ESSAYS IN APPLIED DEMAND AND PRODUCTION ANALYSIS

by

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B.Sc., University of Asmara, Eritrea, 1997
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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2010

Abstract

This dissertation is composed of two essays in applied microeconomics. Using farm level data, the first essay applied nonparametric methods to test the adherence of individual farm's production choices to profit maximization objective. Results indicate that none of the farms consistently satisfy the joint hypothesis of profit maximization. The study took into account the uncertainty prevalent in agricultural production by systematically modeling the optimization behavior of farms. Departures of observed data of individual farms from profit maximization objectives were attributed more due to stochastic influences caused by output production decisions than input use decisions. Results also support the existence of technological progress during the study period for Kansas farms. At an alpha level of 5%, assuming both input and output quantities as stochastic, only 5.3% of the farms violated the joint hypothesis of profit maximization with standard error exceeding 10%. Whereas when only input quantities are considered stochastic, a total of 71.73% and 2.09% of the farms had minimum standard errors of greater than 10% and 20% respectively required for the joint profit maximization hypothesis to hold. When only output quantity measurements were assumed as stochastic, a total of 80.10 % and 18.84 % of the farms had minimum standard errors of greater than 10% and 20% respectively required for the profit maximization hypothesis to hold.

The second essay examines the demand for alcoholic beverages (beer, wine and distilled spirits) for the U.S. using time series data from 1979-2006. The estimation is done using an error correction form of the Almost Ideal Demand System . Results indicate that there is a significant difference between short run and long run elasticity estimates. The paper addresses the exogeneity of log of prices and log of real expenditures. For the beer and wine equations, the hypothesis of joint exogeneity of price index and real expenditure cannot be rejected at all the

conventional levels of significance. For the spirits equation, the tests strongly reject the simultaneous exogeneity of price index and real expenditure. When independently tested, price index appears to be endogenous variable where as real expenditure seems exogenous variable. Based on these results, the real expenditure was considered as an exogenous variable, where as the price index for spirits as an endogenous variable.

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"Trust in the LORD with all your heart and do not lean on your own understanding.

In all your ways acknowledge Him, and He will make your paths straight." Proverbs 3:5-6

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Dedication

This dissertation is dedicated to my mother, Bahgu Ghebremedhin, and to the memory of my father Abrehe Zereyesus, grandparents Zereyesus Woldesamuel and Hiwet Ghender, my uncle Asfaha Ghebremedhin and Berhane Melke.

ESSAY 1 - FARM LEVEL NON PARAMETRIC ANALYSIS OF PROFIT MAXIMIZATION BEHAVIOR WITH MEASUREMENT ERROR

1. INTRODUCTION

1.1. Problem Statement

The use of parametric empirical production analysis involves imposing flexible functional forms capable of locally approximating an arbitrary function. This type of production analysis proceeds by first postulating a parametric form for the production function (e.g. Cobb-Douglas, Translog, and Quadratic) and then using standard statistical techniques to estimate the unknown parameters from the observed data (Varian, 1984). This type of parametric analysis is sensitive to the functional forms used (Shumway and Lim 1993) and can lead to different elasticity estimates conditioned on the choice of the flexible functional forms (Chavas and Cox, 1995). This procedure also does not allow the maintained objective to be directly tested (Hanoch and Rothschild, 1972; Varian, 1984). However, nonparametric production analysis does not require specification of a particular functional form and furthermore allows testing consistency of observed behavior with optimization rules such as profit maximization, cost minimization or revenue maximization.

In general, deterministic nonparametric production analysis approaches often reject the maintained behavior of profit maximization tests. When conducting deterministic tests, as Varian (1985) puts it “the data are assumed to be observed without error, so that the tests are ‘all or nothing’: either the data satisfy the optimization hypothesis or they don’t.” However, data used in the analysis of firm behavior could fail the test because producers make decision errors, don't always operate on the efficient boundary (e.g. as in technical or allocative inefficiencies), or because observations are not perfect measurements (Hanoch and Rothschild, 1972; Varian, 1985) or due to lack of generality of the optimization theory, such as in decision making under risk (McElroy, 1987). When real world data are exposed to stochastic influences, application of nonparametric stochastic tests allow testing the consistency of data contaminated with error with the theoretical optimizing behavior.

Varian (1984, 1985) hypothesized that one of the reasons for the rejection of profit maximization may be due to errors in data. He proposed an approach to conduct a statistical test that takes into account the possibility of measurement error in observed data. However, many previous studies addressing optimizing behavior and the structure of technology typically used national or state level aggregated data rather than individual farm data. Microeconomic theory is based upon optimization by individual agents. Featherstone, Moghnieh, and Goodwin (1995) argue that the use of aggregate data to characterize individual agents' optimization behavior can cause problems by possibly introducing aggregation bias due to summing across farms.

Empirical evidence shows that when firm level data are used, the cost minimization or profit maximization hypothesis is rejected in most cases, whereas the optimization hypothesis is not rejected when aggregate data are used. This necessitates consideration of the level of analysis and type of data used. This observation has led Love (1998) to suggest that stochastic nonparametric test procedures be used when testing firm-level data for cost-minimizing or profit maximizing behavior.

Given the widespread use of profit maximization as a primary objective in economics, testing its validity is important for economic analyses, management decisions and policy recommendations. If a farm's behavioral objective is different from maximizing profit[1], results based on this assumption could be misleading. It is essential to investigate the relevance of maintained behavior (i.e. firms maximize profit in this case) with observed farm behavior. Furthermore, when the observed data violates the assumed objective, a formal test of the significance of this violation in view of measurement error in variables is necessary (Varian 1985, Lim and Shumway, 1992a). Although, the theoretical nonparametric production approaches that test adherence to these behavioral objectives have been developed for quite some time, empirical application of such tests has been limited (Fawson and Shumway 1988; Chavas and Cox1995) especially Varian's approach of estimating measurement error in variables (Kuosmanen, Post, and Scholtes, 2007).

In the presence of risk and uncertainty, farmers commit production resources with an expected output price and expected output quantity in mind. It appears that there is higher fluctuation in realized output than in input use. Inherently there is more variability in yield, at least in agricultural crop production, implying that the stochastic nature in output production is different from input use. This may mean that departures of farmers' behavior from hypothesized optimization objectives such as profit maximization may be attributed more to output error than input use. This is to say that higher measurement errors in the output quantity data may occur for profit maximization to hold. We also expect to have lower measurement error when we consider perturbations in the input side only and even lower when both inputs and outputs are considered

[1]Those who advocate for the *market selection argument* would predict that significant deviation from maximizing profit may eventually force a firm to leave the market (for a discussion on this see Dutta and Radner, 1999 and Blume and Easly, 1992)

stochastic. This essay uses a rich farm level data set on 377 Kansas farms applying Varian's nonparametric production approach allowing for measurement error in variables to meet the following objectives.

1.2. Objectives

The objective of this essay is to determine the minimum amount of measurement error necessary for farm level production data to be consistent with profit maximization. The specific objectives are:

1. Determine the minimum amount of measurement error in variables (input and output) necessary for farm level production data to be consistent with profit maximization.

2. Determine the minimum amount of measurement error in output variables necessary for farm level production data to be consistent with profit maximization.

3. Determine the minimum amount of measurement error in input variables necessary for farm level production data to be consistent with profit maximization.

1.3. Conceptual Framework

Profit maximization is one of the maintained behavioral objectives of the neoclassical theory of firm. Profit is defined as total revenue minus total cost. Economic analysis of a typical firm occurs by formulating a profit function (Π) such that $\Pi = P * y - w * x$, where P is output price, y is quantity of output produced by the firm, w is input price, and x is input quantity used by the firm. Adopting the convention that positive numbers denote outputs and negative numbers denote inputs so that y represents the input-output vector (also known as netput vector), we can write the profile function as $\Pi = P * y$. Then we can say that Profit (Π_t) at any time, *t*, is the product of the netput vector, y_t, and its price vector, P_t .

A fundamental precondition for production analysis based on the revealed preference approach is that all farms maximize profit at the given prices. Assuming firms are prices takers, any firm maximizes profit (Π) by choosing the quantity produced[2,3]. It is of interest then to check the validity of the maintained rule of profit maximization (Hanoch and Rothschild, 1972) because economic decisions and policy recommendations are formulated assuming this fundamental behavior of firms.

The following graphical demonstration adapted from Mas-collel et al. (1995) relates the firm's profit maximization problem and the set of profit-maximizing vectors, referred to as *supply correspondence* at *p, y (p).* In Figure 1-1, the optimizing vector *y (p)* lies at the point in Y associated with the highest level of profit. The quantity, *y (p)* therefore lies on the *iso-profit* line that intersects the production set furthest to the northeast and is, therefore, tangent to the boundary of Y at *y (p).*

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[2] Varian's nonparametric approach of cost minimization developed in this type of analysis is appropriate under a competitive market structure. The formulation of such objective functions do not apply when there is a deviation from a competitive market setting (e.g. as in non-competitive or uncertain market environments), and specific assumptions about the objective functions should be made. Varian (1984) provided a modification of the deterministic test for models of imperfectly competitive behavior.

[3] A derivation of profit maximizing output for a competitive firm is contained in the appendix.

Figure 1-1: The Profit Maximization Problem

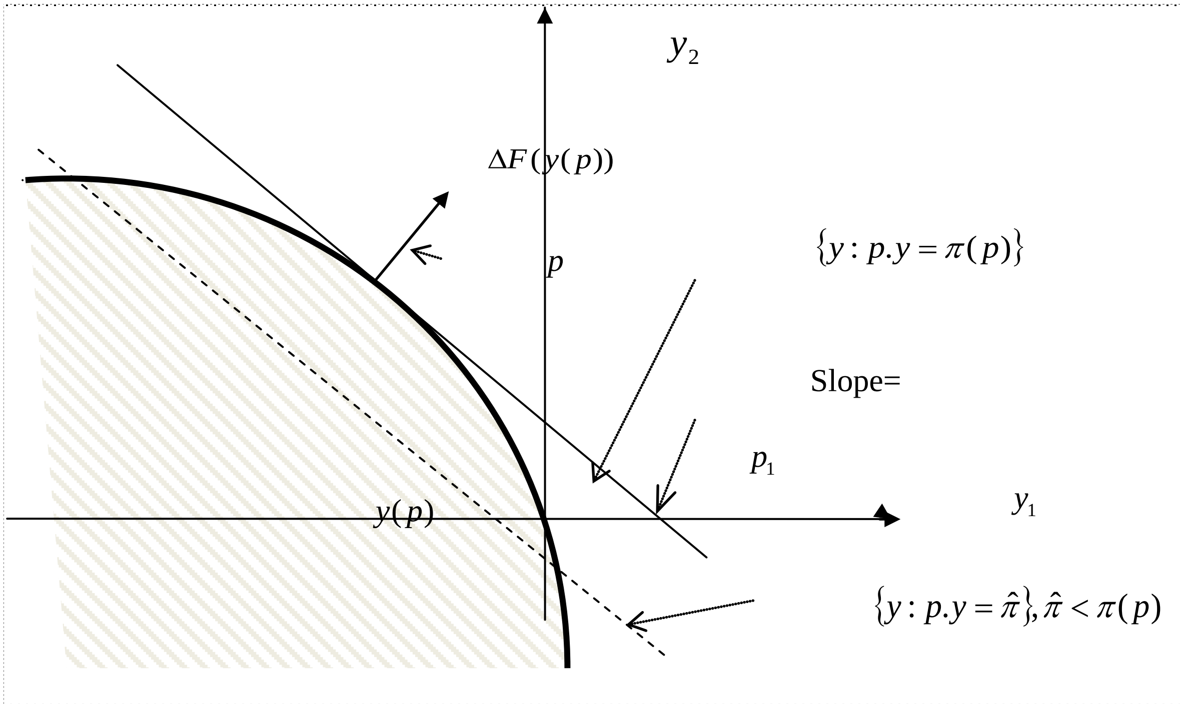
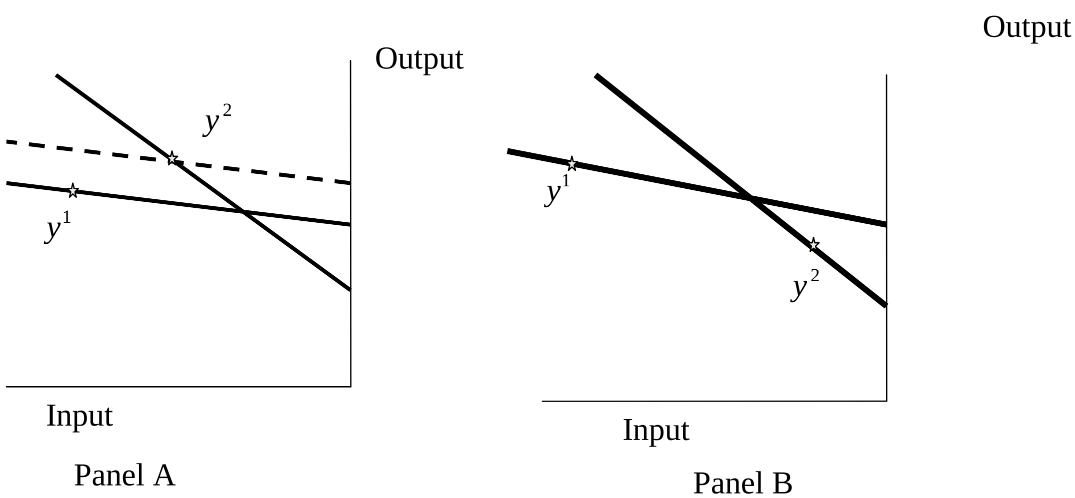


Figure 1-2: The Weak Axiom of Profit Maximization



So, if we have observed data on P_t *and* $y(P_t)$, the profit maximization model implies that if profit is maximized given P_t, then that profit should be greater than or equal to any other profit generated by any other set of outputs and inputs evaluated at P_t. This can be formally expressed as $P_tY_t \geq P_tY_s$ for all $t, s = 1, 2, ..., n$. The Weak Axiom of Profit Maximization (WAPM) is demonstrated with a graphical presentation, due to Varian (1992, pp 36.), using two observations that *violate* and *satisfy* the condition $P_tY_t \geq P_tY_s$. In panel A, the WAPM is violated since $P_1Y_2 \geq P_1Y_1$, where as in panel B, it is *satisfied*.

In practice, theoretically implied hypotheses can be tested using either firm or aggregate data. Aggregation theories and procedures have been developed for production analysis to indicate the consistency of aggregate industry production functions with the aggregation of micro production functions (Grunfeld and Griliches, 1960; Zarembka, 1968), and hence using industry level aggregate data for analysis of a representative firm. This is crucially important because it can be used to generalize the behavior of a representative firm. Use of aggregated data also can overcome the problem with data availability on individual farms. However, aggregation over farms may also result in the loss of estimation and testing power (Orcutt, Watts, and Edwards, 1968) as well as more inconsistency with optimization behaviors (e.g. Fawson and Shumway, 1988). Such inconsistency is also more likely to occur when nonparametric tests are of a deterministic type. i.e. where the tests are ‘sharp’ with no probabilities attached to the hypotheses tests. This is why Love (1998) suggested that stochastic nonparametric procedures be used when testing firm-level data for cost-minimizing or profit maximizing behavior.

1.4. Summary of Problem Statement, Objectives, and Conceptual Framework

All things kept constant, the practice of locally approximating an arbitrary function by flexible functional forms may introduce errors in empirical parametric economic analysis approaches, because no one knows for sure what that exact function is. The fact that nonparametric approaches do not require specifying functional forms makes them particularly attractive to avoid this kind of error related to misspecification bias. Given this desirable feature of nonparametric approaches, it is acknowledged that deterministic nonparametric approaches lack formal statistical significance testing of hypothesis tests and a case is developed in favor of stochastic tests that do allow formal statistical hypothesis test. In a competitive environment and given a well behaved technology, one of the most widely asserted behavioral objective of firms is to maximize profit. Formal stochastic nonparametric tests of this hypothesis are often rejected, especially when national aggregate data are used. Therefore, stochastic nonparametric tests are applied using firm level data to determine the minimum amount of measurement error (or standard error) necessary for farm level production data to be consistent with profit maximization.

2. LITERATURE REVIEW

Nonparametric approaches are of two types. One type compares a firm with another firm for a given year. This approach aims at developing reference technologies against which to calculate the efficiency of observations in data sets (Farrell, 1957; Fare, Grosskopf, and Lovell, 1985). The second type, which is used in this essay, compares current input/output choices to decisions made previously for the purpose of testing data sets for consistency with regularity conditions on technology and behavioral objectives (Hanoch and Rothschild, 1972; Varian, 1984). Banker and Maindiratta (1988) developed a technique based on efficiency analysis to test the consistency of data with technology restrictions and behavioral objectives, thus creating a link between these two nonparametric approaches.

Hanoch and Rothschild (1972), as well as Afriat (1967, 1972) and later Diewert and Parkan (1983, 1985) were among the first to propose a nonparametric method to test the validity of production theory assumptions and restrictions. These two approaches have been refined and extended by many researchers. Varian (1983, 1984) extended these methods in several directions to test demand and production data for consistency with maintained hypotheses, test technology restrictions such as constant returns to scale**,** homotheticity, and separabilty, and also proposed a way to forecast firm behavior under different scenarios. Chalfant and Alston (1988) provide (while studying the demand for meat in the U.S. and Australia) a support for the use of nonparametric approaches to account for changes in tastes and argue for the stability of a set preferences; as well as rejecting previous conclusions of structural changes in demand.

Other extensions to nonparametric test methods include testing technical change and the separability hypotheses about the production technology for U.S. Agriculture (e.g. Chavas and Cox, 1988; Chavas and Cox, 1990; Cox and Chavas, 1990; Chavas and Cox, 1992). These studies extend Varian's nonparametric approach by generalizing the weak axioms of profit maximization and cost minimization hypotheses to allow for technical change; by specifying a technology index in the production function and proposing a linear programming problem for empirical implementation of their approaches; by extending previous analysis of production decisions in light of the assumption that technical progress increases the effectiveness of inputs in the production of outputs[4,5]. U.S. data were used to test separability of inputs and outputs from other inputs and outputs and technology change in the production function. Strong support for the aggregation of inputs into capital, labor, and materials was found by Chavas and Cox (1988), although Lim and Shumway (1992b) found no empirical evidence to support this result. Fawson and Shumway (1988) empirically tested consistency of farm behavior-using data from production regions in the United States- with the joint hypothesis of profit maximization, convex technology, and monotonic nonregressive technical change. They observed differences in the rejection of hypotheses due to level of aggregation of the data used. For example, greater inconsistency with the joint hypothesis was observed when using disaggregated commodity data than when using aggregated data. Using U.S. and Japanese manufacturing data, Chavas and Cox (1988, 1990) obtained results that showed the existence of a production function exhibiting Hicks neutral technical change. Chavas and Cox (1992) further modeled technical progress as a function of lagged research expenditures, enabling the investigation of the separate effects of

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[4] Under the modeling approach section of this essay, we build on these extensions to examine technological change in production function.

[5] The assumption that technical progress increases the effectiveness of inputs in the production of outputs falls under the subject of augmentation hypothesis (Chavas and Cox 1990).

private research and public research on technical progress and agricultural productivity. Their findings indicate that public funding on research generate an internal rate of return (IRR) of 28% on agricultural productivity compared to a private funding which generates an IRR of 17%. Chavas and Cox noted that at least 30 years of lags are necessary to capture the effects of public expenditures on research. In conclusion, for the U.S. data, they found strong empirical support to the existence of technical change in agricultural production. In a separate study, Chavas and Cox (1995) demonstrated estimation of supply response in U.S. agriculture using the nonparametric approach, generating estimates of supply-demand elasticities for six outputs and ten inputs. In this study, Chavas and Cox also established that their approach can also be applied for data not consistent with production theory, such as in cases where some data points conflict with the profit maximization rule due to, for example, either technical change or production inefficiencies.

Bar-Shira and Finkelshtain (1999) extended and formalized the work done by Fawson and Shumway (1988) to account for both monotonic and non-monotonic technical changes. Their findings were consistent with previous results (e.g. Chavas and Cox) which found that the technological change for U.S agriculture between the years 1948 to 1994 was (Hicks) neutral. They further found empirical evidence that observed data were not consistent with profit maximization and monotonic technological progress, but consistent with cost minimization and monotonic technological progress.

One of the drawbacks of deterministic nonparametric hypotheses tests was the inability of these tests to provide a mechanism that attaches a probability to rejection to the null hypotheses (Varian, 1985, 1990, Chavas and Cox 1988). The deterministic test is not a statistical testing procedure but is instead an analysis in which observed data are unambiguously consistent with the optimization behavior (Lim and Shumway, 1992). Failure to adhere to the ‘exact’ optimization behavior would then result in rejection of the optimizing rule. Cognizant of this limitation, Varian (1985, 1990) derived a test statistic that permits stochastic tests to be interpreted in terms of classical statistics. One of his approaches was to determine the minimum perturbation in variables to cause the firm behavior to be optimal. This was the motivation for stochastic approaches to test for data contaminated by measurement error in variables. The other approach Varian suggested was to determine minimum deviations from the possible maximum profit or minimum cost. Silva and Stefanou (1996) relaxed the linear homogeneity restriction imposed on a production function by Hanoch and Rothschild and Varian to assess the underlying degree of homogeneity of a production function. They demonstrated that for data consistent with homothetic production technology and optimizing behavior, nonparametric tests can be used to test consistency of data with a production function of homogeneity of any degree. Silva and Stefanou (2003) further introduce dynamic aspects to the previous static nonparametric production and behavioral assumption tests. Building on the foundations of dynamic production analysis in the context of intertemporal cost minimization, Silva and Stefanou developed nonparametric approach to check consistency of data with constant returns to scale and homotheticity in a dynamic production structure. Silva and Stefanou (1996, 2003) allowed for deterministic and stochastic tests in line with Varian’s proposition. Kuosmanen, Post, and Scholtes (2007) further generalized the stochastic tests to include perturbations not only in variables that define the objective function, but also in variables that constitute the constraint set by relying on efficiency measures. Their approach uses only quantity measurement, hence avoiding the need to use price observations.

The stochastic tests have been applied in empirical analysis of agricultural technology (e.g. Lim and Shumway, 1992a, 1992b; Featherstone, Moghnieh, and Goodwin, 1995). Lim and Shumway (1992a) applied nonparametric techniques to statewide aggregate production data for the United States from 1956 through 1982. They estimated measurement errors of about 3% from the stochastic tests and conclude consistency with the profit-maximization hypothesis in nearly all states. Lim and Shumway (1992b) also used nonparametric analysis to investigate separability in state-level agricultural technology. Although there was variability in results among states and among alternative categories, their findings did not rule out a reasonable amount of data aggregation among inputs and outputs.

Featherstone, Moghnieh, and Goodwin (1995) applied nonparametric techniques to analyze agricultural technology and production behavior for a sample of 289 Kansas farms, using annual farm level data for an 18-year period, 1973 to 1990. Their results rejected strict adherence of the observed data to the hypotheses of cost minimization and profit maximization. Based on relatively larger number of rejection and greater percentage of deviation of the profit maximization than the cost minimization tests, Featherstone, Moghnieh, and Goodwin (1995) concluded that the sample of Kansas farms may be more cost minimizing than profit maximizing farms. A similar conclusion was reached by Tauer (1995) that a group of New York dairy farms were not very successful in maximizing profits, but came close to displaying cost minimization behavior.

For a sample of Pennsylvania dairy operators during the time period 1986-1992, Silva and Stefanou (2003) found observed data inconsistent with the hypothesis of a weak axiom of dynamic cost minimization; and rejection of the joint hypothesis of dynamic cost minimization and constant returns to scale. Using stochastic dynamic cost minimization tests, they found the minimum standard error required for consistency of observed data with dynamic cost minimization hypotheses in the range between 25.87% and 39.05% across years. They also found that the lower bound of the standard error in the input quantity data for the hypothesis of homotheticity and dynamic cost minimization tests ranged from 78.69% to 120.02% across years. Taking 10% measurement error as a rejection criterion, they concluded that the deviations from the optimizing rules in both tests were statistically significant.

2.1. Summary of Literature Review

Since its development, the literature on nonparametric production analysis focused on two distinct approaches. The first approach compares a firm with another firm for a given year in an attempt to develop reference technology with which to compare efficiency scores of observed data sets (Farrell, 1957; Fare, Grosskopf, and Lovell, 1985). The second approach, the main focus of this literature review, compares current input/output choices to decisions made previously to test data sets for consistency with behavioral objectives and technology regularity conditions (Hanoch and Rothschild, 1972; Varian, 1984). Later on, a link between these two approaches was established as demonstrated by Banker and Maindiratta (1988) and Fare and Grosskopf (1995).

The contribution of many researchers to the development of nonparametric production analysis is documented (e.g. Afriat, 1967, 1972; Hanoch and Rothschild, 1972; Diewert and Parkan, 1983, 1985). Varian (1984, 1985) helped popularize the approach by extending it in several directions. Notably, Varian introduced stochastic tests that formalized the deterministic tests to conform with classical statistical hypothesis testing in the presence of measurement error. The work of other (e.g. Chavas and Cox, 1988, 1990, 1992; Cox and Chavas, 1990; and Fawson and Shumway, 1988) who have done extensive work to test consistency of data with optimization rules.

In addition to theoretical developments, the nonparametric approach has been applied empirically to test consistency of observed data with behavioral objectives and technology regularity conditions using national aggregate data (e.g. Fawson and Shumway, 1988; Lim and Shumway, 1992a, 1992b) and firm level data (e.g. Featherstone, Moghnieh, and Goodwin, 1995; Tauer, 1995), predominantly on U.S. agriculture.

3. MODELING APPROACH

3.1. Nonparametric Production Analysis

Varian (1984, 1985) developed a deterministic test of profit maximization and a stochastic test of the magnitude of measurement error required for consistency with the profit maximization behavior when some observations violate the deterministic test. In the deterministic test, the entire test fails if the optimizing hypothesis is violated once. The stochastic test allows for measurement error in data when considering consistency with the optimizing behavior.

3.2. Deterministic Tests

Following Varian (1984), let **T** be the production possibility set of all input-output bundles (-x, y) compatible with available technology. The set of feasible netput vector, termed as the *production set,* represents the production activities or production plans. The production possibility set **T** is nonempty, closed, bounded from above, convex, and allows for free disposal. The property of non-emptiness implies that the firm can produce the output with at least one set of input. The production possibility set **T** is closed indicates that the set **T** includes its boundary. Free disposal implies that it is always possible to absorb any additional amounts of inputs without any reduction in outputs. It can be interpreted that any extra amount of input can be disposed of at no cost. The convexity assumption says that if *t*, *t*' $\in$ **T** and $\alpha \in [0, 1]$, then $\alpha\, t$+ *(1-* α) *t*' $\in$ **T** (Mas-Colell, Whinston, and Green, 1995).

A specific production set at time *t* is represented by a netput vector **Y** = (Y_1, . . ., Y_m) in **T**, where positive Y_i s represent outputs and negative Y_i s represent inputs. The set of all feasible production plans, **Y**, a subset of **T**, is closed, convex, and negative monotonic. This negative monotonic property corresponds to the free disposal hypothesis (Varian, 1984). The boundary of the convex set reflects an efficient production frontier, because no other way exists to produce the given output with fewer inputs or to produce more output with given inputs. This implies that profit (Π_t) at any time, *t*, is the product of the netput vector, $\mathbf{Y_t}$, and its price vector, P_t. Varian (1984, 1985) showed that the following conditions are equivalent: (1) There exists a production set that p-rationalizes[6] the data; (2) $P_tY_t \geq P_tY_s$ for all *t, s = 1, 2,... ,n* and (3) there exists a closed, convex, negative monotonic production set that p-rationalizes the data.

Under constant technology over the sample period, consistency of the observed data with competitive profit maximization requires:

$$P_tY_t \geq P_tY_s \quad \textit{for all } t, s = 1, 2, ..., n, \qquad (1)$$

where Y_t is in $\mathbf{Y}$. Varian (1984) calls this Weak Axiom of Profit Maximization (WAPM). This axiom implies that if profit is maximized given P_t, then that profit should be greater than or equal to any other profit generated by any other set of outputs and inputs evaluated at P_t. In practice, this would require checking *equation 1* to test for adherence of the observed data set with the profit maximization rule. This would require n^2 pair wise comparisons and $n^2 - n$ pair wise comparisons excluding the equality constraints. Condition (2) or *equation (1)* is a *necessary* and *sufficient condition* for profit maximization (Samuelson, 1947; Hanoch and

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[6] A production set $\mathbf{Y}$ is said to p-rationalize the data (p_t, y_t) if $p_ty_t \geq p_ty$ for all $\mathbf{y}$ in $\mathbf{Y}$ for t= 1, . . . , n (Varian 1984).

Rothschild, 1972; Varian, 1984). Reconciliation of condition (2) in view of the classical derivation of first and second order conditions for a profit maximization problem is shown in Appendix.

The test in *equation (1)* assumes constant technology. Technological progress increases the efficiency of inputs used in the production of output. Chavas and Cox (1988) assert that it is possible that failure to consider technological change over the period of study can contribute to rejection of the maintained hypothesis. Chavas and Cox (1995 pp.87) state that "*Technical progress shifts the production function up, causing "older" data points to appear technically inefficient and thus inconsistent with profit maximization based on a stable technology*". They extended the nonparametric approach to include technological change by specifying a technology index in the production function. Thus to account for monotonic nonregressive technical change i.e. to insure that any technology used in production period *s* is also available in production period *t* for all $s < t$, we can introduce the following technology restriction as:

$$P_t Y_t \geq P_t Y_s \quad \textit{for all } t, s = 1, 2, ..., n, \text{ only for } s < t \qquad (2)$$

This technology restriction, $s < t$, reduces the number of pair wise comparisons to check for consistency of the observed data with the deterministic profit maximization rule to $\frac{n^2 - n}{2}$.

3.3 Stochastic Tests

The deterministic test fails if the optimizing behavior is violated even once. However, the observed data could fail the test for many reasons. These can be attributed to producers making decision errors, or due to technical and allocative inefficiencies, and/or because of a random environment or observations aren't perfect measurements (Hanoch and Rothschild, 1972; Varian,

1985) or due to lack of generality of the optimization theory, such as the case of decision making under risk (McElroy, 1987).

Varian (1985) proposed a general nonparametric method of statistical hypothesis testing when data are subject to measurement error. Following Varian's (1985) notation, consider the null hypothesis, H_O, that the data (Y_t , p_t) satisfy the joint hypothesis of profit maximization and convex technology. Assume that the true netput k quantity for observation t is related to the observed netput quantity in the following manner:

$$Q_{tk} = Y_{tk}(1+\varepsilon_{tk}) \qquad (3)$$

where Q_{tk} is the true netput quantity, Y_{tk} is the observed netput quantity, and ε_{tk} is a random error term that is independently and identically distributed N $(0,\sigma^2)$. Since netputs are measured in different units (e.g., tons, bushels, acres etc), the use of proportional error proposed by Varian (1985) and applied by Lim and Shumway (1992a , 1992b) helps overcome the problem of differences in measurement units of the netput.[7] However, this set up requires that observed data should be greater than zero in all of the netput vector in any given year[8]. Given this condition, the following test statistic can be developed:

[7] Varian (1985), and Lim and Shumway (1992a) used these equations to relate optimization problems for cost minimization and profit maximization with measurement errors.

[8] Later in this section, we postulate an additive error and provide a way how to deal with this formulation as well.

$$T = \sum_{t=1}^{n} \sum_{k=1}^{m} (Q_{tk} / Y_{tk} - 1)^2 / \sigma^2 \qquad (4)$$

Under the null hypothesis, equation (4) follows a chi-squared distribution with $n \ x \ m$ degrees of freedom. Although we can choose critical values (C_α) for given α levels, in practice we don't know the values of Q_{tk} and the true σ^2. However, we can use the variance from observed data to obtain a critical lower bound estimate of the error variance when the null hypothesis is true. To do so, the following quadratic programming problem is formulated:

$$Min_z R = \frac{\sum_{t=1}^{n} \sum_{k=1}^{m} (Z_{tk} / Y_{tk} - 1)^2}{\sigma^2}$$

Subject to

$$\sum_{t=1}^{m} p_{tk} Z_{tk} \geq \sum_{t=1}^{m} p_{tk} Z_{sk} \quad \textit{for all t, s=1, 2,..., n} \qquad (5)$$

where Z_{tk} and Z_{sk} are solutions to the quadratic programming problem that minimize the sum of squared proportional residuals, R. Under the null hypothesis, the true data (Q_t, P_t) satisfy the constraints. Hence, under this H_O, the minimum sum of squared errors, R, must not exceed the critical values C_α for a given level of α from the true distribution. In other words, we will fail to accept the null hypothesis if $R > C_\alpha$. If we denote the numerator sum of squared residuals $\sum_{t=1}^{n} \sum_{k=1}^{m} (Z_{tk} / Y_{tk} - 1)^2$ by K, and rearrange the inequality, the null hypothesis is not accepted if $\sigma^2 < \frac{K}{C_\alpha}$. The critical lower bound estimate of the standard error at α can be computed as $\overline{\sigma}$

$=\left[\dfrac{K}{C_\alpha}\right]^{0.5}$ and the H_O is not accepted if the standard error of measurement of the data is less than $\bar{\sigma}$.

Following Fawson and Shumway (1988) and Chavas and Cox (1988), the joint hypothesis of profit maximization; convex technology; and monotonic, non-regressive, technical change may be tested by changing the indexes *t* and *s* to reflect technology indexes in (4) as follows:

$$Min_z R = \frac{\sum_{t=1}^{n} \sum_{k=1}^{m} (Z_{tk} / Y_{tk} - 1)^2}{\sigma^2}$$

Subject to

$$\sum_{k=1}^{m} p_{tk} Z_{tk} \geq \sum_{k=1}^{m} p_{tk} Z_{sk} \text{ for all } t, s=1, 2,\ldots,n \text{ and } s < t, \qquad (6)$$

The technology restriction $s < t$ in equation *(6)* reduces the number of pair wise comparisons to $\frac{n^2 - n}{2}$, with $n\ x\ m$ degrees of freedom used to compute the C_α from the Chi-squared distribution.

If some of the observed netput data equal to zero, a proportional error specification as in *equation (3)* poses computational problems during the minimization of the squared residuals in *equations (5)* and *(6)*. Because the observed netput quantity vector (Y_{tk}) appears in the denominator of the equation, division by zero will make the objective function undefined. Therefore, in addition to the proportional error used by Lim and Shumway (1992a), we further modify the analysis to use an additive error formulation with transformed data when some of the netputs are equal to zero. The use of additive error avoids zero observations and also provides a unified framework to accommodate for multiproduct analysis with flexibility to deal with data when some outputs are not produced for some years or when some farms produce only one output. To proceed with the additive error formulation, we first normalize each of the elements in the netput vector by dividing the corresponding mean of the observations $t = 1, 2, ..., n,$ such that the mean is equal to one. The transformed netput vector is then unit invariant and the additive error model can be used. In this manner, the true netput and observed netput vectors are related as:

$$Q_{tk} = Y_{tk} + \varepsilon_{tk} \qquad (7)$$

when Q_{tk} is the true netput quantity, Y_{tk} is the observed netput quantity, and ε_{tk} is a random error term that is independently and identically distributed with mean zero and constant variance. Now, if the true data, (Q_{tk}), could be observed, the test statistic could be calculated as:

$$T = \sum_{t=1}^{n} \sum_{k=1}^{m} (Q_{tk} - Y_{tk})^2 / \sigma^2 \qquad (8)$$

Under the null hypothesis, equation (8) has a chi-squared distribution with $n \ x \ m$ degrees of freedom. Although the true σ^2 is unknown, we can use the variance from the observed data to obtain a critical lower bound estimate of the error variance when the null hypothesis is true. In a similar fashion as in the proportional disturbances, the following quadratic programming problem is formulated:

$$Min_z R = \frac{\sum_{t=1}^{n} \sum_{k=1}^{m} (Z_{tk} - Y_{tk})^2}{\sigma^2}$$

Subject to

$$\sum_{k=1}^{m} p_{tk} Z_{tk} \geq \sum_{k=1}^{m} p_{tk} Z_{sk} \quad \textit{for all } t = 1,2,\ldots,n \tag{9}$$

where Z_{tk} and Z_{sk} are solutions to the quadratic programming problem that minimize the sum of squared additive residuals, R. Under H_O the true data (Q_t, p_t) satisfy the constraints in *equation (9)*. Following the same analogy as in *equation (5)*, we fail to accept H_O if the standard error of measurement of the data is less than the critical lower bound estimate of the standard error $\overline{\sigma}$.

To impose monotonic nonregressive technological change, the above equations can be modified as:

$$Min_z R = \frac{\sum_{t=1}^{n} \sum_{k=1}^{m} (Z_{tk} - Y_{tk})^2}{\sigma^2}$$

Subject to

$$\sum_{k=1}^{m} p_{tk} Z_{tk} \geq \sum_{k=1}^{m} p_{tk} Z_{sk} \quad \textit{for all } t = 1, 2,\ldots,n \quad \textit{, and } s \leq t \tag{10}$$

Varian (1985) first analyzed cost minimizing behavior where only input variables are considered to contain errors and outputs are assumed to be measured with full accuracy. He developed an aggregate cost function that accounts for only stochastic input quantities. Similarly, Silva and Stefanou (2003) assumed only input demand data were measured with error to analyze production behavior of Pennsylvania dairy operators during the time period 1986-1992. They constructed a dynamic cost function as an aggregate measure of the behavioral objective of the dairy farms. Kuosmanen, Post, and Scholtes (2007) further noted that a similar approach can be used to regard as the measurement error occurring in the outputs, where inputs are assumed to be measured with full accuracy, such that revenue maximizing behavior can be considered as an aggregate measure. When profit maximization is used as an aggregate measure, the measurement errors are considered to account for both the input and output side. Although any measurement is likely to be contaminated with some sort of error, the sensitivity of the joint hypothesis might depend on what constitutes the error structure, i.e. whether it is more on the input side or output side. Given that decision making in agriculture is done under risk and uncertainty and that farmers commit production resources with an expected output price and expected output quantity in mind, their response to output risk is not the same as in input use risk. Inherently there is variability in yield, at least in agricultural crop production. It is of practical interest then to hypothesize that the stochastic nature in input use is different from output production, which in turn implies that the severity of measurement error can be different on the input side from the output side. This exercise can also provide an upper and lower bound on the magnitude of the measurement error depending on whether the error occurs in the input or output side. In other words, given that farmers consider risk when making output decisions, relatively greater deviation from the profit maximization objective would result due to output decisions. This is to say that higher percentage standard errors in the output quantity data would be required for the specified joint hypothesis of profit maximization to hold at a given significance level and hence relatively higher probability of rejecting the joint hypothesis. Conversely, we may expect to have lower measurement error when we consider the input side only and even lower when both inputs and outputs are considered stochastic.

Based on these farm characteristics, we can examine the composition of the error terms in the above *equations (4) and (7)* to include only output or input quantities. To investigate measurement error only for outputs, we assume that the input side is measured with full accuracy. Based on this assumption, define the following minimization objective function of a proportional error as $Min_z R = \frac{\sum_{t=1}^{n} \sum_{k_1=1}^{m_1} (Z_{tk_1} / Y_{tk_1} - 1)^2}{\sigma^2}$ such that the Z_{tk_1} and Y_{tk_1} pertain to outputs constrained by the profit maximization restrictions, but only the output side is stochastic. To incorporate this information into Varian's basic profit maximization constraint set, we have partitioned the netput vector into inputs and outputs such that k_1 and m_1 refer to the outputs and k_2 and m_2 refer to inputs, in which the observed input is the same as with the true input. Hence the modified constraint will be;

$$\sum_{k_1=1}^{m_1} p_{tk_1} Z_{tk_1} + \sum_{k_2=1}^{m_2} p_{tk_2} Y_{tk_2} \geq \sum_{k_1=1}^{m_1} p_{tk_1} Z_{sk_1} + \sum_{k_2=1}^{m_2} p_{tk_2} Y_{sk_2} \quad \textit{for all } t,s=1, 2,\ldots,n \qquad (11)$$

where Z_{tk_1} and Z_{sk_1} are solutions to the quadratic programming problem that minimize the sum of squared proportional output residuals, R. The task is to find a critical lower bound estimate of the standard error computed at α as $\overline{\sigma} = \left[\frac{K}{C_\alpha} \right]^{0.5}$ with $n \ x \ m_1$ degrees of freedom. To impose monotonic nonregressive technological change, we put a technology restriction to *equation (11)* as:

$$\sum_{k_1=1}^{m_1} p_{tk_1} Z_{tk_1} + \sum_{k_2=1}^{m_2} p_{tk_2} Y_{tk_2} \geq \sum_{k_1=1}^{m_1} p_{tk_1} Z_{sk_1} + \sum_{k_2=1}^{m_2} p_{tk_2} Y_{sk_2} \;\; \textit{for all t, s=1, 2,…, n and } s \leq t, \qquad (12)$$

Performing the analysis for the additive error involves changing the minimization objective function to $Min_z R = \dfrac{\sum_{t=1}^{n} \sum_{k_1=1}^{m_1} (Z_{tk_1} - Y_{tk_1})^2}{\sigma^2}$ and imposing the profit maximization restrictions same as in *equations (11) and (12)* for constant technology and technological change respectively.

When inputs only are allowed to be stochastic where as the outputs assumed to be measured with full accuracy, the minimization objective function of a proportional error will be defined for the input side as $Min_z R = \dfrac{\sum_{t=1}^{n} \sum_{k_2=1}^{m_2} (Z_{tk_2} / Y_{tk_2} - 1)^2}{\sigma^2}$ where the Z_{tk_2} and Y_{tk_2} pertain to inputs constrained by the profit maximization restrictions . The profit maximization restriction for this objective function will be:

$$\sum_{k_1=1}^{m_1} p_{tk_1} Y_{tk_1} + \sum_{k_2=1}^{m_2} p_{tk_2} Z_{tk_2} \geq \sum_{k_1=1}^{m_1} p_{tk_1} Y_{sk_1} + \sum_{k_2=1}^{m_2} p_{tk_2} Z_{sk_2} \;\; \textit{for all t,s=1, 2,…,n} \qquad (13)$$

where Z_{tk_2} and Z_{sk_2} are solutions to the quadratic programming problem that minimize the sum of squared proportional input residuals, R. The critical lower bound estimate of the standard error is computed at α as $\overline{\sigma} = \left[\dfrac{K}{C_\alpha}\right]^{0.5}$ with $n \; x \; m_2$ degrees of freedom, as in the previous cases.

To impose monotonic nonregressive technological change, we put a technology restriction to *equation (11)* as:

$$\sum_{k_1=1}^{m_1} p_{tk_1} Y_{tk_1} + \sum_{k_2=1}^{m_2} p_{tk_2} Z_{tk_2} \geq \sum_{k_1=1}^{m_1} p_{tk_1} Y_{sk_1} + \sum_{k_2=1}^{m_2} p_{tk_2} Z_{sk_2} \;\; \textit{for all t, s=1, 2,…,n and } s \leq t\,, \qquad (14)$$

Performing the analysis for the additive error involves changing the minimization objective function to $Min_z R = \dfrac{\sum_{t=1}^{n} \sum_{k_2=1}^{m_2} (Z_{tk_2} - Y_{tk_2})^2}{\sigma^2}$ and imposing the profit maximization restrictions same as in *equations (13) and (14)* for constant technology and technological change respectively.

3.4. Summary of Modeling Approach

Under the nonparametric approach, deterministic and stochastic tests are available. The deterministic is 'an all or none' test in that the entire test fails if the optimizing hypothesis is violated even once. The deterministic test checks consistency of observed behavior with maintained profit maximization rules. This entails checking if observed behavior using data on a vector of quantity and prices of inputs and of outputs conform with the joint hypothesis of a closed, convex, negative monotonic production set that profit-rationalizes the data. Empirically this is equivalent with checking the inequality $P_t Y_t \geq P_t Y_s$ for all *t, s = 1, 2,..., n* (Varian, 1984) which is a *necessary* and *sufficient* condition for a profit maximization rule (Samuelson, 1947; Hanoch and Rothschild, 1972; Varian, 1984). The joint hypothesis of profit maximization plus monotonic nonregressive technical change in the production function is checked by imposing the restriction $s < t$ to the above inequality (Chavas and Cox, 1988, 1995).

Stochastic nonparametric tests are developed when the deterministic tests fail for reasons such as farms are not technically or economically efficient, or there is measurement error in the data or due to farms' objectives other than profit maximization. Proportional and additive models are specified to capture the measurement error between the true quantity data and observed data. Assuming that the measurement errors are random and independently and identically distributed with $(0, \sigma^2)$, the models are formulated such that the squared measurement errors (residuals) follow a chi-squared distribution. The main task is to find the lower bound/threshold measurement error (and hence the lower bound standard error) required for consistency of the observed data with the joint hypothesis of profit maximization. The joint null hypothesis of profit maximization is rejected if the standard error present is believed to be less than the computed threshold level standard error.

The models are developed to test behavioral objectives of farms other than profit maximization. For example, only output decisions are allowed to be stochastic in the models to reflect cases where farms act in a way to minimize output risks. In cases where the stochastic influences are believed to have come from decisions related with inputs quantities, the models also incorporate this behavior such that input quantities are made stochastic. The models also allow perturbations to occur in both the input and output quantities.

In all the models, the joint profit maximization hypothesis is modified to allow testing of technological change. Empirical implementation is done with a nonlinear minimization problem using GAMS.

4. DATA AND METHODS

The nonparametric approach is used to evaluate the profit maximization behavior of 377 Kansas farms observed from 1988 to 2007. In particular, consistency with deterministic profit-maximization behavior with and without technological change will be tested for each of the farms. Adherence to stochastic profit-maximization behavior with and without technological change is examined for each of the farms. A total of 190 farms are used for the analysis under proportional error specification after removing farms that have no production in one or more years; and all 377 farms are used under the additive error specification.

The analysis applied nonlinear optimization using GAMS (General Algebraic Modeling System) to determine the minimum perturbation of the input and output set to calculate the magnitude of measurement error necessary for observed data to be consistent with profit maximization rule for each of the farms.

Income and balance sheet data for 377 farms are obtained from the Kansas Farm Management Association (Langemeier, 2007; Mugera, 2009). Two outputs: crops and livestock are defined. The physical output quantities are calculated by dividing the farms' gross income in each of the two output categories by the price of each output as follows:

Livestock Quantity = Gross livestock Income / Livestock Price.

Crop Quantity= Gross Crop Income/ Crop Price.

The farms are defined to have three inputs: labor, purchased inputs and capital inputs. Labor includes hired, family, and operator labor inputs. The components of the purchased inputs and capital inputs are as described below.

Purchased Input: includes fuel and oil, seed and other crop expense, fertilizer and lime, dairy expense, irrigation energy, crop marketing and storage, herbicide and insecticide, feed purchased, veterinarian expense, livestock marketing and breeding, organizational fees and publications, utilities, and crop insurance.

Capital Input: Includes machinery repair, irrigation repair, machine hire, auto expense, building repair, conservation, cash interest, cash farm rent, real estate tax, property tax, general farm insurance, depreciation, and opportunity interest charge on owned equity.

Price indexes for inputs and outputs are obtained from USDA's Kansas Agricultural Statistics (USDA, 2007a) and Agricultural Prices (USDA, 2007b). Physical input indices for quantities are obtained by dividing the farms' cash operating expenses in each of the three input categories by the price for each input.

For the additive error model, the netput and price vectors are scaled so that the mean of each netput and price vectors is equal to one. From (7), we have that

$$\varepsilon_{tk} = Q_{tk} - Y_{tk}$$

We can normalize this relationship by dividing the true and observed quantities by the mean of each netput vector, and get a new normalized additive error term expressed in terms of the normalized true netput and normalized observed netput quantities as follows:

$$\frac{\varepsilon_{tk}}{\overline{Y}_k} = \frac{Q_{tk}}{\overline{Y}_k} - \frac{Y_{tk}}{\overline{Y}_k}$$

So that we have the following relationship

$$\varepsilon^*{}_{tk} = Q^*{}_{tk} - Y^*{}_{tk}$$

where $\varepsilon^*{}_{tk} = \frac{\varepsilon_{tk}}{\overline{Y}_k}$, $Q^*{}_{tk} = \frac{Q_{tk}}{\overline{Y}_k}$ *and* $Y^* = \frac{Y_{tk}}{\overline{Y}_k}$.

Based on the above transformations, the new error term from the additive model (and hence the standard errors from the minimization problem) is interpreted as a proportion of the mean.

4.1. Kernel Density Estimation

Histograms are often used for easy presentation and analyses of results. Histograms are a useful but limited way to estimate or visualize the true, underlying density of some observed data with an unknown distribution. Histograms are discontinuous step functions. So, if it is believed that data are generated by a continuous density, then another estimation procedure such as Kernel density estimation might be preferable (The Wolfram Demonstration Project, 2010).

It was already assumed in the theory section that the squared error term (R) is an independently and identically distributed random variable. The goal of density estimation as applied in this essay is to approximate the probability density function *f*(.) of the random variable R . Assuming *n* independent univariate observations r_1, r_2 ,…, r_n from the random variable R, the kernel density estimator of the density value $f(r)$ at point r is defined as:

$$\hat{f}(r) = \frac{1}{nh}\sum_{t=1}^{n} k\left(\frac{r_i - r}{h}\right)$$

where *k* (.) is a symmetric probability density satisfying the following conditions:

$$\sum_{-\infty}^{\infty} k[z]dz = 1; k \geq 0; k(r) = k(-r)$$

r is the observation that the kernel is centered on, *n* is the number of observations, and *h* is the optimal bandwidth. The restriction on the kernel function *k* (.) is that it is nonnegative and integrated to 1 over its support (Pagan and Ullah, 1999).

There are many kernels that satisfy the above conditions, including the Gaussian, Epanechnikov, triangular, biweight, and rectangular (Silverman, 1986). For the construction of kernel densities of the squared measurement errors in this study, the Epanechnikov method was applied. For a large sample, any kernel function will be close to an optimal one and, therefore, the choice of kernel is a minor issue (Pittau and Zelli, 2004). Silverman (1986) evaluated the efficiency of many potential kernels in terms of mean integrated squared errors, an accuracy statistic computed as the sum of the integrated square bias and the integrated variance relative to the true density. Silverman concluded that, while there are few differences between the potential kernels, the Epanechnikov kernel is the most efficient among kernels that are themselves probability density functions where efficiency is defined as minimizing mean integrated squared error (MISE). The Epanechnikov kernel function is defined as:

$$k(z) = \frac{3}{4\sqrt{5}}\left(1 - \frac{z^2}{5}\right), \quad if\left|z\right| \leq 5 \text{ , otherwise } k(z) = 0$$

4.2. Summary of Data and Methods

The deterministic and stochastic nonparametric approaches were used to evaluate the profit maximization behavior of 377 Kansas farms observed from 1988 to 2007. A total of 190 farms are used for the analysis under proportional error specification after removing farms that have no production in one or more years; and all 377 farms are used under the additive error specification. A nonlinear optimization problem using GAMS (General Algebraic Modeling System) was formulated to determine the minimum perturbation of the input and output data set to calculate the magnitude of measurement error necessary for observed data to be consistent with profit maximization rule for each of the farms.

The farms are assumed to have two outputs: crops and livestock and three inputs: labor, purchased inputs and capital inputs. These data were obtained from the Kansas Farm Management Association databank (Langemeier, 2007; Mugera, 2009). Price indexes for inputs and outputs are obtained from USDA's Kansas Agricultural Statistics (USDA, 2007a) and Agricultural Prices (USDA, 2007b).

Kernel density estimation is done to summarize the results.

5. EMPIRICAL RESULTS

5.1. Deterministic Tests

With 20 years of data, checking for the deterministic nonparametric tests involve 380 price-output comparisons. The number of profit maximization violations for the individual farms ranged from 184 to 207, with a mean of 191.5. The standard deviation of violations was 2.9. All farms violated Varian's deterministic WAPM. Under monotonic non-regressive technical change, a total of 190 price-output comparisons are possible. For these deterministic WAPM tests, the number of violations of profit maximization ranged from 8 to 167, with a mean of 72.9, and a standard deviation of 44.8 (Table 1-1).

Because all the farms violated the deterministic WAPM rules, it is of interest to find out the magnitude of these violations.

Table 1-1: Summary Statistics for Deterministic Profit Maximization Tests for 377 Kansas Farms

Hypothesis	Mean	Standard deviation	Minimum	Maximum
Deterministic profit maximization violations	191.5	2.9	184	207
Deterministic profit maximization under non-regressive technical change	72.9	44.8	8	167

5.2. Stochastic Tests

The stochastic test results are organized in three sections. Each section represents a specific production characteristic relating to the possible influences on the perturbations in the observed quantity data. The first section provides results where the measurement errors can originate from both inputs and outputs. The second section contains results where the stochastic influences come from the output side of the quantity data and the inputs are measured with full accuracy. The sources of the measurement error in the third section are assumed to be composed of the input side of the quantity data while output quantities are assumed to be deterministic.

Under each section, the results of the proportional and additive measurement error specifications are presented, followed by comparison of results of these two specifications. In addition, the results for each specification are presented with and without technological change.

5.2.1. Stochastic Input and Output Variables

5.2.1.1. Proportional Error Specification

The minimized proportional residual (R) values estimated using *equation (5)* follow a chi-square distribution with 100 degrees of freedom. These minimized R values were used to calculate the critical standard error ($\bar{\sigma}$) values with an alpha level of 0.05. With the assumption of no technological change over the sample period, i.e. allowing the subscripts *s* and *t* to take any values as in the constraint in *equation (5)*, the minimum $\bar{\sigma}$ required to maintain the hypothesis of profit maximization ranged from 0.1015 to 0.3803 with a mean of 0.1901 and median of 0.1748 and a standard deviation of 0.0575 (Table 1-2). These critical values are used to test the null hypothesis that the profit maximization rule holds in *equation 5.* For example, using the mean value of the minimum $\bar{\sigma}$, 0.1901, we would reject the joint hypothesis of profit maximization at the 5% level of significance had the quantity data been measured with standard error of less than 19.01 %.

Consistency of the joint profit maximization hypothesis under technological change was tested using *equation (6)*. The constraint function in this equation restricts $s \leq t$ insuring that any technology used in production period *s* is also available in production period *t.* The technology index restriction $s \leq t$ on the constraint function reduces the number of pair wise comparisons from 380 to 190. With an alpha level of 0.05, the minimum critical R values follow a chi-square distribution with 100 degrees of freedom. The critical minimum $\bar{\sigma}$ ranged from 0.0198 to 0.1288 with a mean value of 0.0644 and median value of 0.0617 and with a standard deviation of 0.0196 (Table 1-3). Under this, we would have required on average a standard error of measurement of the data not more than 6.43 % to reject the null hypothesis of joint profit maximization.

Table 1-2: Summary of Standard Errors of Measurement with Constant Technology

Model	Mean	Med.	Standard Deviation	Min.	Max.
Proportional Error Models					
Stochastic input and outputs quantities	0.1901	0.1748	0.0575	0.1015	0.3803
Stochastic input and deterministic output quantities	9.7978	6.3178	13.3846	0.5222	146.0338
Stochastic output and deterministic input quantities	1548.188	99.1769	7373.104	0.4069	75281.45
Additive Error models					
Stochastic input and output quantities	0.2633	0.2077	0.2010	0.0952	1.5779
Stochastic input and deterministic output quantities	6.0272	3.9363	8.5361	0.6388	94.4272
Stochastic output and deterministic input quantities	208.4570	25.0941	1510.393	0.3130	26447.02

It is noticeable here that the $\bar{\sigma}$ computed under no technological change assumption were larger than those computed under the assumption of technological change. All farms had a minimum $\overline{\sigma}$ that exceed 0.10 to be consistent with the joint hypothesis of profit maximization under constant technology. In contrast, under technological change, 94.7% of the farms had minimum $\overline{\sigma}$ of less than 0.10 required for the profit maximization hypothesis to hold and 22.5 % had $\overline{\sigma}$ of less than 0.05.

Table 1-3: Summary of Standard Errors of Measurement with Technical Change

Model	**Mean**	**Med.**	**Standard Deviation**	**Min.**	**Max.**
Proportional Error Models					
Stochastic input and outputs quantities	0.0644	0.0617	0.0196	0.0196	0.1288
Stochastic input and deterministic output quantities	0.1210	0.1181	0.0357	0.0416	0.2712
Stochastic output and deterministic input quantities	0.1567	0.1333	0.1016	0.0376	1.1948
Additive Error models					
Stochastic input and output quantities	0.1398	0.0897	0.1565	0.0239	1.0261
Stochastic input and deterministic output quantities	0.2306	0.1460	0.2560	0.0385	1.6371
Stochastic output and deterministic input quantities	0.3505	0.2194	0.4106	0.0582	2.6113

In absolute terms, the change in the $\overline{\sigma}$ before and after restricting the technology index ranged from a minimum decline of 0.0351 to a maximum decline of 0.1626 with mean 0.1257 and standard deviation of 0.0573. In percentage wise, the change in the magnitude of $\overline{\alpha}$ before and after accounting for a technological change ranged from a minimum reduction of 24.84 % to a maximum reduction of 90.76 % with a mean of 63.89 % and standard deviation of 12.97%. In general, a smaller percent standard error of measurement is needed in the data to reject the joint hypothesis of profit maximization in the presence of technological change than with no technological change.

5.2.1.2. Additive Error Specification

The minimized additive residual (R) values calculated using *equation (9)* also follow a chi-square distribution with 100 degrees of freedom. These minimized R values were used to calculate the critical standard error ($\overline{\sigma}$) at an alpha level of 0.05. With the assumption of constant technology over the sample period, the minimum $\overline{\sigma}$ required for the profit maximization hypothesis to hold ranged from 0.0952 to 1.5778 with a mean of 0.2632 and median of 0.2077 and a standard deviation of 0.2010 (Table 1- 2). We notice that the range of the results is influenced by the large number of farms included as well as the behavior of data for individual farms used in the analyses. The highest $\overline{\sigma}$ values are for those farms with zero outputs (mostly livestock) for most of the years. Investigation of the data showed that the farm with the largest $\overline{\sigma}$ had only livestock output only in one year (year 1997) and all other years, there had not been any production. Similarly, the farms with the second and third largest $\overline{\sigma}$ had livestock quantity only in the first year of the study period and none thereafter. Those farms may have discontinued livestock production and completely shifted to crop production. This behavior of suddenly switching from one enterprise to another or exhibiting irregular production patterns implies inefficient production behavior and hence causing significant deviation from the optimization objective.

Consistency of the profit maximization hypothesis under technological change was tested using *equation (10)*. The constraint function in *equation (10)* restricts $s \leq t$ insuring that any technology used in production period *s* is also available in production period *t*. The minimum $\overline{\sigma}$

for this test ranged from 0.0239 to 1.0261 with a mean value of 0.1398 and median value of 0.0897 and a standard deviation of 0.1565 (Table 1- 3).

Under no technological change assumption, a total of 99.73 % of the farms require a minimum $\overline{\sigma}$ greater than 0.10 to maintain the hypothesis of profit maximization. In contrast, under technological change, a total of 39.78 % of the farms had minimum $\overline{\sigma}$ that exceed 0.10 required for the profit maximization hypothesis to hold.

In absolute terms, the change in the minimum standard error of measurement before and after restricting the technology index ranged from a minimum decline of 0.0039 to a maximum decline of 1.0755 with mean decline of 0.1234 and standard deviation of 0.0917. In percentage wise, the change in the magnitude of $\overline{\sigma}$ before and after accounting for a technological change ranged from a minimum reduction of 0.88 % to a maximum reduction of 96.2124 % with a mean reduction of 51.1978 % and standard deviation of 17.68%. The $\overline{\sigma}$ computed under constant technology assumption were larger than those computed under the assumption of technological change.

5.2.1.3. Comparison of Results from the Proportional and Additive Error Specifications

Although we used all 377 farms to do the analysis for the additive residual specifications, to avoid possible bias in the quantity data due to the farms that had zero observations in some years, we isolated the additive residual results of those 191 farms that were also used to compute the proportional residuals. It turns out that there is a remarkable similarity between these two results as shown in table 1-4. Both results suggest that one would need to attribute much smaller standard error of measurement in the quantity data to reject the joint hypothesis of profit maximization with technological change than with no technological change. Specifically, on average we would have to have less than 10 % of standard error of measurement in the data for the joint hypothesis of profit maximization with technological change to be rejected compared with less than 20% with no technological change.

The distributions of the residuals for the stochastic profit maximization hypothesis with and without technological change are shown in Figures 1-3 and 1-4, respectively. In Figures 1-3 and 1-4, the upper panels show the histogram of residuals for proportional error models and the lower panels show the histogram of residuals for additive error models. A visual investigation of the histograms in these two figures reveals a similar pattern of skewness in the distribution of the residuals. Applying the Epanechnikov method, the kernel densities for these two model specifications were also fitted to the distribution of the residuals as shown in Figure 1-5 when constant technology was assumed and 1- 6 when technological change was assumed. Relatively speaking, the kernel densities in Figure 1-5 seem to give similar densities for both additive and proportional specifications.

Table 1-4: Comparison of Standard Errors of Measurement with Stochastic Input and Output Variables

Model Specification	Constant Technology			Technological Change		
	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation
Additive Residual	0.1911	0.1829	0.0538	0.0767	0.0726	0.0240
Proportional Residual	0.1901	0.1748	0.0575	0.0644	0.0617	0.0196

An ordinary least squared (OLS) regression was fitted to relate the standard errors from the two error specifications. The regression output is shown in table 1-5. Using the standard errors of measurements from the additive model as a right hand side variable to relate with the standard errors of measurement for the proportional model as a left hand side variable, we find a positive and significant relationship between the results of these two specifications. For example, for a constant technology assumption, we have an R-squared of 0.8266 implying that 82.66% of the variance of the proportional residual can be explained by the variance of the additive residuals. Or using the additive residuals, we are able to predict the values of proportional residuals pretty well.

Out of the 377 farms, 186 farms did not consistently produce output either for crop or livestock or both outputs. The results of standard errors for those farms which consistently produced outputs excluding these 186 farms are shown in the Tables 1-4 and 1-5. There are close similarities between the additive and proportional standard errors of measurement values. However, there is greater variance as well as higher minimum standard error of measurement required for the hypothesis of profit maximization to hold for these 186 farms. A summary of these results is shown in Tables 1-10 and 1-11.

5.2.2. Stochastic Output and Deterministic Inputs Quantities

5.2.2.1. Proportional Error Specification

At an alpha level of 0.05, the minimum critical R values also follow a chi-square distribution with 40 degrees of freedom. The minimized residual (R) values, with the assumption of constant technology over the sample period required to maintain the hypothesis of profit maximization ranged from 0.4069 to 75281.45 with a mean of 1548.188 and median of 99.17693 and a standard deviation of 7373.104 (Table 1-2). The results for most of the farms were exceedingly high.

Table 1-5: Relationship between Proportional and Additive Residuals Specification for Stochastic Input and Output Variables

Estimates	Constant Technology	Technological Change
Constant	0.0212^{**}	0.0299^{***}
	(0.0087)	(0.0040)
Beta Coefficient	0.8837^{***}	0.4490^{***}
	(0.0438)	(0.0495)
R squared	0.6832	0.3036
Correlation	0.8266	0.5510

Note: *, **, and *** represents significance at the 10%, 5% and 1% alpha levels, respectively

Consistency of the profit maximization hypothesis under technological change was tested using *equation (12)*. Allowing for technological change over the study period, by imposing the technology restrictions, $s \leq t$, consistency of the profit maximization hypothesis was tested. The minimum critical R values also follow a chi-square distribution with 40 degrees of freedom, at an alpha level of 0.05. The critical $\overline{\sigma}$ ranged from 0.0377 to 1.1949 with a mean value of 0.1567 and median value of 0.1333 and with a standard deviation of 0.1017 (Table 1-3). A total of 80.10 % of the farms had minimum standard errors of greater than 0.10 required for the profit maximization hypothesis to hold.

5.2.2.2. Additive Error Specification

Under the assumption of constant technology over the sample period, the minimum standard error of measurement required for the profit maximization hypothesis to hold ranged from 0.3129 to 26447.02 with a mean of 208.457 and median of 25.0941 and a standard deviation of 1510.393 (Table 1- 2). The standard error results are very high here as well.

Consistency of the profit maximization hypothesis under technological change was tested imposing the technology index restriction as in *equation (12)* to the additive error minimization objective function. By restricting the technology index, $s \leq t$, to insure that any technology used in production period *s* is also available in production period *t*, the hypothesis of profit maximization was also tested. The standard errors of measurement ranged from 0.0582 to 2.6113 with a mean value of 0.3505 and median value of 0.2194 and with a standard deviation of 0.4109 (Table 1-3). In this test, only 1.86% of the farms had a minimum standard error of less than 0.10 and 55.17 % greater than 0.20 and 26 farms had standard error of measurement that exceeded 1 required for the profit maximization hypothesis to hold.

5.2.2.3. Comparison of Results from the Proportional and Additive Error Specifications

Using the results of the same 191 farms used for both additive and proportional residual specifications, the standard errors of measurements were compared. There is also a relatively notable similarity between the central tendencies measures (mean and median) of these results as shown in the table 1-6 with technological change assumption imposed in the analysis. However, the density distributions of the residuals from these two specifications as shown in Figure 1-7 do not seem fairly similar. This is further shown in the kernel density estimates in Figure1- 8. Relaxing the technical change constraint resulted in greater discrepancy between these two model specifications as shown in table 1-6 as well as the regression results in table 1-7, in which case the R-squared value is close to 0.

5.2.3. Stochastic Input Quantities and Deterministic Outputs

5.2.3.1. Proportional Error Specification

The minimum critical R values also follow a chi-square distribution with 60 degrees of freedom, at an alpha level of 0.05. Under the assumption of constant technology, the minimum standard error of measurement required to maintain the hypothesis of profit maximization ranged from 0.5222 to 146.0338 with a mean of 9.7977 and median of 6.3178 and a standard deviation of 13.3846 (Table 1-2). The results for no technological change appear to be very high with 97.91 % of the farms scoring standard error of greater than greater than 1.

Consistency of the profit maximization hypothesis under technological change was tested using *equation (14)*. Allowing for technological change over the study period, by imposing the technology restrictions, $s \leq t$, consistency of the profit maximization hypothesis was tested. The minimum critical R values follow a chi-square distribution with 60 degrees of freedom, at an alpha level of 0.05. These ranged from 0.0417 to 0.2712 with a mean value of 0.1210 and median value of 0.1181 and a standard deviation of 0.0357 (Table 1-3). A total of 71.73% of the farms had minimum standard errors of greater than 0.10 required for the profit maximization hypothesis to hold.

5.2.3.2. Additive Error Specification

With the assumption of constant technology over the sample period, the minimum standard errors of measurement required to maintain the hypothesis of profit maximization ranged from 0.6388 to 94.4272 with a mean of 6.0272 and median of 3.9363 and a standard deviation of 8.5361(Table 1-2). All farms had standard error of greater than 0.6388 for the hypothesis of profit maximization to hold and 96.82% with greater than 1.

Table 1-6: Comparison of Standard Errors of Measurement with Stochastic Output and Deterministic Input Variables

Model specification	Constant Technology			Technological Change		
	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation
Additive Residual	276.4677	25.6178	1984.179	0.1849	0.1745	0.0610
Proportional Residual	1548.1877	99.1769	7373.1039	0.1528	0.1333	0.0717

Table 1-7: Relationship between proportional and additive residuals for with Stochastic Output and Deterministic Input Variables

Estimates	Constant Technology	Technological Change
Constant	1331.587**	0.0360*
	(527.9624)	(0.0217)
Beta Coefficient	0.7835***	0.6528***
	(0.2642)	(0.1115)
R squared	0.0445	0.1536
Correlation	0.2110	0.3919

Note: *, **, and *** represents significance at the 10%, 5% and 1% alpha levels, respectively

Consistency of the profit maximization hypothesis under technological change was tested imposing the technology index restriction as in *equation (14)* to the additive error minimization objective function. By restricting the technology index, $s \le t$, to insure that any technology used in production period *s* is also available in production period *t*, the hypothesis of profit maximization was also tested. For this test, the critical standard errors ranged from 0.0385 to 1.6371 with a mean value of 0.2306 and median value of 0.1460 and with a standard deviation of

0.2561(Table 1-3). A total of 80.11 % of the farms had minimum standard errors of greater than 0.10 required for the profit maximization hypothesis to hold.

5.2.3.3. Comparison of Results from the Proportional and Additive Error Specifications

Using the results of the same 191 farms used for both additive and proportional residual specifications, the standard errors of measurements were compared. The discrepancy in the summary values is relatively smaller when the technical change constraint was imposed in the test compared to no technical change condition. These two observations are shown in table 1-8 as well as the regression output in table 1-9 with an estimated coefficient that exceeded 2 units for each unit change in the additive error.

Table 1-8: Comparison of Standard Errors of Measurement with Stochastic input and deterministic output variables

Model specification	Constant Technology			Technological Change		
	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation
Additive Residual	4.8733	3.5085	5.3835	0.1263	0.1216	0.0393
Proportional Residual	9.7978	6.3178	13.3846	0.1210	0.1181	0.0357

Table 1-9: Relationship between proportional and additive residuals for stochastic input and deterministic output variables

Estimates	Constant Technology	Technological Change
Constant	-1.0614^{*}	0.0558^{***}
	(0.5816)	(0.0072)
Beta Coefficient	2.2283^{***}	0.5161^{***}
	(0.0802)	(0.0544)
R squared	0.8033	0.3225
Correlation	0.8963	0.5679

Note: *, **, and *** represents significance at the 10%, 5% and 1% alpha levels, respectively

Table 1-10: Summary of standard error of measurement with constant technology for all farms and for farms with missing observations only

Model	Mean	Med.	Standard Deviation	Min.	Max.
Additive Error models					
Stochastic input and output quantities	0.3373	0.2613	0.2612	0.1198	1.5778
	(0.2632)	(0.2076)	(0.2010)	(0.0952)	(1.5778)
Stochastic input and deterministic output quantities	7.2120	4.3228	10.7490	0.63888	94.4272
	(6.0272)	(3.9362)	(8.5361)	(0.6388)	(94.4272)
Stochastic output and deterministic input quantities	138.6181	24.3399	763.8792	0.4547	10066
	(208.457)	(25.094)	(1510.39)	(0.3129)	(26447)

The values without parenthesis refer to results for only the 186 farms that had some missing quantity observations in the data in some years either for crop or livestock or both outputs and the values in parenthesis refer to results for all 377 farm including these 186 farms.

Table 1-11: Summary standard error of measurement with technological change

Model	Mean	Med.	Standard Deviation	Min.	Max.
Additive Error models					
Stochastic input and output quantities	0.2046	0.1338	0.2021	0.0389	1.0261
	(0.1398)	(0.0896)	(0.1565)	(0.0239)	(1.0261)
Stochastic input and deterministic output quantities	0.3377	0.2197	0.3300	0.0606	1.6371
	(0.2306)	(0.1459)	(0.2560)	(0.0385)	(1.6371)
Stochastic output and deterministic input quantities	0.5205	0.3250	0.5309	0.1001	2.6113
	(0.3504)	(0.2194)	(0.4108)	(0.0581)	(2.6113)

The values without parenthesis refer to results for only the 186 farms that had some missing quantity observations in the data in some years either for crop or livestock or both outputs and the values in parenthesis refer to results for all 377 farm including these 186 farms.

5.3. Summary of Results

Results indicated that all farms violated Varian's deterministic Weak Axiom of Profit Maximization (WAPM). Because all the farms violated the deterministic WAPM, the next step was to determine the minimum amount of measurement error necessary for farm level production data to be consistent with the joint hypotheses of profit maximization, closed and convex technology and monotonic nonregressive technological change. This was achieved by the stochastic test analysis. The results of the stochastic tests were analyzed in three ways. The first way was when the sources of measurement errors are assumed to originate from both the input and output side of the observed quantity data. The second was where the stochastic influences on the data are assumed to have come from the output side of the quantity data while the inputs are assumed to be deterministic. The third way was when the perturbations in the quantity data are assumed to have occurred on the input side of the observed quantity data. For each way, results of a proportional and additive measurement error models with a multiproduct setting were presented. The results also reflect the characteristics of agricultural production behavior with and without technological change along the years under study.

The stochastic test was formulated as a quadratic programming problem that minimizes the sum of squared residuals (R). These residual values that minimize the implied measurement error follow a chi-square distribution. The R values were used to compute the critical standard error ($\overline{\sigma}$) with an alpha level of 0.05 as $\overline{\sigma} = \left[\frac{K}{C_\alpha}\right]^{0.5}$. For the proportional measurement errors specification, when both input and output quantities were considered to be stochastic, the minimum $\overline{\sigma}$ required to maintain the hypothesis of profit maximization ranged from 0.1015 to 0.3803 with a mean of 0.1901 and median of 0.1748 and a standard deviation of 0.0575. When technical change was imposed, these values ranged from 0.0198 to 0.1288 with a mean value of 0.0644 and a median value of 0.0617 and a standard deviation of 0.0196. For the additive measurement error specification, with constant technology over the sample period, the minimum $\overline{\alpha}$ ranged from 0.0952 to 1.5778 with a mean of 0.2632 and median of 0.2077 and a standard deviation of 0.2010. With technological change constraint imposed, these values varied from 0.0239 to 1.0261 with a mean value of 0.1398 and median value of 0.0897 and a standard deviation of 0.1565. Although we used all 377 farms to do the analysis for the additive residual specification, to avoid possible bias in the quantity data because of farms that had no output production in some years, the additive residual results were summarized again for those 191 farms that were used to compute the proportional residuals. For these farms, the minimum $\overline{\alpha}$ ranged from 0.0952 to 0.3741 with a mean of 0.1911 and median of 0.1829 and a standard deviation of 0.0538. With technical change constraint imposed, these values ranged from 0.0239 to 0.1657 with a mean of 0.0767 and median of 0.0726 and a standard deviation of 0.0240. These later results from the additive error model are similar to those from proportional error model. The correlation between these two model results is also positive and strong before and after technological change constraint was imposed.

When quantity of output observations are believed to account the majority of the stochastic influence on the data, the $\overline{\sigma}$ values for the proportional error model constrained for technical change varied from 0.0377 to 1.1949 with a mean value of 0.1567 and median value of 0.1333 and with a standard deviation of 0.1017. The corresponding $\overline{\sigma}$ values for the additive error model varied from 0.0582 to 2.6113 with a mean value of 0.3505 and median value of 0.2194 and with a standard deviation of 0.4109. However, for the 191 farms only the $\overline{\alpha}$ values ranged from 0.0582 to 0.4409 with a mean of 0.1849 and median of 0.1745 and a standard deviation of 0.0610. Here again, when the technological index in the constraint function were allowed to take any values such that constant technology is implied, the minimized residuals were too high.

When the perturbation in the quantity data was assumed to be solely influenced by the input quantities whereas the output quantities considered to be deterministic, again for the proportional measurement error model, the $\overline{\sigma}$ ranged from 0.0417 to 0.2712 with a mean value of 0.1210 and median value of 0.1181 and a standard deviation of 0.0357 when technical change was imposed. For the additive measurement error model, these values ranged from 0.0385 to 1.6371 with a mean value of 0.2306 and median value of 0.1460 and with a standard deviation of 0.2561. Using those 191 farms that were also used to compute the proportional residuals, these critical standard errors ranged from 0.0385 to 0.2552 with a mean value of 0.1263 and median value of 0.1216 and a standard deviation of 0.0393 . There is strong and positive correlation between the results of these two specifications. Furthermore, the values of the standard errors with constant technology were exceedingly high.

In a nutshell, for the stochastic tests, a 10% standard error of measurement has been used as a benchmark (as in some empirical studies such as by Lim and Shumway 1992a and Silva and Stefanou 2003) against which the results of the tests could be compared. With technological change, assuming both input and output quantities as stochastic, at an alpha level of 5%, only 5.3% of the farms violated the joint hypothesis of profit maximization with the minimum critical standard error exceeding 10%. Whereas when only inputs quantities are considered stochastic, a total of 71.73% and 2.09% of the farms had minimum standard errors of greater than 0.10 and 0.20 respectively required for the profit maximization hypothesis to hold. In contrast, when assuming only stochastic output quantity measurements, a total of 80.10 % and 18.84 % of the farms had minimum standard errors of greater than 0.10 and 0.20 respectively required for the profit maximization hypothesis to hold.

Relatively speaking, the additive error model with stochastic output and deterministic input had the largest critical lower bound mean value of standard error of 0.3505 with technical change assumed. Therefore, we would have rejected the joint hypothesis of profit maximization, closed and convex technology and monotonic nonregressive technical change at the 5% level of significance had any of the quantity data been measured with standard error of less than 35.05 %. The proportional error model with stochastic input and output quantities had the smallest lower bound mean value of standard error of 0.0644. In this case, we would have needed a much smaller standard error, i.e. less than 6.44 % to reject the joint hypothesis of profit maximization with technological change. For this model, with the technical change restriction relaxed, the minimum critical lower bound standard error was 0.1901 and hence we would have required a standard error of measurement less than 19.01 % to reject the joint hypothesis of profit maximization.

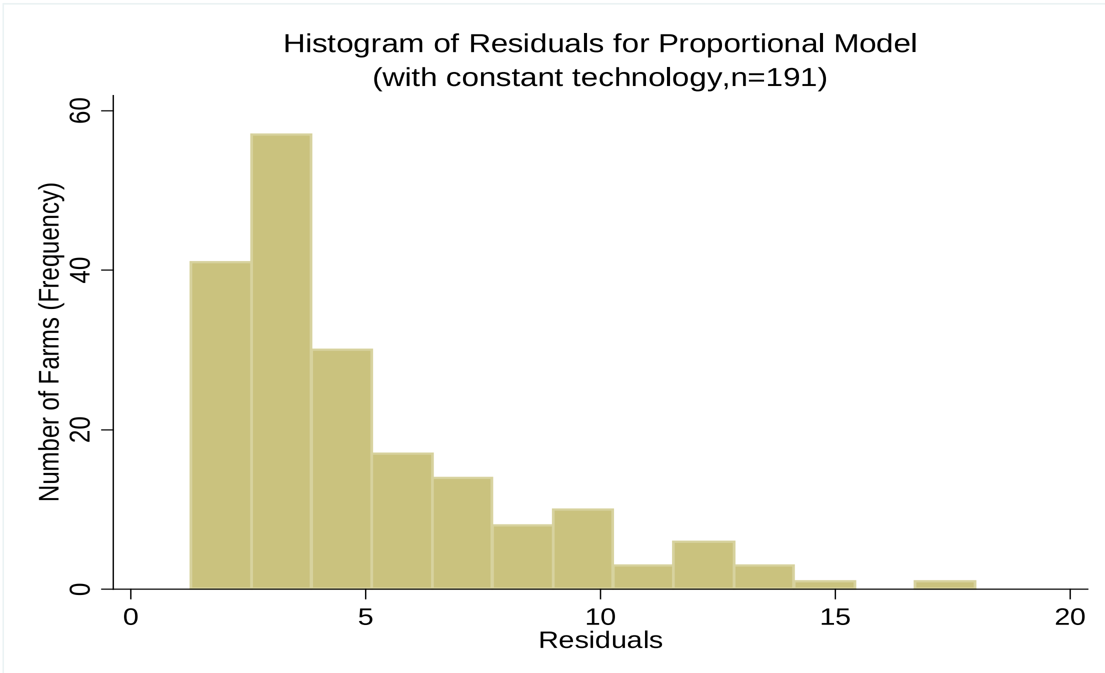
6. CONCLUSION AND IMPLICATIONS

Results indicate that none of the farms perfectly satisfy the joint hypothesis of profit maximization, closed and convex technology set with and without technological change. The empirical evidence also seems to support the existence of technological change over the study period. Given that farmers consider risk and uncertainty when making output decisions, results of the current study may indicate that relatively greater deviations from the joint hypothesis of profit maximization objective may be due to perturbations associated with output decisions. As expected, on average higher percentage standard errors in the output quantity data were required for the joint hypothesis of profit maximization to hold at 5% significance level, implying that there was higher probability of rejecting the joint hypothesis. An additive error specification developed in this study also provided similar implications on the behavioral characteristics of the Kansas farms.

The use of nonparametric tests of a type used in this paper has been suggested as a pre-test method to aid in the selection of an appropriate parametric functional forms and behavioral hypotheses in production analysis. Given the widespread use of profit maximization as a primary objective in economic analyses, testing its validity using the approach developed in the current study is helpful for accurate economic analyses, sound management decisions and appropriate policy recommendations.

The study could be extended to include farm size and degree of specialization into account. More specifically, we can ask whether farm size affects the behavioral motivation of farms. We may also look at the degree of output specialization as in the case of multi-product/multi-output versus single output farms in view of the general farm behavioral objectives. Another venue would be to consider the efficiency of the farms with respect to technological regularity conditions and behavioral motivations. How do the different measures of efficiency (e.g. technical and allocative efficiencies) of farms relate with their behavioral objectives? We may also test all the previous conditions with a more disaggregated data of input use by farms. Theoretically, it can be extended to test behavioral objectives other than profit maximization such as expected utility of profit maximization with probabilities attached to the prices and quantities.

Figure 1-3: Histogram of Residuals for Proportional and Additive Error Models with Constant Technology



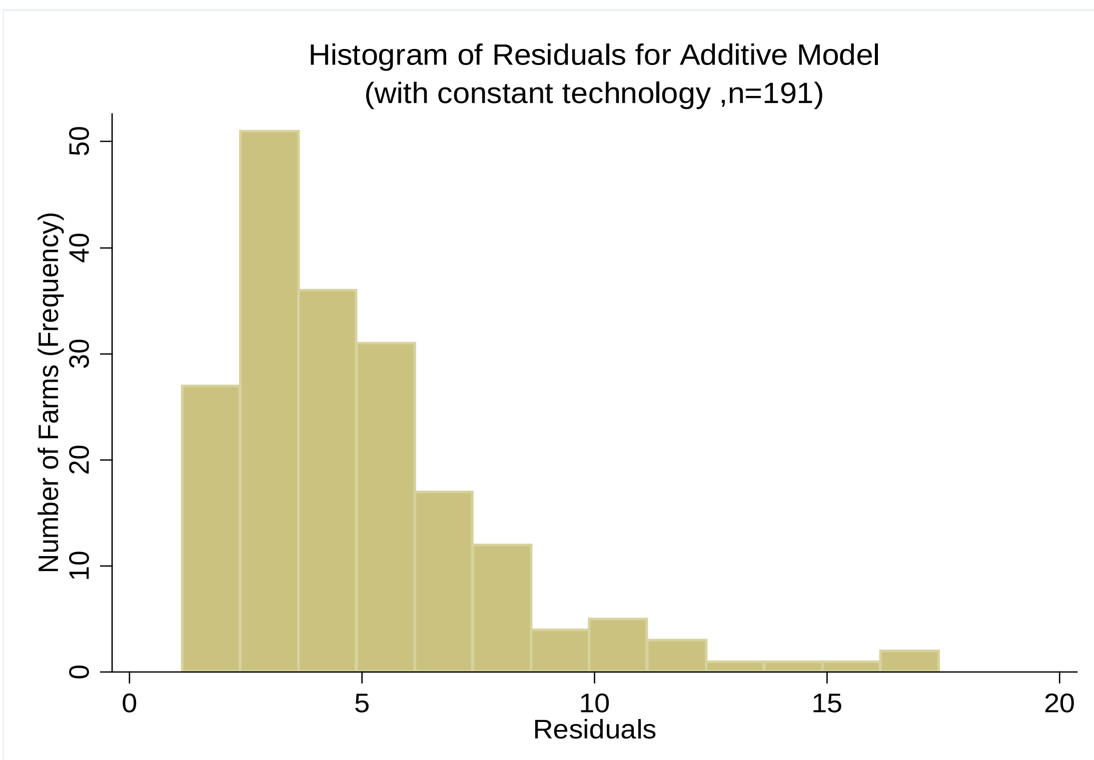
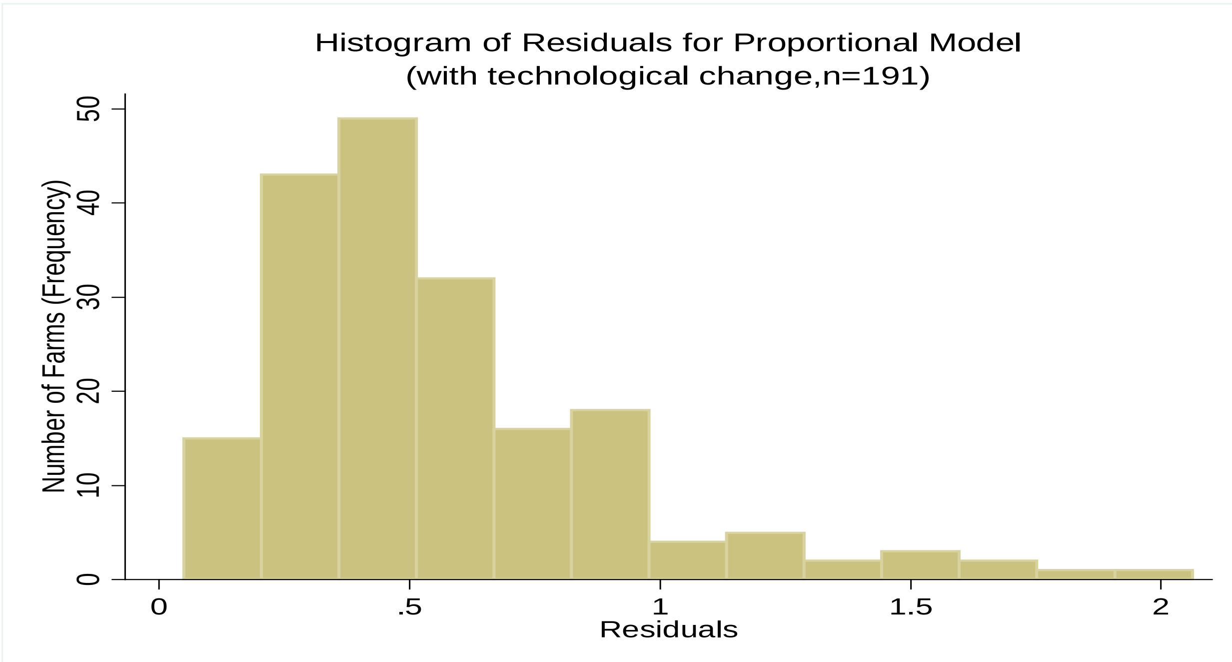


Figure 1-4: Histogram of Residuals for Proportional and Additive Error Models with Technological Change



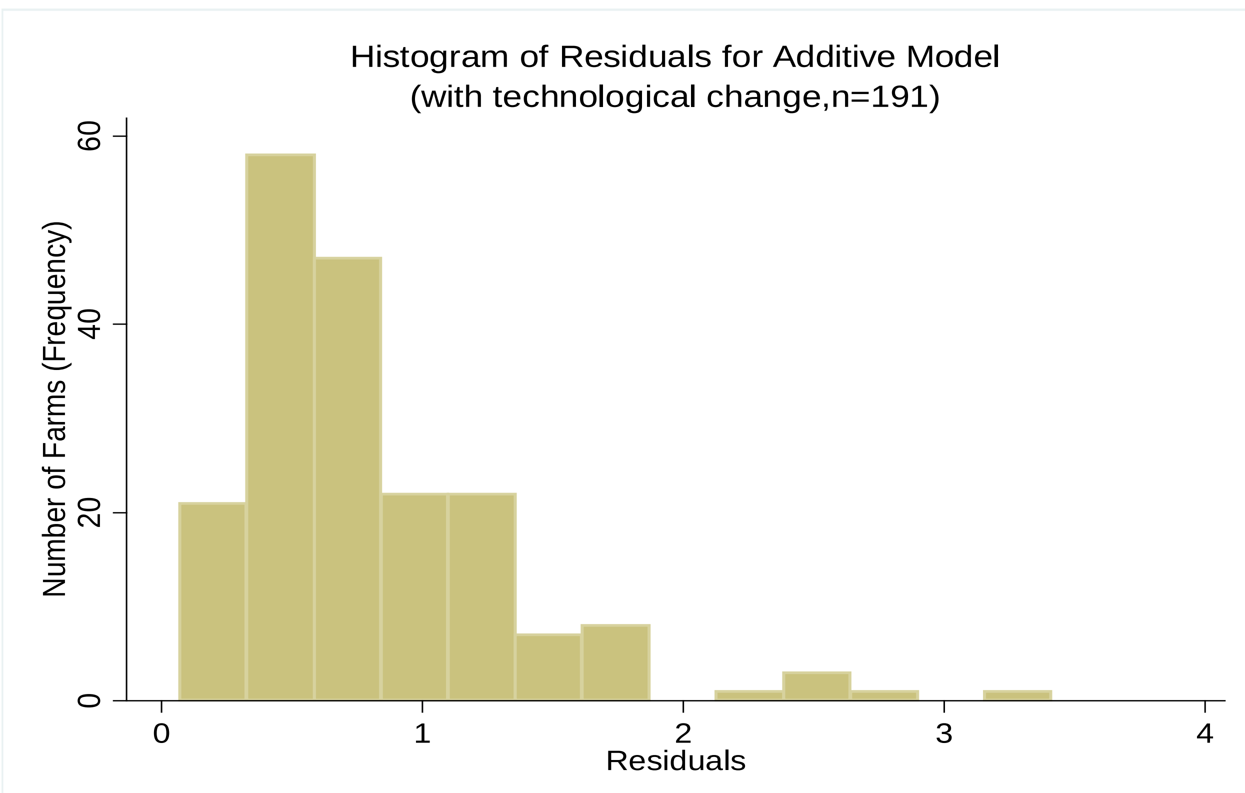


Figure 1-5: Kernel Density Estimation of Proportional and Additive Residuals Models with Constant Technology

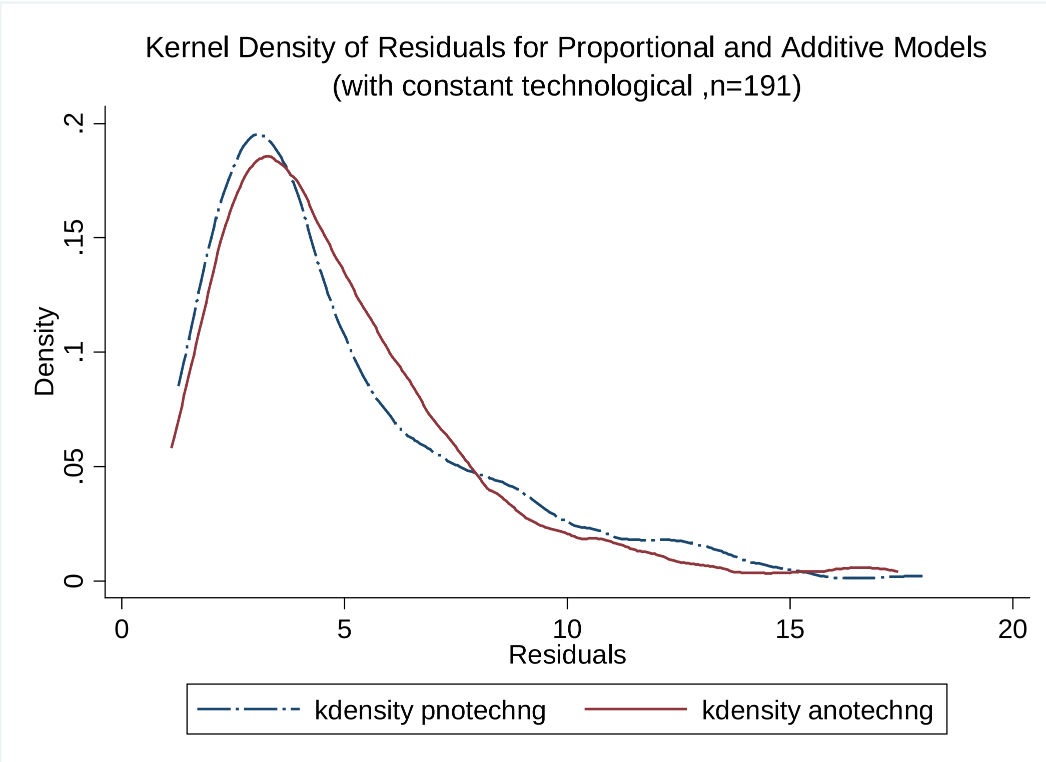


Figure 1-6: Kernel Density Estimation of Proportional and Additive Residuals Models with technological change

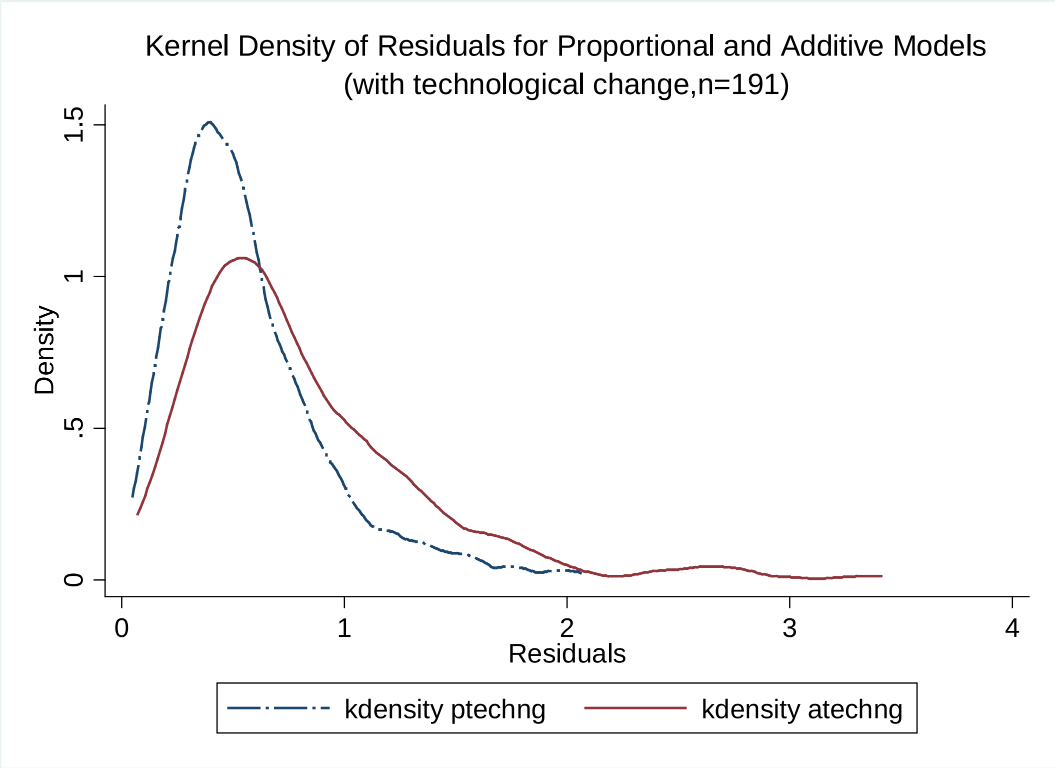
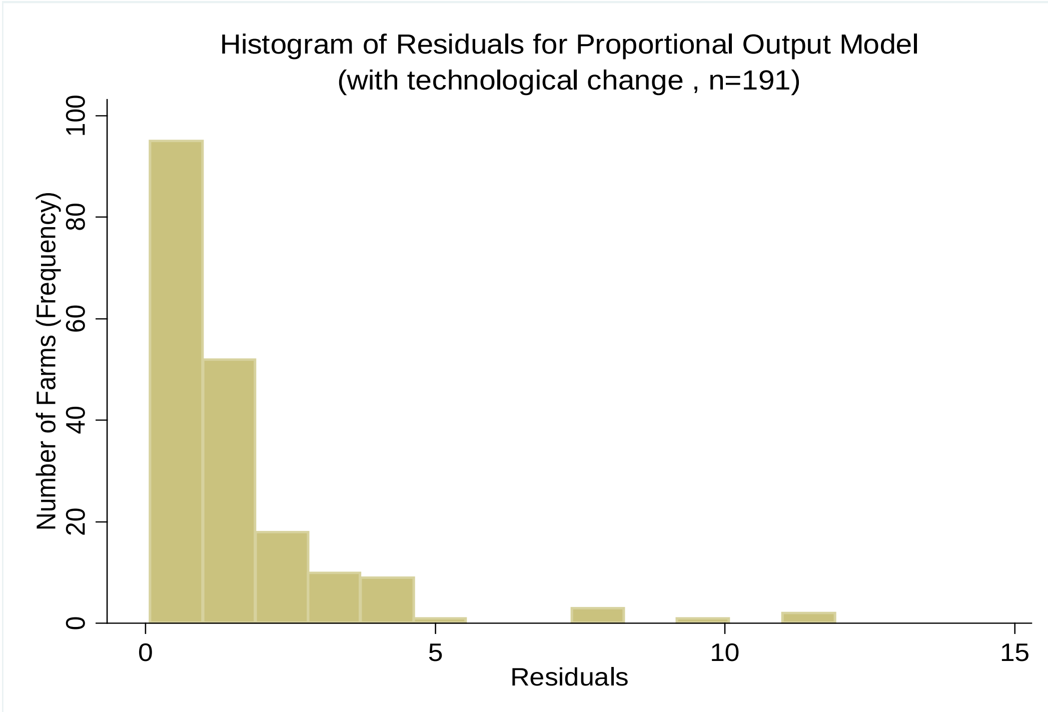


Figure 1-7: Histogram of Residuals for Proportional and Additive Error Models for Stochastic Output Only with Technological Change



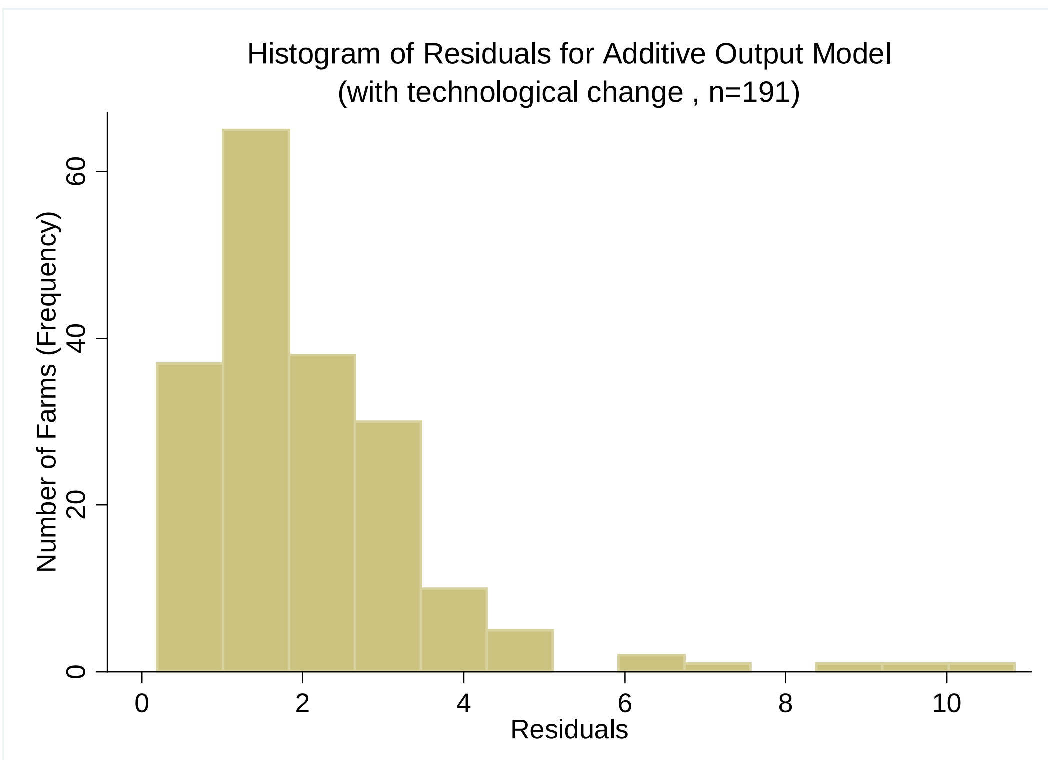


Figure 1-8: Comparison of Kernel Densities of Proportional and Additive Residuals Models for Stochastic Output Only with technological change

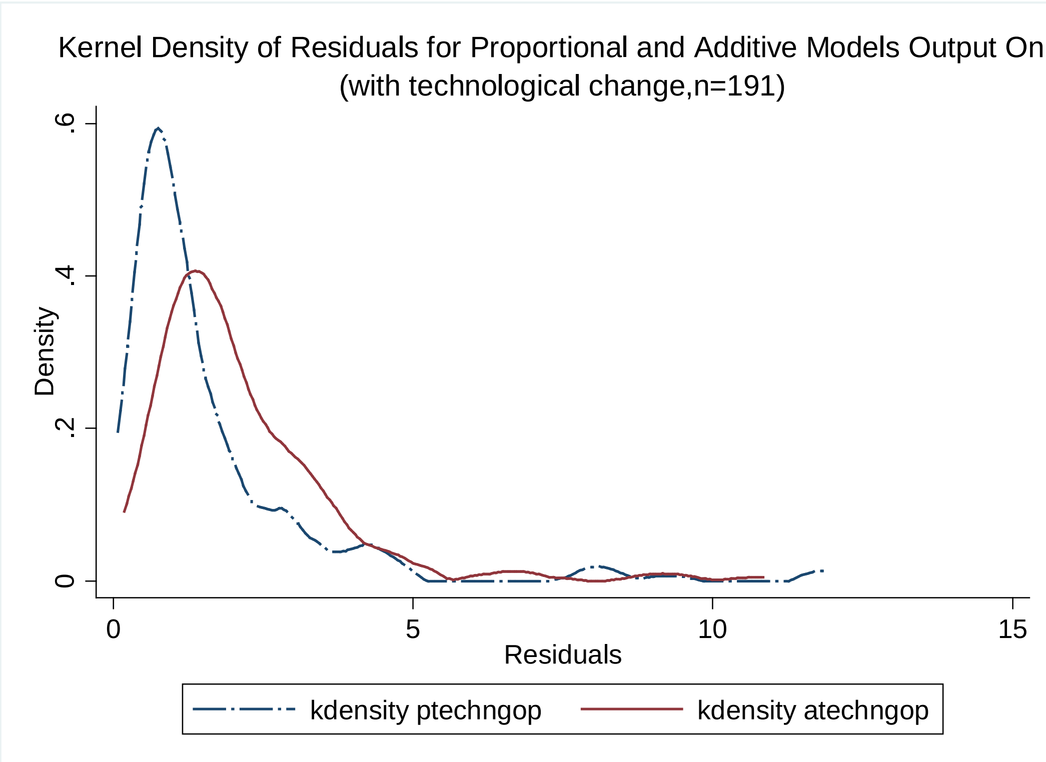
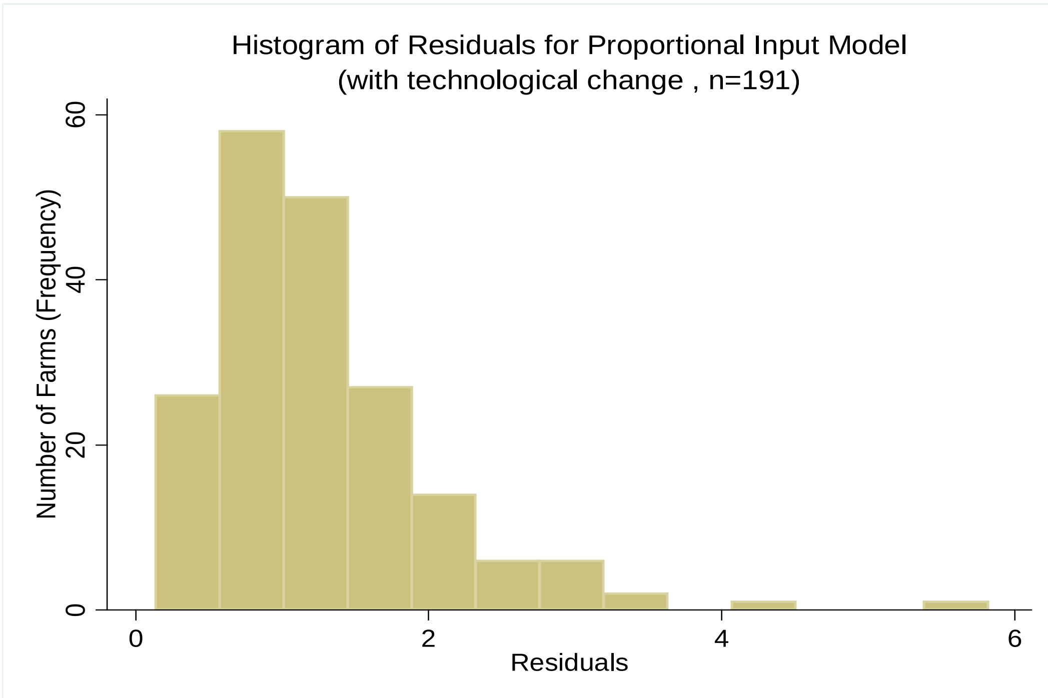


Figure 1-9: Histogram of Residuals for Proportional and Additive Error Models for Stochastic Input Only with Technological Change



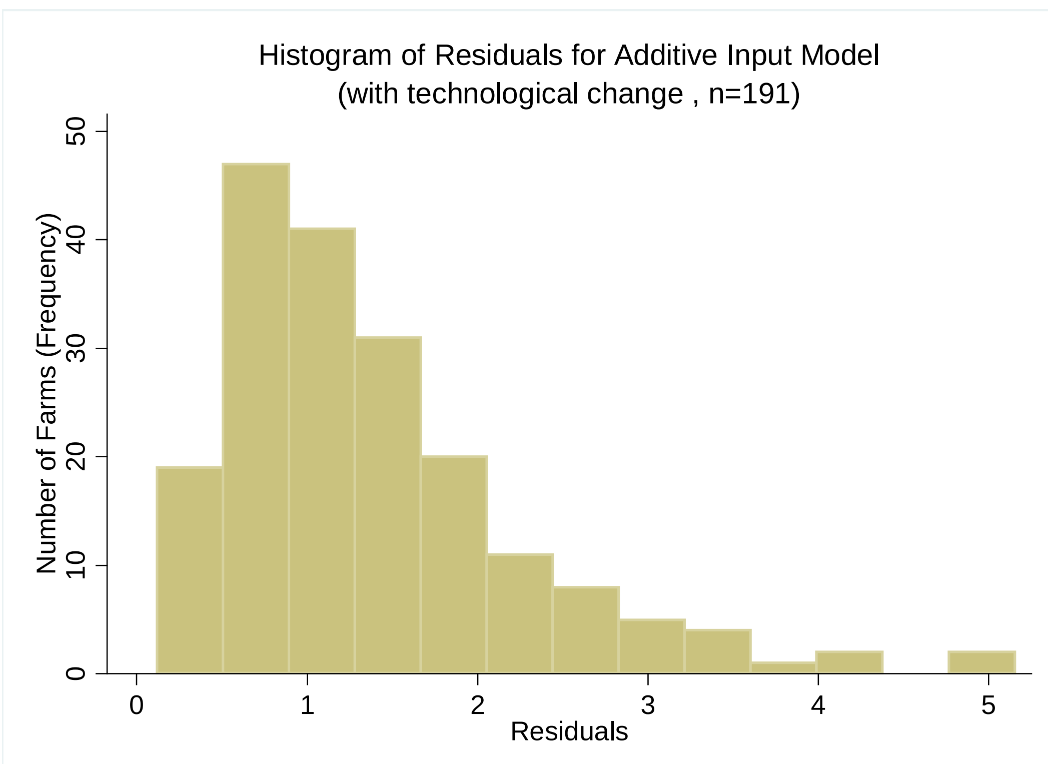
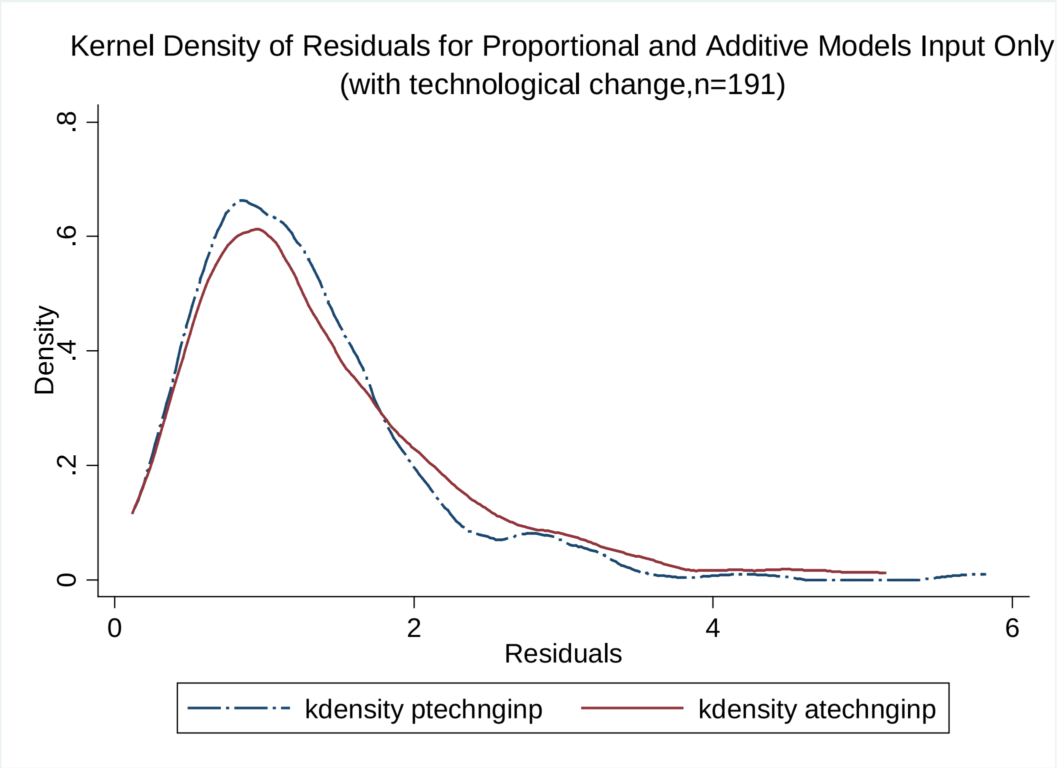


Figure 1-10: Comparison of Kernel Densities of Proportional and Additive Residuals Models for Stochastic Input Only with technological change



REFERENCES

Afriat, S.N. “The Construction of a Utility Function from Expenditure Data.” *International Economic Review* 8(1967):67-77.

Afriat, S.N. “Efficiency Estimation of Production Function.” *International Economic Review* 13(1972):568-98.

Blume, L. and D. Easley. “Evolution and Market Behavior.” *Journal of Economic Theory* 58(1992):9-40.

Banker, R.D., and A. Maindiratta. “Nonparametric Analysis of Technical and Allocative Efficiencies in Production.” *Econometrica* 56 (1988)6: 1315–1332.

Bar-Shira, Z. and I. Finkelshtain “ Simple Nonparametric Tests of Technological Change: Theory and Application to U.S. Agriculture” *American Journal of Agricultural Economics* 81(November 1999)4: 850-864.

Chalfant, J.A., and J.M. Alston. “Accounting for Changes in Tastes.” *Journal of Political Economy* 96 (April 1988):391-410.

Chavas, J. P., and T. L. Cox. “A Nonparametric Analysis of Agricultural Technology.” *American Journal of Agricultural Economics* 70 (1988):303-310.

___________ “A Non-Parametric Analysis of Productivity: The Case of U.S. and Japanese Manufacturing.” *The American Economic Review* 80 (June, 1990)3: 450-464.

___________ “A Nonparametric Analysis of the Influence of Research on Agricultural Productivity” *American Journal of Agricultural Economics* 74(August, 1992) 3:583-591.

___________ “ On Nonparametric Supply Response Analysis” *American Journal of Agricultural Economics* 77(February 1995)1: 80-92.

Cox, T. L., and J. P. Chavas. “A Nonparametric Analysis of Productivity: The Case of U.S. Agriculture.” *European Review of Agricultural Economics* 17(1990):449-464.

Diewert, W. E., and C. Parkan. “Linear Programming Tests of Regularity Conditions for Production Functions” in Wolfgang Eichhorn et al. (eds.), Quantitative Studies on Production and Prices (Wurzburg, Germany: Physica-Verlag, 1983):131-158.

Dutta, P.K. and R. Radner “Profit Maximization and Market Selection Hypothesis.” *Review of Economic Studies* 66 (1999):769- 798.

Fare, R., S. Grosskopf, and C.A.K. Lovell. *The Measurement of Efficiency of Production*. Boston, MA: Kluwer-Nijhoff Publishing, 1985.

Fare, R., and S. Grosskopf “ Non-parametric tests of regularity, Farrell efficiency, and goodness of fit.” *Journal of Econometrics* 69(1995): 415–425.

Farrell, M.J. “The Measurement of Productive Efficiency.” *Journal of the Royal Statistical Society Series A* 120(1957):253–281.

Fawson, C. and C.R. Shumway. “A Nonparametric Investigation of Agricultural Production Behavior for U.S. Subregions.” *American Journal of Agricultural Economics* 70(1988):311-317.

Featherstone, A.M., G.A. Moghnieh, and B.K. Goodwin. “Farm-Level Nonparametric Analysis of Cost- Minimization and Profit-Maximization Behavior.” *Agricultural Economics* 13 (November, 1995):111-120.

Grunfeld, Y., and Z .Griliches. “Is Aggregation Necessarily Bad?” *Review of Economics and Statistics* 42 (1960):1-13.

Hanoch, G. and M. Rothschild. “Testing the Assumptions of Production Theory: A Nonparametric Approach.” *The Journal of Political Economy* 80 (1972)2:256-275

Kuosmanen, T., T. Post, and S. Scholtes. “Non-parametric Tests of Productive Efficiency with errors- in-variables.” *Journal of Econometrics* 136 (2007):131–162

Langemeier, L.M. *Farm Management Data Bank*. Staff Paper. No 03-02. Manhattan, KS: Department of Agricultural Economics, Kansas State University, 2007.

Lim, H., and C. R. Shumway. "Profit Maximization, Returns to Scale, and Measurement Error." *The Review of Economics and Statistics* 74(August, 1992a) 3: 430-438.

_____________. "Separability in State-level Agricultural Technology." *American Journal of Agricultural Economics* 74(August, 1992b):120-131.

Love, H. A. "Conflicts between Theory and Practice in Production Economics." *American Journal of Agricultural Economics* 81 (August, 1999) 3: 696-702.

Mas-Colell, A., M.D. Whinston, and J.R. Green. *Microeconomic Theory*. New York: Oxford University Press, 1995.

McElroy M.B. "Additive General Error Models for Production, Cost, and Derived Demand or Share Systems." *The Journal of Political Economy* 95 (August, 1987) 4: 737-757.

Mugera, A.W. "Productivity Growth, Convergence, and Distribution Dynamics in the Kansas Farm Sector" PhD diss., Kansas State University, 2009.

Orcutt, G.H., H. W.Watts, and J.B. Edwards. "Data Aggregation and Information Loss." *The American Economic Review* 58 (September, 1968) 4: 773-787.

Pagan, A., and A. Ullah. *Nonparametric Econometrics, Themes in Modern Econometrics*.

Cambridge: University Press, Cambridge. 1999: 9-23.

Pittau, M.G., and R. Zelli. "Testing for Changing Shapes of Income Distribution: Italian Evidence in the 1990s from Kernel Density Estimates." *Empirical Economics*.29(2004):415-430.

Samuelson, P. "Foundations of Economic Analysis." Cambridge, Massachusetts: Harvard University Press, 1947.

Shumway, C.R., and H.Lim. "Functional Form and U.S. Agricultural Production Elasticities." *Journal of Agricultural Resource Economics* 18(December, 1993):266-76.

Silva,E., and S.E. Stefanou. "Generalization of Nonparametric Tests for Homothetic Production." *American Journal of Agricultural Economics* 78 (August, 1996)3:542-546.

__________ “Nonparametric Dynamic Production Analysis and the Theory of Cost.” *Journal of Productivity Analysis*19(January, 2003):5-32.

Silverman, R.W. Density Estimation for Statistical and Data Analysis. London: Chapman and Hall, 1986.

Tauer, L.W. “Do New York Dairy Farmers Maximize Profits or Minimize Costs?” *American Journal of Agricultural Economics* 77(May, 1995)2: 421-429.

The Wolfram Demonstrations Project. "Kernel Density Estimation.” Accessed August 19, 2010 http://demonstrations.wolfram.com/KernelDensityEstimation.

USDA. *Kansas Agricultural Statistics.* KS Board of Statistics, KS, 2007a.

USDA. *Agricultural Prices*. Washington, DC, 2007b.

Varian, H.R. “Nonparametric Tests of Consumer Behaviour.” *Review of Economic Studies* 50(1983): 99-110.

_______. “The Nonparametric Approach to Production Analysis.” *Econometrica* 52(1984):579-597.

_______. “Nonparametric Analysis of Optimizing Behavior with Measurement Error.” *Journal of Econometrics* 30(1985):445-458.

_______. “Goodness-Of-Fit in Optimizing Models.” *Journal of Econometrics* 46(1990):125-140.

_______.*Microeconomic Analysis,* 3rd ed. New York: W.W. Norton, 1992.

Zarembka, P. “A Note on Consistent Aggregation of Production Functions.” *Econometrica* 36 (April, 1968)2:419-420.

APPENDIX

The derivations of the equations for a profit to be maximized by a firm are contained in any standard economic text book. In the general case, a firm maximizes its profit, $\pi(q) = R(q) - C(q)$, by choosing output q. To get the *necessary condition* for a maximum at a positive level of output, differentiating profit with respect to q and set the derivative equal to zero as in equation (A1) below:

$$\frac{d\pi(q^*)}{dq} = \frac{dR(q^*)}{dq} - \frac{dC(q^*)}{dq} = 0 \tag{A1}$$

where q^* is the profit-maximizing output. Equation (A1) implies that $\frac{dR(q^*)}{dq} = \frac{dC(q^*)}{dq}$ where the expression on the left hand side is marginal revenue at q^* and the expression on the right hand side is marginal cost at q^*. The next step is to find the *sufficient condition* for profit to be maximized at $q^* > 0$, that is the second-order condition as in equation (A2) below:

$$\frac{d^2\pi(q^*)}{dq^2} = \frac{d^2R(q^*)}{dq^2} - \frac{d^2C(q^*)}{dq^2} = \frac{dMR(q^*)}{dq} - \frac{dMC(q^*)}{dq} < 0 \tag{A2}$$

Equation (A2) can also be rewritten as

$$\frac{dMR(q^*)}{dq} < \frac{dMC(q^*)}{dq} \tag{A3}$$

It follows that a *sufficient condition* for a maximum is that the slope of the marginal revenue (MR) curve is less than that of marginal cost (MC) curve and that MC curve cuts the MR curve from below at q^*.

For a competitive firm, where $\pi(q) = pq - C(q)$, the necessary condition for profit to be maximized will be

$$p = MC(q^*) \qquad \text{(A4)}$$

Equation (A4) says that a profit maximizing, competitive firm sets its output at q^* where its marginal cost equals its price (marginal revenue). Because a competitive firm's marginal revenue, p, is a constant, and following equation (A3), we have $\frac{dMR}{dq} = \frac{dp}{dq} = 0$. Thus for a competitive firm, a *sufficient condition* for profit to be maximized, equation (A3) can be rewritten as

$$0 < \frac{dMC(q^*)}{dq} \qquad \text{(A5)}$$

In the theory section, it was discussed that the following conditions are equivalent: (1) There exists a production set that profit-rationalizes the data; (2) $P_tY_t \geq P_tY_s$ for all *t, s = 1, 2... n* and (3) there exists a closed, convex, negative monotonic production set that p-rationalizes the data. This is Varian's *Theorem 3* (1984). It had been shown that Condition (2) is a *necessary* and *sufficient condition* for profit maximization (Samuelson, 1947; Hanoch and Rothschild, 1972; Varian, 1984). Silva and Stefanou (2003) also provide a proof of these two conditions for a dynamic cost minimization rule.

ESSAY 2 - THE DEMAND FOR ALCOHOLIC BEVERAGES IN THE U.S: AN ERROR CORRECTION APPROACH

1. INTRODUCTION

1.1. Problem Statement

There is a much research that investigates the consumption of alcoholic beverages due to the economic and social significance of these commodities. From a social point of view, driving under the influence of alcohol is a serious issue. There are also health concerns associated with the consumption of alcoholic beverages in terms of physical and physiological damage to the consumer as well as loss of productivity due to excessive intake of alcohol. However, consumption of alcoholic beverage generates revenue for the government, generally in terms of sales tax and sin taxes. If consumed responsibly, alcoholic beverages are sources entertainment. Because of the reasons mentioned above, the analysis of demand for alcoholic beverages has received considerable attention in Britain, Canada, Australia, United States and Ireland (Thom, 1984; Duffy, 1987; Selvanathan, 1991; Nelson and Moran, 1995; Wang et al., 1996; Andrikopoulous et al., 1997; Blake and Nied, 1997; Larivirea, Larueb, and Chalfant, 2000). For example Heien and Pompelli (1989) modeled alcoholic beverage demand as a system including non-alcoholic beverages by specifically taking into account the effect of demographic variables . Their results indicated that demographic effects play an important role in determining consumers' alcoholic beverage consumption decisions. In another study, Lariviere, Larueb, and Chalfant, (2000) discovered the ineffectiveness of advertising in enlarging markets in Ontario, and that the estimated demand elasticities were sensitive to the specification of the advertizing.

They also found that the effectiveness of advertising varied across beverage types. In general, the majority of previous studies on demand of alcoholic beverages were examined under static model specifications. However, consumers' adjustment in demand in response to changes in price, expenditure, and other factors is usually smaller in the short run than in the long run, especially for the consumption of goods like alcoholic beverages and tobacco products. Thus, a model incorporating this dynamic demand behavior is more appropriate for alcoholic beverages.

In one of their classic paper, Deaton and Muellbauer (1980a) developed a static Almost Ideal Demand System (AIDS) model to explain consumers' behavior in terms of budget share equations as function of prices and real expenditures. The parameter estimates from this static model specification does not allow short-run elasticity measures to differ from the long-run estimates. Attempts have been made to add more reality to consumer decisions over time and capture intertemporal dynamics in the AIDS model by recognizing the time series properties of the data (Johnson et al., 1992; Balcombe and Davis, 1996; Karagiannis and Velentzas, 1997; Karagiannis et. al, 2000; Coulson et. al, 2001; Eakins and Gallagher, 2003). These studies show that the short-run estimates do differ from their long-run counter parts. These studies are responses to the suggestion made by Deaton and Muellbauer (1980a) that the AIDS model in its static form may not satisfactorily explain consumers' behavior.

The intertemporal adjustment behavior of alcoholic beverage consumption has not been adequately addressed to account for an evolution of possible long term relationship (cointegration) of the economic variables. Given that most time series data are first-order integrated, use of first differenced series can result in a stationary demand model and then dynamic regression models may be specified. However, this differencing approach may eliminate the opportunity to estimate possible relationships between the levels of the dependent and independent variables. In such a situation, the use of an error correction approach is recommended (Engle and Granger, 1987; Davidson and Mackinnon, 1993).

Karagiannis et al. (2000) made the case that based on the time series properties of the data and as long as cointegration between the dependent and a linear combination of independent variables is ensured, an error correction mechanism for the AIDS model can be established. The evidence of cointegration between budget shares, log of prices, and log of total real expenditure in U.S for alcoholic beverages (beer, wine, and distilled spirits) is already supported with a study conducted by Coulson et al., (2001) using quarterly U.S. data as well as in a similar study conducted in Ireland by Eakins and Gallagher (2003). This latter study found that beer, wine, and distilled spirits had price inelastic demand in the short run, with the demand for wine switching from being price inelastic in the short run to price elastic in the long run.

The exogeneity of explanatory variables in a demand system may have a consequence on the efficiency of parameter estimates. When applying an error correction approach, the exogeneity of prices and real expenditures are not assumed to be known a priori (Fanelli and Mazzocchi, 2002); especially when estimating a conditional demand system using time-series data. Research suggests that the potential endogeneity of prices and real expenditures need to be examined (LaFrance, 1991) because these have consequences on the efficiency of system parameter estimates. It is well established that when explanatory variables are endogenous, that is when the explanatory variables and error terms are correlated, then Ordinary Least Squares (OLS) gives biased and inconsistent estimates of the causal effect of an explanatory variable on the dependent variable.

1.2. Objective

This essay aims to investigate the existence of long-run equilibrium relationships between economic variables that influence alcohol consumption. The specific objectives of the essay are to:

1. Examine whether alcohol budget shares, prices and expenditures are cointegrated, and if so apply error correction approach to model dynamic demand model.

2. Inspect the exogeneity of prices and real expenditure in a conditional alcoholic beverages demand model.

1.3. Conceptual framework

1.3.1. Utility Function and Separability of Utility Function

Assume that a utility function (U) represents a continuous, locally non-satiated preference on R_{+}^{L}, and differentiable function. The continuity property of the utility function implies that consumer preferences cannot exhibit sharp "jumps" in the preferences of elements (Mas-Colell et al., 1995). Furthermore, assume that the consumer's objective is to maximize utility by choosing the existing affordable consumption bundle. Formally, given a vector of prices (p >> 0) and wealth level (w > 0), the consumer's most preferred consumption bundle can be stated as a utility maximization problem, i.e.

$$Max_{x\geq 0}\ U(x)$$

s.t. $px \leq w$

It follows that the optimal demand correspondence (or function, if single-valued) for the consumer can be expressed as a function of prices and given wealth , i.e. $x^*(p,w)$, known as the Marshallian demand correspondence/function, or the 'uncompensated' demand correspondence/function. Unlike the Hicksian demand function described under expenditure minimization, that requires the optimization analysis to maintain a certain level of utility, the Marshallian analyses does not require a particular adjustment or "compensation" via wealth/income to changes in prices to maintain a given level of utility and hence the name 'uncompensated' demand function.

Now, consider an individual whose preferences are represented by a utility function with m number of goods. A direct utility function expressed as $v(q_1,...,q_G,...,q_N)$ is said to exhibit "*weak separability*" if there exists a partition of the m goods into n subsets, n functions $v_i(q_i)$, and a function V such that

$$V(q) = f[v_1(q_1),...,v_G(q_G),...,v_N(q_N)]$$

where $n \geq 2$ and q_i is the vector of goods in the i^{th} subset. This utility function is *weakly separable* if and only if the marginal rate of substitution involving two goods from the same subset depends only on the goods in that subset. A *necessary* and *sufficient* condition for *weak separability* is that the marginal rate of substitution between any two goods within a group is independent of goods outside the group.

1.3.2. Expenditure Minimization Problem

The expenditure minimization problem is the dual to the utility maximization problem. Instead of maximizing utility for a given budget constraint, one can consider the dual problem of minimizing the expenditures necessary to obtain a given level of utility. Thus, the consumer chooses the consumption bundle for which expenditure is minimized, i.e.

$$Min_{x\geq 0} \quad p.X$$

s.t. $U(x) \geq U$

The set of consumption bundles that are solutions to the expenditure minimization problem at prices p and required utility U is denoted as $h(p,U) \subseteq R_{+}^{L}$ and we will refer to it as the Hicksian demand correspondence (or function, if single-valued). Hicksian demand is also called compensated demand, because if prices increase, expenditure is implicitly adjusted as needed in order to keep utility constant. But the consumption bundle x may change to make the increase in expenditures as small as possible.

1.3.3. Two stage budgeting

Another important assumption for the construction of the model in this essay is the assumption of weak separability. The assumption of weak separability implies a two-stage model for consumer behavior. This makes it attractive to empirical estimations, which narrow the focus, reduces the data requirements and conserves statistical degrees of freedom in empirical work (Swofford and Whitney, 1987). In the first stage of budgeting, the consumer allocates expenditures among broad categories of goods. Then, in the second stage the consumer allocates expenditures among the goods within each broad category based only on the relative prices of the goods in that category.

1.3.4.Theoretical restrictions of demand functions

Generally, the following properties of demand function, discussed in detail in Deaton and Muellbauer (1980b), hold for both Hicksian and Marshallian demand functions.

Adding Up: the total value of demand equals to the total expenditure, that is,

$\sum ph(p,U) = \sum px(w,p) = w$

Homogeneity**:** the Hicksian demand functions are homogenous of degree zero in prices, and the Marshallian demand functions are homogenous of degree zero in total expenditure and prices together, that is, for scalar θ

$h_i(\theta p,U) = h_i(p,U)$ and $x(w,p) = g(w,\theta p)$

Symmetry: the cross price derivatives of the Hicksian demands are symmetric, that is, for all $i \neq j$

$$\frac{\partial h_i(p,U)}{\partial p_j} = \frac{\partial h_j(p,U)}{\partial p_i}$$

Negativity: the n-by-n matrix formed by the elements $\frac{\partial h_j(p,U)}{\partial p_i}$ is negative semi-definite.

1.4. Summary of Problem Statement, Objectives and Conceptual Framework

Alcoholic beverage demand has been studied in many countries. The majority of those studies adopt the specifications of static models, assuming the parameter estimates remain constant over time**.** However, consumers' adjustment in demand in response to changes in price, expenditure, and other factors may be smaller in the short run than in the long run, especially for the consumption of goods like alcoholic beverages and tobacco products. The exogeneity issue of prices and real expenditure has largely been overlooked in previous studies on U.S. alcohol demand.

This essay aims to investigate the existence of long-run equilibrium relationships between economic variables that influence alcohol consumption. The specific objectives of the essay are to:1) Examine if the alcohol budget shares, prices and expenditures are cointegrated, and if so apply error correction approach to model dynamic demand model, and 2)Examine the exogeneity of prices and real expenditure in a conditional alcoholic beverages demand model.

The consumer's utility maximization problem and expenditure minimization problems are briefly reviewed to lay the conceptual framework for the subsequent demand models to be developed. The importance of the assumptions of weak separability and two stage budgeting are also briefly highlighted in view of the empirical estimation of demand models. Theoretical restrictions that pertain to the conditional demand system are also reviewed.

2. MODELING APPROACH

Our modeling strategy assumes that the utility function is weakly separable. We also assume two-stage budgeting of household consumption decisions whereby alcoholic beverage consumption is weakly separable[9] from the consumption of all other items. In the first stage, consumers decide how much of their total expenditure will be allocated to alcoholic beverages, and then, in the second stage, the demand for each of the alcoholic beverage is determined by the prices of the individual beverage and expenditures.

The assumption of weak separability allows the utility function to be partitioned into at least two subsets, one including alcoholic beverages and another one for all other goods. In this instance, the demand for a good in a particular subset can he expressed as a function of the prices of the goods in that subset and the level of expenditure spent on those goods (Pollak and Wales, 1992). The prices of goods belonging to the other subset and the level of expenditure spent on all subsets influences the demand for a good in a given subset only through the level of expenditure allocated to the given subset. Weak separability is not a sufficient condition for treating expenditures of a given subset as exogenous (LaFrance, 1991). Hence, the estimation of conditional demand systems should endogenize subset expenditures.

Formally, the implication of the weak separability assumption is that the direct utility function of each consumer can be written in the form:

$$\mu = v(q) = f[v_1(q_1),...,v_G(q_G),...,v_N(q_N)] \qquad (1)$$

[9] Wang et al. (1996) tested the weak separability between non-alcoholic drinks and alcoholic beverages using a level Rotterdam model. Their results failed to reject the null hypothesis that alcoholic beverages are weakly separable from other drinks.

where $v(q)$ is a strictly quasi-concave, increasing and differentiable function, q is the commodity vector, f is some increasing function and v_1, v_G, v_N are well-behaved subutility functions (e.g utility derived from the consumption of food items, leisure, alcohol etc.) with non-overlapping subvectors $q_1, q_G, ..., q_N$.

A utility function of the form of *equation (1)* gives rise to second stage Marshallian demands for all goods *i* of group G of the form:

$$q_i = g_{Gi.\bar{h}}(X_G, P_G) \qquad (2)$$

where X_G is expenditure on group G and P_G is the vector of within-group prices. For example, X_G is total expenditures on alcoholic beverage and P_G is the vector of prices for beer, spirits and wine. The second stage demands are a result of the maximization of v_G subject to $\sum p_i q_i = X_G$ and have all the usual properties of demand functions because they are derived from the standard utility maximization procedure. The function $q_i = g_{Gi.\bar{h}}(X_G, P_G)$ is a conditional demand function for the i^{th} good. It is conditional demand function because the expenditure on all alcoholic beverages ($\bar{h}$) is assumed to be preallocated and therefore, weak separabilty implies that expenditure and the prices of goods other than the subset that contains alcoholic beverages enter the demand function for alcoholic beverages only through their effect on total expenditures on alcoholic beverages. The utility maximizing values of q_i are independent of the preallocated goods.

2.1. The Almost Ideal Demand System

This essay builds on the static model developed by Deaton and Muellbauer (1980a), commonly referred to as the Almost Ideal Demand System (AIDS). This model is a flexible demand specification obtained from the PIGLOG (price-independent generalized logarithmic) expenditure function consistent with economic theory. The alcohol expenditure function in logarithmic form is defined as

$$\ln e(p,V) = (1-V)\ln\{a(p)\} + V\ln b(p) \qquad (3)$$

where e is the minimum level of expenditure that is necessary to achieve utility level V at given prices, and a(p) and b(p) can be regarded as the expenditures on subsistence and bliss respectively defined as:

$$a(p) = \alpha_0 + \sum_{i=1}^{N}\alpha_i \ln(p_i) + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\gamma^*{}_{ij} \ln p_i \ln p_j \qquad (4)$$

$$b(p) = \ln a(p) + \beta_0 \prod p_i^{\beta_i} \qquad (5)$$

where the *i*th commodity price is denoted by p_i and $\gamma^*{}_{ij}$ is the parameter on the natural log (ln) of the *i*th commodity price and the natural log of the *j*th commodity price. Applying Shephard's Lemma to the expenditure function (i.e. differentiating with respect to ln p_i), and rearranging, the expenditure shares ($w^*{}_i$) on each type of alcoholic beverage in terms of total alcohol expenditure are:

$$w^*{}_i = \alpha_i + \sum_{j=1}^{N}\gamma_{ij} \ln p_j + \pi_i \ln\left(\frac{X^*}{P}\right) + u_i \qquad (6)$$

where γ_{ij} is the parameter on the log of the *j*th alcoholic beverage price, u_i is an error term, and π_i is the parameter on the log of expenditure (X^*) divided by P, where P is the price index given by:

$$\ln P = \alpha_0 + \sum_{i=1}^{N} \ln p_i + \frac{1}{2}\sum_{i=1}^{N} \sum_{j=1}^{N}\gamma_{ij} \ln p_i \ln p_j \qquad (7)$$

and

$$\gamma_{ij} = \frac{1}{2}\left(\gamma_{ij}^* + \gamma_{ji}^*\right) \qquad (8)$$

The use of a non-linear price index *P* in equation (7) raises some empirical difficulties, especially when aggregate annual time-series data are used. Deaton and Muellbauer (1980a) suggest the use of the Stone Geometric Price Index to overcome this difficulty. This index can be formulated as follows:

$$\ln P = \sum_{i=1}^{N} w_{it} \ln p_{it} \qquad (9)$$

Economic theory requires that the demand functions satisfy the *adding up, homogeneity* and *symmetry* restrictions. The restriction on adding up implies the alcoholic beverage budget shares add up to total alcohol expenditure ($\sum_i w_i = 1$), which can be imposed by not estimating one of the equations in the demand system. This implies $\sum_i \pi_i = 0$ and $\sum_i \gamma_{ij} = 0$ and $\sum_i \alpha_i = 1$. The homogeneity restriction requires $\sum_j \gamma_{ij} = 0$ implying the demand functions are homogenous of degree zero in prices and real expenditure, while symmetry implies $\gamma_{ij} = \gamma_{ji}$. Homogeneity of degree zero implies that the feasible consumption bundle in the utility maximization problem does not change when all prices and wealth (income) are multiplied by a constant $\alpha > 0$.

The compensated ($e^{H}{}_{ij}$) and uncompensated ($e^{M}{}_{ij}$) price elasticities are computed as follows:

$$e^{H}{}_{ij} = \frac{\gamma_{ij}}{w_i} + w_j - \delta_{ij} \qquad (10)$$

$$e^{M}{}_{ij} = \frac{\gamma_{ij}}{w_i} - \frac{\pi_i}{w_i} w_j - \delta_{ij} \qquad (11)$$

where δ is the Kronecker delta defined equal to 1 if $i = j$ and 0 if $i \neq j$.

The elasticity of alcoholic beverage demand with respect to the real expenditure on any type of alcoholic beverage is given by:

$$\eta_i = 1 + \frac{\pi_i}{w_i} \qquad (12)$$

Empirical evidence shows that many economic time series are not stationary. However, if the nonstationary economic variables of interest are cointegrated, there exists a long-run relationship between them. Furthermore, it can be established that the short-run dynamics can be described by an error correction form (Hendry et al., 1984; Engle and Granger, 1987). As long as there is evidence of cointegration, an error correction form for the AIDS model can be constructed to characterize the short run adjustment process towards the long run equilibrium relationships (Karagiannis and Velentzas, 1997).

If the data series are integrated, we normally can transform the data into stationary series by differencing. Given that most time series data are first order integrated, first differencing of the AIDS model can often transform it to stationary model, and then dynamic regression models may be specified. This differencing approach may eliminate the opportunity to estimate possible relationships between the levels of the dependent and independent variables. In such a situation, Davidson and MacKinnon (1993) warn that using differenced data simply is often not an appropriate strategy.

Building on the concept of cointegration, the single equation error correction model specified by Davidson and MacKinnon (1993) can be applied to the AIDS model in a system as follows[10]:

$$\Delta w_{i,t} = z_{i,t}\alpha + \beta_i \left(w_{i,t-1} - \sum_{j=1}^{N} \lambda_{ij} \ln p_{j,t-1} - \eta_i \ln\left(\frac{X^*}{P}\right)_{t-1} \right) + \sum_{j=1}^{N} \gamma_{ij} \Delta \ln p_{j,t} + \pi_i \Delta \ln\left(\frac{X^*}{P}\right)_t + v_{i,t}$$

$$v_{i,t} \sim IID\ (0, \sigma^2) \qquad (13)$$

The vector $z_{i,t}$ includes a constant term and other independent variables. This model can be modified to incorporate age group effects which may be important in alcoholic beverage consumption. We can incorporate age variables by defining $Z_{i,t} = Z_{i0} + \sum_{k=1}^{m} Z_{ik} d_k \quad i = 1,\ldots,n$ where z_{i0} and the z_{ik} are parameters to be estimated and the d_k are age variables (Heien and

[10] Balcombe and Davis (1996) and Karagiannis et al. (2000) were among the first to use the error correction form in the AID system model.

Pompelli, 1989).To capture dynamics sufficiently, we may include more lags of the price and real expenditure variables and increasing the lag on the error-correcting terms.

In most cases, λ_j and η_i in equation (13) will not be known. One way to estimate dynamic AIDS model to be of an error correction form of the static AIDS model (Karagiannis et. al, 2000; Eakins and Gallagher, 2003), as in the Engel-Granger two step method (Engel and Granger, 1987), which specifies the disequilibrium component separate from the long-run equilibrium and thus gives short-run relationship between the demand variables. In this dynamic version, the error term $u_{i,t}$ from equation (7) is calculated as the equilibrium error in the short-run which is then used to bind the short-run adjustment behavior of the dependent variable to its long-run value. The disequilibrium $u_{i,t}$ can be computed as:

$$u_{i,t} = w^{*}{}_{i,t} - \alpha_{i,t} + \sum_{j=1}^{N} \gamma_{ij} \ln p_{j,t} + \pi \ln\left(\frac{X^{*}}{P}\right)_{i,t} \qquad (14)$$

Therefore, the dynamic AIDS model is given by:

$$\Delta w^{*}{}_{it} = \delta_0 + \sum_{j=1}^{N} \gamma_{ij0} \Delta \ln p_j + \pi_{i0} \Delta \ln\left(\frac{X^{*}}{P}\right)_t + \delta_i D + \beta_i u_{it-1} + \varepsilon_t \qquad (15)$$

where Δ represents the first difference operator, u_{it-1} is the estimated error terms lagged from the AIDS cointegrating equation (equation 14), w^{*} and X^{*} are defined as before. The vector of age variables is represented by D and the price of each alcoholic beverage is represented by p_j. The problem with the Engel-Granger two-step procedure is that it often does not work well in finite samples as evidenced by a number of Monte Carlo experiments (Banerjee et. al, 1986, 1993). Referring to the estimates from the Engel-Granger two-step method applied in finite samples, Davidson and MacKinnon, (1993 pp. 724) state that, "*The problem is that the estimates are severely biased. The problem appears to be least severe when the* R^2 *of the cointegrating regression is close to 1, as it must be when the sample size is sufficiently large. Thus a relatively low value of the* R^2 *from the cointegrating regression should be taken as a warning that the two step procedure may not work well*."

Davidson and MacKinnon (1993) provide a general model as an alternative to the Engel-Granger two step procedures. We modify this model specification to suit the estimation of the AIDS model as:

$$\Delta w_t = z_t \alpha + \beta_i w_{t-1} - \sum_{j=1}^{N} \delta_{ij} \ln p_{j,t-1} - \theta_i \ln\left(\frac{X^*}{P}\right)_{t-1} + \sum_{j=1}^{N} \gamma_{ij} \Delta \ln p_{j,t} + \pi_i \Delta \ln\left(\frac{X^*}{P}\right)_t + u_t \quad (16)$$

in which the new parameters δ_{ij} and θ_i are -$\beta_i \lambda_{ij}$ and -$\beta_i \eta_i$ respectively. The β_i is the speed of adjustment (short run multiplier) to the long run equilibrium. If β_i is large or closer to one in absolute value then there is a rapid adjustment, i.e. the disturbance quickly disappears and we are back along the long-run path. The smaller the β_i is, the slower the adjustment to long run equilibrium. In turn, the long run parameters of interest, λ_{ij} and η_i, can be estimated by $\hat{\lambda}_{ij} = -\hat{\delta}_{ij} / \hat{\beta}_i$ and $\hat{\eta}_i = -\hat{\theta}_i / \hat{\beta}_i$ respectively.

2.2. Endogeneity Issues

When estimating a conditional demand system using time-series data, as is true in our case, the potential endogeneity of prices and real expenditure needs to be examined (LaFrance, 1991). The problem of endogeneity occurs when an explanatory variable is related to the error term in the population model of the data generating process. When explanatory variables are endogenous, Ordinary Least Squares (OLS) gives biased and inconsistent estimates of the causal effect of an explanatory variable on the dependent variable.

2.3. Instrumental Variable (IV) Estimation

Suppose we have the following linear equation as $y = X\beta + \varepsilon$ such that if observations on the explanatory variables (***X***) are unrelated to draws from the error terms ($\boldsymbol{\varepsilon}$), then the OLS estimators have the desirable properties of being consistent estimators. But if there is strong correlation between the ***X*s** and εs, then in general the OLS estimators are not consistent estimators of βs, because of endogenous regressors.

We want to investigate whether one or more of the stochastic regressors (***X***) is contemporaneously correlated with the error vector $\boldsymbol{\varepsilon}$. The presence of endogenous regressors has an effect on the parameter estimates and instrumental variables (IV) techniques are required. The instrumental variable should be one that is uncorrelated with the error term but correlated with the potentially endogenous variable (Maddala, 2001). The IV estimator uses one or more instruments to predict the value of the potentially endogenous regressor. The predicted values are then used as regressors in the original model. We can develop the IV estimators in a general form as follows[11]:

[11] For more details on the IV estimators and their properties see Griffiths et al. (1993 Pp 472-475); Davidson, R. and MacKinnon , (1993, Pp. 215-224)

Let matrix **Z** contains the set of all the variables that could serve as instrument regressors. The simple IV estimator is then of the form:

$$\begin{aligned}
\beta_{IV} &= (X^T Z(Z^T Z)^{-1} Z^T X)^{-1} X^T Z(Z^T Z)^{-1} Z^T y \\
&= (Z^T X)^{-1}(Z^T Z)(X^T Z)^{-1} X^T Z(Z^{T'} Z)^{-1} Z^T y \\
&= (Z^T X)^{-1}(Z^T Z)(Z^T \;\; Z)^{-1} Z^T y \\
&= (Z^T X)^{-1} Z^T y
\end{aligned}$$

The IV estimation is done in two steps: First regress the endogenous variable(s) on all the exogenous variables. Second, use the fitted values from the first step, plus the actual values of any regressors that serve as their own instruments, as regressors in the original equation. This procedure is referred to as Two-Stage Least Squares (TSLS). Given that the instruments are correlated with the endogenous variable but uncorrelated with the error term, the IV estimates of the effect of the endogenous variable are consistent.

2.4. Durbin-Wu-Hausman Exogeneity Tests

A test first developed by Durbin (1954) and later extended by Wu (1973) and Hausman (1978), commonly referred to as DWH test, provides a procedure to test the null hypothesis that the error terms are uncorrelated with all the regressors against the alternative hypothesis that they are correlated with some of the regressors, and not with the instrumental variables. Applying Davidson and MacKinnon's (1993, 2004) notation, denote the matrix of the instrumental variables by the vector **Z** and we can formally put the null and alternative hypotheses for the DWH test as:

$$H_0 : y = X\beta + \varepsilon , \qquad \varepsilon \sim IID(0, \sigma^2 I), \qquad E(X^T \varepsilon) = 0$$

$$H_1 : y = Z\beta + \varepsilon , \qquad \varepsilon \sim IID(0, \sigma^2 I), \qquad E(Z^T \varepsilon) = 0$$

Under the null hypothesis, both the OLS estimator and the IV estimator $\hat{\beta}_{IV}$ are consistent, while under the alternative hypothesis only the $\hat{\beta}_{IV}$ is consistent. That is to say under the H_0 *plim* ($\hat{\beta}_{IV}$ - $\hat{\beta}_{OLS}$) is equal to zero and under the H_1, it is different from zero. Hence the DWH test is essentially testing whether the difference ($\hat{\beta}_{IV}$ - $\hat{\beta}_{OLS}$) is significantly different from zero or not using the given sample. The following derivations[12], after Davidson and MacKinnon (1993), called vector of contrast can be developed:

$$\begin{aligned} \hat{\beta}_{IV} - \hat{\beta}_{OLS} &= (Z^T X)^{-1} Z^T y - (X^T X)^{-1} X^T y \\ &= (Z^T X)^{-1} (Z^T y - (Z^T X)(X^T X)^{-1} X^T y \\ &= (Z^T X)^{-1} (Z^T (I - (X(X^T X)^{-1} X^T) y) \end{aligned}$$

Now, denoting the expression in the middle $I - (X(X^T X)^{-1} X^T)$ by M_X, the above equation reduces to:

$$\hat{\beta}_{IV} - \hat{\beta}_{OLS} = (Z^T X)^{-1} (Z^T M_X y)$$

Using the methods outlined in Davidson and MacKinnon (1993, 2004), the logarithm of price indices/real expenditure is first regressed on all the other right hand side variables in the demand system and a set of the instrumental variables. The demand in budget share form is then estimated with the residual from this regression as an additional regressor. If the estimated coefficient of the residual is significantly different from zero, then the null hypothesis of

[12] The notations used here are modified to be consistent with previous notations introduced in this essay.

exogenous prices/real expenditure is rejected. An F-test is applied to determine whether the vector of the residuals in the second stage regression are significantly different from zero or not.

2.5. Testing for Cointegration

The concept of cointegration introduced by Granger (1981) and Granger and Weiss (1983) and elaborated in Engle and Granger (1987) relates short run dynamics with long run equilibrium. More generally, if a linear combination of a set of I (1) variables is I (0), then the variables are said to be cointegrated. This implies that these variables are related with one or more long run relationships, although they may wander from these relationships in the short run. Engle and Granger (1987) give the following formal definition of cointegration:

Definition: The components of the vector $\mathbf{x_t}$ are said to be co-integrated of order d, b, denoted x_t CI~ (d, b), if (i) all components of $\mathbf{x_t}$ are I (d); (ii) there exists a vector Π so that $\Pi' \mathbf{x_t}$ ~I (d -b), b>0. The vector Π is called the co-integrating vector.

If $\mathbf{x_t}$ has N>2 components, then there may be more than one cointegrating vector Π. It is then possible for several equilibrium relations to regulate the joint behavior of the variables. If there are exactly *r* linearly independent co-integrating vectors, with $r \leq$ N - 1, then these can be gathered together into the N x *r* matrix Π. This *r* is the rank of Π and is termed as *co-integrating rank* of $\mathbf{x_t}$ (Engle and Granger, 1987).

It is important to run unit root tests on the variables to check whether they are I(1) or not. Once the order of integration of the variables is established, then we proceed to test for cointegration. One method to test for cointegration is the residual based method (Engle and Granger, 1987). This involves running a regression of the form as in equation (6) and uses the estimated residuals as in equation (13) as a proxy for the true residuals. We then apply unit root tests on the estimated residuals. Rejecting the null hypothesis of a unit root is evidence in support of cointegration.

A second approach is to use a dynamic modeling procedure proposed by Banerjee et al. (1986) and Kremers et al. (1992). This procedure uses the lagged residuals from the OLS regression of equation (6) to test for cointegration in the ECM as in equation (14). In this case, the null hypothesis that the coefficient of the EC term (β_i) is not statistically different from zero is tested using a conventional *t*-test. If the null hypothesis is rejected, then the variables under consideration are cointegrated.

A third approach is the Johansen's maximum likelihood estimates of the cointegrating relationships (Johansen, 1988). In general, for a group of cointegrated variables, we can write the ECM as:

$$\Delta x_t = \Pi x_{t-1} + \sum_{j=1}^{k-1} \Gamma_j \Delta x_{t-j} + e_t \qquad (17)$$

when Π has less than full rank but is not equal to zero, Π can be decomposed as $\Pi = \alpha\beta^{'}$ which is the cointegration matrix, where α and β are *n* x *r* matrices. We can interpret α as the speed of adjustment towards long run equilibrium. The Johansen procedure (1988) requires calculation of eigenvalues of the matrix Π which implies that the number of cointegrating vectors for the elements of $\mathbf{x_t}$ depends on the rank of Π. There are two likelihood ratio tests for determining the rank of Π proposed by Johansen.

The first test, called the eigenvalue trace test, is used to test the null hypothesis that there are less than or equal to *r* cointegrating vectors versus a general alternative hypothesis. We can compute the Likelihood Ratio (LR) test by

$$-T\sum_{i=r_1+1}^{n}\ln(1-\lambda_i) \qquad (18)$$

here T is the number of observations and $\lambda_1 > \lambda_2 > ... > \lambda_n$ are the eigenvalues from the estimated Π matrix.

The trace test is conducted as follows:

i. H_0: r=0, (at most zero cointegration) cannot be rejected →stop

Rejected →next test

ii. H_0: r<=1, (at most one cointegration) cannot be rejected →stop→r=1

Rejected →next test

iii. H_0: r<=2, (at most two cointegration) cannot be rejected →stop→r=2

Rejected →next test

The second test which we use in this study, called the maximal eigenvalue test, has the test statistic given by

$$-T\ln(1-\lambda_{\max}) \qquad (19)$$

Where $\lambda_{\max}$ is maximum eigenvalue, after the estimated eigenvalues of Π are sorted in descending order. The null hypothesis is that there are r cointegrating vectors versus the alternative hypothesis of r + 1 cointegrating vectors. The $\lambda_{\max}$ test is preferred to the Trace test due to its sharper alternative hypothesis.

The $\lambda_{\max}$ test is conducted as follows:

H_0: $r= r_0$ Vs. H_1: $r= r_0 +1$

i. H_0: r=0 Vs. H_1: r=1; if reject H_0 then

ii. H_1: r=1 Vs. H_2: r=2; if reject H_1 then

iii. H_2: r=2 Vs. H_3: r=3; …

iv. H_{k-1}: r=k-1 Vs. H_k: r=k

In situations where there are multiple explanatory variables and where there is a possibility of multiple cointegrating vectors exist, Johansen's maximum likelihood cointegrating technique is preferred (Johansen, 1988; Johansen and Juselius, 1990).

2.6. Summary of modeling approach

This part begins by assuming weak separabilty of consumer preferences and two stage budgeting. The assumption of weak separability is appealing to empirical researchers because weak separability implies a two-stage budgeting for consumer behavior. In the first stage, the consumer allocates expenditures among the various broad categories of goods. In the second stage the consumer allocates expenditures among the goods within each broad category based only on the relative prices of the goods in that category.

The static Almost Ideal Demand System (AIDS) developed by Deaton and Muellbauer (1980a) is adopted to construct the dynamic demand model of an error correction form. This demand model is attractive for many reasons. It is flexible demand specification obtained from expenditure function consistent with economic theory. It satisfies exactly the axioms of choice and it is easy to estimate. During empirical estimation, the problem of using a non-linear price index in the conditional demand model can be overcome using the Stone Geometric Price Index.

Deaton and Muellbauer (1980a) observed that the rejection of homogeneity in demand analysis in a static set up may be due to insufficient attention to the dynamic aspects of consumer behavior. Many empirical studies also reveal that the short run elasticity estimates do differ from their long run counterparts. On top of this, empirical evidence also shows that many economic time series are not stationary. If the nonstationary economic variables of interest are cointegrated, there exists a long-run relationship between them. Furthermore, it can be established that the short-run dynamics can be described by an error correction form. As long as there is evidence of cointegration, an error correction form for the AID system model can be constructed to characterize the short run adjustment process towards the long run equilibrium relationships.

Building on the concept of cointegration, the single equation error correction model specified by Davidson and Mackinnon (1993) can be successfully applied to the AID system model in a system as in *equation (1).* In most empirical estimations, the dynamic AID system modeled to be of an error correction form of the static AID system model as in the Engel-Granger two step method which specifies the disequilibrium component separated from the long-run equilibrium and thus gives short-run relationship between the demand variables. The error term $u_{i,t}$ from a static model, is calculated as the equilibrium error in the short-run which is then used to bind the short-run adjustment behavior of the dependent variable to its long-run value. The problem with the Engel-Granger two step procedures is that it often does not work well in finite samples as evidenced by a number of Monte Carlo experiments.

Davidson and Mackinnon (1993) provide a general model as an alternative to the Engel-Granger two step procedures. Based on their alternative procedure, we specify a dynamic AID system model with an error correction form for the demand for alcoholic beverages as in *equation (4).*

Based on the concept of cointegration, short run dynamics are related with long run equilibrium. Generally, if a linear combination of a set of I (1) variables is I (0), then the variables are said to be cointegrated. This implies that these variables are related with one or more long run relationships, although they may wander from these relationships in the short run. Three methods are suggested in conduct cointegration tests. One method to test for cointegration is the residual based method. A second approach is to use a dynamic modeling procedure. A third approach which is used in this study is the Johansen's maximum likelihood estimates (MLE) of cointegrating relationships. In situations where there are multiple explanatory variables and where there is a possibility of multiple cointegrating vectors exist, Johansen's maximum likelihood cointegrating technique is preferred (Johansen, 1988; Johansen and Juselius, 1990).

The need to examine the potential endogeneity of prices and real expenditure especially in a conditional demand modeling is emphasized, because the presence of endogenous regressors has an effect on the parameter estimates. The Durbin-Wu-Hausman test, commonly referred to as DWH test, provides a procedure to test the null hypothesis that the error terms are uncorrelated with all the regressors against the alternative that they are correlated with some of the regressors, and not with the instrumental variables. Applying the methods outlined in Davidson and MacKinnon (1993), the logarithm of price indices/real expenditure is first regressed on all other right hand side variables in the demand system and a set of the instrumental variables. The demand in budget share form is then estimated with the residual from this regression as an additional regressor. If the estimated coefficient of the residual is significantly different from zero, then the null hypothesis of exogenous prices/real expenditure is rejected.

3. DATA AND METHODS

A time series data collected from the U.S. Department of Agriculture, Economic Research Service (ERS) from 1979 to 2006 were used. The three alcoholic beverages are beer, wine and distilled spirits. The ERS food availability (per capita) data system includes three distinct but related data series on food consumption. The data serve as popular proxies for actual consumption. CPI on price was obtained from U.S. Consumer Expenditure Survey and Bureau of Labor Statistics[13].

Researchers noted that alcohol use declines with age, especially among the elderly, and the proportion of abstainers increases with age for both sexes (Hilton and Clark 1987) and with changes in the proportion of all age groups. The U.S. drinking patterns are likely to be affected by a decrease in the college-aged population that began in 1981 and by an increase in the elderly population. Nelson (1997) suggested empirical studies that examine average per capita consumption should include variables that capture the changes taking place in both tails of the population age distribution. In this paper, we will include two population age distributions (Figure 2-1). These variables might help capture the change in alcoholic beverage consumption in the U.S and might enhance the explanatory power of the demand system model. Data for these variables were obtained from Population Division, U.S. Census Bureau.

[13] The Bureau of Labor Statistics uses retail prices to compute the CPI- http://www.bls.gov/opub/hom/pdf/homch17.pdf

We test for cointegration of the budget shares and the price indices and the total real expenditure employing Johansen's maximum likelihood cointegration analysis. The AID system model was estimated as two share equations for beer and spirits and the wine share equation was dropped when estimating a set of share equations. The estimation was done using both the multivariate regression and iterated Seemingly Unrelated Regressions (SUR). This procedure adjusts for cross-equation contemporaneous correlation and consequently takes into account the optimization process behind the demand system. Eales and Unnevehr (1989) noted that assuming the AID system type preferences, SUR estimates of the AID system model are appropriate when prices are predetermined and quantities endogenous. A constant term was included in the regression equations with first differences. While applying this procedure if the coefficient is found to be significant, then it may imply a linear trend in the levels original equation (Maddala, 2001; Deaton and Muellbauer 1980a). Price and expenditure elasticities were estimated for three different categories of alcohol: beer, spirits and wine. These elasticities are estimated for both short run and long run.

3.1. Summary of data and methods

A time series data set collected by the U.S. Department of Agriculture, Economic Research Service (ERS) from 1979 to 2006 is used. The three alcoholic beverages are beer, wine, and distilled spirits. Consumer price index (CPI) is obtained from U.S. Consumer Expenditure Survey and Bureau of Labor Statistics. In this paper, we include two variables for age distributions. These variables might help capture the change in alcoholic beverage consumption and might enhance explanatory power of the demand system model. Data for these variables were obtained from Population Division, U.S. Census Bureau.

We test for cointegration of the budget shares, the price indices, and the total real expenditure by using Johansen's maximum likelihood and the residual based cointegration analysis. The AID system model is estimated as two share equations for beer and spirits and the wine share equation is dropped when a set of share equations is estimated. The estimation is conducted using both the multivariate regression and iterated Seemingly Unrelated Regressions (ITSUR). Price and expenditure elasticities are estimated for three different categories of alcohol: beer, spirits and wine. These elasticities are estimated for both short run and long run.

4. EMPIRICAL RESULTS

4.1. Analysis of the Endogeneity/Exogeneity tests for Prices Indices and Real Expenditure

We run the exogeneity tests for price indexes and total real expenditure using instrumental variables (IV) method outlined above. We tested individually and jointly for both variables. Under the assumptions that the instruments are correlated with the endogenous explanatory variable but have no direct association with the outcome under study, we have used all-less-food–and-beverage /energy/Medicare CPI measures one at a time as instruments for alcoholic beverage price indices; and per capita median income 2000 dollar and trend as instruments for real expenditure.

4.1.1. All less food and beverage CPI, per capita median income and trend as instruments

For the Beer equation, when the test was conducted treating both variables jointly, both price index and real expenditure were exogenous at an acceptable levels of significance. For wine, in both independent and joint tests, the null hypothesis that both price index and real expenditure are exogenous cannot be rejected at all acceptable levels of alpha. When independently tested, both wine price index and real expenditure seem exogenous variables. The result is a little different for Spirits, in that when the test is conducted treating both variables simultaneously, the null hypothesis that both price index and real expenditure are exogenous was strongly rejected. In the first stage regression for the predicted value of spirits price and real expenditure, the F test for the joint significance of the coefficients was rejected for both the predicted values of spirits price and real expenditure. However, when independently tested, price index appears to be endogenous variable, whereas real expenditure seems exogenous variable.

4.1.2. Energy CPI, per capita median income and trend as instruments

For the beer equation, both independent and joint tests indicated that price index and real expenditure appears to be exogenous variables, at an acceptable levels of significance. For the spirits equation, when the test was conducted for both variables simultaneously, the null hypothesis that both price index and real expenditure are exogenous was strongly rejected. Investigation of the first stage regressions may provide more information on the quality of instruments, such as the F test for the joint significance of the coefficients was rejected for the predicted values of spirits price while it failed to reject the joint significance of the coefficients for the predicted value of real expenditure. In the case of wine equation, the results were in conclusive in that when independently tested, both wine price index and real expenditure seem exogenous variables, where as in the joint test , the null hypothesis that both price index and real expenditure are exogenous cannot be rejected at all acceptable levels of alpha. In the first stage regression for the predicted value of spirits price, The F test for the joint significance of the coefficients was strongly rejected, while for the predicted value of real expenditure, the joint non significance of the coefficients was rejected at all acceptable levels of alpha.

4.1.3. Medicare CPI, per capita median income and trend as instruments

For beer, the joint test showed that both price index and real expenditure were exogenous at an acceptable level of significance. In the case of the spirits equation**,** when the test is conducted for both variables simultaneously, the null hypothesis that both price index and real expenditure are exogenous cannot be rejected 1% and 5 % level of significance, but was rejected at 10% alpha level. In the first stage regression for the predicted value of spirits price, the F test for the joint significance of the coefficients was strongly rejected, while for the predicted value of real expenditure, the joint significance of the coefficients cannot be rejected at acceptable levels of significance. In the wine equation, similarly when the test is conducted treating both variables simultaneously, the null hypothesis that both price index and real expenditure are exogenous cannot be rejected at all acceptable levels of alpha. Further investigation indicates that, in the first stage regression for the predicted value of spirits price, the F test for the joint non-significance of the coefficients was strongly rejected, while for the predicted value of real expenditure, the joint non-significance of the coefficients cannot be rejected at acceptable levels of significance.

In summary, as we have seen from the previous results analysis, the all-less-food-and-beverage CPI used in combination with per capita median income and trend as instruments performed better than alternative energy CPI and Medicare CPI and because in the joint exogeneity tests, the F-tests are significant for both price index and real expenditure. The F test in the first-stage regression is a rough guide to the quality of IV estimates as suggested by Bound et al. (1995).

Based on the indications of the above results, we considered the real expenditure as an exogenous variable, where as the price index for spirits as an endogenous variable.

4.2. Dynamic demand specifications

Whether or not the demand system can be modeled in the error correction form is determined by the existence of long run relationships between the variables in the model and the appropriateness of the data series for the dynamic specifications. Applying the residual based co-integrating test, the ADF test was used to see if the residuals appear stationary. For the beer equation, the ADF test showed that the null hypothesis of unit root in the residuals was rejected at 5% alpha level and hence the beer budget share and the price and real expenditure appear to be cointegrated. The same conclusion was reached for the wine equation although at 10% alpha level (p-value 0.0787). However, for the spirits equation, the null hypothesis of unit root in the residuals was not rejected at conventional alpha levels.

Further application of Johansen's maximum eigenvalue test revealed that the null hypotheses of no cointegrated relationship between the variables of interest were rejected in all equations. This implies that all the budget shares and the log of prices and log of total real expenditure are cointegrated, with more than one cointegrated vectors found in all equations, thus justifying the use of an error correction approach (Table 2-3).

Using equation 15, the dynamic AID system is estimated applying an ITSUR procedure. In general, the adjusted R^2 in the dynamic specification was much better than the static specification in both the beer and spirits equations. More than half of the estimated coefficients are found to be significant at acceptable statistical levels of significance. The log of total real expenditure seems to explain the budget allocation by consumers more in the long run than in the short run as can be seen from the higher significance level in the long run coefficients.

In general, the equations including age group variables performed better in terms of goodness of fit. In each equation, the adjusted R^2 was higher when these age variables were included. For comparison purposes, the regressions result from the static AID model without the age group variables is reported on table 2-11.

4.2.1. Long run estimates

We run standard Augmented Dickey-Fuller (ADF) tests (Dickey and Fuller, 1981) for the presence of unit roots in all the data series used in the estimation of demand equations. The result of these tests is presented in table 2-1. All the data series in levels have unit roots and are found to be nonstationary, while after first-differencing all of the data series were found to be stationary.

The results of the long run coefficient estimates are presented in Table 2-4. Note that these results are obtained using instrumented price of spirits. Furthermore, the estimation results are those that are obtained using ITSUR after deleting the wine equation[14]. Testing the theoretical restrictions of homogeneity for the beer equation could not be rejected at all standard significance levels, where as the homogeneity restriction for the spirits equation was strongly rejected. Symmetry restriction also could not be rejected at all standard significance levels. Hence, the estimation results shown in Table 2-4 are after imposing homogeneity restriction in the beer equation as well as symmetry restriction. Although the analysis here is made based on the estimation results of equation (16), we have also estimated the demand relationships following equation (15), the Engel-Granger two step model, for the sake of comparing this two model specification (tables 2-8 and 2-9).

The own-price estimates for beer and spirits show a negative relationship with their budget shares, and the own price estimate for wine shows positive relationship with its budget

[14] We have run the ITSUR deleting one equation at a time for each of the alcoholic beverages, and the estimated results were almost the same regardless of which equation was deleted.

share. The total real expenditure does not seem to strongly explain the budget allocation towards any of the alcoholic beverages, although for beer the significance level is just slightly above the 10% alpha level. Both age variables significantly explain the budget share of the spirits equation and the age group 40-60 variable also explains the beer budget share equation significantly, implying that the more the age proportion of the U.S in this group, the less they tend to allocate their budget to beer.

The long run uncompensated own price elasticities are -4.060 , -1.273 , -1.278 for beer, spirits and wine respectively and the compensated own price elasticities are -0.592, -1.265,-1.026 for beer, spirits and wine respectively. The absolute magnitudes of the uncompensated price elasticities are larger than the compensated price elasticities for all three alcoholic beverages.

The expenditure elasticities are 3.996, 0.131, and 3.377 for beer, spirits and wine respectively. Thus, both beer and wine appear to be luxury goods, while spirits is a necessity good as per the model.

The error correction term β_i for beer is -0.048. This implies that 4.8 % of the disturbance to the long-run equilibrium in the previous period is corrected or adjusted back to long-run equilibrium in this period. The speed of adjustment for spirits is much higher (-0.510), with 51% of the disequilibrium is corrected within one period (year). The speed of adjustment for wine similar to spirits (0.558), with 55.8 % of the disequilibrium is corrected within one period (year).

4.2.2. Short run estimates

Both the proportion of the age group 20 to 34 and age group 40 to 64 variables were significant. For the beer equation, the age group 20 to 34 was positively related with the beer share and the age group 40 to 64 was negatively related to the beer share. Conversely, the age group 20 to 34 was negatively related with the spirits share and the age group 40 to 64 was positively related to the spirits share.

4.3. Summary of Results

Under the assumptions that the instruments are correlated with the endogenous explanatory variable but have no direct association with the error terms, we have used all-less-food–and-beverage /energy/Medicare CPI measures one at a time as instruments for alcoholic beverage price indices; and per capita median income 2000 dollar and trend as instruments for real expenditure. The test results are included in table 2-1. In summary, the all-less-food-and-beverage CPI used in combination with per capita median income and trend as instruments performs better than alternative energy CPI and Medicare CPI. Based on test results, we consider the real expenditure as an exogenous variable, while consider the price index for spirits as an endogenous variable.

Whether or not the demand system can be modeled in the error correction form is determined by the existence of long run relationships between the variables in the model and the appropriateness of the data series for the dynamic specifications. Standard Augmented Dickey-Fuller (ADF) tests for the presence of unit roots in all the data series used in the estimation of demand equations. The results of these tests are presented in table 2-2. All the data series in levels have unit roots and are found to be nonstationary, while after first-differencing all of the data series are found to be stationary.

Application of Johansen's maximum eigenvalue test reveals that the null hypotheses of no cointegrated relationship between the variables of interest are rejected in all equations (table 2-3). This implies that all the budget shares, the log of prices, and the log of total real expenditure are cointegrated, with more than one cointegrated vectors found in all equations, thus justifying the use of an error correction approach.

The results of the long run coefficient estimates and elasticities are presented in tables 2-4 and 2-5 and the results for the short run model are included in tables 2-6 and 2-7. The long run estimation results in table 2-4 are obtained using instrumented price of spirits. Homogeneity for the beer equation cannot be rejected at all standard significance levels, while the homogeneity restriction for the spirits equation is strongly rejected. Symmetry restriction also cannot be rejected at all standard significance levels. Hence, we impose homogeneity and symmetry and obtain the estimation results in table 2-4.

The own-price estimates for beer and spirits show a negative relationship with their budget shares, and the own price estimate for wine shows positive relationship with its budget share. The total real expenditure does not seem to strongly explain the budget allocation towards any of the alcoholic beverages, although for beer the significance level is just slightly above the 10% level. Both age variables significantly explain the budget share of the spirits equation and the age group 40-60 variable also explains the beer budget share equation significantly, implying that the higher the proportion in this age group, the less they tend to allocate their budget to beer.

The long run compensated own price elasticities are -0.592, -1.265,-1.026 for beer, spirits, and wine, respectively. The absolute magnitudes of the uncompensated price elasticities are larger than the compensated price elasticities for all three alcoholic beverages. The expenditure elasticities are 3.996, 0.131, and 3.377 for beer, spirits and wine respectively. Thus, both beer and wine appear to be luxury goods, while spirits is a necessity good as per the model (table 2-5). The values of price and expenditure elasticities in this paper are within the value range of the corresponding elasticities reported by the existing literature (table 2-10).

The error correction term β_i for beer is -0.048. This implies that 4.8 % of the disturbance to the long-run equilibrium in the previous period is corrected to long-run equilibrium in this period. The speed of adjustment for spirits is much quicker (-0.510), with 51% of the disequilibrium is corrected within one period (year). The speed of adjustment for wine is similar to spirits (0.558), with 55.8 % of the disequilibrium is corrected within one period (year).

Both the proportion of the age group 20 to 34 and age group 40 to 64 variables are significant. For the beer equation, the age group 20 to 34 is positively related with the beer share and the age group 40 to 64 is negatively related to the beer share. Conversely, the age group 20 to 34 is negatively related with the spirits share and the age group 40 to 64 is positively related to the spirits share.

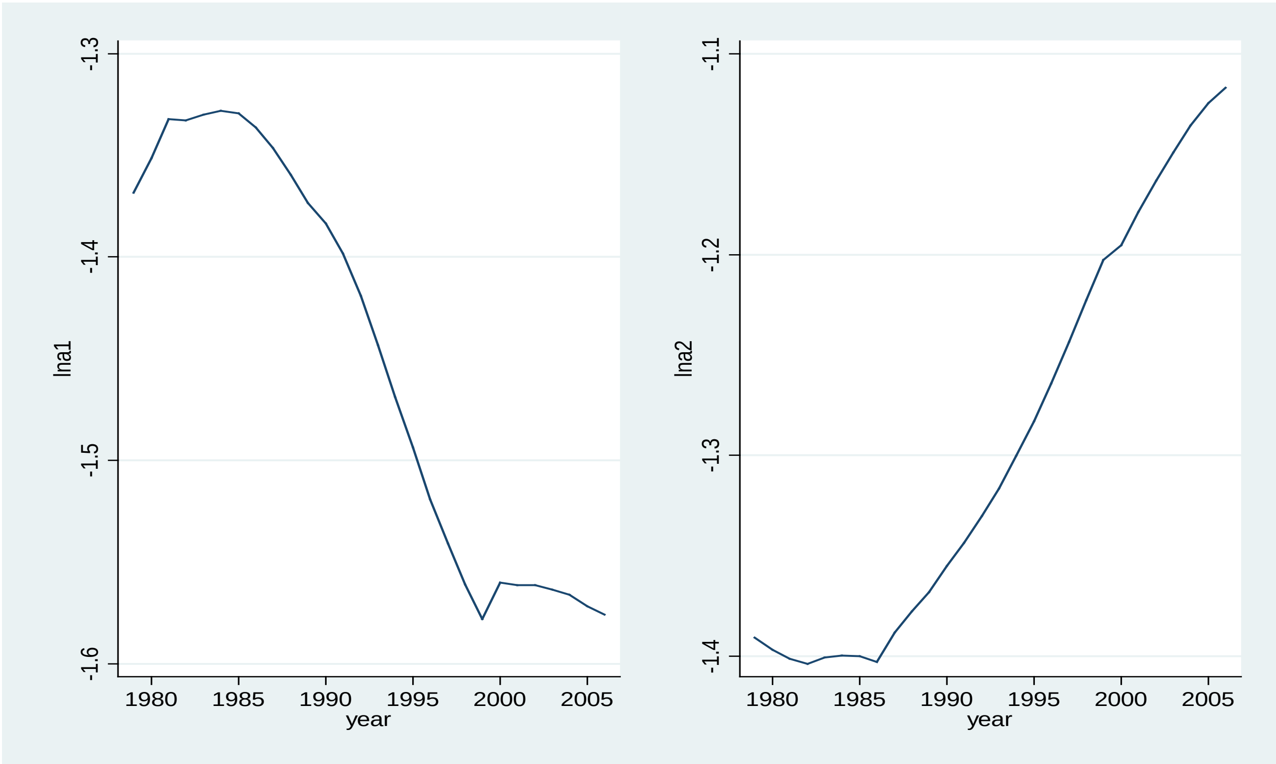
5. CONCLUSION AND IMPLICATIONS

The paper applied time-series econometrics for estimating an error-corrected Almost Ideal Demand System (AIDS) model for three alcoholic beverages (beer, spirits and wine) using annual data from 1979 to 2006. Assuming weak separability, the demand system is modeled at the second stage of a two-stage budgeting procedure based on a consumer expenditure minimization problem. Using Johansen's ML test, cointegration was established for the budget shares and price indices and total real expenditure on the three alcoholic beverages, thus justifying the use of an error correction AID system model. During the empirical estimation of the error correction model, the Engel-Granger two step method is widely used. However, at times it may not be the best option as demonstrated in this essay. It is widely recognized that in demand analysis that demonstrates that the choice of a functional form has a strong incidence on calculated elasticities (Larivierea, Larueb, & Chalfant, 2000). The one step alternative model developed in this essay also has the ability to provide estimates of both short- and long-run demand elasticities with due investigation of time series properties of the data. Age group variables also play an important role in explaining consumer consumption decisions. The estimated elasticities in this study are within the range of previous estimated elasticities (table 2-10).

Exogeneity tests of the variables have produced interesting results. For the beer and wine equations, the hypothesis of joint exogeneity of price index and real expenditure cannot be rejected at all the conventional levels of significance. For spirits equation, the tests strongly reject the simultaneous exogeneity of price index and real expenditure. When independently tested, price index appears to be endogenous variable where as real expenditure seems exogenous variable. Based on these results, the real expenditure was considered as an exogenous variable, where as the price index for spirits as an endogenous variable.

Although the use of annual time series data has been extensively used to study the demand for alcoholic beverages, there is some concern that its use may not reflect the full range of demand variability, because the consumption of alcoholic beverages displays substantial seasonal variation (Nelson, 1997). When conditions permit, it would be interesting and more informative to employ more frequent data observations such as quarterly data. Another point to consider in alcoholic beverage consumption is expenditures on advertizing. Some studies have shown that advertizing has little to no impact on the demand for alcoholic beverages, apart from influencing brand choices or choices between beverage types. It is also reported that normally the advertising of a given beverage lasts less than a year and hence when using time series data we may not expect to capture the effect of advertising. This feature may also warrant use of more frequent data when trying to incorporate advertising in the model.

Figure 2-1: U.S. Population Proportion by Age Group



a) Age group 20-34 b) Age group 40-64

Source: Population Division, U.S. Census Bureau

Table 2-1: Summary of the independent and joint endogeneity/exogeneity tests for prices indices and real expenditure using various instrumental variables

All-less-food-and-beverage CPI, per capita median income and trend as instruments									
	Beer			Spirits			Wine		
	1%	5%	10%	1%	5%	10%	1%	5%	10%
Price alone	NR	NR	**RJ**	**RJ**	**RJ**	**RJ**	NR	NR	NR
Expenditure alone	NR	NR	NR	NR	NR	NR	NR	NR	NR
Both price and expenditure	NR*,*	NR	NR	**RJ*,***	**RJ**	**RJ**	NR*,-	NR-,**	NR
Energy CPI, per capita median income and trend as instruments									
	Beer			Spirits			Wine		
	1%	5%	10%	1%	5%	10%	1%	5%	10%
Price alone	NR	NR	NR	NR	NR	**RJ**	NR	NR	NR
Expenditure alone	NR	NR	NR	NR	NR	NR	NR	NR	NR
Both price and expenditure	NR*,-	NR	NR	**RJ*,-**	**RJ**	**RJ**	NR*,-	NR	NR
Medicare CPI, per capita median income and trend as instruments									
	Beer			Spirits			Wine		
	1%	5%	10%	1%	5%	10%	1%	5%	10%
Price alone	NR	**RJ**	**RJ**	**RJ**	**RJ**	**RJ**	NR	NR	NR
Expenditure alone	NR	NR	NR	NR	NR	NR	NR	NR	NR
Both price and expenditure	NR*,-	NR	NR	NR*,-	NR	**RJ**	NR*,-	NR	NR

RJ=rejected-implying Endogeneity

NR=not rejected- implying Exogeneity

, significance of F-test (the first asterisk is for price index, and the second asterisk is for real expenditure)

Table 2-2: Augmented Dickey Fuller unit root tests of the data series

Series	Level Series					
	none	5% critical value	drift	5% critical value	trend	5% critical value
Log Price of Beer	1.7191	-1.95	-1.4389	-2.93	-1.8209	-3.50
Log Price of Spirits	2.5024	-1.95	-1.5751	-2.93	-0.8858	-3.50
Log Price of Wine	2.5272	-1.95	-1.1807	-2.93	-0.7983	-3.50
Log real expenditure	-1.2777	-1.95	-1.0218	-2.93	-1.2966	-3.50
Beer Budget Share	-0.0264	-1.95	-1.6654	-2.93	-1.1425	-3.50
Spirits Budget Share	0.8316	-1.95	-2.8647	-2.93	-0.0057	-3.50
Wine Budget Share	-0.2374	-1.95	-1.9206	-2.93	-1.6601	-3.50

Series	First Differenced Series					
	none	5% critical value	drift	5% critical value	trend	5% critical value
Log Price of Beer	-1.7321	-1.95	-3.1958	-2.93	-3.0125	-3.50
Log Price of Spirits	-1.1662	-1.95	-3.7209	-2.93	-3.2058	-3.50
Log Price of Wine	-1.5557	-1.95	-3.6607	-2.93	-2.9525	-3.50
Log real expenditure	-1.0481	-1.95	-3.1915	-2.93	-1.6465	-3.50
Beer Budget Share	-1.7516*	-1.95	-1.6761	-2.93	-2.2327	-3.50
Spirits Budget Share	-2.2043	-1.95	-1.915	-2.93	-2.7385	-3.50
Wine Budget Share	-2.185	-1.95	-2.4102	-2.93	-2.1996	-3.50

* Significant only at 10% alpha value (10% critical value is -1.61)

Table 2-3: Johansen's MLE cointegration test

Hypothesized # of C.I.'s	**Beer budget share equation**		**Spirits budget share equation**		**Wine budget share equation**	
	Test statistic	5% critical value	Test statistic	5% critical value	Test statistic	5% critical value
None	**52.37**	34.40	**54.50**	34.40	**52.75**	34.40
At most 1	**44.12**	28.14	**39.98**	28.14	**30.80**	28.14
At most 2	16.94	22.00	**26.05**	22.00	14.24	22.00
At most 3	10.52	15.67	13.64	15.67	11.65	15.67
At most 4	7.03	9.24	4.37	9.24	8.24	9.24

Figures in bold indicate significance at 5% alpha level.

Table 2-4: Iterative Seemingly Unrelated Regression results of the long run estimates for the dynamic AIDS model

Variable	Beer	Spirits	Wine
Real expenditure	2.600	-0.050	0.178
Beer price	-0.399	-0.041*	-0.072
Spirits price	1.355**	-0.019	0.099
Wine price	-0.480	0.037***	-0.008
age 20-34	-0.118	0.077**	
age 40-64	-0.115**	0.079***	
β_i	-0.048	-0.510***	0.558
	(.151)	(.109)	

*, **, and *** represent significance at the 10%, 5% and 1% alpha level, respectively

Table 2-5: Long run estimates of demand elasticities for the dynamic AIDS model

Equation	Beer	Spirits	Wine
		Uncompensated	
Beer	-4.060	1.390**	-0.777
Spirits	0.040*	-1.273	0.706
Wine	-3.024	1.194	-1.278
		Compensated	
Beer	-0.592	1.619**	-0.478
Spirits	0.154*	-1.265	0.716
Wine	-0.093	1.388	-1.026
		Expenditure	
	3.996	0.131	3.377

Note: The elasticities are computed at mean values.

*, **, and *** represent significance at the 10%, 5% and 1% alpha level, respectively

Table 2-6: Iterative Seemingly Unrelated Regression results of the short run estimates for the dynamic AIDS model

	Beer Coefficient (Std. error)	Spirits Coefficient (Std. error)	Wine Coefficient
Real expenditure	0.005	0.010	-0.015
	(0.058)	(0.013)	
Beer price	0.079**	-0.034***	-0.045
	(0.032)	(0.010)	
Spirits price	-0.034***	-0.016	0.050
	(0.010)	(0.017)	
Wine price	-0.045	0.028***	0.016
	(0.029)	(0.010)	
age 20-34	-0.151	0.081***	0.070
	(0.111)	(0.027)	
age 40-64	-0.196	-0.017	0.214
	(0.195)	(0.051)	
R^2	0.649	0.937	-

*, **, and *** represent significance at the 10%, 5% and 1% alpha level, respectively

Table 2-7: Short run estimates of demand elasticities for the dynamic AIDS model

Equation	**Beer**	**Spirits**	**Wine**
		Uncompensated	
Beer	-0.914**	-0.040***	-0.052
Spirits	-0.748***	-1.282	0.478***
Wine	-0.419	0.679	-0.765
		Compensated	
Beer	-0.041**	0.018***	0.023
Spirits	0.272***	-1.214	0.566***
Wine	0.270	0.725	-0.705
		Expenditure	
	1.006	1.175	0.794

Note: The elasticities are computed at mean values.

*, **, and *** represent significance at the 10%, 5% and 1% alpha level, respectively

Table 2-8: Long run estimates of demand elasticities for the static AIDS model, from the first step of Engel-Granger two step model

	Beer	**Spirits**	**Wine**
Uncompensated Own Price Elasticity	-0.826	0.179	-0.353
Compensated Own Price Elasticity	-0.005	0.237	-0.232
Expenditure Elasticity	0.947	0.999	1.62

Note: The elasticities are computed at mean values.

Table 2-9: Short run estimates of demand elasticities for the static AIDS model, from the second step of Engel-Granger two step model

	Beer	**Spirits**	**Wine**
Uncompensated Own Price Elasticity	-0.899	-0.448	-0.463
Compensated Own Price Elasticity	-0.053	-0.377	-0.380
Expenditure Elasticity	0.975	1.233	1.115

Note: The elasticities are computed at mean values.

Table 2-10: Summary of selected elasticities

Study	Country	Time period and data type	Own price			Income/Expenditure		
			beer	spirits	wine	beer	spirits	wine
Johnson et al. (1992)	Canada	1956-83 (annual)	-0.14	0.37	-1.17	0.27	1.02	2.19
Blake and Neid (1997)	U.K.	1963-92 (annual)	-0.95	-1.32	-0.93	0.89	0.98	1.61
Selvanathan and Selvanathan (2004)	Australia	1956–1999 (annual)	-0.16	-0.62	-0.31	0.66	2.47	0.83
Coulson et al. (2001)	U.S.A.	1970-1990 (quarterly)	-0.27	-0.33	-0.59	-0.27	0.41	0.76
Duffy (1982)	U.K.	1979-1987 (monthly)	-0.17	-0.84	-1.14	0.49	1.65	1.50
Median Elasticities† Gallet (2007)			–0.360 (315)	–0.679 (294)	–0.700 (300)	0.394 (278)	1.000 (245)	1.100 (240)
Only AID System model*								
Eakins and Gallagher(2003)	Ireland	1960-1998 (annual)	-0.77 to -0.42	-.93 to 0.84	-1.95 to -0.36	0.77 to 1.05	0.82 to 1.15	1.26 to 2.33
Blake and Neid (1997)	U.K.	1952- 1991(annual)	-0.95	-1.32	-0.95	0.89	0.98	1.61
Nelson and Moran (1995)	U.S.A.	1964-1990 (annual)	-0.08	-0.08	-0.26	0.79	1.26	1.06
Thom (1984)	Ireland	1969-1980 (quarterly)	-0.59 to -0.76	-1.29 to -1.54	-1.61 to -1.6	0.8	1.386	1.23
Jones (1989)	U.K.	1964-1983 (quarterly)	-0.27	-0.95	-0.77	0.31	1.14	1.15
Gao et al. (1995)	U.S.A.	1987-1989 (cross sectional)	-0.23	-0.4	-0.25	-0.09	5.03	1.21
Minimum (absolute)			-0.08	-0.08	-0.25	-0.09	0.083	1.06
Maximum (absolute)			-0.95	-1.54	-1.61	0.96	5.03	2.33

†Median elasticities correspond to the median across all elasticities surveyed by Gallet (2007). E.g., across the 315 previous price elasticities (indicated in parenthesis) surveyed for beer, the median equals –0.360.

* The lower part of the table shows previous elasticities estimated via the AID system model

Table 2-11: Iterative Seemingly Unrelated Regression results of static AID system model with no demographic variables

	Beer Coefficient (Std. error)	Spirits Coefficient (Std. error)	Wine Coefficient
Real expenditure	-0.077*	0.0014	0.076
	(0.040)	(0.019)	
Beer price	0.090***	-0.039**	-0.051
	(0.034)	(0.017)	
Spirits price	-0.034	0.013	0.021
	(0.060)	(0.029)	
Wine price	-0.0201	-0.009	0.029
	(0.033)	(0.016)	
R^2	0.339	0.446	-

*, **, and *** represent significance at the 10%, 5% and 1% alpha level, respectively

REFERENCES

Andrikopoulos, A., Brox, J., and Carvalho, E. "The Demand for Domestic and Imported Alcoholic Beverages in Ontario, Canada: A Dynamic Simultaneous Equation Approach." *Applied Economics* 29(1997) 945–53.

Barnerjee, A., Dolado, J., Hendry, D., and Smith, G., "Exploring Equilibrium Relationships in Econometrics through Static Models: Some Monte Carlo Evidence." *Oxford Bulletin of Economics and Statistics* 48 (1986) 2:253 – 278.

Barnerjee, A., Dolado, J.J, Galbraith J.W., and Hendry, D.F. "Co-integration, Error Correction, and the Econometric Analysis of Non-stationary Data" *Oxford: Oxford University Press,* 1993.

Balcombe, K. G., and Davis, J. R. "An Application of Cointegration Theory in the Estimation of the Almost Ideal Demand System for Food Consumption in Bulgaria."*Agricultural Economics* 15(1996) 47-60.

Blake, D. and Nied, A. "The Demand for Alcohol in the United Kingdom." *Applied Economics* 29(1997)12: 1655–72.

Bound, J., Jaeger, D. A., and Baker, R. M. "Problems with Instrumental Variables Estimation when the Correlation between the Instruments and the Endogeneous Explanatory Variable is Weak." *Journal of the American Statistical Association,* 90 (June, 1995) 430: 443-450

Coulson, N.E., Moran, J.R., and Nelson, J.P. "The Long-Run Demand for Alcoholic Beverages and the Advertising Debate: A Cointegration Analysis." *Advertising and Differentiated Products:* book series Advances in Applied Microeconomics, 10 (2001) 31-54.

Davidson, R., and MacKinnon, J. G. "Estimation and Inference in Econometrics." New York:Oxford University Press, 1993.

Deaton, A. S., and Muellbauer, J. “An Almost Ideal Demand System” *American Economic Review* 70 (1980a) 312–26.

______. “Economics and Consumer Behavior.” Cambridge, UK: Cambridge University Press, 1980b.

Dickey, D. A., and Fuller, W. A. “Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root.” *Econometrica* 49(1981)1057–72.

Duffy, M. “The effect of advertising on the total consumption of alcoholic drinks in the United Kingdom: some econometric estimates” *Journal of Advertising* 1(1982)105-117.

Duffy, M. “Advertising and the Inter-Product Distribution of Demand: A Rotterdam Model Approach.” *European Economic Review* 31(1987) 1051–70.

Durbin, J. “Errors in Variables”. *Review of the International Statistical Institute* 22 (1954) 23-32.

Gao, X., Wailes, E. and Cramer, G. “A microeconometric model analysis of US consumer demand for alcoholic beverages” *Applied Economics* 27(1995), 59–69.

Eakins J.M. and Gallagher, L.A. “Dynamic Almost Ideal Demand Systems: An Empirical Analysis of Alcohol Expenditure in Ireland.” *Applied Economics* 35(2003) 1025–1036

Eales, J.S., and Unnevehr L.J. “Simultaneity and Structural Change in U.S. Meat Demand.”*American Journal of Agricultural Economics* 75(1989) 253-261.

Engle, R. F. and Granger, C. W. J. “Cointegration and Error Correction: Representation, Estimation and Testing.” *Econometrica* 55(1987) 251–76.

Fanelli, L. And Mazzocchi, M. “A Cointegrated VECM Demand System for Meat in Italy”*Applied Economics*, 34(2002) 1593-1605

Gallet, C. A. “The demand for alcohol: a meta-analysis of elasticities” *The Australian Journal of Agricultural and Resource Economics* 51(2007)121–135

Granger, C. W. J. "Some Properties of Time Series Data and Their Use in Econometric Model Specification" *Journal of Econometrics* (1981) 121-130.

Granger, C. W. J., and Weiss, A. A. "Time Series Analysis of Error-Correcting Models," in *Studies in Econometrics, Time Series, and Multivariate Statistics*. New York: Academic Press (1983) 255-278.

Heien, D. and Pompelli G. "The Demand for Alcoholic Beverages: Economic and Demographic Effects." *Southern Economic Journal* 55 (1989) 3:759-770.

Hendry, D. A., Pagan, A. R. and Sargan, J. D. "Dynamic Specification" in *Handbook of Econometrics*, Vol.II, Chapter 18, (1984) (eds.) Z. Griliches, and M.D. Intriligator, North-Holland, Amsterdam.

Hilton M.E, Clark W.B. "Changes in American Drinking Patterns and Problems, 1967-1984." *Journal of Studies on Alcohol* 48(1987) 515-22.

Hausman, J. 1978. "Specification Tests in Econometrics". *Econometrica* 46(6):1251-1271.

Johnson, J., Oksanen, E., Veall, M. and Fretz, D. " Shortrun and Long-Run Elasticities for Canadian Consumption of Alcoholic Beverages: An Error-Correction Mechanism/ Cointegration Approach" *Review of Economics and Statistics* 74(1992)64–74.

Jones, A. M. "A systems approach to the demand for alcohol and tobacco" *Bulletin of Economic Research* 41(1989) 86 -101.

Johansen, S. "Statistical Analysis of Cointegration Vectors" *Journal of Economic Dynamics and Control* 12 (1988) 231–254.

Johansen, S. and K. Juselius. "Maximum Likelihood Estimation and Inference on Cointegration- with Applications to the Demand for Money." *Oxford Bulletin of Economics and Statistics* 52 (1990) 169–210.

Karagiannis, G., Velentzas, K. "Explaining Food Consumption Patterns in Greece." *Journal of Agricultural Economics* 48(1997) 83-92.

Karagiannis, G., Katranidis, S., and Velentzas K. "An Error Correction Almost Ideal Demand System for Meat in Greece." *Journal of Agricultural Economics*. 22(2000)29-35.

Kremers, J., Ericsson, N., and Dolado, J.“ The Power of Cointegration Tests.” *Oxford Bulletin of Economics and Statistics*. 54(1992)2: 325 – 348.

Larivirea E., Larueb, B., Chalfant, J. “Modeling the demand for alcoholic beverages and advertising specifications” *Agricultural Economics* 22 (2000) 147-162

LaFrance, J. “When Is Expenditure ‘Exogenous’ in Separable Demand Models?” *Western Journal of Agricultural Economics* 16(1991) 1: 49–62.

Maddala, G.S. “Introduction to Econometrics” 3rd edn. John Wiley and Sons, 2001.

Mas-Colell, A., M.D. Whinston, and J.R. Green. *Microeconomic Theory*. New York: Oxford University Press, 1995.

Nelson, J. P., and Moran, J. R. “Advertising and US Alcoholic Beverage Demand: System-Wide Estimates.” *Applied Economics* 27(1995) 1225–36.

Nelson, J. P. “Economic and Demographic Factors in U.S. Alcohol Demand: A Growth-Accounting Analysis”1997, *Empirical Economics* 22(1997)83-102

Pollak, R.A. “Conditional Demand Functions and Consumption Theory” *The Quarterly Journal of Economics* 83 (February, 1969) 1:60-78.

Pollak, R.A., Wales, T.J., 1992. Demand System Specification and Estimation. Oxford University Press, New York, NY.

Selvanathan, E. A. “Cross-Country Alcohol Consumption Comparison: An Application of the Rotterdam Demand System.” *Applied Economics* 23(1991) 1613–22

Selvanathan, E. A., and Selvanathan, S. “Economic and demographic factors in Australian alcohol demand” Applied Economics 36 (2004) 2405–2417

James L. Swofford and G. A. Whitney “Nonparametric Tests of Utility Maximization and Weak Separability for Consumption, Leisure and Money.” (1987): The Review of Economics and Statistics, Vol. 69, No. 3 (Aug., 1987):458-464

Thom, D. R. “The Demand for Alcohol in Ireland.” *Economic and Social Review* 15(1984) 325–36.

Wang, J., Gao, X. M., Wailes, E. J., and Cramer G. L. “U.S. Consumer Demand for Alcoholic Beverages: Cross-Section Estimation of Demographic and Economic Effects”, *Review of Agricultural Economics* 18 (1996) 3: 477-489.

Wu, D.M. “Alternative Tests of Independence between Stochastic Regressors and Disturbances.” *Econometrica* 41 (1973) 4: 733-750.