and Opsomer, 2004).

4.4.2.3.Kernel functions and bandwidth selection

The computation of both the *NIAM* mean estimator $\hat{g}(\boldsymbol{X}_i)_{NIAM}$ and the error density function estimator $\hat{\hat{f}}_{\varepsilon}(z)$ involve kernel functions: $K_k(\cdot)$'s in equation (4.10) and $W_b(\cdot)$ in in step (iii.b). I first discuss the specific kernel functions selected in each case and then I talk about the selection of the bandwidth parameters. The kernel functions were selected based on asymptotic properties and on their ability to model both continuous and categorical data.

With respect to the kernel functions used to estimate $\hat{g}(\boldsymbol{X}_i)_{NIAM}$ I consider three different kernel functions. For continuous explanatory variables I consider a 2th-order Epanechnikov kernel[19]. For discrete variables with or without natural order I consider the kernel functions proposed by Racine and Li (2004). The kernel function for the kth continuous variable $K_k^c(\cdot)$ is given by

$$K_k^c\left(x_{ik}, x_{jk}, h_k^c\right) = \frac{3}{4h_k^c}\left\{1 - \left(\frac{x_{ik}-x_{jk}}{h_k^c}\right)^2\right\} \times \mathbf{1}_K\left(\left|\frac{x_{ik}-x_{jk}}{h_k^c}\right| < 1\right), \tag{4.13}$$

where $\mathbf{1}_K(\cdot)$ is an indicator function and $h_k^c > 0$. For the kth unordered discrete variable the kernel function $K_k^{uod}(\cdot)$ is given by (Racine and Li, 2004)

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[19] The 2th-order Epanechnikov kernel function is referred as the "optimal kernel" because it possesses the minimum mean integrated squared error (MISE) among available kernel functions (Cameron and Trivedi, 2005, p. 303).

(4.14) $$K_k^{uod}(x_{ik}, x_{jk}, h_k^{uod}) = \begin{cases} 1 & if\ x_{ik} = x_{jk} \\ h_k^{uod} & if\ x_{ik} \neq x_{jk} \end{cases},$$

where $0 \leq h_k^{uod} \leq 1$. Finally, the kernel function for the k^th^ ordered discrete variable $K_k^{od}(\cdot)$ is given by (Racine and Li, 2004)

(4.15) $$K_k^{od}(x_{ik}, x_{jk}, h_k^{od}) = h_k^{od^{|x_{ik}-x_{jk}|}},$$

where $0 \leq h_k^{od} \leq 1$.

The kernel function $W_b(\cdot)$ in iteration step (iii.b) needed for estimation of the error density function $\hat{f}_\varepsilon(z)$ is set to be equal to the 2^th^-order Epanechnikov kernel

(4.16) $$W\left(\frac{v}{b}\right) = \frac{3}{4}\left\{1 - \left(\frac{v}{b}\right)^2\right\} \times \mathbf{1}_W\left(\left|\frac{v}{b}\right| < 1\right),$$

where $\mathbf{1}_W(\cdot)$ is an indicator function.

The kernel functions in expressions (4.13) – (4.16) depend on the bandwidth or smoothing parameters: h_k^c , h_k^{uod} , h_k^{od} and b. Since the bandwidth choice is more crucial for the quality of the estimates than the kernel choice itself, the bandwith parameters were selected using cross validation procedures (Cameron and Trivedi, 2005, p. 303). The bandwidth parameters for the kernels used to estimate $\hat{g}(\boldsymbol{X}_i)_{NIAM}$ were selected by the generalized cross-validation (GCV) procedure described in Kauermann and Opsomer (2004). This procedure aims to minimize the mean squared error adjusted by degrees of freedom. More precisely, one choose the vector $\boldsymbol{h} = (h_1^c, \dots, h_{d^c}^c, h_1^{uod}, \dots, h_{d^{uod}}^{uod}, h_1^{od}, \dots, h_{d^{od}}^{od})$ that minimizes

(4.17) $$GCV(\boldsymbol{h}) = \frac{(\boldsymbol{Y}_{\mathbf{imp}} - \hat{\boldsymbol{g}}(\boldsymbol{X})_{NIAM})^t(\boldsymbol{Y}_{\mathbf{imp}} - \hat{\boldsymbol{g}}(\boldsymbol{X})_{NIAM})}{n\{1 - \sum_k \mathrm{tr}(\boldsymbol{S}_k^*)/n\}^2},$$

where $\widehat{\boldsymbol{g}}(\boldsymbol{X})_{NIAM} = (\hat{g}(\boldsymbol{X}_i)_{NIAM}, \dots, \hat{g}(\boldsymbol{X}_n)_{NIAM})^t$, and for illustration purposes it is assumed that there are d^c continuous variables, d^{uod} unordered categorical variables and d^{od} ordered categorical variables such that $d^c + d^{uod} + d^{od} = d$. Note that $\widehat{\boldsymbol{g}}(\boldsymbol{X})_{NIAM}$ and the $\boldsymbol{S}_k^*$'s depend on bandwidth vector $\boldsymbol{h}$, even though this is suppressed in the notation.

The likelihood cross-validation (LCV) method proposed by Braun et *al*. (2005) was modified[20] to estimate the bandwidth parameter b of the error density function in expression (4.16). Braun et *al*. (2005) proposed to redefine the observed intervals in terms of a series of disjoint intervals and then drop specific intervals form the original data based on their contribution to the presence of the created disjoint intervals. Instead of creating a series of disjoint intervals as in Braun et *al*. (2005), I proposed to evaluate the estimator of the error density, $\hat{f}_\varepsilon$, *n* times using the observed error intervals and leaving out one error interval from the estimation at a time. Specifically, the cross-validation method proposed aims to maximize the log of LCV

(4.18) $$\ln LCV(b) = \sum_{i=1}^{n} ln\left[\int_{I_{\varepsilon_i}} \hat{f}_\varepsilon^{(-i)}(t)d_t\right],$$

with respect to b, where $\int_{I_{\varepsilon_i}} \hat{f}_\varepsilon^{(-i)}(t)d_t$ is obtained by dropping the interval-censored error I_{ε_i} when estimating $\hat{f}_\varepsilon$. Dropping an error interval is achieved by removing that particular error interval in addition to all estimated error intervals on iteration step (iii.a)

[20] The Braun et *al*. (2005) likelihood cross-validation procedure was adapted because the error intervals in DBCV data present a high level of overlapping, resulting in very small disjoint intervals which makes difficult or impossible to delete error intervals in the original data that are completely enclosed by specific disjoint intervals.

that are completely enclosed by the error interval of interest. Once again, the bandwidth b is suppressed in the notation, even though $\hat{f}_\varepsilon^{(-i)}(t)$ depends on it.

4.4.3. Nonparametric and Parametric ML Estimators

The nonparametric ML estimation is based on the distribution-free approach for interval-censored data proposed in Turnbull (1974, 1976). The parametric ML estimation is based on the procedures described by Cameron (1988) and in Chapter Three of this dissertation. In the DBDC elicitation format every respondent i is presented with an initial bid B_i and asked if he is willing to pay that amount. If the respondent answers "yes" to the first bid, a second WTP question is asked using a higher bid amount B_i^u. If the respondent answers "no" to the first bid, the second WTP question used a lower bid B_i^l. Consequently, every Y_i (i.e., WTP) is observed to fall into one of the four intervals: $(-\infty, B_i^l)$, $[B_i^l, B_i)$, $[B_i, B_i^u)$ and $[B_i^u, +\infty)$, $i = 1, \dots, n$.

Denoting the lower bound of the observed i$^{\text{th}}$ interval (I_i) as L_i and the upper bound as R_i, the probability that Y_i is in the I_i interval is given by

$$P(L_i \leq Y_i < R_i) = \mathrm{F}(R_i) - \mathrm{F}(L_i) \quad i = 1, \dots, n, \tag{4.19}$$

where $\mathrm{F}(\cdot)$ is the cumulative density function (CDF) of Y. Since the number of different bids used in the DBDC questions is usually less than the number of observations in the sample, some of the observed intervals are the same across individuals; resulting in $M \leq n$ unique observed intervals $\mathcal{I}_m$, m=1, …, M, with boundary values of $\mathcal{L}_m$ and $\mathcal{R}_m$. Consequently, the log likelihood function for the interval-censored Y_i's can be written as

$$\begin{aligned} \ln L &= \textstyle\sum_{i=1}^{n} ln[\mathrm{F}(R_i) - \mathrm{F}(L_i)] \\ &= \textstyle\sum_{m=1}^{M} n_m ln[\mathrm{F}(\mathcal{R}_m) - \mathrm{F}(\mathcal{L}_m)], \end{aligned} \tag{4.20}$$

where $n_m, m = 1, \dots M$, is the number of observations for whom both $L_i = \mathcal{L}_m$ and $R_i = \mathcal{R}_m$.

The parametric model (*PM*) assumes that Y_i follows a normal distribution with mean $\mathbf{x}_i'\boldsymbol{\beta}$ and variance σ^2 (see Chapter Three). The conditional parametric mean estimator $\hat{g}(\boldsymbol{X})_{PM}$ is estimated as the average $\mathbf{x}_i'\boldsymbol{\beta}$ across all individuals

(4.21) $$\hat{g}(\boldsymbol{X})_{PM} = n^{-1} \sum_{i=1}^{n} \mathbf{x}_i'\boldsymbol{\beta} .$$

Estimation of the nonparametric ML model was carried out using the nonparametric approach for interval-censored data proposed by Turnbull (1976). First, we need to expressed each unique observed interval $\mathcal{I}_m$, m=1,…, M, as an union of Q disjoint closed intervals of the form $[a_{q-1}, a_q)$, $q = 1, \dots, Q$, called innermost intervals[21], such that $\mathcal{I}_m = \bigcup_{q=1}^{Q} d_{mq}[a_{q-1}, a_q)$, where d_{mq} is a dummy variable that indicates whether the q[th] innermost interval is used to express the m[th] unique interval. Specifically,

(4.22) $$d_{mq} = \begin{cases} 1 & if\ \ \mathcal{L}_m \le a_{q-1}\ and\ \mathcal{R}_m \ge a_q \\ 0 & otherwise \end{cases}, m = 1, \dots, M; q = 1, \dots, Q.$$

Assuming that Y is non-negative, the complete set of Q innermost intervals is $[a_0, a_1), [a_1, a_2) \dots \left[a_{Q-1}, a_Q\right)$, where $0 = a_0 < a_1 < \cdots < a_Q$. In the case of DBDC data, the boundaries of the innermost intervals (a_q's) are given by the bid amounts used in the WTP questions. The log likelihood function in (4.20) is then expressed in terms of the innermost intervals

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[21] The innermost intervals A_q, $q = 1, \dots, Q$, are defined as "*all the disjoint intervals which are non-empty intersections of the observed intervals I_i, $i = 1, \dots, n$, such that for all possible i and q, $A_q \cap I_i = \emptyset$ or A_q (Yu et al., 1998)*".

$$\text{(4.23)} \qquad \ln L = \sum_{m=1}^{M} n_m ln \sum_{q=1}^{Q} d_{mq}[\mathrm{F}(a_q) - \mathrm{F}(a_{q-1})].$$

The Turnbull procedure considers each $F_q = F(a_q)$ in (4.23) as a parameter to be estimated and imposes the restriction that $0 = F_0 \leq F_1 \ldots \leq F_Q = 1$. Estimation is then carried out using Turnbull's self-consistent algorithm (Day 2007; Gomez et *al*., 2004; Turnbull 1976). The mean value of Y can thus be written as (Haab and McConnell, 1997):

$$\text{(4.24)} \qquad E(Y) = \int_0^{a_Q} Y\, d_{F(Y)} = \sum_{q=1}^{Q} \int_{A_q} Y d_{F(Y)}.$$

As mention earlier, the Turnbull approach does not provide a point estimate of the mean WTP, but only upper and lower bounds of its value. Therefore, to facilitate comparison across models, I used the Turnbull midpoint approximation of the expected value of Y $(\hat{g}_T)$

$$\text{(4.25)} \qquad \hat{g}_T = \hat{E}(Y) = \sum_{q=1}^{Q} \frac{a_{q-1}+a_q}{2} (\hat{F}_q - \hat{F}_{q-1}),$$

where the $\hat{F}_q$'s are the solution to the log likelihood function in (4.23).

One limitation of the nonparametric ML estimation is that estimator of the CDF of Y, $\hat{F}$, is only defined at the endpoints of the innermost intervals (Braun et *al*., 2005). Also note the Turnbull approach does not allow the inclusion of covariates, thus no marginal effects can be estimated using this procedure.

4.4.4. Probability Distribution Estimation

The iteration process used in the *SPILM* and *NIAM* approaches can also be used to recover the CDF and probability density function (PDF) of WTP at any point. Estimation of the probability distribution of Y is possible since

$$f_Y(y) = f_\varepsilon\big(y - g(\boldsymbol{X})\big), \tag{4.26}$$

where f_Y is the PDF of Y.

Equation (4.26) suggests the following estimators for the PDF and CDF of Y:

$$\hat{f}_Y(y)_\xi = \hat{f}_\varepsilon\big(y - \hat{g}(\boldsymbol{X})_\xi\big) \tag{4.27}$$

and

$$\hat{F}_Y(y)_\xi = \int_0^y \hat{f}_\varepsilon\big(y - \hat{g}(\boldsymbol{X})_\xi\big) d_y, \tag{4.28}$$

respectively, where $f_\varepsilon(\cdot)$ and $g(\boldsymbol{X})$ in (4.26) are replaced by estimates and ξ = *SPILM*, *NIAM*.

4.4.5. Data and Study Design

The relative performance of the *SPILM*, *NIAM* and Turnbull estimation procedures was evaluated using simulated data sets. Estimated mean values and marginal effects were compared to those obtained from a parametric model estimated using the distribution used in the simulations. The three models were employed to estimate producers' WTP for the services provided by an Electronic Trade Platform in a data set described and analyzed in Chapter Three of this dissertation.

4.4.5.1.<u>Monte Carlo simulation</u>

A total of 100 data sets (simulations) containing n observations each,$\{Y_i, \boldsymbol{X}_i\}_{i=1}^n$, $n \in \{100, 200\}$, were generating using the following regression model containing both continuous and categorical predictor variables

$$Y_i = 40 + 3X_{1i} + 3X_{2i} + 3X_{3i}^{d1} - 2X_{3i}^{d2} + 2\epsilon_i, \tag{4.29}$$

where the X_{1i}'s are i.i.d observations from an Uniform distribution in the ranges [-10, 10], $X_{2i} \in \{0,1\}$ with $Pr(X_{2i} = 0) = Pr(X_{2i} = 1) = 0.5$, $X_{3i}^{d_j} \in \{0,1\}$, $j = 1, 2$, indicate the occurrence of the jth category of X_{3i}, $X_{3i} \in \{1,2,3\}$ with $Pr(X_{3i} = \iota) = 1/3$ for $\iota = 1,2,3$, and ϵ_i is an i.i.d. observation from a Normal distribution with mean zero and variance equal to one. The resulting Y_i's from (4.29) can be seen as the individuals' true valuation (e.g., individuals' WTP value) given a set of observable characteristics, $\boldsymbol{X}$. In practice, individuals' WTP values are usually not observed, instead individuals' WTP values are interval-censored. The data generating process considered in this study mimics the one employed in CV using a DBDC elicitation format. Four initial bid amounts were randomly assigned to each observation in the generated data: \$24, \$36, \$48 and \$60. The initial bids, respectively, are the 20th, 40th, 60th and 80th percentiles of an empirical distribution in a 50 observation sample simulated with the regression model in (4.29) with no error term[22]. The corresponding follow-up bid amounts were \$18 (10th percentile), \$24, \$36 and \$48 if the initial bid assigned to the observation was higher than the true WTP value. On the other hand, if the initial bid assigned to the observation was lower than the true WTP value, corresponding higher follow-up bids of \$36, \$48, \$60 and \$66 (90th percentile) were assigned. Based on the sample distribution used to generate the bids, the lower bound for those observations answering "no/no" was set to \$0 and the upper bound for those answering "yes/yes" was set to \$80 in *SPILM*, *NIAM* and Turnbull approach.

[22] The initial bids were chosen following the methods employed in Calia and Strazzera (2012).

Using the observations generated in (4.29) I estimate the distribution mean WTP using *SPILM*, *NIAM* and Turnbull procedures (equations (4.7), (4.12) and (4.25)) and the marginal effects from *SPILM*. In the case of the *NIAM*, the estimated relationship between each explanatory variable and Y is compared to the true relationship for a random sample generated using expression (4.29).

The conditional mean ($\hat{g}(\boldsymbol{X})_{PM}$) of the true parametric model (*PM*) was estimated as described in the previous section and their marginal effects were calculated following the procedure described in Cameron (1988) and in Chapter Three. The performance of all four mean estimators ($\hat{g}(\boldsymbol{X})_{SPILM}$, $\hat{g}(\boldsymbol{X})_{NIAM}$, $\hat{g}_T$ and $\hat{g}(\boldsymbol{X})_{PM}$) and marginal effect estimators from the *SPILM* and *PM* was analyzed using the squared-root of the Mean Squared Error (RMSE),

$$RMSE(\hat{\theta}) = \sqrt{\frac{1}{100}\sum_{s=1}^{100}\left[\hat{\theta}^{(s)} - \theta^{(s)}\right]^2}, \tag{4.30}$$

bias

$$bias(\hat{\theta}) = \frac{1}{100}\sum_{s=1}^{100}\left[\hat{\theta}^{(s)} - \theta^{(s)}\right] \tag{4.31}$$

and standard error (SE)

$$SE(\hat{\theta}) = \sqrt{\frac{1}{100}\sum_{s=1}^{100}\left[\hat{\theta}^{(s)} - \bar{\hat{\theta}}\right]^2}, \tag{4.32}$$

where $\hat{\theta}^{(s)}$ and $\theta^{(s)}$ are the estimated and true parameter function of interest (e.g., mean or marginal effect) of the s^{th} data set, and $\bar{\hat{\theta}} = \frac{1}{100}\sum_{s=1}^{100}\hat{\theta}^{(s)}$. In the case of the *NIAM* mean estimator, $\hat{g}(\boldsymbol{X})_{AM}$, a continuous kernel was used to model X_1, an unordered kernel for X_2 and a ordered kernel for the discrete explanatory variable X_3 in (4.29). The RMSE, bias and SE of the corresponding estimators from the *SPILM*. *NIAM*, Turnbull and *PM* are reported over 100 replications.

4.4.5.2.Empirical application: producers' WTP study

The *SPILM*, *NIAM* and Turnbull estimator were also evaluated using a real DBDC data set. The data was described and analyzed in Chapter Three of this dissertation using parametric techniques, where the WTP measure was found to follow a log-logistic distribution. The main objective of the study was to estimate the monetary value that registered producers placed on the services provided by an Electronic Trade Platform (i.e., MarketMaker).

The initial bids used to capture producers' WTP were $25, $50, $75, $100, $150, and $200; and the corresponding follow-up annual bids were $15, $25, $50, $75, $100, and $150 when the initial response was a "no", and $50, $75, $100, $150, $200, and $250 when the initial response was a "yes". A reduced set of available explanatory variables was used as an illustration of the attributes of the proposed estimation techniques. Covariates employed in the estimation of the WTP models are type of user based on frequency of use (USER_TYPE), marketing contacts gained due to participation in MarketMaker (CONTACTS), and firm total annual sales (SALES). In the *NIAM*, the continuous variable SALES was modeled using the continuous kernel depicted in (4.13), whereas the ordered categorical variables USER_TYPE and CONTACTS were modeled using the ordered kernel described in (4.15).

The mean WTP was estimated for the *SPILM*, *NIAM* and Turnbull method. Marginal effects and covariate-mean relationships were estimated for the *SPILM* and

NIAM approaches, respectively. The standard errors of the estimated means and marginal effects of *SPILM* were calculated using the bootstrapping procedure outlined by Cameron and Trivedi (2005, p.362) using a total of 100 replications. For the *NIAM*, the relationships between covariates and mean WTP are not constant across individuals; hence the pointwise standard error bands suggested by Buja et *al*. (1989) were used as a measure of dispersion of the estimated smooth functions. The standard error bands represent the fitted curve ± 2 estimated standard error. The standard error of each smooth function was estimated as the mean standard error across the 100 replications at each unique covariate value. Finally, the underlying PDF and CDF of the producers' WTP for MarketMaker were calculated using expressions (4.27) and (4.28), respectively.

The different bandwidths parameters of the *SPILM* and *NIAM* estimators were calculated using the 227 observations in the original data, then the smooth parameter (b) of the error density function in iteration step (iii.b) was fixed at these values in each replication of the bootstrapping procedure[23]. Fixing the bandwidth at predetermined values removes some of the variability attributed to the smoother parameters used to construct the estimators, which might results in a better comparison of the performance of the different estimators (Escanciano and Jacho-Chavez, 2011).

[23] The bandwidth parameter b in the *SPILM* and *NIAM* were estimated to be equal to 5.30 and 7.01, respectively.

4.5. Results

The performance of the *SPILM*, *NIAM* and Turnbull estimator was analyzed using finite samples generated through Monte Carlo simulations. In terms of mean prediction, simulation results show that the conditional mean estimator of both *SPILM* and *NIAM* dominates the unconditional Turnbull mean estimator in terms of RMSE, bias and SE. Furthermore, the *SPILM* mean estimator performed as well as the benchmark correctly specified *PM* estimator. The RMSE, bias and standard error of the different mean estimators are presented in Table 4.1.

Simulation results were also used to evaluate marginal effect predictions of the *SPILM* and *NIAM*. Marginal effects obtained with the *SPILM* were compared to the ones generated by the correctly specified *PM* (Table 4.2). Based on the results presented in Table 4.2, there is no a clear superior model between the *SPILM* and *PM*. In general terms, marginal effects of the *SPILM* presented lower RMSE and SE values, but had higher bias compared to their counterparts estimated using the *PM*. In the case of the *NIAM*, two random Monte Carlo samples ($n = 100$, 200) were generated to illustrated the predicted relationship between each covariate in (4.29) and Y. It is important to remember that in the *NIAM* each fitted smooth function ($\mu_k(\cdot)$) trace out the predicted marginal effect of its corresponding explanatory variable on the mean of Y (Cameron and Trivedi, 2005, p.327). The fitted smooth functions of every explanatory variable are displayed on Figure 4.1. Based on data generator process described in (4.29), the true effect of X_1 on Y is given a straight line with slope of 3, while in the *NIAM* this relationship is estimated in the two fitted smooth functions presented in the upper plots of

Figure 4.1. In the case of the discrete variables X_2 and X_3, marginal effects can be thought as the difference in the smooth function between each point of X_2 and X_3. For example, in the 100 observation sample, the difference in Y between an observation with $X_2 = 1$ and one with $X_2 = 0$ is estimated to be 3.16 units (compare to a difference of 3 units in the true model).

The iteration process used in the *SPILM* and *NIAM* can also be used to recover the CDF and PDF of Y. For illustration purposes, the two random samples used to present the covariate-mean relationships in the *NIAM* were used to estimate their underlying distribution functions using *SPILM* and *NIAM* approaches. The estimated CDF and PDF of the *SPILM* and *NIAM*, as well as their counterparts estimated using the true conditional *PM* and Turnbull approach are displayed in Figure 4.2. The marked difference between the *SPILM*, *NIAM* and *PM* CDF estimates and those from the Turnbull approach are attributed to the fact that the formers are conditional estimates while the Turnbull CDF is estimated without considering the effect of covariates.

The *SPILM*, *NIAM* and Turnbull approach were also employed in a real DBDC data set to model producers' WTP for MarketMaker. The *SPILM*, *NIAM* and Turnbull mean estimates in addition to the conditional parametric estimate calculated using the log-logistic model presented in Chapter Three of this dissertation are reported in Table 4.3. The *SPILM* estimates that each registered producers, on average, are willing to pay \$36.82 annually for the services provided by MarketMaker, and the *NIAM* estimates that, on average, producers are willing to pay \$36.58 for such services.

In contrast to the Turnbull procedure, the *SPILM* and *NIAM* approaches allow estimation of the effect of producers' characteristics on their valuation of MarketMaker. Specifically, *SPILM* estimation results indicate that active users of MarketMaker are willing to pay $17.08 more per year than their passive counterparts. The *SPILM* also predict that each additional marketing contact received due to participation with MarketMaker increases the annual WTP by $1.58. Lastly, *SPILM* results indicate that a $1,000 increase in total annual sales is expected to increase the annual WTP by only $0.03. Table 4.4 present the marginal effects of the different covariates employed in the *SPILM*.

In the case of *NIAM*, the relationships between each covariate – USER_TYPE, CONTACTS and SALES – and annual producers' WTP for the serviced provided by MarketMaker are presented in Figure 4.3. In term of USER_TYPE, *NIAM* estimation results indicate that active users are willing to pay $16.13 more per year than passive users. NIAM results also indicate that producers' WTP is positively related to CONTACT and SALES. Additionally, from Figure 4.3 we can see that the impact of CONTACT and SALES on WTP fluctuate more as these variables increase.

Finally, as an illustration, both *SPILM* and *NIAM* approaches were used to recover the conditional underlying probability function of producers' WTP for the services provided by MarketMaker. The PDF and CDF estimates of producers' WTP for the different models are displayed in Figure 4.4.

4.6. Summary and Conclusions

The purpose of this study was to develop alternative distribution-free estimation approaches that can be used to analyze interval-censored WTP data obtained using the DBDC elicitation method. The proposed estimators (i.e., *SPILM* and *NIAM*) involve iterated procedures that combine nonparametric kernel density estimation of the errors of the WTP function with parametric or nonparametric estimation of its conditional mean function. Although estimation of mean WTP can be extended in principle to other modeling techniques, this study focused on parametric linear and nonparametric additive models.

The proposed *SPILM* and *NIAM* can be thought as alternatives to the standard distribution-free methods employed to analyzed DBDC responses such as the Turnbull approach. In contrast to Turnbull approach, the proposed estimation techniques provides a point estimate of the mean WTP, allows the estimation of the marginal effects of covariates on the mean WTP, as well as the estimation of the underlying WTP probability distribution function at any point.

Monte Carlo simulation techniques were employed to compare the performance of the proposed estimators with those of the Turnbull approach and the true parametric model. Simulation results show that the *SPILM* and *NIAM* perform substantially better than the Turnbull approach, and that conditional mean and marginal effect estimates of the *SPILM* and *NIAM* are analogous to the ones obtained using the benchmark correctly specified parametric model. A real data set was also used to illustrate the usefulness of the proposed estimation techniques in practice.

Table 4.1. Mean Estimator Comparison using Monte Carlo Finite Samples.

n	Estimator	RMSE	Bias	SE
100	SPILM	0.456	0.003	1.752
	NIAM	0.686	0.022	1.774
	Turnbull	1.205	-0.096	2.145
	PM	0.456	0.008	1.775
200	SPILM	0.327	-0.004	1.323
	NIAM	0.406	0.010	1.310
	Turnbull	0.772	-0.213	1.548
	PM	0.323	0.002	1.328

Table 4.2. Marginal Effect Estimator Comparison using Monte Carlo Finite Samples.

n	Estimator	Marginal Effect	RMSE	Bias	SE
100	SPILM	X_1	0.124	0.038	0.119
		X_2	1.096	0.098	1.097
		X_3^{d1}	1.186	-0.162	1.181
		X_3^{d2}	1.111	-0.096	1.112
	PM	X_1	0.132	0.025	0.130
		X_2	1.122	0.105	1.123
		X_3^{d1}	1.199	-0.140	1.197
		X_3^{d2}	1.111	-0.108	1.111
200	SPILM	X_1	0.075	0.017	0.073
		X_2	0.807	0.077	0.807
		X_3^{d1}	0.858	0.042	0.862
		X_3^{d2}	0.852	-0.080	0.853
	PM	X_1	0.077	0.007	0.077
		X_2	0.815	0.068	0.816
		X_3^{d1}	0.870	0.034	0.874
		X_3^{d2}	0.822	-0.068	0.823

Table 4.3. Mean Producers' WTP by Estimator, MarketMaker Valuation Data.

Estimator	Mean Estimate	SE
SPILM	36.815	3.675
NIAM	36.584	3.849
Turnbull	28.435	3.166
Log-logistic PM	41.197	6.772

Table 4.4. *SPILM* Marginal Effect Estimates, MarketMaker Valuation Data.

Variable	Marginal Effect		SE
Constant	24.212	***[a]	4.947
USER_TYPE (Active user =1, Passive user=0)	17.078	**	9.493
CONTACTS	1.584	*	1.061
SALES ($1,000)	0.026	**	0.013

[a] Significance levels of 0.01, 0.05 and 0.10 are indicated by ***, ** and * respectively.

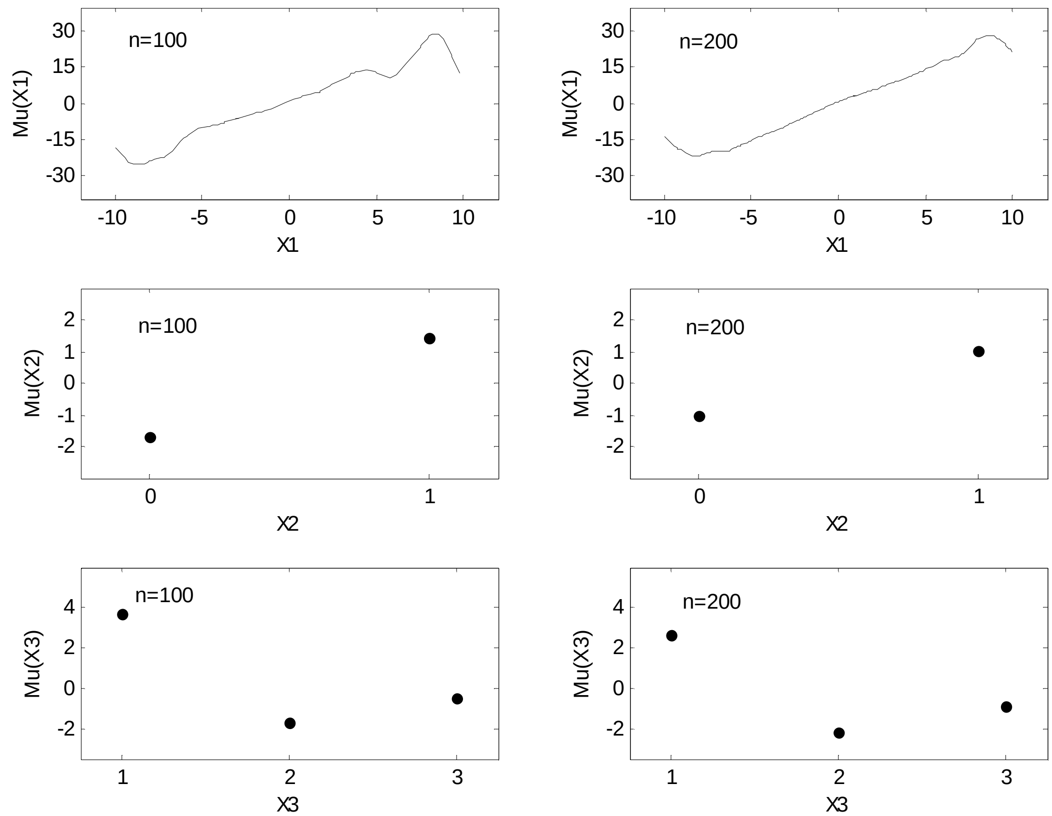

Figure 4.1. *NIAM* Fitted Smooth Functions Using Two Random Monte Carlo Finite Samples.

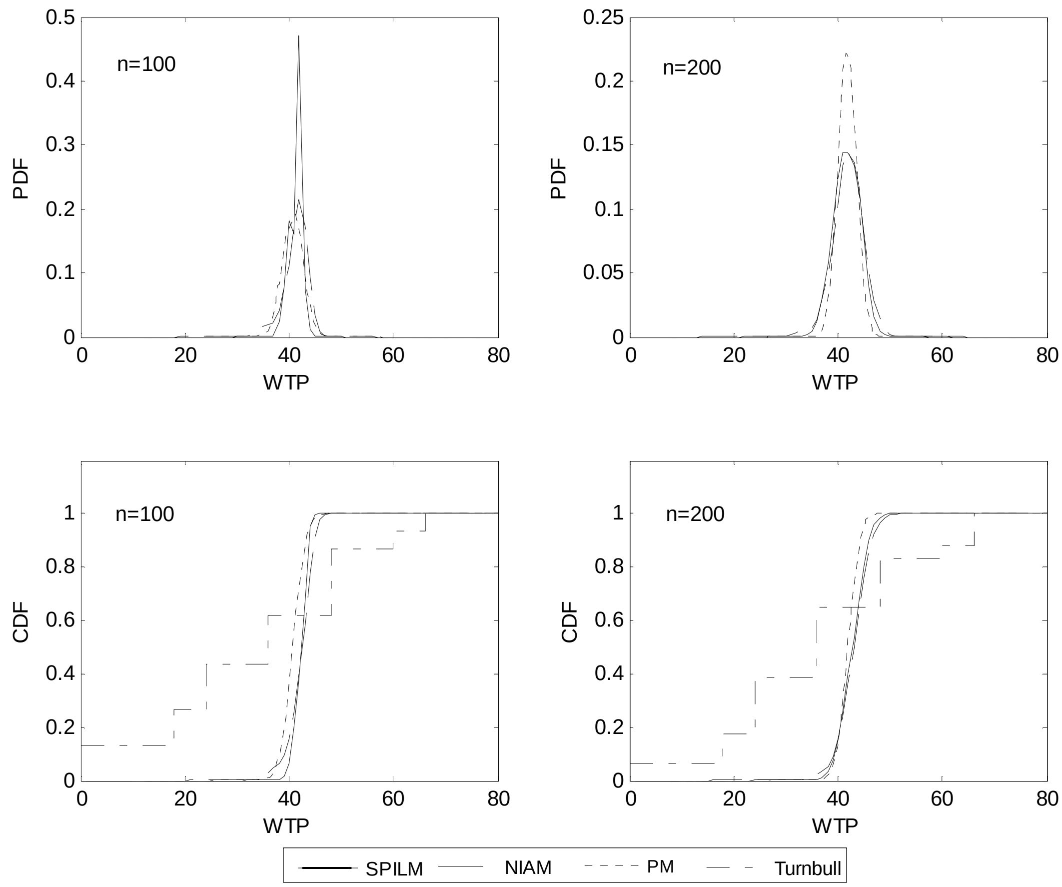

Figure 4.2. Distribution Function Estimates Using Two Random Monte Carlo Finite Samples.

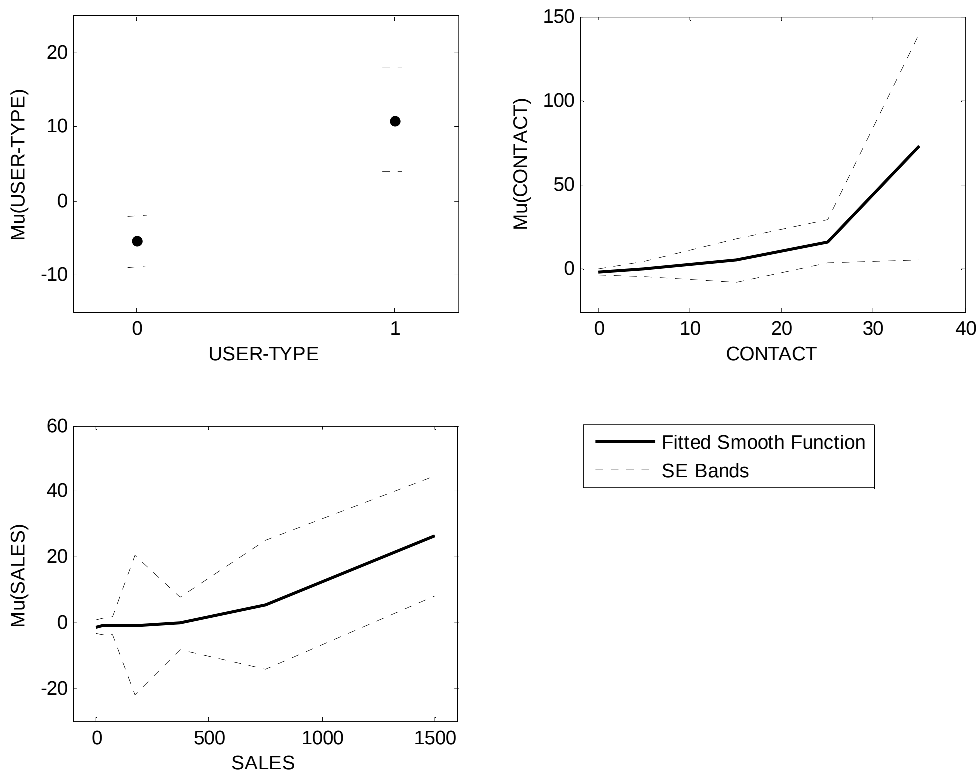

Figure 4.3. *NIAM* Fitted Smooth Functions and Standard Error Bands, MarketMaker Valuation Data.

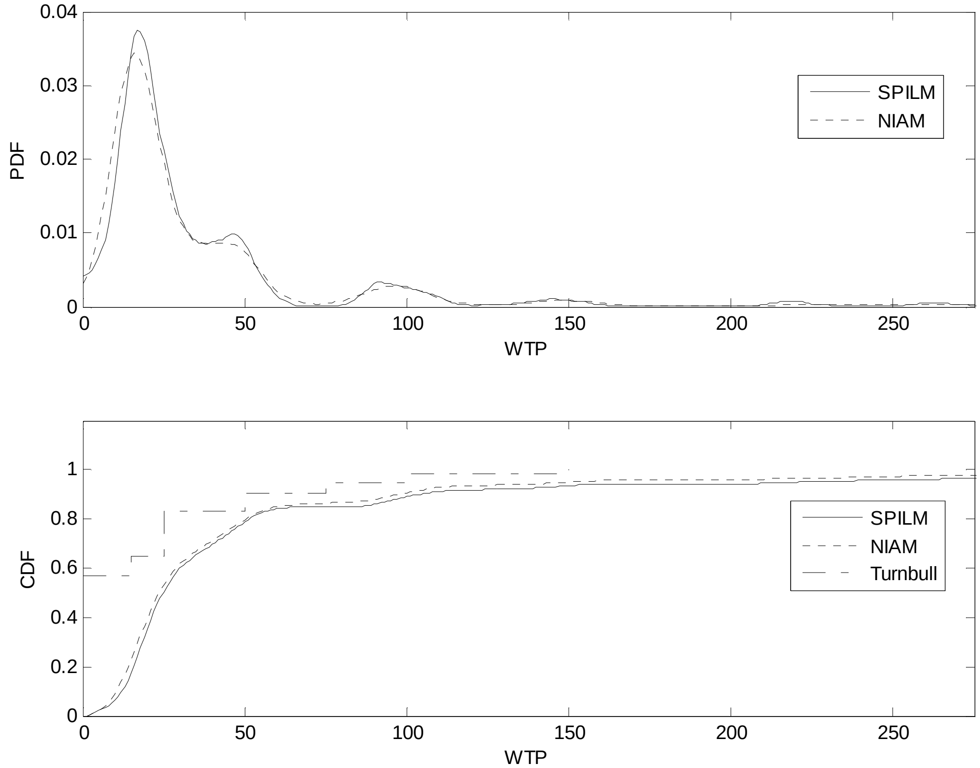

Figure 4.4. Distribution Function Estimates, MarketMaker Valuation Data.

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CHAPTER FIVE

DISSERTATION SUMMARY AND CONCLUSIONS

This dissertation investigated the theoretical foundation, applications and estimation of the contingent valuation (CV) method with special emphasis on producers and agribusiness. The first essay analyzes the theoretical underpinnings of producers' willingness to pay (WTP) measures for new inputs. In addition to conceptualizing the producer WTP function, its comparative statics are derived and it is shown how these properties can be used to estimate the new quantity demanded or supplied and, in some cases, price elasticities. Implications of this relationship to specify empirical WTP models and survey design are also discussed. The WTP model presented was developed within the context of neoclassical theories of utility and profit maximization. More specifically, the variation function, or producers' WTP, for novel inputs or technologies is derived using individual indirect utility function in combination with the firm's profit function.

The theoretical results imply that the maximum amount of money that a producer is WTP for a new production factor is equal to the difference between the *ex post* and *ex ante* firm's profit levels. Moreover, the results suggest that the producers' WTP is a function of output and input prices and input *ex ante* and *ex post* quality levels. Comparative statics results show that producers' WTP is a decreasing function of the upgraded input price, its initial quality level, and an increasing function of output price and final quality level.

In the second essay, CV methods using online and mail surveys are employed to estimate the economic value that registered producers place on the services received from an Electronic Trade Platform (i.e., MarketMaker). Estimation of the WTP model was carried out using parametric maximum likelihood estimation procedures. The WTP estimation results indicate that, on average, producers are willing to pay $47.02 annually for the services they receive from MarketMaker. This value is a measure of the increase in annual profits attributed to the use of MarketMaker. Moreover, the estimated average annual producer WTP was used to estimate the aggregate value that registered producers place on the services provided by MarketMaker. Specifically, the estimated aggregate annual economic value is $361,959.

The second essay also analyzes the effect of producers' characteristics and perceptions on their economic valuation of the site. Estimation results indicate that registration type, time registered on MarketMaker, time devoted to the website, type of user, the number of marketing contacts received and firm total annual sales have a significant effect on producers' WTP for the serviced provided by MarketMaker.

In the third essay, alternative semiparametric and nonparametric estimation techniques are proposed to analyze double-bounded dichotomous choice (DBDC) data in CV studies. The proposed estimators involve iterated procedures that combine nonparametric kernel density estimation of the errors of the WTP function with parametric linear or nonparametric kernel regression of its conditional mean function.

Although the estimation of the mean WTP can be extended in principle to other modeling techniques, this essay focuses on least squares and nonparametric additive models. In contrast to the Turnbull approach, the proposed estimation techniques provides a point estimate of the mean WTP, allows the inclusion of covariates in the modeling of WTP estimates, as well as the thorough recovery of its underlying probability distribution. Monte Carlo simulations are employed to compare the performance of the proposed estimator with that of the Turnbull estimator. Simulation results show that proposed estimators perform substantially better than the Turnbull approach, and that conditional mean and marginal effect estimates of these models are analogous to the ones obtained using the benchmark correctly specified parametric model. The usefulness of proposed models is illustrated using a real data set.

Future research need to be conducted to fully implement the theoretical model described in Chapter Two of this dissertation. The theoretical model can be used to predict the new quantities of inputs demanded and output supplied, and their corresponding price elasticities. To this end, the empirical data should include information regarding the explanatory variables identified in the model: input prices, output price, and *ex ante* and *ex post* input quality levels; as well as previous information of the original quantities of inputs demanded, output supplied and price elasticity values. *Ex ante* input quality levels might not be available, thus additional information about input characteristics needs to be collected to create them. For example, the quality level of labor can be constructed using workers characteristics such as years of education and expertise. In terms of the *ex post* input quality levels, variability needs to be introduced in order to estimate the final input quality effects, thus different hypothetical *ex post* input quality levels can be used in the WTP questions.

Even though the distribution-free methods proposed in Chapter Four of this dissertation were found to perform well, in some occasions the time required for the algorithms to converge was surprisingly long. For these reason, alternative algorithms and estimation routines need to be developed to estimate the proposed models more efficiently. The models also need to be evaluated in both simulated and real data sets with larger sample sizes than those considered in this study. Additionally, future work could also concentrate in alternative mean estimators beyond those employed in this study or in variations to the proposed estimators by considering different kernel functions to model discrete variables.