MODELING STRUCTURAL CHANGES IN MARKET DEMAND AND SUPPLY

A Dissertation

by

Beom Su Park

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

DOCTOR OF PHILOSOPHY

August 2010

Major Subject: Agricultural Economics

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Approved by:

Chair of Committee,	James W. Richardson
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ABSTRACT

Modeling Structural Changes in Market Demand and Supply. (August 2010)

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Chair of Advisory Committee: Dr. James W. Richardson

Economic events may cause structural changes in markets. To know the effect of the economic event we should analyze the structural changes in the market demand and supply. The purpose of this dissertation is to analyze the effect of selected economic events on market demand and supply using econometric models. Structural changes can be modeled according to the types of changes. For an abrupt and instantaneous break, a dummy variable model can be used. For a smooth and gradual movement, proxy variables which represent the event can be applied, if we know the variables. If we don't know the appropriate proxy variables, a smooth transition regression model can be employed.

The BSE (Bovine Spongiform Enchphalopathy) outbreak in the U.S. in 2003 is assumed to make abrupt and instantaneous changes in Korean meat consumption. To analyze the effect on Korean meat consumption, the Korean demands of beef, pork, chicken, and U.S. beef are estimated using an LA/AIDS (Linear Approximate Almost Ideal Demand System) model with the dummy variable specifying the time before and after the BSE. From the results we can confirm that food safety concerns caused by the

BSE case changed Korean meat consumption structure. Korean beef and U.S. beef became less elastic, and pork and chicken got more elastic to budget. Korean beef became less price elastic, but pork and U.S. beef got more price elastic.

The changes of U.S. natural gas supply caused by technology development and depletion in reserves are analyzed using a smooth transition regression model. From the results, we can confirm that the productivity improvement by technology development is greater than the labor cost increase by depletion, but not greater than the capital cost increase by depletion in mid-2000s.

The effects of posting the winning bid in a repeated Vickrey auction are examined using a proxy variable. By applying an unobserved effect Tobit model to the experimental auction done by Corrigan and Rousu (2006) for a candy bar, we can confirm that the changes of bidding behavior are significant, especially when the winning bid is high. By extracting the bid affiliation effects, we showed that true willingness to pay can be estimated.

DEDICATION

I would like to dedicate this doctoral dissertation to all my friends in the Ministry of Food, Agriculture, Forestry, and Fisheries of Korea. There is no doubt in my mind that without their continued support I could not have completed this dissertation.

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CHAPTER I

INTRODUCTION

Modeling and analyzing structural changes in market demand and supply is one of the most popular subjects in empirical economic studies (Holt et al, 2009). What market participants such as policy makers, consumers, and producers want to know is the response of a market to particular events in the market. The reason is that without considering the response they may make a wrong decision, and it can lead to a big loss. So analysis of structural changes in market demand and supply is the pursuit of many economists.

The structures of demand and supply can be characterized by parameters in demand and supply functions such as elasticities. Structural changes in this study will mean changes in parameters. This is in agreement with the literature, as most structural change studies looked at parameter changes implicitly (Moschini and Mielke, 1989, Phillips, 2001, Cai, 2007, Holt et al, 2009). The changes in elasticities or parameters are very informative to market participants, such as, consumers, producers, and policy makers. If they understand the changes, they can adjust more quickly, and may change their expectations.

Structural changes are recognized in the time dimension, because parameter changes are identified by the comparison between before and after changes. In terms of

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

the time taken for changes to take place, structural changes can be categorized into two types: abrupt and instantaneous shifts, and smooth and gradual movements. This classification is meaningful because a different modeling technique should be applied for each type. First, for an abrupt and instantaneous shift by an economic event, a dummy variable model can be used to capture the effects. Second, for a smooth and gradual movement by an economic event, proxy variables to cause the movement can be used to estimate the effects of the movement if we know the relevant proxy variables and if we can quantify the proxy variables. If the proxy variables are not known, a smooth transition regression model can be an alternative to estimate the changing paths of coefficients.

The purpose of this dissertation is to analyze the effect of selected economic events on market demand or supply using econometric models by identifying structural changes and the effects of the changes can be estimated and analyzed by identifying the structural changes. As an example of an abrupt and instantaneous break, the effects of BSE (Bovine Spongiform Encephalopathy) outbreak in the U.S. in Dec. 2003 on Korean meat consumption will be analyzed in Chapter II using a dummy variable model. Model specification testing methods will also be examined in Chapter II.

In Chapter III, the effects of technological changes and depletion in the U.S. natural gas supply will be investigated. A smooth transition regression model will be applied to capture the smooth and gradual movement of U.S. natural gas supply by technological development. The effects of smooth and gradual changes in U.S. natural gas reserves will be analyzed using a proxy variable to represent the level of depletion in reserves.

The effects on bidding behavior in a repeated second-price sealed bid experimental auction by the event of posting the winning bid will be analyzed in Chapter IV. Using proxy variables the changes of bid price and the true willingness to pay (a kind of demand) will be estimated. To estimate consistent and efficient coefficients an unobserved effects Tobit model will be employed.

CHAPTER II

MODELING AND ANALYZING STRUCTURAL CHANGES OF KOREAN MEAT DEMANDS BY BSE IN THE U.S. 2003

Introduction

Recently, the Korean meat market experienced the shock of an overseas animal disease outbreak: BSE (Bovine Spongiform Encephalopathy) in the U.S. (December 2003). The Korean government banned beef imports from the U.S. just after the BSE case in the U.S. was reported by USDA, and reopened to U.S beef very restrictively after confirming every measure had been taken for removing the risk of BSE.

The U.S. was the largest supplier of imported beef in the Korean meat market (Figure 1). The market share of U.S. beef among beef, pork, and chicken was increasing from 1998 to 2003, and the market share in 2003 was over 10% (Figure 2). However, it fell to zero after 2003[1] during the embargo. The consumption of Korean beef was decreasing during 1998-2003, but it has increased to 10% of market share after 2003. The quantity of pork consumed increased continuously during 1998-2007. The market share of pork maintained a steady share of 52-54% during 1996-2003 except 2000 and 2002 when FMD (Foot and Mouth Disease) broke out (MIFAFF, 2003), but it rose to

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[1] The consumption data of Korean beef, pork, chicken, and all imported beef were obtained from NACF (National Agricultural Cooperatives' Federation). U.S. beef consumption was calculated as:

$$(all\, imported\; beef\;\; consumption) \times \frac{U.S.beef\;\; imports\,(ton)}{All\, beef\;\; imports\,(ton)}.$$

57% in 2004. Chicken consumption and market share increased overall with the highest share of 25.7% in 2006 except when AI (Avian Influenza) occurred in 2003-2004 (MIFAFF, 2008).

From the market share changes during 1996-2007, we can hypothesize that there were changes in the Korean meat demand structure caused by the 2003 BSE outbreak in the United States. The primary purpose of this study is to investigate the structural change of Korean meat demands caused by the U.S. BSE outbreak in 2003. To analyze the effects of BSE, we will estimate the two models of Korean meat demand. Model A is the system of Korean beef, pork, chicken, and U.S. beef. Because U.S. beef was not imported during Jan. 2004-Mar. 2007, the meat demand structure before 2004 will be compared with that after Mar. 2007. Model B is the system of Korean beef, pork, and chicken. The demand structure of three periods (before 2004, Jan. 2004-Mar. 2007, and after Mar. 2007) will be compared in Model B. From these models we calculate the demand parameters such as income elasticities, own price elasticities, and cross price elasticities. Changing demand elasticities may be an indication of the structural change in the Korean meat market.

Literature Review

A number of reports about BSE and other animal disease shocks on the demands for meat have been published. Burton and Young (1996) studied the impact of BSE in the U.K. Verbeke and Ward (2001) examined the change of consumer's response in meat markets caused by a BSE outbreak in Belgium. Piggot and Marsh (2004) investigated impacts on meat demand when U.S. consumers were informed about food safety problems. Peterson and Chen (2005) examined the impact of the BSE outbreak in Japan. Most of those reports showed a negative effect on beef consumption.

There are numerous empirical studies about structural changes in demands. Moschini and Meilke (1989) suggested modeling the pattern of structural change in the U.S. meat market with an AIDS (Almost Ideal Demand System) model using dummy variables. Chalfant and Alston (1988) and Cortez and Senauer (1996) focused on testing the taste and preference changes in the demand for food.

For the Korean meat market case, Lee et al (1999) and Shin et al (2004) estimated the meat demand parameters using the data prior to the U.S. BSE shock. However, the effect of the U.S. BSE case on the Korean meat demand in terms of structural change has not yet been examined. Song and Chae (2007) estimated the Korean social welfare change caused by the U.S. BSE shock, but they used the demand parameters from Shin et al (2004). So they assumed the U.S. beef import ban caused no structural changes. Henneberry and Hwang (2007) investigated the Korean meat demand using a source-differentiated AIDS model, but they used the quarterly wholesale level data between 1996 and 2003. So they did not include the effect of the U.S. BSE outbreak in their model.

Park, Jin, and Bessler (2008) tested the structural break in Korean meat market caused by the impacts of animal diseases. They showed FMD in 2000, and AI in 2003, and the U.S. BSE in 2003 induced structural changes in the Korean meat price series, and the effects of the animal diseases on prices lasted over 1 year using an error correction model and historical decomposition method with directed acyclic graphs. Lee and Kennedy (2009) studied how the differences in prices and qualities of beef from other sources affected the Korean beef market.

Theoretical Framework (LA/AIDS model)

To estimate the complete meat demand system we can apply LES, Rotterdam, LA/AIDS, translog or other hybrids of Rotterdam and AIDS models with restrictions, such as homogeneity, adding-up, and symmetry. While the LES model assumes separable goods, it rules out complementary goods. The Rotterdam model does not satisfy integrability conditions necessary to derive the fundamental demand equations (Brown and Deaton, 1972). In other words, it does not assume consumer's demand theory like utility maximization or expenditure minimization. Barten (1993) emphasized two conditions of specifying the desirable consumer demand functional form – satisfaction of theoretical properties of consumer demand and empirical performance. Based on two criteria, Barten suggested a hybrid of the AIDS and Rotterdam model.

The AIDS model developed by Deaton and Muelbauer (1980), Working (1943), and Leser (1963) is a more flexible model relative to Rotterdam and the translog model, and it satisfies the properties of demand theory, and demand restrictions such as homogeneity and symmetry can be easily tested. Also, the AIDS model is relatively easy and simple to do empirical estimation (Buse, 1994), and at the same time its empirical performance is little different from a hybrid demand model (Barten, 1993). In this study we will apply a liner approximate AIDS (LA/AIDS) model.

The linear approximate AIDS (LA/AIDS) model is usually specified with:

(1) $$w_{it} = \alpha_i + \sum_j \gamma_{ij} Ln(p_{jt}) + \beta_i Ln(y_t / P_t^*) + u_{it}$$

(2) $$Ln(P^*) = \sum_i w_{it} Ln(p_{it})$$

where *(i, j)* = 1, …, n index the goods, *t = 1, …, T* indexes time, *p* denotes nominal price, *w = pq/y* means expenditure share with *q* being the quantity consumed, and *y* being the total expenditure on n goods. P^* denotes the price index approximated by Stone's geometric index. In addition, we can apply the triad demand restrictions if needed:

(3) Adding-up $\sum_i \alpha_i = 1;\quad \sum_i \gamma_{ij} = 0;\quad \sum_i \beta_i = 0$

(4) Homogeneity $\sum_j \gamma_{ij} = 0$

(5) Symmetry $\gamma_{ij} = \gamma_{ji}$.

Deaton and Muelbauer (1980) suggested the first differenced form of an AIDS model. Because dynamic adjustment properties of meat demand is important, Eales and Unnevehr (1988), and Henneberry and Hwang (2007) also used the first differenced form. The first differenced form of equation (1) is

(6) $$\Delta w_{it} = \sum_j \gamma_{ij} \Delta Ln(p_{jt}) + \beta_i \Delta Ln(y_t / P_t^*) + \Delta u_{it}.$$

In this study, we will try both level equation form (1) and first differenced form (6), and check which form is better.

We can calculate elasticities using the coefficient estimates of equation (1) or (6). Assuming $dln(P^*)/dln(p_j)=w_j$, elasticities are (Green and Alston, 1990):

(7) Expenditure elasticity $\eta_i = 1 + \beta_i / w_i$

(8) Uncompensated own-price elasticity $\varepsilon_{ii} = -1 + \gamma_{ii} / w_i - \beta_i$

(9) Uncompensated cross-price elasticity $\varepsilon_{ij} = \gamma_{ij} / w_i - \beta_i (w_j / w_i) \quad (i \neq j)$.

Incorporating Structural Changes in the System of Equations

Moschini and Meilke (1989) analyzed the gradual structural changes using time path variables h_t, and assumed the time path follows a proportionally decreasing pattern during the structural break period as Ohtani and Katayama (1986) suggested. Eales and Unnevehr (1988) used a simple dummy variable to test one-time-only shifts (instant intercept shifts only) in the demand curve. The assumption that h_t followed a linear path for the Korean meat market case is not clear, and the U.S. BSE shock was inferred not to cause a gradual change, but to cause an instant change in the Korean meat demands (Song and Chae, 2007). This research uses a dummy variable model with intercept shifter and slope shifters. The overall and average changes of demand parameters after the BSE shock can be detected by slope shifters. If we include two structural change dummy variables and seasonal dummy variables to account for the effect of seasonal consumption and trend, the equation (1) and (6) will be:

(10)
$$w_{it} = \alpha_i + \delta_{1i} D_{1t} + \delta_{2i} D_{2t} + \sum_j (\gamma_{ij} + \phi_{1ij} D_{1t} + \phi_{2ij} D_{2t}) Ln(p_{jt}) +$$
$$(\beta_i + \tau_{1i} D_{1t} + \tau_{2i} D_{2t}) Ln(y_t / P_t^*) + \sum_k (\theta_{ik} + \rho_{1ik} D_{1t} + \rho_{2ik} D_{2t}) S_k + u_{it}$$

(11)
$$\Delta w_{it} = \delta_{1i} \Delta D_{1t} + \delta_{2i} \Delta D_{2t} + \sum_j (\gamma_{ij} \Delta Ln(p_{jt}) + \phi_{1ij} \Delta(D_{1t} Ln(p_{jt})) +$$
$$\phi_{2ij} \Delta(D_{2t} Ln(p_{jt}))) + (\beta_i \Delta Ln(y_t / P_t^*) + \tau_{1i} \Delta(D_{1t} Ln(y_t / P_t^*))) +$$
$$\tau_{2i} \Delta(D_{2t} Ln(y_t / P_t^*))) + \sum_k (\theta_{ik} \Delta S_k + \rho_{1ik} \Delta(D_{1t} S_k) + \rho_{2ik} \Delta(D_{2t} S_k)) + \Delta u_{it}$$

where D_{1t} equals 1 during Jan. 2004-Mar. 2007 when U.S. beef import was banned because of BSE, otherwise D_{1t} equals 0. D_{2t} equals 1 after Mar. 2007 when U.S. beef import restrictions were disabled, otherwise D_{2t} equals 0. For Model A (a system of Korean beef, pork, chicken and U.S. beef), D_{1t} is not meaningful because U.S. beef were not imported during Jan. 2004-Mar. 2007. S_k indexes a specific seasonal dummy variable, and k denotes each month for monthly data. From this specification the elasticities of (7) - (9) will be:

(12) Expenditure elasticity: $\eta_i = 1 + (\beta_i + \tau_{1i} (or\ \tau_{2i})) / w_i$

(13) Uncompensated Own-price elasticity:

$$\varepsilon_{ii} = -1 + 1/w_i (\gamma_{ii} + \phi_{1ii} (or\, \phi_{2ii})) - (\beta_i + \tau_{1i} (or\, \tau_{2i}))$$

(14) Uncompensated Cross-price elasticity:

$$\varepsilon_{ij} = 1/w_i (\gamma_{ij} + \phi_{1ij} (or\, \phi_{2ij})) - (\beta_i + \tau_{1i} (or\, \tau_{2i}))(w_j / w_i)\ (i \neq j).$$

The demand equation for each meat is not independent of others ($Cov(u_i, u_j) \neq 0$), since consumers' decisions to purchase a meat inevitably depends on the other meats. Thus, in this study, we estimate the four equations as a system of equations.

Testing Statistical Assumptions

To estimate the unbiased, consistent, and efficient estimators of equations (10) and (11), some statistical assumptions are needed. The choice of estimation method depends on whether those assumptions are satisfied or not. The meaningful and important assumptions to choose the estimation method are as follows[2]:

a. Well defined functional form: there are no serious omitted variable biases;

b. Normality: the error terms for each equation follow the multivariate normal distribution;

c. No endogeneity: explanatory variables are orthogonal to the error term;

d. Homoskedasticity: the error terms are not varying over explanatory variables and time;

e. Independence (No Autocorrelation): the error terms are not time varying;

f. No perfect collinearity: the explanatory variables are not perfectly linear with each other, so the explanatory variable vector has full rank.

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[2] Besides *a-f*, McGuirk et al (1993, 1995) included 'Parameter Stability' which means there were no structural breaks. In this study we will include all significant structural change dummy variables in the models such as BSE, FMD as explanatory variables which are proved by Park, Jin and Bessler (2008). So, we will not test parameter stability assumption. Also we will not comment on collinearity because collinearity problem was not found anywhere in our model.

McGuirk et al (MDAH) (1993, 1995) suggested strategies to test the above assumptions. MDAH asserted that the assumptions are to be tested jointly for a multi-equation model, but equation by equation tests would be useful too. We will test above assumptions jointly, as well as separately, based on their suggestion.

Functional Form

If the functional form to be estimated it is not well defined, there may be some omitted variables, causing omitted variable bias. MDAH proposed using the RESET test introduced by Ramsey (1969) for equation by equation testing, and they suggested multivariate RESET2 and Kolmogorov-Gabor (KG) functional form tests for joint equation testing.

In this study, the RESET test is applied for equation by equation testing for equation (10), the level equation. If the level equation is well defined, the first-differenced form can be assumed to be well defined. Using the potential omitted variables such as foot-and-mouth (FMD) disease effect of 2000, 2002, and avian influenza (AI) effect of 2003, 2005, we will test three types of models – type 1: equation (10) which considers only the BSE shock, type 2: equation (10) + FMD shock as an intercept shifter (dummy variable, F_{it}=1 if t=Mar. 2000-Sep. 2001 and May 2002-Aug. 2002, otherwise 0), and type 3: equation (10) + FMD and AI shock as an intercept shifter (dummy variable A_{it}=1 if t=Dec. 2003-Sep. 2004, Dec. 2006-Apr. 2007 and Apr. 2008-Jul.2008, otherwise 0)[3].

[3] The period of FMD and AI is from the FMD white paper (MIFAFF, 2003), and the AI

Instead of the multivariate RESET2 and KG test for the joint equation testing, the three types of joint models above are compared using the Baysian information criteria (BIC). Also, equation (10) (level form) and equation (11) (first-differenced form) are compared to select the better form for the joint equation. We will test whether the interaction terms of BSE shock and seasonality (ρDS) are needed. If ρs are zero, those terms (ρDS) are meaningless.

Table 1,A. contains the RESET test results of functional form by equations. All of the type 1 (only BSE shock is included) equations in Model A, type 2 (BSE and FMD included) and type 3 (BSE, FMD, and AI included) equations in Model B are not problematic in omitted variable bias based on 5% significance level. The chicken equation for type 2 and type 3 in Model A and pork equation for type 1 in Model B are suspected of omitted variable bias at the 5% significance level, but not at less than 4% level. From the results of joint equation comparison in table 1,B, all interaction terms of BSE shock and seasonality are considered to be zero ($\rho_{ij}=0$ *for all* i,j). Also the models without ρDS terms are better in BIC for all cases than with ρDS terms. In addition, when we exclude ρDS terms, type 2 is the best among all types in BIC for both Model A and Model B, and the level form is not much different from the first differenced form in terms of BIC.

This study uses model type 2 without ρDS terms because it has the best BIC. In addition, the level form (equation (10)) is applied because it is simpler and does not much differ from first differenced form. This changes the model into:

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white paper (MIFAFF, 2008). The slope shifters of FMD and AI were not significant from SUR estimation, so we didn't include in the models.

$$(15) \quad \begin{aligned} w_{it} &= \alpha_i + \delta_{1i} D_{1t} + \delta_{2i} D_{2t} + \delta_{3i} FMD_t + \sum_j (\gamma_{ij} + \phi_{1ij} D_{1t} + \phi_{2ij} D_{2t}) Ln(p_{jt}) + \\ &(\beta_i + \tau_{1i} D_{1t} + \tau_{2i} D_{2t}) Ln(y_t / P_t^*) + \sum_k \theta_{ik} S_k + u_{it} \end{aligned} .$$

Normality

If we know the exact distribution function of the error term, we can use the MLE method which guarantees consistent and the most efficient estimation. MDAH proposed the skewness and Kurtosis test of D'Agostino for equation by equation testing, and C_w^2 omnibus test of Mardia and Foster for joint testing. We will apply the normality tests suggested by D'Agostino et al (1990) and Royston (1991) (skewness and kurtosis test), Shapiro-Wilk (1965), and Shapiro-Francia (1972) for equation by equation testing. For the joint equation test, we will apply the graphical multivariate normality test developed by Stevens (1986), Thompson (1990), and Goldstein (1991).

For the joint equation test, Mahalanobis distance (MD2), a measure of the distance from the mean is defined as:

$$(16) \quad MD2_t = (e_t - \bar{e}) \Sigma^{-1} (e_t - \bar{e})'$$

where e_t is an error term vector of four equations at time t from error term matrix $E = (e_1 \ e_2 \dots e_T)$, $\bar{E} = (\bar{e}_1 \ \bar{e}_2 \dots \bar{e}_T)$ is a mean matrix of *E*, and Σ is a variance-covariance matrix of *E*, ($\frac{(E - \bar{E})'(E - \bar{E})}{T - 1}$) (Mahalanobis, 1936, Velleman and Welsch, 1981). If e_t follows a multivariate normal distribution, *MD2* follows the chi-square distribution. The probability corresponding to $MD2_j$ (Prob($\chi_T^2 \geq MD2_j$)) can be approximated by the rank of ascending order of $MD2_j$ such as $1-\frac{rank_j - 0.5}{T}$ under the null hypothesis of multivariate normality. If we calculate the chi-square value ($chi2_j$) corresponding to the approximated probability (Prob($\chi_T^2 \geq chi2_j$)= $1-\frac{rank_j - 0.5}{T}$), *MD2-chi2* plot will show one-to-one matching on a 45 degree line.

Table 2,A. contains the equation by equation test results of normality. All equations except chicken's demand function in Model A do not clearly satisfy the normality assumption. Figure 3 shows that *MD2-chi2* plots are not on a 45 degree line. Table 2,B. contains the Hotelling's T^2 test results of comparing two series ($MD2_t$, $chi2_t$). Because the vector of variance is considered not to be the same, we can conclude the two series are not the same. Thus, we cannot assume normality, and will not use the MLE method.

Endogeneity

If some explanatory variables are not exogenous, OLS estimation cannot guarantee consistent estimators. In this case, instrumental variable (IV) regression should be used to minimize the endogeneity problems. The Durbin-Wu-Hausman (DWH) test is applied to check for an endogeneity problem for all potential endogenous variables ($ln(p_{it})$, and $ln(y_t/P^*_t)$). The test is for each level equation of (13), because if endogeneity is not problematic in each level equation, we can assume it is not problematic in the joint level equations and the first-differenced form. For the endogeneity test, we will use AI shock, the consumer price index (CPI), gross domestic final consumption expenditure (FCE), a price index of livestock feeds paid by farmers (FPI), lagged dependent variables (w_{it-1}), lagged independent variables ($ln(p_{it-1})$, and $ln(y_{t-1}/P^*_{t-1})$), and quantity consumed (q_{it}) as IVs. To test the appropriateness of IVs, the partial R^2 proposed by Shea (1997) is applied, along with the Kleibergen-Paap (2006) rank Lagrange multiplier (KPrkLM) statistic and Hansen's (1982) *J* statistic (Baum and Schaffer, 2007, Baum et al, 2003)[4].

The test results contained in Table 3,A. indicate that the IVs are highly correlated to the potential endogenous variables. Shea's Partial R^2s from the auxiliary regression for potential endogenous variables with IVs are all near one, so the IVs are well suited for potential endogenous variables. The rejection of the null hypothesis of under identification from KPrkLM statistic shows that the matrix $Q_{XZ} = E(X_i'Z_i)$ has full column rank where X_i is the explanatory variable matrix from the original regression $y_i=X_i\beta+u_i$, and Z_i is the IV matrix (Baum et al, 2003). From those results, we can confirm that the IVs used to test endogeneity here are relevant to the potential endogenous variables. Hansen's *J* statistic in Table 3,B. shows that the null hypothesis of orthogonality between IVs and error term cannot be rejected. So, the test results in Table 3,A. and 3,B. show that IVs used in this study are well defined. DWH test results in Table 3,C. show that the null hypothesis of exogenous IVs cannot be rejected for all equations which means that the IV regressions are not systematically different from the original regressions[5]. This result confirms that the IVs are not needed.

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[4] Also see ivreg2.hlp in STATA journal on line (available at http://www.stata-journal.com/software/sj7-4/st0030_3/ivreg2.hlp).
[5] Here, we compare IV regression with SUR regression.

Homoskedasticity, Independence

If the error terms in equation (15) are not homoskedastistic or serially correlated, OLS regression cannot guarantee efficient estimators. In that case 'Generalized Least Squares (GLS)' estimation is one of the best alternatives. To test static homoskedasticity by equations, the Breusch and Pagan (1979) and Cook and Weisberg (1983) tests are used. For dynamic homoskedasticity, the ARCH LM test suggested by Engel (1982) is applied. To test for serial correlation, the general dynamic autocorrelation test method developed by Breusch (1978) and Godfrey (1978) is employed. Also, the Ljung-Box Q test is used to check for white noise. For the joint equation testing, the multivariate Ljung-Box Q test can be used. If the homoskedasticity and independence in equation (15) are problematic, the GLS will be applied to equations (15).

Table 4 contains the homoskedasticity and independence test results. Even if multivariate Ljung-Box Q test results verify that the error terms from joint equation models are white noise, the equation by equation test results (Table 4.A) show that we cannot be sure that the error terms are homoskedasticitic and independent. Thus the GLS estimation method for equations (15) is employed.

Model Specification and Estimation Method

Based on the test results above, equations (15) are analyzed. All equations are estimated as a whole (one equation will be dropped for the adding-up restrictions) using

SUR estimation with the GLS method without IV. Then, demand elasticities are calculated with equations (7)-(9), and (12)-(14).

Data

The data used in this study are monthly data from 1996 to 2008. Price data are retail price (Korean won) per kg. The retail price data of Korean beef, pork, and chicken are obtained from the KAMIS (Korea Agricultural Marketing Information System) database provided by KAFTC (Korean Agro-Fisheries Trade Corporation). The retail prices of beef and pork are announced by grades and parts. In this study, the price of third grade beef (mostly rump part) for *bulgogi* (Korean barbecue) and pork belly for *samgyupsal* (Korean grilled bacon) are used as representative prices because those parts are the most commonly used in Korea.

The quantity consumed data are yearly data downloaded from NACF (National Agricultural Cooperatives Federation). The monthly data are estimated by a calculated monthly slaughtered head ratio (number of heads slaughtered a month divided by number of heads slaughtered a year). The number of head slaughtered per month is from MIFAFF (Ministry of Food, Agriculture, Forestry, and Fisheries).

Because imported U.S. beef retail prices are not officially reported anywhere (KAFTC reports them only after 2007), the reported prices to the Korean customs office were downloaded from the KATI (Korean Agricultural Trade Information) database provided by KAFTC. The yearly quantity consumed for all imported beef data are obtained from MIFAFF. Monthly consumption levels of all imported beef are estimated by the yearly consumption level multiplied by the ratio of the quantity imported for the month and the quantity imported for the year (the quantity consumed in the month = the quantity consumed in the year × (the quantity imported in the month / the quantity imported in the year)). Because only the total consumption level of all imported beef is reported, the consumption level of U.S. beef is estimated by the quantity consumed of all imported beef multiplied by the ratio of the quantity imported from the U.S. and the quantity imported from all countries (the U.S. beef consumption = all imported beef consumption × (the quantity imported from the U.S. / the quantity imported from all countries)). The import quantity data are from the KATI database. The CPI, FPI, and FCE used to test endogeneity come from the KOSIS (Korean Statistical Information System) provided by Statistics Korea. FMD and AI data are obtained from MIFAFF.

Testing Restrictions

Estimating a complete demand system by using total expenditures (*y*) and expenditure share (*w*) data in a LA/AIDS model allows for the imposition of adding-up restrictions. Those restrictions can reduce the number of parameters to be estimated, and thus relieve the degree of freedom problem, because the fourth equation is automatically estimated by only estimating three equations. Adding-up restrictions on equations (15) will be:

(17) Adding-up
$$\sum_i \alpha_i = 1,\ \sum_i \gamma_{ij} = 0,\ \sum_i \beta_i = 0,\ \sum_i \delta_i = 0,\ \sum_i \phi_{ij} = 0,\ \sum_i \tau_i = 0$$
$$\sum_i \theta_{ik} = 0,$$
.

Homogeneity and Symmetry

If consumers adjust their consumption decisions instantaneously when prices and income change, homogeneity and symmetry conditions hold. However, in the real world it takes time for consumers to adjust to the changes (Henneberry and Hwang, 2007). If homogeneity and symmetry conditions hold, the degree of freedom problem is also highly relieved. So, we test homogeneity and symmetry first to decide whether these restrictions can be imposed on equations (15).

If homogeneity and symmetry hold in equations (15), the following restrictions should hold:

(18) Homogeneity $\sum_j \gamma_{ij} = 0,\ \sum_j \phi_{1ij} = 0\ ,\ \sum_j \phi_{2ij} = 0$

(19) Symmetry $\gamma_{ij} = \gamma_{ji}\ ,\ \ \phi_{1ij} = \phi_{1ji}\ ,\ \phi_{2ij} = \phi_{2ji}$ (*for all i, j, i≠j*).

Table 5 shows the Wald test results for homogeneity and symmetry. From the results, the null hypothesis of homogeneity and symmetry for both Model A and Model B are rejected at the 1% significance level.

Separability

Moschini, Moro, and Green (1994) indicated that many previous studies just assumed weak separability of demand systems, and did not test for separability (Moschini and Meilke, 1989). However, separability should be tested before estimating demand systems, because if some goods are not separable, the goods should not be treated as one good as a whole even if the goods can be categorized as one group conceptually (Moschini, Moro, and Green, 1994, Henneberry and Hwang, 2007). Because each meat (beef, pork, chicken, U.S. beef, respectively) in this study is indivisible (lower level price data are not reported), the separability of each meat cannot be tested, and thus the separability of each meat is inevitably assumed. Instead, we will test whether each meat can be aggregated and treated as one good as a group with others by the concept of separability.

The original concept of separable utility requires that the marginal rate of substitution between two goods is independent of the consumption of the other goods, but marginal utilities in most cases are not observable, so empirical testing of separability is problematic (Nayga and Capps, 1994). Many studies suggested testing equations for separability (Moschini, Moro, and Green, 1994, Eales and Unnevehr, 1998, Sellen and Goddard, 1998, Nayga and Capps, 1994). In this study, we apply Moschini, Moro, and Green's suggestion. They showed the conditions for direct weak separability as:

(20) $$\frac{\sigma_{ik}}{\sigma_{jm}} = \frac{\eta_i \eta_k}{\eta_j \eta_m}$$

where i, j are in the same commodity group, k,m are in the same commodity group different from the group i, j are in ($i=j$, $k=m$ are possible). σ_{ij} denotes Allen-Uzawa elasticity of substitution which is the ratio of the compensated cross-price elasticity and expenditure share. For equation (13) of an AIDS model, equation (18) is changed into:

(21) $$\frac{\gamma_{ik} + w_i w_k}{\gamma_{jm} + w_j w_m} = \frac{(w_i + \beta_i)(w_k + \beta_k)}{(w_j + \beta_j)(w_m + \beta_m)}$$ (for Model A and Model B),

$$\frac{\gamma_{ik}+\phi_{1ik}+w_i w_k}{\gamma_{jm}+\phi_{1jm}+w_j w_m}=\frac{(w_i+\beta_i+\tau_{1i})(w_k+\beta_k+\tau_{1k})}{(w_j+\beta_j+\tau_{1j})(w_m+\beta_m+\tau_{1m})} \text{ (only for Model B),}$$

$$\frac{\gamma_{ik}+\phi_{2ik}+w_i w_k}{\gamma_{jm}+\phi_{2jm}+w_j w_m}=\frac{(w_i+\beta_i+\tau_{2i})(w_k+\beta_k+\tau_{2k})}{(w_j+\beta_j+\tau_{2j})(w_m+\beta_m+\tau_{2m})} \text{ (for Model A and Model B).}$$

Table 6 contains the summary statistics of the each meat's observed market share. Table 7 shows the non-linear Wald test results of separability at the mean value of observed market share ($\overline{w}$) in table 6. The test results indicate that every kind of meat should not be aggregated with others, so meat product as a group including Korean beef, pork, chicken and U.S. beef is not separable.

Results and Discussion

Table 8 contains the estimated model evaluation indicators. All demand equations for both Model A and Model B fit the observed data well. R^2s of all equations are over 0.83 and RMSEs are all less than 0.031. Tables 9.A and 9.B contain the estimated coefficients for model A and model B. From these results, the affects of BSE in the U.S in late 2003 can be tested. Table 10 contains the test results. Comparing period 1 (before Dec. 2003) with period 3 (after Mar. 2007) in Model A (period 2 (Jan. 2004-Mar. 2007) are not included in Model A), the intercept change is not significant (p-value is 0.2306), but slope shifters with respect to prices and expenditure are all significant (all p-values are almost zero). For Model B the intercept and slope shifters from period 1 to period 2 are all significant (all p-values are almost zero). Comparing period 1 with period 3 in Model B, changes are significant overall (p-value is 0.0238), but intercept and price shifters are not significant (p-values are 0.5399 and 0.0809, respectively) at the 5% significance level. So, we can confirm that the BSE effects are significant overall for both Model A and Model B. However, the seasonal consumption trends proved not to be changed by the discovery of BSE in the U.S. in late 2003. As we see in Table 1.B, seasonal consumption pattern changes are zero for both Model A (p-value is 0.0816) and Model B (p-value is 0.6653) when we include ρDS in type II equations. The results suggest that the monthly meat consumption pattern is so stable that it is not easily changed.

The Korean monthly meat consumption pattern can be traced by the estimated coefficients (θ) of seasonal dummy variables in Table 9. The negative sign of θ_{ik} in a specific month k for the i-th equation means that the meat i is consumed less in month k than in the base month (January in this study, θ_{Jan}=0). Inversely, a positive sign for θ_{ik} means more consumption in month k than in the base month. The estimated θ for both Model A and Model B in Table 9 shows Korean beef is consumed more in January and September. The reason is because beef is expensive relative to other kinds of meats, so it is consumed more in the special holiday season (*Sollal*: lunar new years' day in late January or early February, and *Chusok*: full moon's day celebrating good harvest in September). The U.S. beef variable in Model A shows a seasonal consumption pattern similar to Korean beef. Chicken is consumed more during the summer season (May-Aug.). It can be explained by the long Korean tradition of eating *samgyetang* (chicken soup boiled with ginseng and other herbs) as a tonic food during the summer.

Pork is consumed more during the period of spring (Mar.-May) and winter (Oct.-Dec.) when the consumption of other kinds of meats is relatively less. Pork consumption in the spring has been increasing in recent years. The market share of pork in March-May was around 50% in 1997, but grew to about 66% by 2007. Increased spring pork consumption is related to the wind carrying yellow dust from China in the spring causing respiratory ailments, which has increased since the late 1990s. Korean traditional medicine suggests pork as a treatment for dust leading Koreans to increase their spring pork consumption.

The Marshallian demand and expenditure elasticities using the estimated coefficients in Table 9 are reported in Table 11. We can check the structural demand changes attributable to the 2003 U.S. BSE case by comparing the elasticities of period 1, period 2 and period 3.

First, expenditure elasticities are all positive and significant which means all meat products are normal goods. The expenditure elasticities of Korean beef changed from 1.2476 (period 1) to 1.0082 (period 3) in Model A, and from 1.1392 (period 1) to 1.4002 (period 2) and 1.0106 (period 3) in Model B. The U.S. beef expenditure elasticity was highly elastic to a budget change in period 1 (2.1992), but most notably it was less elastic in period 3 (1.0678). The expenditure elasticity of pork decreased in period 2, but it recovered in period 3 to slightly greater than the level of period 1 (Model A: 0.8594 → 0.9932, Model B: 0.9875 → 0.7485 → 0.9955). The expenditure elasticity of chicken increased significantly (Model A: 0.5322 → 0.8772, Model B: 0.5653 → 1.2153 → 0.9910). From these results, we support the contention that Korean consumers will increase pork and chicken consumption more (U.S. beef less) after the U.S. BSE case as their budgets increase. The U.S. BSE case in 2003 has contributed to changes in Korean consumers' preferences from U.S. beef to chicken.

Second, own price elasticities are all negative except chicken in period 1 in Model A. Marshallian elasticities are uncompensated, so they can be positive. The positive own price elasticity says the good may be an inferior good, even a Giffen's good. However, the estimated own price elasticity of chicken in Model A is not significant (p-value is 0.5094), so we cannot be sure chicken is an inferior good. The own price elasticity of Korean beef decreased in period 2, and recovered (but not significant) in period 3 (Model A: -1.0272 → -0.6794, Model B: -0.9450 → -0.4226 → -0.7834). This result means that beef is no longer a luxury good as Korean consumers' quality and safety perception of beef changed due to the U.S. BSE case, and that consumers' decision on beef consumption is less dependent on beef price after U.S. BSE case. The price elasticity of pork became more inelastic in period 2, and it recovered to the similar level of period 1 (Model A: -0.4358 → -0.6482, Model B: -0.5715 → -0.4143 → -0.5422). The price elasticity of chicken was near zero (not significant) in period 1. In period 2 and period 3 it was still inelastic, but it became more elastic than in period 1. That means consumers' quality and safety recognition of chicken improved after the U.S. BSE case. The own price elasticity for U.S. beef became more elastic in period 3 relative to period 1 (Model A: -0.4636 → -1.1379). It looks strange because logically it should be less elastic after the U.S. BSE case. This change can be explained by the Korean consumption structure of U.S. beef after the BSE case. During 2004-2006, U.S. beef imports were totally banned. Only after Mar. 2007, U.S. beef began to be imported, but still the quantity imported was very small (2003: 170,799 ton → 2007: 13,108 ton). Furthermore, the number of buyers was very small in 2007, and mostly they were not individual consumers, but restaurant chains or food manufacturing companies with highly price elastic demand[6].

Third, we examined the changing relationship among Korean beef, pork, and chicken. Because Marshallian demand elasticity is uncompensated, and we do not impose symmetry restrictions, it is ambiguous in many cases whether one is a substitute or a complement for other meats. Whether two goods are substitutes or complements to each other in terms of Marshallian price elasticity depends on the relative contribution to consumption changes from the income effect and price effect. If the price effect is greater, two goods are substitutes for each other, but if the income effect is greater, two goods can be complements.

Korean beef was a complement to pork as the price of pork changed in period 1. The complementarity in period 2 got stronger, but in period 3 it is weaker than in period 1 ($\varepsilon_{Kor\ beef,\ pork}$ in Model A: -0.8021 → -0.4643, Model B: -0.7215 → -1.1022→ -0.5979). Pork was a weak complement to Korean beef as the price of Korean beef changed in period 1. However after the U.S. BSE case, the complementarity became insignificant. We cannot reject the null hypothesis of zero elasticity ($\varepsilon_{pork,\ Kor\ beef}$) in period 3. When chicken price changed, Korean beef was a complement to chicken in period 1 (ε^{A}_{Kor}

[6] See the newspaper article (May 29. 2008) by Hyunsoo Kim (available at http://economy.hankooki.com/lpage/industry/200805/e2008052917543247670.htm).

$_{beef,chicken}$: -0.3406, $\varepsilon^{B}_{Kor\ beef,chicken}$: -0.2128), but chicken was a substitute for Korean beef when the price of Korean beef changed in period 1 (($\varepsilon^{A}_{chicken,Kor\ beef}$: 0.2720, $\varepsilon^{B}_{chicken,Kor\ beef}$: 0.2348). However after the BSE case, the cross price elasticities between Korean beef and chicken are not significant (p-values are all greater than 6%). The cross price relationship between pork and chicken were not significant with price changes in period 1 (p-values are all greater than 12%). The complementarity between pork and chicken was still inelastic but got stronger after the BSE case ($\varepsilon_{pork,\ chicken}$: 0.0523 → -0.3389 (Model A), -0.0264 → -0.2326 → -0.3291 (Model B), $\varepsilon_{chicken\ ,pork}$: -0.1456 → -0.7594 (Model A), -0.2188 → 0.1349 → -0.8801 (Model B)). Thus we can say that the BSE case made the cross price relationship between Korean beef and pork (or chicken) insignificant, but made the complementary relationship between pork and chicken stronger. We can infer the changes of cross price elasticities are caused by the U.S. BSE case. Korean beef consumers came to put more emphasis on food safety or quality than the price changes of related goods.

The fourth is the relationship between the U.S. beef and other meats. Before the BSE case, U.S. beef was a substitute for Korean beef, and a complement to pork and chicken. However, the cross price relationship between U.S. beef and others are not significant in period 3 (p-values are all above 25% except $\varepsilon_{U.S.\ beef,\ chkcken}$=1.9208). This result suggests that for U.S. beef consumers (mostly restaurant chains and food manufacturers) in period 3, the price of related goods are not significant factors in deciding U.S. beef consumption.

Summary and Concluding Remarks

In summary, we estimated a LA/AIDS model to analyze the structural changes in Korean meat demands caused by an outbreak of BSE in the U.S. in 2003. Using recently developed model specification testing methods, we specified the empirical model, and estimated the model with a SUR-GLS estimation method.

The estimation results show that Korean meat demands changed significantly after the embargo on U.S. beef in Dec. 2003. The demand for Korean beef and U.S. beef has been changed to be less elastic to budget than before. On the contrary, pork and chicken demands have changed to be more elastic to budget. Korean beef has changed to be less Marshallian own price elastic or not significant after 2003, but pork and chicken have changed to be more elastic. This result for U.S. beef is because the beef imports from U.S. were small in 2007 relative to the quantity imported in 2003, and most of the imported U.S. beef was consumed by the highly price elastic food industries. So, the Marshallian own price elasticity of U.S. beef was greater after the BSE case than before 2004. The cross price elasticities of Korean beef and U.S. beef with pork and chicken became insignificant after the BSE case. We can infer that all those changes come from food security concerns for beef caused by the outbreak of BSE in the U.S. in 2003 and the import embargo by Korea. So the food safety concern made Korean consumers change their meat consumption structure from beef to pork or chicken, and made beef consumption less elastic to budget and prices.

These results suggest that food safety concerns and policies are likely to have far reaching impacts. The effects of a multiple year embargo of a U.S. food product or commodity has the potential for increasing demand for domestic foods and creating demand resistance to U.S. commodities once the embargo is lifted. The results from the U.S. beef embargo by Korea suggest that U.S. beef promotion efforts need to be expanded greatly to offset the effects of the demand changes that occurred.

CHAPTER III

STRUCTURAL CHANGES OF NATURAL GAS SUPPLY CAUSED BY TECHNOLOGY CHANGES AND DEPLETION

Introduction and Background

Natural gas is becoming more important as an energy source because it is one of the cleanest, safest, and most useful of all energy sources (NGAS: Natural Gas Supply Association, available at http://www.naturalgas.org). Natural gas production grew rapidly until the early 1970's when supply decreased until the mid 1980's when supply began increasing (Figure 4). NGSA accuses the U.S. government regulation policy for the supply decline and price irregularity. In 2008, dry natural gas[7] made up 28% of primary energy production (EIA: Energy Information Administration – Annul Energy Outlook 2010), but EIA projected that it will decrease gradually to 26% by 2030 (Figure 5). Natural gas provided 22 percent of total energy consumed in the U.S. in 2005 (EIA – Annual Energy Outlook 2007).

In the past 20 to 30 years, the environment around the natural gas production has been changing. The changes are mostly due to policy changes, technology development, and depletion of reserves (NGSA, Cuddington and Moss, 1996). First, the policy for

[7] Usually the extracted natural gas is wet at first. The wet natural gas (free gas or gas in solution with crude oil) contains liquefiable hydrocarbon (methane, ethane, propane, butane, etc.) and any volumes of non-hydrocarbon gases (water vapor, nitrogen, carbondioxide, hydrogen sulfide etc.). Dry natural gas is made from wet natural gas by removing the hydrocarbon and non-hydrocarbon gases.

energy market has been heading for deregulation (NGAS, available at http://www.naturalgas.org). Because of the natural monopoly problem, interstate sales and delivery of natural gas, and building an interstate pipeline was controlled by the FPC (Federal Power Commission) based on the Natural Gas Act of 1938. After the Supreme Courts decision in Phillips Petroleum Co. v. Wisconsin case in 1954, FPC oversighted over wellhead price. However, after experiencing the supply shortages in the late 1970's, the federal government began to allow market forces to set wellhead prices and sales (The Natural Gas Policy Act of 1978, FERC Order No. 436 and 636, The Natural Gas Wellhead Decontrol Act of 1989). Now, the regulations by FERC are focused on only the sales of natural gas from interstate pipeline companies to local distribution companies.

Second, technology of finding, drilling, storing, transporting, and distributing natural gas has been greatly developed. The technology development has played a role in reducing the production cost of natural gas. For example, 3-D and 4-D seismic imaging technology made it easy to explore gas reserves. Coiled tubing, slimhole drilling, and offshore drilling technology reduced the cost of drilling. CO_2-sand fracturing technology enabled producers to extract more from underground formations. Liquefying technology of natural gas reduced the storing costs, and the technology of natural gas powered fuel cells made it possible to generate electricity more efficiently (NGAS, available at http://www.naturalgas.org). In addition to the well known big changes above, there were many other technology developments in natural gas production. Cuddington and Moss (1996) summarized the diffusion of computer technology in natural gas production.

Third, the problem of depletion in natural gas reserves is controversial. NGSA insists that natural gas is not running out quickly, and that there is much remaining. However, some communities or research groups like "The Oil Drum" claim that conventional (relatively easy to produce) gas depletes fast, and unconventional gas (deep sea gas, tight gas, gas-containing shales, coal bed methane, arctic & subsea methane and so on) is hard to find and costly. Furthermore, they argue that there is a treadmill effect which means drilling more to stay at current consumption levels requires more costs for finding new reservoirs and producing it even if technology reduces production costs (Nate Hagens, 2006[8]). The world proven natural gas reserve was estimated to be about 6,183 trillion cubic feet (tcf) by EIA (Oil & Gas journal, 2006), and the world's original endowment of conventional gas was estimated to be 10,000 tcf by Bently (2002). Bently (2002) indicated that the depletion of conventional gas is not problematic now, but as the dependency on oil as an energy source decreases and consumption of natural gas increases, the production of conventional gas production will be at its peak in perhaps 20 years. Raymond, the CEO of EXXON Mobil in 2005, told reporters at the Reuters Energy Summit in 2005 that the North American natural gas production had already peaked, and it would continue to decline[9]. Reynolds (2009) forecasted that the North American natural gas production will be at its peak in 2013.

Since there were many previous studies about the effect of deregulation policy on the natural gas market (MacAvoy, 2000), the primary objective of this study is to quantify the effects of technology changes and depletion on the U.S. natural gas supply.

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[8] Available at http://www.theoildrum.com/story/2006/11/8/6636/36918
[9] Available at http://www.reuters.com/article/Utilities/idUSN2163310420050621

To achieve the objective, I will estimate the supply function for natural gas including the effects of depletion in natural gas reservoirs and technological development. The estimated supply function will be used to analyze the changes of supply elasticities caused by the effects of technology change and depletion.

Literature Review

There are many studies about estimating the supply of natural gas, but most of the studies did not explicitly take into consideration the effects of technology changes and depletion. Early studies were focused on the effects of regulatory policy on the price responsiveness of new discoveries of natural gas. Erickson and Spann (1971) estimated the new discoveries and drilling function of natural gas using Fisher's (1964) model. They found the new drilling and new discoveries depends on economic incentives such as wellhead prices, but the price responsiveness is lower than expected because of regulatory policies. Khazzom (1971) estimated a new discovery function for natural gas using ceiling price (policy price), price of oil, and price of gas liquids. He recognized the possibility of under or over estimating the price responsiveness caused by the effects of technology development and depletion, but he did not find conclusive evidence of the effects of technology development and depletion on the price responsiveness with the 1960's data. MacAvoy and Pindyck (1973) also estimated the new discoveries function for natural gas, and found that the shortage of natural gas supply was due to the low wellhead ceiling prices. Pindyck (1974) and Walls (2002) summarized the methodologies and results of the previous studies.

Recently, Cuddington and Moss (1996, 2001) analyzed the effects of technology change and depletion on the cost of natural gas and the U.S. petroleum industry. They used proxy variables: a technology diffusion index for technology changes and past cumulative production level for depletion. By using two proxy variables, they captured the effects of technology changes and depletion separately. They found the cost reduction effects of technology development have largely offset the cost increasing effects of depletion.

The classical literature for modeling the supply of depletable resources with technology development focused on finding the dynamic optimal production path. Hotelling (1931) first developed the dynamic optimization model of exhaustible resource. However, Hotelling assumed a fixed technology level (constant marginal cost), so the later empirical work failed to support Hotelling's model (Barnett and Morse, 1963, Slade, 1982). Smith (1968) and Pindyck (1978) also developed a dynamic model of nonrenewable natural resources with allowing technology changes. Smith suggested an optimal dynamic supply model including the capital stock invested. Pindyck included the average production cost changes by technology changes and he showed that the optimal exploratory activity for finding new reserved of depletable resources depends not only on initial reserves and rate of depletion but also change of extraction cost.

Productivity growth by technology development has been mostly gradual and smooth since the 1970's (Baumol, 1986, Krugman, 1995, 1996, Phillips, 2001). So, the empirical methods to detect the gradual effect of technology changes focused on how to estimate time-varying coefficients. There are two types of models to test time-varying coefficients (Chen and Hong, 2008). One is a parametric smooth transition regression (STR) which assumes a specific functional form of time-varying coefficients, and the other is a nonparametric approach which does not assume a specific form. Ohtani and Katayama (1986) and Moschini and Mielke (1989) assumed the coefficients are varying linearly over time. Lin and Teräsvirta (1994), Teräsvirta (1994), and Holt and Balagtas (2009) assumed a logistic functional form. Since the functional form assumption in an STR model is rather arbitrary, the nonparametric method is better in terms of fewer restrictions. Robinson (1989, 1991) first applied the nonparametric method to the structural change model. Orbe, Ferreira and Rodriguez-Poo (2000, 2005, 2006), Cai (2007), and Cai, Li and Park (2009) developed the model later. They used the nonparametric method of local linear or local polynomial fitting methods developed by Fan and Gijbels (1996).

Theoretical Framework

If we assume the output level of natural gas extraction at time t (q_t) is a function of labor inputs (*L*), capital inputs (*K*), technology level (*tech*), and given depletion level (*dep*), the production function of natural gas is defined as:

(22) $q_t = f(L_t, K_t, tech_t\ dep_t)$.

In many macro level analyses, R&D investment was used as a proxy variable for $tech_t$ (Solow, 1957, Romer, 1990, Griliches, 1994), but R&D investment for a specific industry is hard to get. Furthermore, R&D investment may not always be correlated with technology changes (Cuddington and Moss, 1996, 2001). Cuddington and Moss (1996, 2001) used actual technology diffusion as a proxy variable for $tech_t$. However, industry level actual technology diffusion data are also hard to estimate. So, in this study, a time varying coefficients model will be applied to capture the effects of technology changes which are assumed to be gradual as Phillips (2002) and Krugman (1996) supported. The dynamic decision of the industry production with respect to the depletion of natural gas can be captured by total initial endowment ($\overline{Q}$) minus past cumulative production ($\sum_{s=0}^{t-1} q_s$). Because $\overline{Q}$ is not known, $D_t = (\sum_{s=0}^{t-1} q_s)^{-1}$ will be used as a proxy variable for dep_t as Cuddington and Moss (1996, 2001) suggested. If we apply the Cobb-Douglas type flexible functional form, the production function of natural gas will be

(23) $$q_t = \alpha_t L_t^{\beta_{1t}} K_t^{\beta_{2t}} D_t^{\beta_{3t}}.$$

Because of the difficulty in obtaining the labor inputs (L_t) and capital inputs (K_t) data , the supply function will be used to analyze the effects of technology changes and depletion. The supply function can be derived from the profit maximization assumption. The profit maximization problem will be:

(24) $$\max_{L_t, K_t} \pi_t = p_t q_t - w_t L_t - r_t K_t$$

where p_t is the unit price of natural gas. The price p_t is actually the expected price of producers when they make the supply decision. Because the import and export of natural gas in the U.S. is free and the futures and option market of natural gas in the U.S. are well developed, we assume the rational producers can expect p_t on average. So, we assume p_t is given in this study. Then from the first order condition we can get the derived input demand function:

$$(25)\quad L_t^{\beta_{it}+\beta_{2t}-1} = \frac{\beta_{1t}^{\beta_{2t}-1} r_t^{\beta_{2t}}}{\alpha_t \beta_{2t}^{\beta_{2t}} w_t^{\beta_{2t}-1} p_t D_t^{\beta_{3t}}}, \qquad K_t^{\beta_{it}+\beta_{2t}-1} = \frac{\beta_{2t}^{\beta_{1t}-1} w_t^{\beta_{1t}}}{\alpha_t \beta_{1t}^{\beta_{1t}} r_t^{\beta_{1t}-1} p_t D_t^{\beta_{3t}}} .$$

If we replace L_t and K_t in the production function (equation (23)) with the derived input demand function (equation (25)), then we can get the supply function of U.S. natural gas:

$$\begin{aligned} \ln q_t &= -\frac{\ln \alpha_t + \beta_{1t} \ln \beta_{1t} + \beta_{2t} \ln \beta_{2t}}{\beta_{1t} + \beta_{2t} - 1} + \frac{\beta_{1t}}{\beta_{1t} + \beta_{2t} - 1} \ln w_t + \frac{\beta_{2t}}{\beta_{1t} + \beta_{2t} - 1} \ln r_t + \\ (26)\qquad & \quad - \frac{\beta_{1t} + \beta_{2t}}{\beta_{1t} + \beta_{2t} - 1} \ln p_t - \frac{\beta_{3t}}{\beta_{1t} + \beta_{2t} - 1} \ln D_t \\ &= a_t + b_t \ln w_t + c_t \ln r_t + d_t \ln p_t + e_t \ln D_t \;\; (-b_t - c_t = d_t) \end{aligned} .$$

In equation (26) the restriction $-b_t$-c_t=d_t means the supply function derived from a profit maximization assumption satisfies the 'homogeneous of degree zero in prices' condition.

Using the estimated coefficients, we can calculate the time-varying supply elasticities (b_t, c_t are the supply elasticities of input prices and d_t is the supply elasticity of output price). If we assume the technology level does not change when time period changes from period zero to one, the input price elasticity is usually negative because the level of the input decreases when marginal cost of input (input price) increases. However, if we take the technology development into account, the input price elasticity can be positive because technology development causes the marginal product of the input to increase. Figure 6 shows the relationship between technology change and input level change. In Figure 6, VMP (value of marginal product = output price × marginal product) is the input demand curve, and P_I (input price) is marginal cost. Assume input demand is VMP_0 with technology level $tech_0$, and marginal cost is P_0 at period zero, the equilibrium input level is I_0, and production level is $q_0=f(I_0)$ (*f* is the production function). If the input price rises to P_1 in period one and technology level does not change, input demand remains $VMP_0(tech_0)$, input level decreases to I´, and production level decreases to $q_1=f(I')$. If technology level increased from $tech_0$ to $tech_1$ and input price increased to P_1, the input demand will change to $VMP_1(tech_1)$, and the input level will decrease to I_1 and output level will also decrease to $q_1=f(I_1)$ because the marginal product increasing effect of technology development is less than the marginal cost increasing effect of the input price rise. However, if the technology level increased the input demand to $VMP_1(tech_2)$, input and output levels will increase to I_2 and $q_1=f(I_2)$, even if the input price rises from P_0 to P_1 because the marginal product increasing effect of technology development is greater than the marginal cost increasing effect of the input price rise. Thus, we can infer that the value of input price elasticities (b_t and c_t) are decided by the relative size of the marginal product increasing effect of technology development and the marginal cost increasing effect of input price increases.

One more thing we should remember is that the growth of marginal product by technology development does not always mean the growth of average production which is usually referred to as a productivity growth. Figure 7 shows the relationship among technology change, average product, and marginal product. When the production function q is f_0 with technology level $tech_0$, and if the producer's input/output decision is $E_0(I_0, q_0)$ at period zero, the average product is q_0/I_0 and marginal product is MP_0. When the production function q is changed to f_1 by the technology development and if the producer's input/output decision is $E_1(I_1, q_1)$ at period one, both average product and marginal product increase to q_1/I_1 (greater than q_0/I_0) and MP_1 (greater than MP_0). However, if producer's input/output decision is $E_2(I_2, q_2)$, marginal product increases ($MP_2>MP_0$) but average product decreases ($q_0/I_0> q_2/I_2$), because input use increases from I_0 to I_2 (Figure 7).

Incorporating Time-varying Coefficients

To estimate a supply function with time-varying coefficients, two models can be applied – STR model and nonparametric local polynomial (NLP) model. Even if the NLP model is better in terms of imposing fewer assumptions, it does not provide the coefficients for every time point (T) but for each band because the NLP model divides the whole time period into multiple bands which are not always the same as T. The STR model estimates the time-varying coefficients at every time point by using an assumed functional form. The STR model will be used in this study. If we express the supply function derived in (26) in matrix form, it will be changed to

(27) $Q_t = X_t \pi_t$, $Q_t = (\ln q_t)$, $X_t = (1 \ln w_t \ \ln r_t \ \ln p_t \ \ln D_t)$, $\pi_t = (a_t \, b_t \, c_t \, d_t \, e_t)$.

STR model suggested by Lin and Teräsvirta (1994) assumes $\pi_t = \pi_1 + \pi_2 F(t)$, and also assumed the logistic functional form of $F(t)$. So the model will be:

$$Q_t = X_t\pi_1 + X_t\pi_2 F(t) + \varepsilon_t$$

$$F(t) = (1+\exp\{-\gamma(t^3+\delta_1 t^2+\delta_2 t+\delta_3)\})^{-1}$$

$$\text{or}$$

(28) $$= 1-\exp\{-\gamma(t-\delta)^2\} \quad .$$

$$\text{or}$$

$$= (1+\exp\{-\gamma(t+\delta)\})^{-1}$$

Various functional forms of F(t) can be applied, but in this study first, second, and third order logistic functions will be tested based on Lin and Teräsvirta (1994), and the best form will be chosen by BIC.

On estimation of equation (28) there may be a identification problem. If $\gamma \to 0$, δ_i cannot be identified (Lin and Teräsvirta, 1994). To avoid this problem, first order Taylor expansion is used. Then the function *F(t)* will be

$$F(t,\gamma) = F(t,0)+F'(t,0)\gamma$$

$$F(t,\gamma) = 1/2+\gamma/4(t^3+\delta_1 t^2+\delta_2 t+\delta_3)$$

$$\text{or}$$

(29) $$= \gamma(t-\delta)^2 \quad .$$

$$\text{or}$$

$$= 1/2+\gamma/4(t+\delta_3)$$

Using equation (29), the supply function in equation (26) of third order logistic functional form can be expressed as:

(30) $$\ln q_t = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + b_0 \ln w_t + b_1 t \ln w_t + b_2 t^2 \ln w_t + b_3 t^3 \ln w_t + c_0 \ln r_t + c_1 t \ln r_t + c_2 t^2 \ln r_t + c_3 t^3 \ln r_t + d_0 \ln p_t + d_1 t \ln p_t + d_2 t^2 \ln p_t + d_3 t^3 \ln p_t + e_0 \ln D_t + e_1 t \ln D_t + e_2 t^2 \ln D_t + e_3 t^3 \ln D_t$$

$$a_t = a_0 + a_1 t + a_2 t^2 + a_3 t^3, \quad b_t = b_0 + b_1 t + b_2 t^2 + b_3 t^3, \quad c_t = c_0 + c_1 t + c_2 t^2 + c_3 t^3$$
$$d_t = d_0 + d_1 t + d_2 t^2 + d_3 t^3, \quad e_t = e_0 + e_1 t + e_2 t^2 + e_3 t^3 \quad -b_t - c_t = d_t \,.$$

For the second order form, (a_3, b_3, c_3, d_3, e_3) are zero, and for the first order form, (a_2, b_2, c_2, d_2, e_2) are also zero.

Data, Empirical Model, and Method

Monthly data from 1976 to 2009 are used in this study. U.S. natural gas wellhead price (cents per million cubic feet) and U.S. natural gas marketed production (million cubic feet) data are used, and are obtained from the EIA database. Wage (dollar per hour) data come from employment, hours, and earnings from the current employment statistics survey by BLS (Bureau of Labor Statistics). It is the national level average hourly earnings of production and nonsupervisory employees in the oil and gas extraction industry. Interest rate (percent) data are from the FRB (Federal Reserve Board) database. The rates are average corporate bond rates of Moody's Aaa industrial bond.

Because the supply function in equation (30) has a non-linear functional form and a non-linear restriction, OLS (ordinary least squares) method by linearization may bear a bias and non-efficiency problem. NLS (non linear least squares) method is used in this study. To analyze the time-varying effects and to compare NLS with OLS, four models are estimated. The models are as follows.

$$Model1: \ln q_t = a + b\ln w_t + c\ln r_t + d\ln p_t + e\ln D_t + \sum_{t=2}^{12} m_t S_t + \varepsilon_t \quad (OLS)$$

$$Model2: \ln q_t = a_0 + a_1 t + b_0 \ln w_t + b_1 t\ln w_t + c_0 \ln r_t + c_1 t\ln r_t + d_0 \ln p_t + d_1 t\ln p_t + e_0 \ln D_t + e_1 t\ln D_t + \sum_{t=2}^{12} m_t S_t + \varepsilon_t \quad (NLS)$$

$$Model3: \ln q_t = a_0 + a_1 t + a_2 t^2 + b_0 \ln w_t + b_1 t\ln w_t + b_2 t^2 \ln w_t + c_0 \ln r_t + c_1 t\ln r_t + c_2 t^2 \ln r_t + d_0 \ln p_t + d_1 t\ln p_t + d_2 t^2 \ln p_t + e_0 \ln D_t + e_1 t\ln D_t + e_2 t^2 \ln D_t + \sum_{t=2}^{12} m_t S_t + \varepsilon_t \quad (NLS)$$

$$Model4: \ln q_t = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + b_0 \ln w_t + b_1 t\ln w_t + b_2 t^2 \ln w_t + b_3 t^3 \ln w_t + c_0 \ln r_t + c_1 t\ln r_t + c_2 t^2 \ln r_t + c_3 t^3 \ln r_t + d_0 \ln p_t + d_1 t\ln p_t + d_2 t^2 \ln p_t + d_3 t^3 \ln p_t + e_0 \ln D_t + e_1 t\ln D_t + e_2 t^2 \ln D_t + e_3 t^3 \ln D_t + \sum_{t=2}^{12} m_t S_t + \varepsilon_t \quad (NLS) \tag{31}$$

Because the data are monthly, seasonal dummy variables (S_t=1 for a specific month, otherwise zero) are included in the models. Four models in equation (10) will be estimated and compared, and the best model will be chosen based on BIC.

Results and Discussion

Table 12 contains the evaluation results of the four models in equation (10). The results show that Model 4 (the third order exponential form of STR model) is the best. Model 4 fits the historical data well (R^2=0.8342), RMSE is the smallest (0.0312), and

BIC is also smallest (-1544.876). So Model 4 is used to estimate time-varying coefficients.

Table 13 shows the estimation results for Model 1 and Model 4. From the results, we can confirm that the assumption of time-varying coefficients is significant. All time varying coefficients except a_2, b_2, and d_2 (a_0, b_0, c_0, e_0 are not time-varying factors) are significant at the 5% significance level. Monthly supply patterns estimated in Model 4 are all significant, and they are almost the same pattern as found in Model 1. During the winter season natural gas is supplied more (intercept shifter for January is 0, December is -0.0195) and in September it is supplied less (intercept shifter of September is -0.1084).

Labor price (wage) elasticity of U.S. natural gas supply in Model 1 is fixed (E^w_1= 0.1809, Table 13), but the time-varying labor price elasticity estimated in Model 4 (E^w_t) increased smoothly for 1976-2009 (Figure 8). The elasticity was negative until May 2004. This result indicates that the marginal product increasing effect of technology development is growing steadily, but it was not greater than the cost (labor price) increasing effect. As explained in Figure 6, the negative elasticity means the change from E_0 to E_1. We can confirm this result by the fact that the average productivity of labor index[10] (Table 14) steadily increased until 2003. That is the case of changing from E_0 to E_1 in Figure 7. After May 2004, E^w_t changed to positive and keep increasing even though the productivity of labor (average product of labor) was decreasing (Table 14). The positive elasticity means that the marginal product increasing effect of technology

[10] Source: BLS (Bureau of Labor Statistics) data base. Available at http://www.bls.gov/lpc/ .

development was greater than the labor cost increasing effect after May 2004 as we see the change from E_0 to E_2 in Figure 6. As explained in Figure 7, the decreasing average product of labor after May 2004 is the case of changing from E_0 to E_2. We can confirm these results based on the increasing number of employees in oil and gas extraction industry, number of gas and gas condensate wells, and drilling activity (number of crude oil and natural gas rotary rigs)[11] after 2003 (Table 14).

Capital price (interest rate) elasticity of U.S. natural gas supply (E^r_1) is -0.1797 (Table 13) in Model 1, but in Model 4 it (E^r_t) was positive until July 2005, and after that it turned negative (Figure 8). It was steadily decreasing until Sep. 1990, and it was stagnant (slightly increasing) around 0.08 to 0.12 in the 1990's. During the 2000's the elasticity decreased steadily. This pattern roughly corresponds to the yearly pattern of average product of capital index in petroleum and coal production industry[12] (Table 14). The index was stagnant in the range of 92 to 94 during 1990-1997, it was decreasing in 2000-2003, and it decreased rapidly after 2004. The positive elasticity in price of capital until July 2005 means that the changes were from E_0 to E_2 in Figure 6, and the negative elasticity means that the changes were from E_0 to E_1.

Output price elasticity of U.S. natural gas in Model 1 is -0.0012, but it is not significant (p-value is 0.872, Table 13). In Model 4, it was negative before Aug. 1981, but we cannot be sure it is significant because during that period natural gas price and production were highly regulated by the U.S. government. Also, after Aug. 1981, the

[11] Source: EIA (Energy Information Administration) data base. Available at http://www.eia.doe.gov/oil_gas/natural_gas/info_glance/natural_gas.html
[12] Source: BLS (Bureau of Labor Statistics) data base. Available at http://www.bls.gov/mfp/

U.S. natural gas supply is highly inelastic and near zero (E^p_t is between -0.0447 and 0.0879, Figure 9). An inelastic price elasticity of U.S. natural gas supply can be explained by the characteristic of natural gas production. Natural gas production needs very expensive and huge amounts of infrastructure and facilities such as finding and drilling machinery, compression facilities, pipelines, and underground storage. Natural gas supply cannot exceed the infrastructure and facilities restriction regardless of natural gas prices. Idling the infrastructure and facilities is very costly even if the output price falls. So we can infer that natural gas supply is inelastic to output prices, and that supply is more dependent on the level of infrastructure and facilities.

Figure 10 shows the response of U.S. natural gas supply to the depletion of U.S. natural gas reserves. The percentage change of U.S. natural gas supply when there is a 1% increase in depletion in Model 1 (E^d_1) is 0.1839 (Table 13). In Model 4, the depletion elasticity (E^d_t) is positive during May 1976-Apr. 2005, and after that it changed to negative (Figure 10). The positive elasticity means that the cost decreasing effect (finding and extracting natural gas from new wells was less costly with new technology) of technology development was greater than the cost increasing effect of depletion (finding and extracting natural gas from new wells was more costly with the same technology as depletion proceeds). This result agrees with the results by Cuddington and Moss (1996). They found technological change prevented the sharp rise of U.S. natural gas production costs due to depletion during 1967-1990. However, since May 2005 the results of Model 4 show that technology development did not cover all the cost increases by depletion because E^d_t has been negative.

Summary and Conclusion

In summary, we conclude that technology change effects in U.S. natural gas supply are gradual, and also conclude that to capture the gradual effects in U.S. natural gas supply the STR model with time-varying coefficients is useful. Also we estimated the time-varying supply elasticities for U.S. natural gas.

The estimation results show that until May 2004 technology development did not cover all of the effects of labor cost increases, but after that technology development overwhelmed the effects of labor cost increases. Until July 2005 the technology development marginal product increasing effect exceeded the capital input cost increases, but after that the technology development effect did not cover all of the capital input cost increases. U.S. natural gas supply is concluded to be highly inelastic to output price because of the characteristic of natural gas industry as a heavy chemical industry requiring huge amounts of infrastructure and investment facilities. Until April 2005, technology development covered the entire depletion problem in U.S. natural gas production, but after that the cost increase due to depletion became greater than the cost decrease from technology development.

CHAPTER IV

MODELING AND ANALYZING THE CHANGES OF BIDDING BEHAVIOR BY BID AFFILIATION IN REPEATED SECOND-PRICE AUCTIONS WITH POSTED PRICES

Introduction and Background

In many cases, the data from market observations are not enough to get meaningful information to test market mechanism or economic theory. To overcome this problem, an experimental method is often used. Experimental auctions have increasingly been used by market researchers to obtain market value of goods or consumers' willingness to pay (WTP) for goods. Usually, the repeated bidding by subjects is employed in experimental auctions because researchers can get many experimental observations with less cost (Alfnes and Rickertsen 2003; Buhr et al. 1993; Fox, Hayes and Shogren 2002; Lusk et al. 2004). In the repeated auction experiments, subjects bid repeatedly on the same goods in each round. After each round, the winning prices are posted for all subjects, and the winner of each round pays his or her bid for the good if the auction is a binding contract. The reason for posting the winning bid is that much information can be sent through a posted price to bidders, and with the information bidders can understand the bidding mechanism better and learn more about the market. The posted price can help subjects to form their willingness to pay prices for the good, and by posting the winning price the researchers can get a more exact market WTP for the good.

However, the posted price may affect the subjects' next bids and bidders may change their bidding behaviours regardless of their true WTP which is called bid affiliation (Harrison et al, 2004, Corrigan and Rousu, 2006). If a bid affiliation in a repeated auction is serious, the actual bid prices may be biased. Harrison *et al* (2004) claimed three fundamental problems in eliciting exact bid values from repeated laboratory auctions. First, *field-price censoring* occurs since a rational subject will not bid more than the price of the outside market she recognizes regardless of her true willingness to pay (WTP). Second, *beliefs about field prices are affiliated* since a subject will adjust her belief about market prices after watching the posted prices when she does not know much about the auction goods. Third, *beliefs about the quality of the auction goods are affiliated* since her perception about the quality of the good will be revised according to the posted prices. Corrigan and Rousu (2006) indicated the six reasons to cause a bid affiliation. First, the subjects derive the value of the products from other participants' bids when they are unfamiliar with the auction items. Second, they may infer the market price from other's bids when they do not know the outside market price. Third, there may be a "*top-dog effect*" when bidders want to be a winner. Fourth, when they feel that there is no chance of winning the auction item, there is a tendency to submit significantly higher bids. Fifth, other participants' high bids increase the credibility of the auction market. And sixth, there is a behavioral "*anchoring effect*" so bidders may adjust their bids around the posted prices.

Many previous studies (List and Shogren, 1999, Alfnes and Rickertsen, 2003, Harrison *et al*, 2004, Corrigan and Rousu, 2006) focused on testing whether there are bid affiliation effects in repeated Vickrey auction with posted prices exist or not. In this study, the primary objective is to suggest a model which enables us to estimate true WTP by analyzing the changes of bidding behavior due to bid affiliation in repeated second-price auction (Vickrey auction) with posted prices. To do this, a bid price function will be estimated, the bid affiliation effects will be tested by using the proxy variables to capture the bid affiliation effects which causes bidders to change their bidding behaviors. Furthermore, the true WTP will be estimated out of the bid price function.

Literature Review

A number of studies have evaluated the issue of bid affiliation in repeated trial auctions. List and Shogren (1999) showed that posted prices affect bidding behaviours especially for unfamiliar products. Specifically, they found that posted prices influence the behaviours of the median naïve bidders but not the behaviours of the median experienced bidders or the bidders for familiar goods. They modelled the bids in round t as a function of the posted price in the previous round and estimated the bid function with fixed/random effects models of panel data. To reduce the bid affiliation bias, they provided bidders with non-price information about the product and to increase their familiarity with the product. Alfnes and Rickertsen (2003), using experimental data of

European consumers' WTP for U.S. beef, estimated a model of individual *i*'s bid at round t using the first difference model of panel data. To capture the bid affiliation effects they included the time variable *t* and the difference between the posted price and *i*'s bid at round *t-1* as the explanatory variable set. They revealed that the coefficient of this variable is positive and concluded that the mean bids increase over rounds and that the bids are affiliated with the posted prices, similar to the finding of List and Shogren (1999).

To prove the bid affiliation effects, Corrigan and Rousu (2006) compared the control group with the treatment group. Some confederate bidders were inserted into the treatment group and were instructed to bid within a certain narrow range. They were directed in advance to place high bids for the products. Corrigan and Rousu estimated a bid function using a random effect model of panel data with a time variable *t* as an explanatory variable, and found that the mean bids increase more after each round in the treatment group than in the control group, which signifies that high posted prices can lead to greater bid affiliation effects.

Harrison *et al* (2004) estimated a bid function using panel Tobit model. They found that bid affiliation was significant in their experiment, and concluded that a one-shot Vickrey auction is better to use than a repeated trial Vickrey auction when eliciting WTP. They also compared one control group (no information about goods) with two treatment groups (giving information and demonstration), and showed that giving information to bidders made bid price increase.

Data

The dataset comes from the study of Corrigan and Rousu (2006) (CR hereafter) that used 10 repeated rounds of a second price auction for a university logo mug and a candy bar to test a bid affiliation effect. In this study, the candy bar case will be analyzed. The participants were university students (Kenyon, OSU, and NC State). The experiment was done for seven groups, and CR used confederate bidders for two groups to test whether high posted prices would subsequently lead to higher bids (the confederate bidders were directed in advance to place high bids). Table 15 shows the characteristics of the seven groups. The group 1 and group 7 are treatment groups, and others are control groups with no treatment. For each group and the all pooled group, bid functions will be estimated, bid affiliation effects will be tested, and the true WTP will be estimated.

Unobserved Effects Tobit Model of Bid Affiliation

Define $BD_{i,t}$ as participant *i*'s bid in the repeated auction round *t*. If we assume the participants have true WTPs for a candy bar and there are bid affiliation effects in the repeated auction, WTP is different from $BD_{i,t}$ and is unobservable. We can only observe $BD_{i,t}$, and not WTP. If WTP_i is person *i*'s true willingness to pay, we can set person *i*'s bids as:

(32) $BD_{i,t} = WTP_i + BA_{i,t} + u_{i,t}$

where $BA_{i,t}$ is bid affiliation bias and $u_{i,t}$ is i.i.d. disturbance term with mean 0. Bid affiliation occurs when bidders incorporate feedback from the previous rounds into their current bid. So we can assume that bidders adjust their bids at round *t* based on their bidding error (winning bid minus their actual bid) of the previous round, and we can also assume that bidders come to know the auction mechanism and the market value of the good as rounds proceed as Alfnes and Rickertsen (2003) suggested. Then we can express the bid affiliation as:

(33) $BA_{i,t} = a_1(BD^w_{i,t-1} - BD_{i,t-1}) + a_2(BD^w_{i,t-1} - BD_{i,t-1})^2 + \ldots + b_1 t + b_2 t^2 + \ldots$

where BD^w is the winning bid and *t* denotes round. The bid affiliation function (33) can have various functional forms such as 3rd or higher order polynomial, logarithmic and so on. Many types of functional forms can be tested, but in this study first, second, and third order polynomial form will be tested and the best will be chosen based on BIC. The true willingness to pay, WTP_i is assumed to be not time varying. This assumption makes sense because participants' *WTP* is more likely to be stable in 1 or 2 hour (it will take 1 or 2 hour for 10 round bid). The bid function can be obtained by replacing $BA_{i,t}$ in equation (32) with equation (33).

(34)
$$\begin{aligned} BD_{it} = WTP_i &+ a_1(BD^w_{i,t-1} - BD_{i,t-1}) + a_2(BD^w_{i,t-1} - BD_{i,t-1})^2 + \\ &a_3(BD^w_{i,t-1} - BD_{i,t-1})^3 + b_1 t + b_2 t^2 + b_3 t^3 + u_{it} \end{aligned}$$

There are some problems in estimating equation (34). First, *WTP* is unobservable, so the OLS estimators without WTP_i are not consistent (missing variable bias may exist). By first differencing equation (34), we can remove WTP_i. However, the first differenced form of equation (34) still has an endogeneity problem. By first differencing, ΔBD_{it} ($=BD_{it} - BD_{it-1}$) is included in the explanatory variable vector, and the error term changes to Δu_{it} ($=u_{it} - u_{it-1}$). Since BD_{it-1} and u_{it-1} are not independent of each other, an endogeneity problem may occur. We can avoid the endogeneity problem by using instrumental variables (IVs). A dynamic panel model suggested by Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998) is an example of IV regression to avoid the endogeneity problem. However, a dynamic panel model still has a censoring problem. BD_{it} is censored at zero because some participants' bids are zero. Table 16 shows the difference between average bids of the group including zero bids and excluding zero bids. From the difference in Table 16, we are certain that the zero bids can cause the estimation bias. To estimate this type of model, Wooldridge (2005) suggested the "unobserved effect Tobit model." He verified MLE can guarantee consistent and efficient estimators with 3 assumptions as:

Assumption 1: The original model such as equation (34) is correctly defined.

Assumption 2: The unobserved effect such as WTP_i can be correctly specified as a functional form.

Assumption 3: The initial condition such as BD_{i1} should be included in the functional form in the assumption 2.

Assumption 1 and 2 are clear to understand. The assumption 3 in Wooldridge's model makes the difference from the Harrison et al (2004) model. Harrison et al also used a panel Tobit model, and they concluded that one-shot Vickrey auction is better to elicit a true WTP because of bid affiliation effects. Their conclusion on one-shot Vickrey auction means that the first bid may contain some information about the true WTP, but they did not include the first bid in their model to analyze the repeated Vickrey auction experiment.

In this study, the Wooldridge's model (2005) is used to estimate equation (34). First, define WTP_i as follows:

$$WTP_i = c_0 + c_1 BD_{i1} + c_2 income_i + c_3 male_i + c_4 GPA_i + v_i \quad (35)$$

where $income_i$ denotes person *i*'s disposable income, $male_i$ is a gender dummy variable, and GPA_i is person *i*'s grade point average. Other variables are not included to estimate WTP_i because only those three (disposable income, gender, GPA) were available in this experiment. By substituting (35) in (34), we can set a unobserved effect Tobit model

$$\begin{aligned} BD_{it}^{*} &= a_1(BD_{i,t-1}^{w} - BD_{i,t-1}) + a_2(BD_{i,t-1}^{w} - BD_{i,t-1})^2 + a_3(BD_{i,t-1}^{w} - BD_{i,t-1})^3 + \\ &\quad b_1 t + b_2 t^2 + b_3 t^3 + c_0 + c_1 BD_{i1} + c_2 income_i + c_3 male_i + c_4 GPA_i + \\ &\quad \sum_{j=2}^{7} d_j g_j + v_i + u_{it} \\ &= Z_{it}\beta_1 + W_i\beta_2 + v_i + u_{it} \\ &= X_{it}\beta + v_i + u_{it} \\ BD_{it} &= max(0, BD_{it}^{*}) \end{aligned} \quad (36)$$

where BD_{it}^{*} is a latent dependent variable (it can be negative) and g_j are the dummy variables to specify the groups of each participant for the pooled model . Finally, I can obtain the likelihood function for MLE.

$$f(BD_{it}) = Pr(BD^*_{it} > 0)^{1(BD_{it}>0)} Pr(BD^*_{it} \le 0)^{1(BD_{it}=0)}$$

$$= Pr(\varepsilon_{it} > -X_{it}\beta)^{1(BD_{it}>0)} Pr(\varepsilon_{it} \le -X_{it}\beta)^{1(BD_{it}=0)}$$

(37) $$= \Phi(X_{it}\beta/\sigma_{\varepsilon})^{1(BD_{it}>0)}[1-\Phi(X_{it}\beta/\sigma_{\varepsilon})]^{1(BD_{it}=0)}, \ (\Phi: normal\ cdf)$$

$$v_i \sim N(0,\sigma^2_v),\ u_{it} \sim N(0,\sigma^2_u),\ \varepsilon_{it} = v_i + u_{it} \sim N(0,\sigma^2_{\varepsilon})$$

$$\hat{\beta} = \underset{\beta}{argmax} \sum\sum ln(f(BD_{it}))$$

From MLE, we can get a consistent and efficient estimator of β, test the bid affiliation effect is significant, and calculate true willingness to pay. From the equations (36) and (37), the expected bid price ($E(\hat{BD}_{it})$) and the expected bid affiliation terms ($E(\hat{BA}_{it})$) of each participant at round t are

(38)
$$E(\hat{BD}_{it}) = 0\ (if\ \ BD_{it} = 0)\ or$$
$$(X_{it}\hat{\beta} + \hat{\varepsilon}_{it})\Phi(X_{it}\hat{\beta}/\hat{\sigma}_{\varepsilon})\ \ (if\ \ BD_{it} > 0)$$
$$E(\hat{BA}_{it}) = 0\ (if\ \ BD_{it} = 0)\ or$$
$$(Z_{it}\hat{\beta}_1)\Phi(X_{it}\hat{\beta}/\hat{\sigma}_{\varepsilon})\ \ (if\ \ BD_{it} > 0)$$
.

Then the estimated true WTP of participant i at round t ($\hat{WTP}_{it}$), and the average WTP at round t ($\overline{WTP}_t$) are

(39)
$$\hat{WTP}_{it} = W_i\hat{\beta}_2 + \hat{\varepsilon}_{it} = E(\hat{BD}_{it}) - E(\hat{BA}_{it})$$
$$\overline{WTP}_t = \frac{1}{n_i}\sum_i \hat{WTP}_{it}\ \ (n_i: the\ number\ of\ \ participants).$$
$$\overline{WTP} = \frac{1}{10}\sum_{t=1}^{10}\overline{WTP}_t$$

Results and Discussion

Table 17 contains the estimation results for each group. To compare each group, the third order form of the bid affiliation function is used. The results show that bid affiliation effects are significant for the treatment group (Group 1 and Group 7). The coefficients a_1, a_2 in Group 1 and a_2, a_3, b_1, b_2, b_3 in Group 7 are significant at the 5% significance level. This result indicates that bidders in a repeated Vickrey auction are affected by the high posted price, and the bidders may increase their bids regardless of their true WTP when the winning bid of the previous round is high. On the contrary, the bid affiliation effects are not always significant for the control groups. For the Group 3 and Group 6, all explanatory variables related to the bid affiliation effect (*a* and *b*) are not significant at the 5% significance level. The b_1, b_2, b_3 for Group 2, b_2, b_3 for Group 4, and a_1, a_2, a_3 for Group 5 are significant at the 5% significance level. Corrigan and Rousu (2006) also showed that bid affiliation effects are significant for the treatment group from their test results. They also concluded that the high posted prices in treatment groups induce bid affiliation and high bids in the next round.

To elicit the true WTP from a bid function, the best functional form of a bid function for each group and all pooled groups is chosen. The BICs of no bid affiliation form, and first-third order bid error (BD^{w}_{t-1}-BD_{it-1}) and trend (*t*) forms are shown in Table 18. The functional form with the smallest BIC is chosen. For Group 1, the second order bid error form is chosen, and first order bid error and first order trend form is selected for Group 2. No bid affiliation form has the smallest BIC for Group 3, and first order bid error form is the best for Group 4. For Group 5, third order bid error form is chosen, and for Group 6, the first order bid error form is selected. Third order bid error form is chosen for Group 7, and for the all pooled group, the third order bid error form is selected.

Table 19 contains the estimated coefficients of the selected form for each group and the all pooled group. From the results of the all pooled group model, we can confirm that each group differs from the others. The coefficients of group dummy variables (d_j) are all significant at the 10% significance level. The base bid price (intercept c_0 plus d_j) for Group 7 is the largest among all groups, that for Group 1 is the second largest, and that for Group 2 is the smallest. For all cases, income is not significant for deciding bid price. We can infer the reason from the fact that the auction good, a candy bar, is a very common good, and it is a small percent of disposable income. Only for Group 1 and the all pooled group, male participants placed bids a little bit higher than female bidders. GPA is also not significant except for Group 4, Group 6, and the all pooled group. For the Group 2, Group 6, and the all pooled group, the initial bid is significant to decide the participants' bid price.

Figure 11 and Table 20 show the estimated average WTP of round *t* calculated with the estimated coefficients in Table 19 for each group and the all pooled group. For Group 1 which is a treatment group, the average actual bid shows an increasing pattern (Figure 11). The average actual bid was 0.28 in round 1 (Table 20), but it increased to 0.73 in round 9. We can confirm that the increase of the actual bid was caused by bid affiliation effects from the fact that a_1 and a_2 are significant for Group 1 (Table 19). That means the average actual bid is not the true willingness to pay. The estimated true WTP for Group 1 ($\overline{WTP}$ for Group 1) is estimated as 0.68 (Table 20), and the estimated WTP at round *t* ($\overline{WTP}_t = \overline{WTP} + \hat{\varepsilon}_{it}$) shows a more stable pattern (no special pattern from round to round because the means of ε_{it} are zero) than the actual bid. $\overline{WTP}_t$ was the lowest (0.63) at round 3, and the highest (0.73) at round 8.

For group 2 which is a control group, the average actual bid changes over rounds (increased from 1 to 4 (0.34-0.42), then decreased), but the changes are less than Group 1 (treatment of high winning bid). However, the bid affiliation effects are significant (b_1 is significant, Table 19). The true willingness to pay ($\overline{WTP}$) is estimated as 0.23, and $\overline{WTP}_t$ is stable (standard deviation is 0.009).

For group 3 (a control group), the average actual bid shows an increasing pattern (Figure 11) over the rounds (but not significant). It was 0.27 at round 1 and 0.42 (the highest) at round 7. $\overline{WTP}_t$ is very stable around 0.27 (standard deviation is 0.002), and the estimated true willingness to pay ($\overline{WTP}$) is 0.27.

The average actual bid and the winning bid for Group 4 (a control group) are the lowest among all groups. The bid affiliation effect is negative (a_1 is estimated as -0.3724, Table 19), which means the true willingness to pay is higher than the actual bid, but bidders placed their bids lower than their WTP because the winning bid is low. The true willingness to pay ($\overline{WTP}$) excluding bid affiliation effects from the actual bid is estimated as 0.34 (Table 20).

The pattern of average actual bids for Group 5 (a control group) does not show a specific form (Figure 11), but it is certain that bidders responded to the previous winning bid as a_1, a_2, a_3 are significant (Table 19). The reason why the pattern is not a specific form can be inferred by the fact that the winning bid does not deviate much (standard deviation is 0.0275, the least among the control groups, Table 20). The true willingness to pay ($\overline{WTP}$) is estimated as 0.51, and $\overline{WTP}_t$ is also stable (standard deviation is 0.003, Table 20).

For Group 6 which is a control group, the pattern of the average actual bid is not clear, but the bid affiliation effect is significant and negatively related (a_1 is significant and negative, Table 19). The unclear actual bid can be explained by the fluctuating winning bid. Because the winning bid fluctuates, the average actual bid moves the opposite way of the winning bid. The true willingness to pay ($\overline{WTP}$) excluding bid affiliation effects from the actual bid is estimated as 0.46 (Table 20), and $\overline{WTP}_t$ is stable (standard deviation is 0.003, Table 20).

Group 7 is a treatment group with intentional high bids. The average actual bid shows the increasing pattern except for round 7 and round 10 (Figure 11, Table 20). The bid affiliation effect is also significant (a_1, a_2, a_3 are significant, Table 19). The winning bids were kept high (1.145 on average, Table 20), and the average actual bid was 0.27 at round 1, 0.60 at round 6 (the highest). The estimated true willingness to pay ($\overline{WTP}$) is estimated as1.22 (Table 20).

For the all pooled group, the winning bid was not much variant over rounds (mean is 1.145, standard deviation is 0.012, Table 20), but the bid affiliation effect is significant (a_2, a_3 are significant, Table 19). The average actual bid was relatively stable (mean is 0.426, standard deviation is 0.04, Table 20) because the winning bid did not vary much. The true willingness to pay ($\overline{WTP}$) is estimated as 0.39 (Table 20), and $\overline{WTP}_t$ is stable (standard deviation is 0.01, Table 20).

From the estimation results of Table 19, Table 20, and Figure 11, we can conclude that the pattern of the average actual bid is increasing when the winning bid is consistently high (Group 1 and Group 7). When the winning bid deviates up and down much, the average actual bid does not much deviate because the winning bid is not credible as an indicator of market value to bidders and bidders can't get much information from the posted prices (Group 2). The pattern is negatively related to the winning bid of the previous round, when the winning bid is not high but the bid tends to deviate up and down (Group 3, Group 4, and Group 6). The negative relationship between the winning bid and the average actual bid means bidders show a negative adjustment (one of bid affiliation effect). In other words, when the winning bid of the previous round increases, bidders are likely to decrease their bid, and when the winning bid of previous round decrease, bidders are likely to increase their bid. When the winning bid deviates not much, the average actual bid also deviates not much because the posted price is informative enough for bidders to decide their WTP (Group 5 and all pooled group).

Summary and Concluding Remark

The repeated Vickrey auction method is now widely used to elicit consumer's WTP because researchers can get more information about WTP with less costs than a one-shot Vickrey auction. However, the bid affiliation effect is always a problem to elicit the true WTP, because the bid affiliation effects change participants' bidding behavior and make a significant difference between the actual bid and the true WTP especially when there are high winning bids.

In this study, an empirical method to separate the bid affiliation effects from the actual bid to elicit true WTP was suggested. To capture the changes of bidding behavior caused by bid affiliation effects, proxy variables such as a function of bidding error (BD^{w}_{t-1}-BD_{it-1}) and trend (t) are used and the unobserved effect Tobit model for panel data is employed. Analyzing the data from the experiment of Corrigan and Rousu's (2006), we concluded that the bid affiliation effect is significant especially when the high winning bid is posted, and the non time-varying, true WTP is estimated using the unobserved effect Tobit model.

One more thing we should remember in using the unobserved effect Tobit model for a repeated Vickrey auction with posted prices is to use a well developed experimental design. A well developed experimental design guarantees to satisfy the three assumptions of the unobserved effect Tobit model. From the data of the well designed experiment, we can decrease the bid affiliation effects and can get a more accurate bid affiliation function (equation (33)) and bid function (equation (34)). Also, when we design the experiment, we should consider in advance what information we need from the participants to estimate the true willingness to pay function (equation (35)).

CHAPTER V

SUMMARY

The effects of an economic event can be evaluated by structural changes, and the structural changes can be estimated by economic parameter changes. Parameter changes over time can be estimated by three ways. First, if the changes are abrupt and instantaneous, dummy variable model can be applied. Second, if structural changes are gradual and smooth, a smooth transition regression model can be used. Third, if we know the proxy variable for the cause of structural changes, the proxy variable can be used to capture the effect of the structural changes.

In Chapter II, it was hypothesized and tested that the BSE outbreak in the U.S. in December 2003 and the subsequent embargo on beef imports by Korea abruptly changed the Korean meat demand structure. An LA/AIDS model with dummy variables was used in this chapter. From the results, it is concluded that the substitutable and complementary characteristics among Korean beef, pork, chicken, and the U.S. beef, and the responsiveness to income had changed because of the BSE 2003. It is inferred that food safety concerns made Korean beef consumption less elastic to budget, and pork and chicken more elastic to budget. Korean beef became less own price elastic, but pork and U.S. beef got more price elastic.

In Chapter III, smooth and gradual structural change was analyzed in regard to the effects of technology development on natural gas production in the United States. Time-varying parameters were estimated to capture the gradual effect of technology change on natural gas supply. A smooth transition regression model with an assumed logistic coefficient function is applied. In addition, the changes in natural gas production caused by depleting reserves are measured by a proxy variable of past cumulative production. The estimation results show that technology development did not cover all of the effects of labor cost increases before 2004, but after that it surpassed the cost increasing effects of labor input. For the capital input, the productivity improvement effect of technology development covered all the cost increasing effects of capital input before 2005, but after that it overwhelmed the effects of capital input cost increase. The supply elasticity of U.S. natural gas for labor showed an increasing pattern from negative to positive, and that for capital showed a decreasing pattern from positive to negative. The supply responsiveness of the U.S. natural gas to the output price is concluded not to be significant and the responsiveness to depletion showed a decreasing pattern from positive to negative.

The effects of posting the winning bid in a repeated Vickrey auction on the bidding behavior were analyzed in Chapter IV. Bidding error (winning bid minus actual bid in the previous round) and trend were used as proxy variables to capture the effects of posting the winning bid. By estimating bid function using an unobserved effects Tobit model, it is concluded that bid affiliation effects are significant when the posted price is high. Also, true willingness to pay for a candy bar auction case done by Corrigan and Rousu was elicited from the estimated bid function by extracting bid affiliation effects.

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APPENDIX A

FIGURES

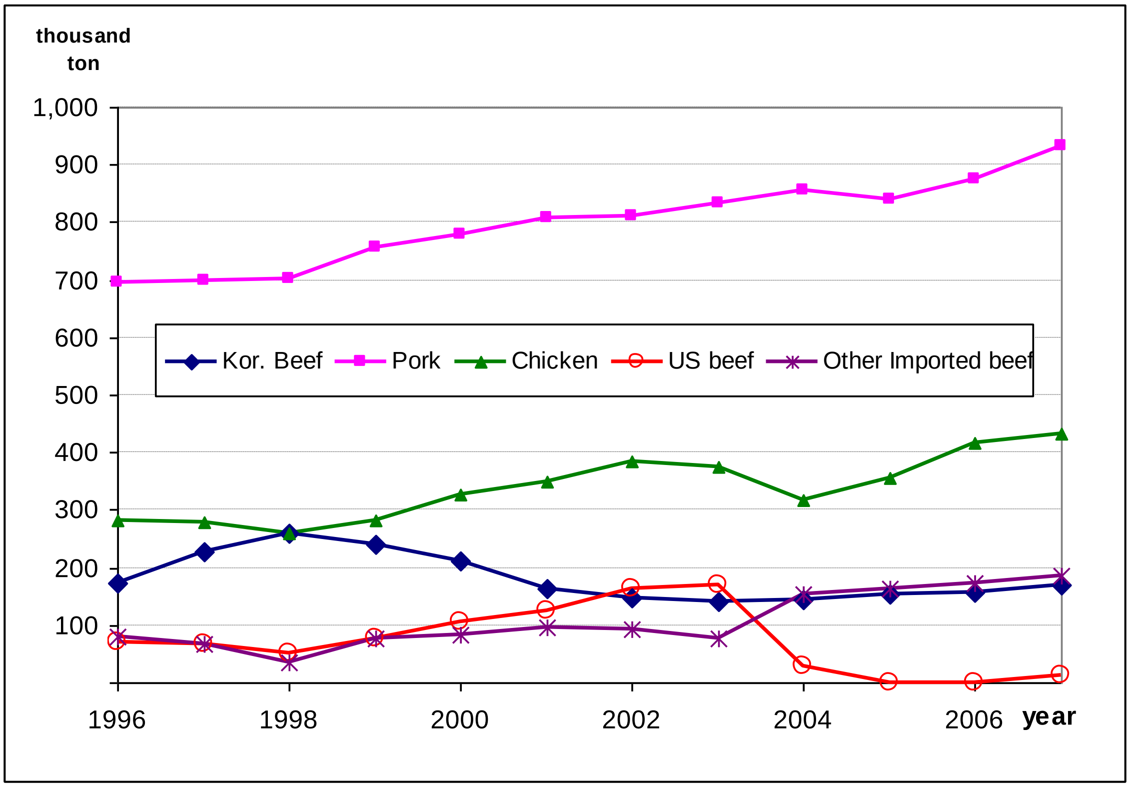


Figure 1. Consumption in Korean meat market

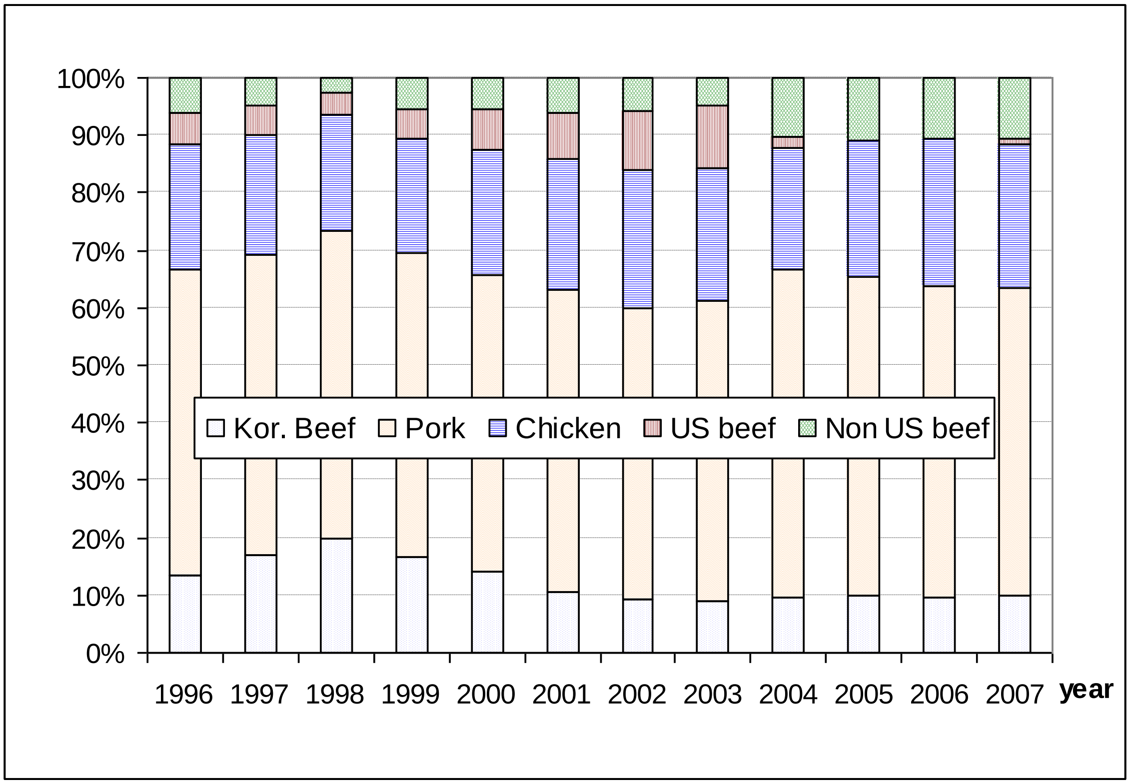


Figure 2. Market shares of Korean meat market

* 45° line means the distribution of error terms is perfect multivariate normal.

Figure 3. Graphical test of multivariate normality

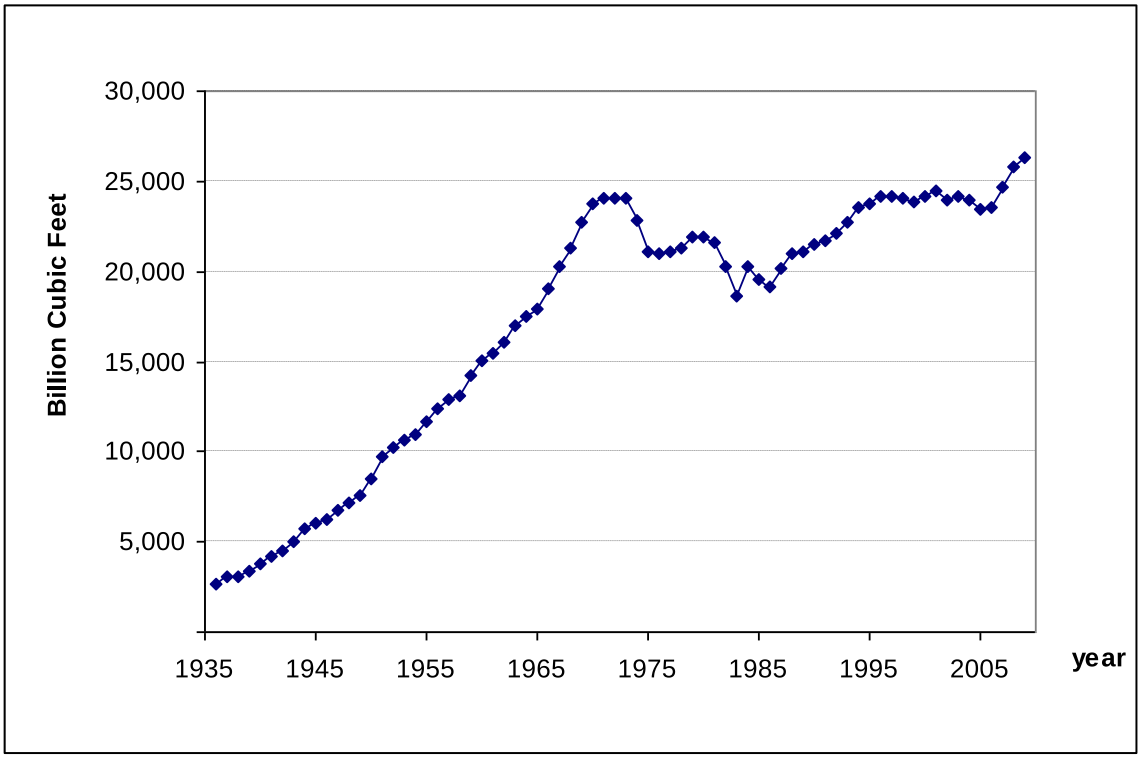
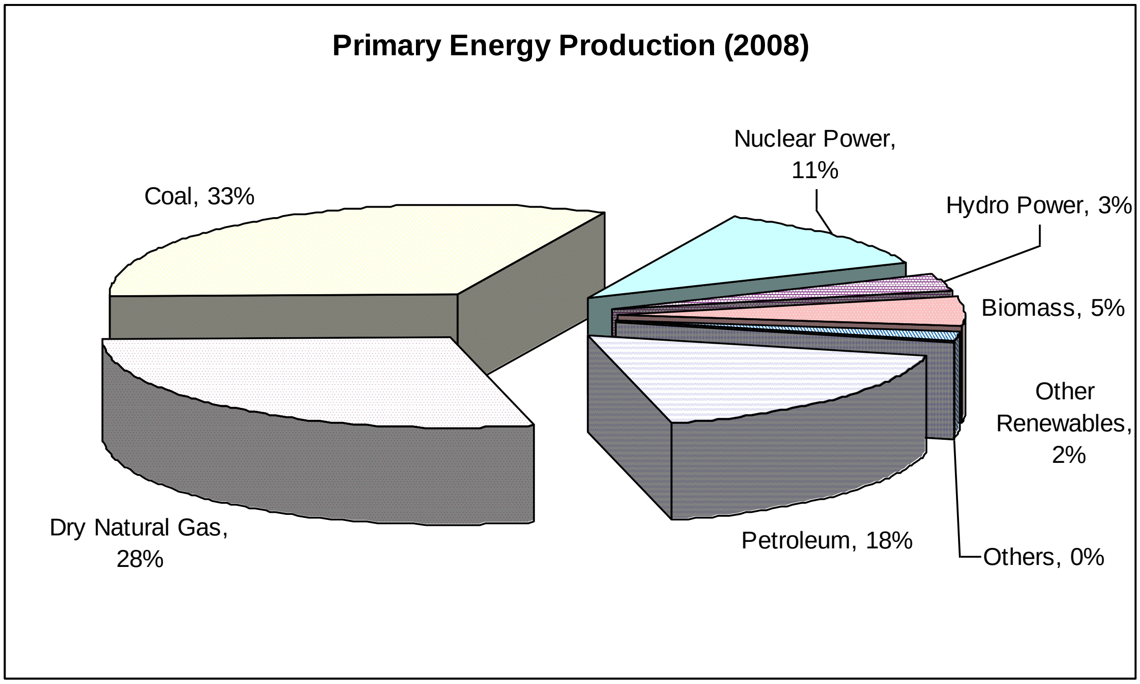


Figure 4. U.S. natural gas gross withdrawals



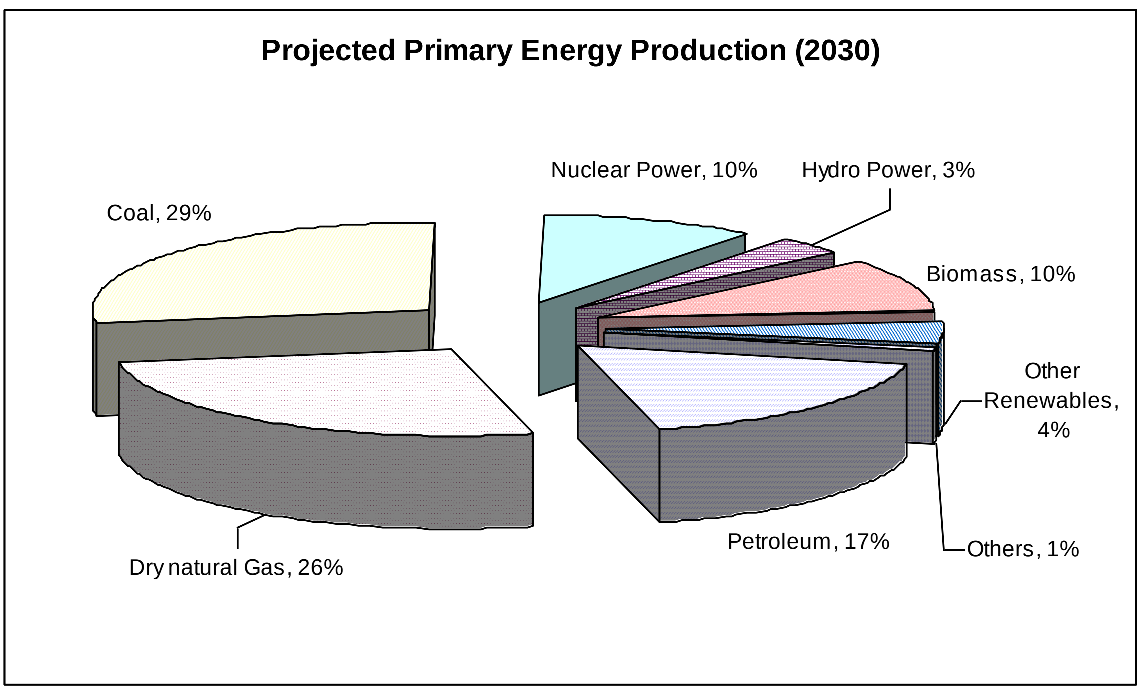


Figure 5. Primary energy production

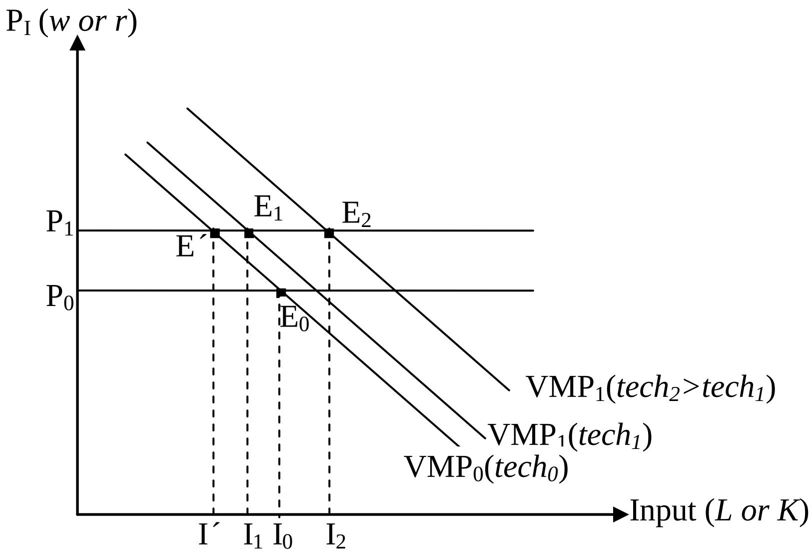


Figure 6. Technology change and input

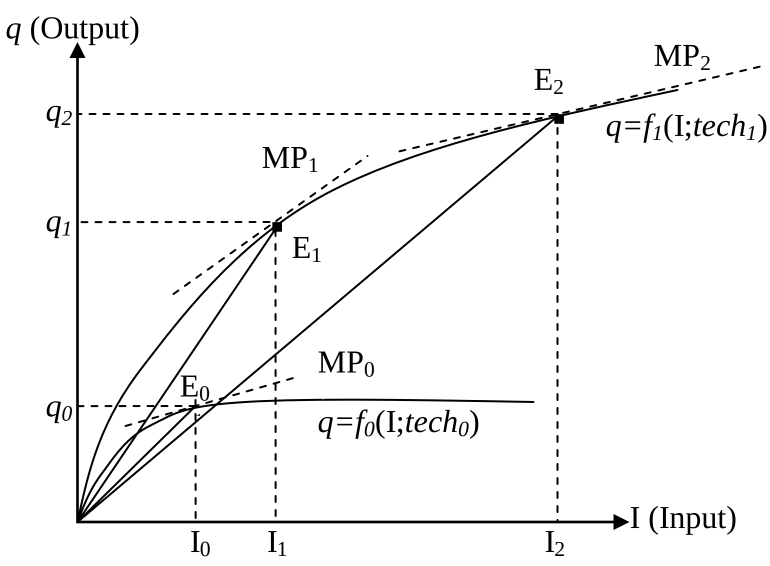


Figure 7. Technology change, average product and marginal product

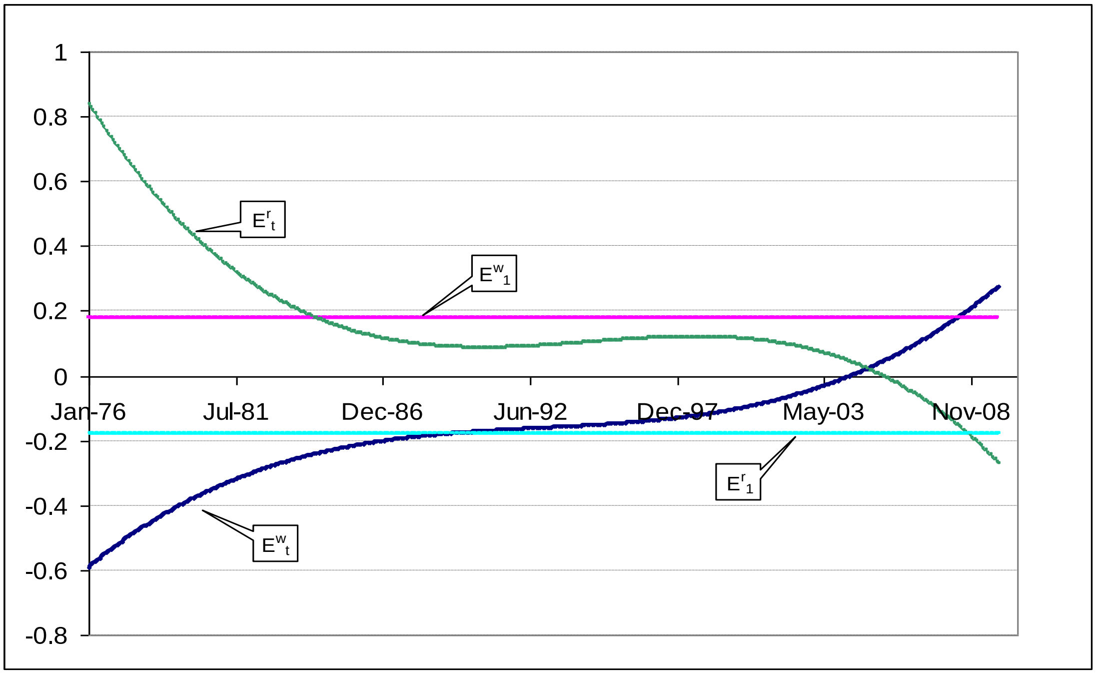


Figure 8. Supply elasticities of U.S. natural gas for labor and capital cost

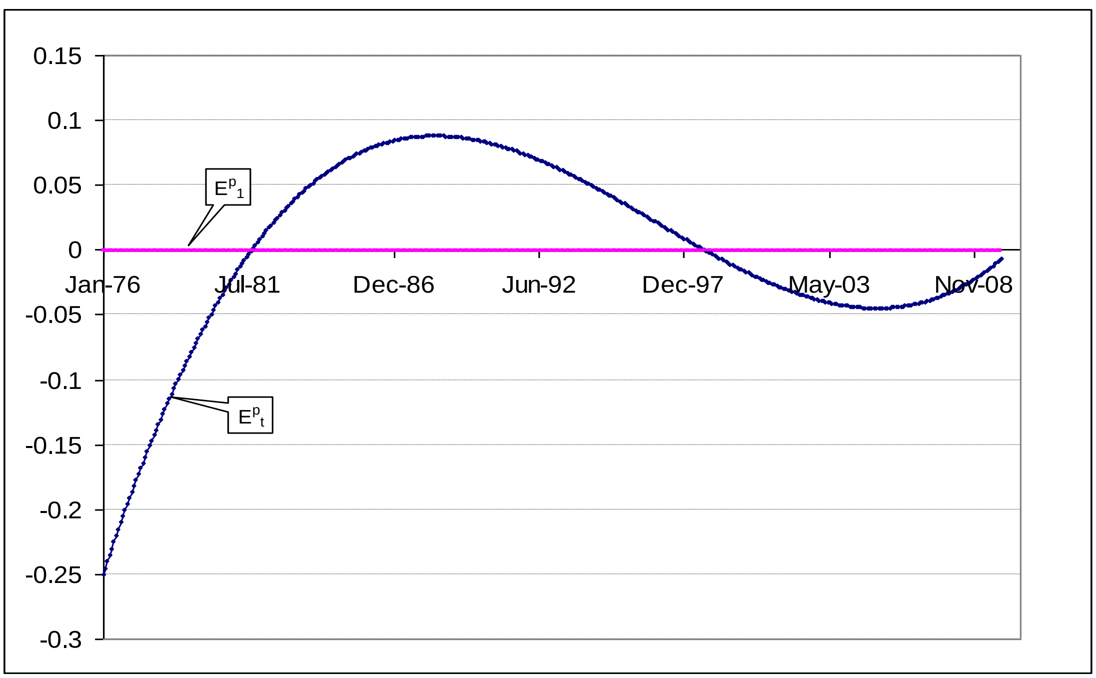


Figure 9. Output price elasticities of U.S. natural gas supply

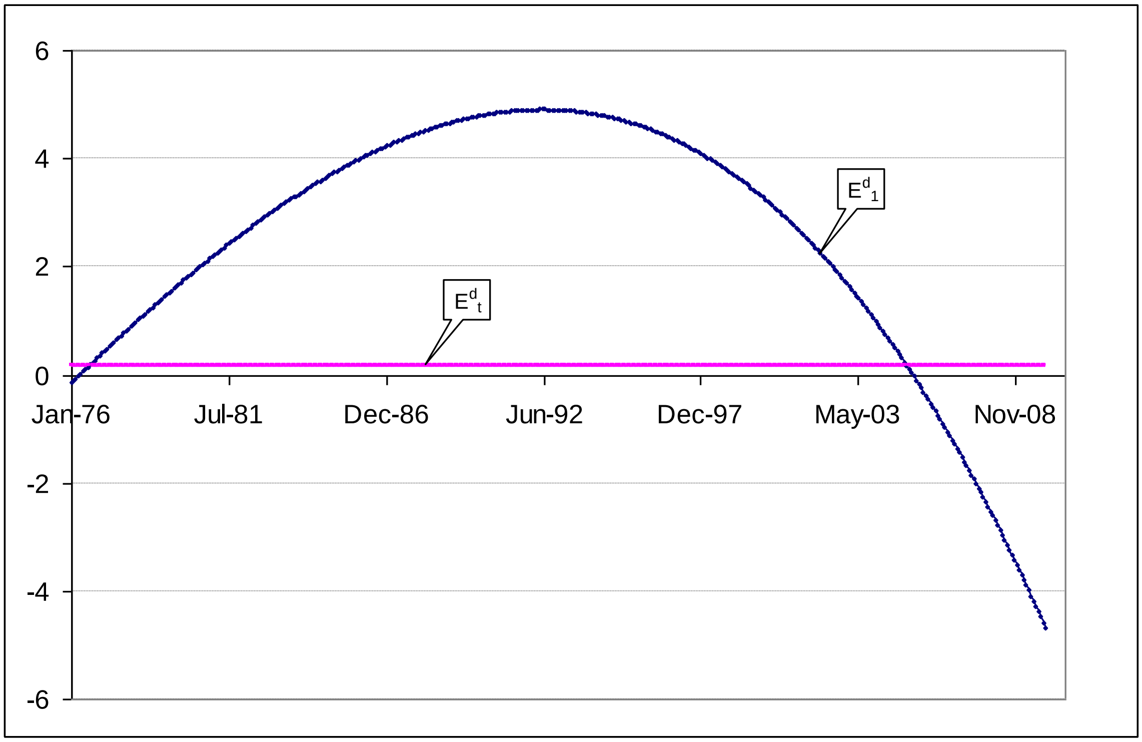


Figure 10. Depletion elasticities of U.S. natural gas supply

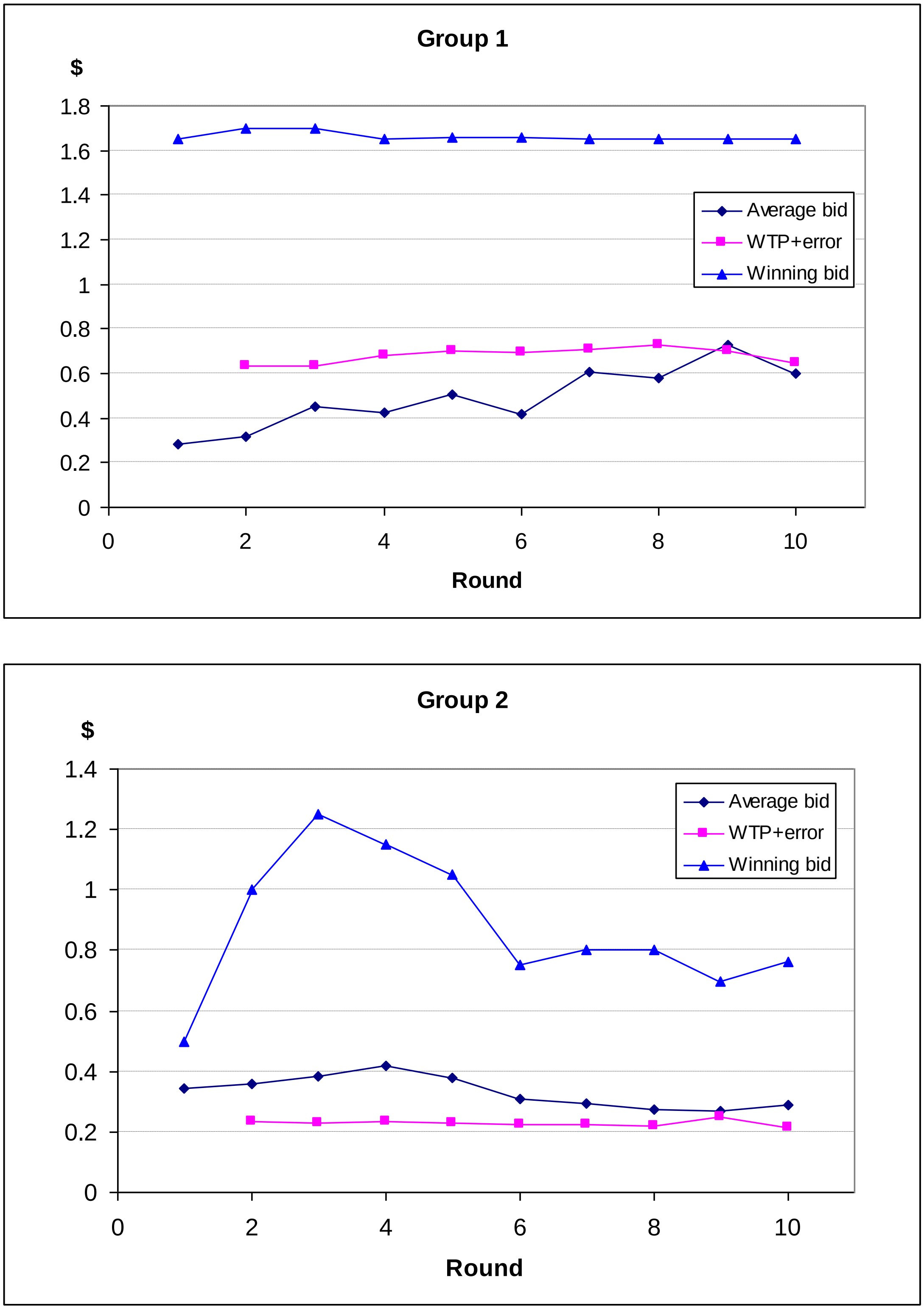
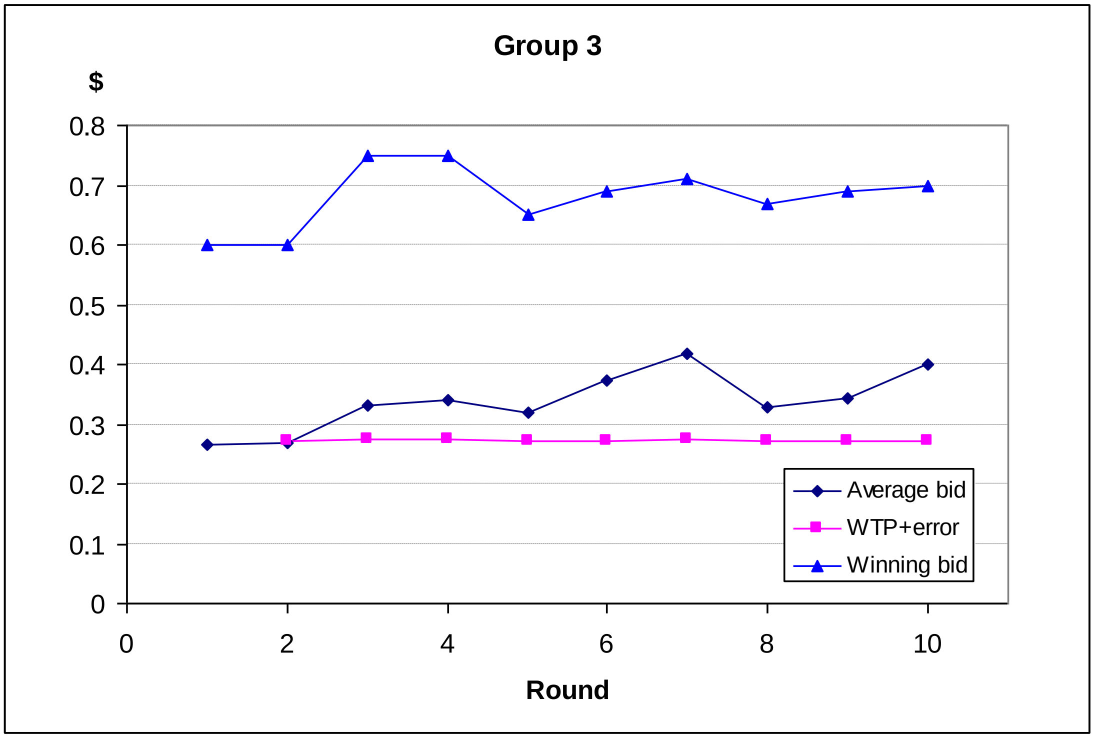


Figure 11. Estimated true willingness to pay



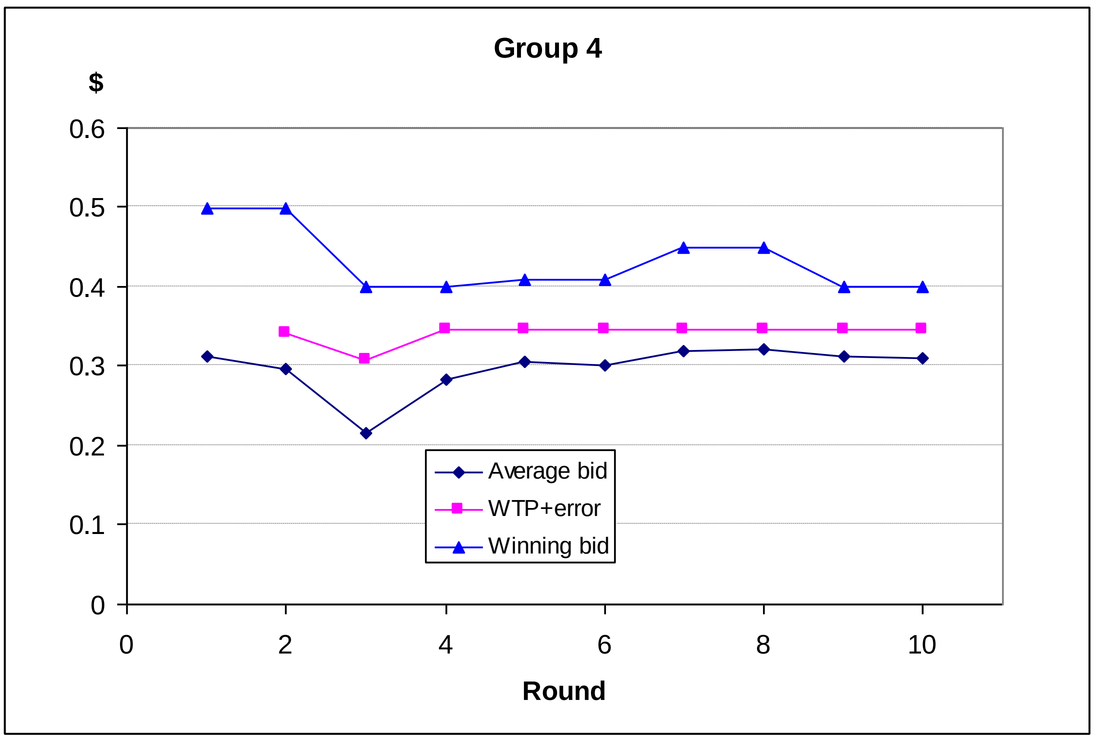
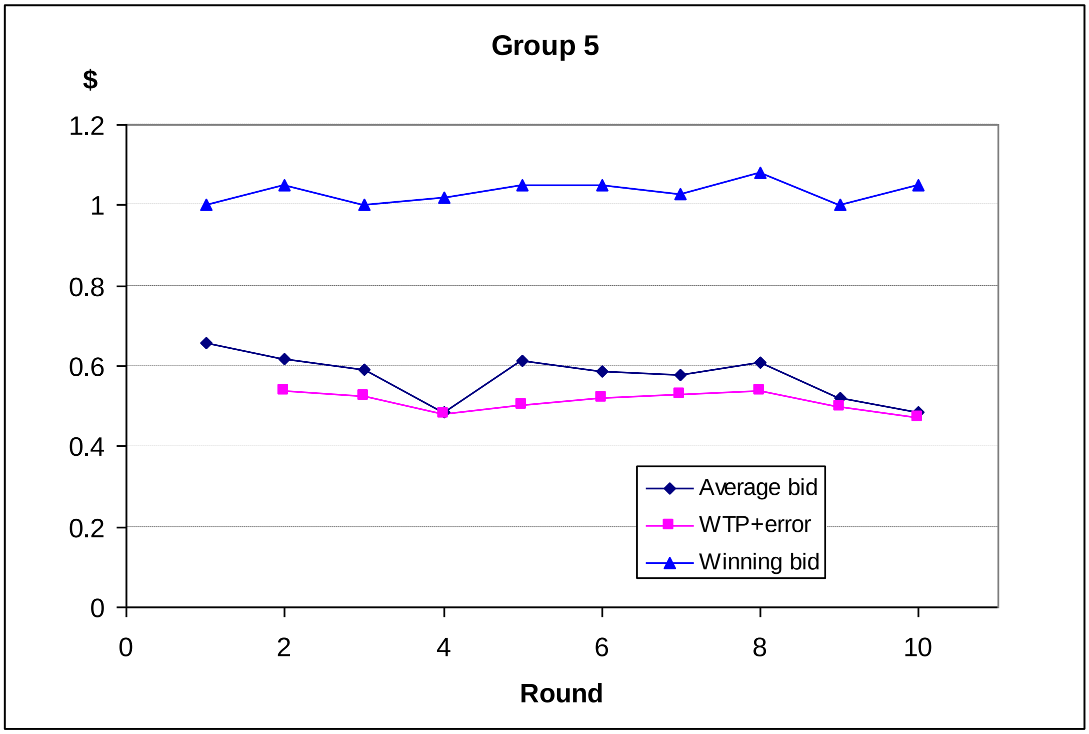


Figure 11. Continued



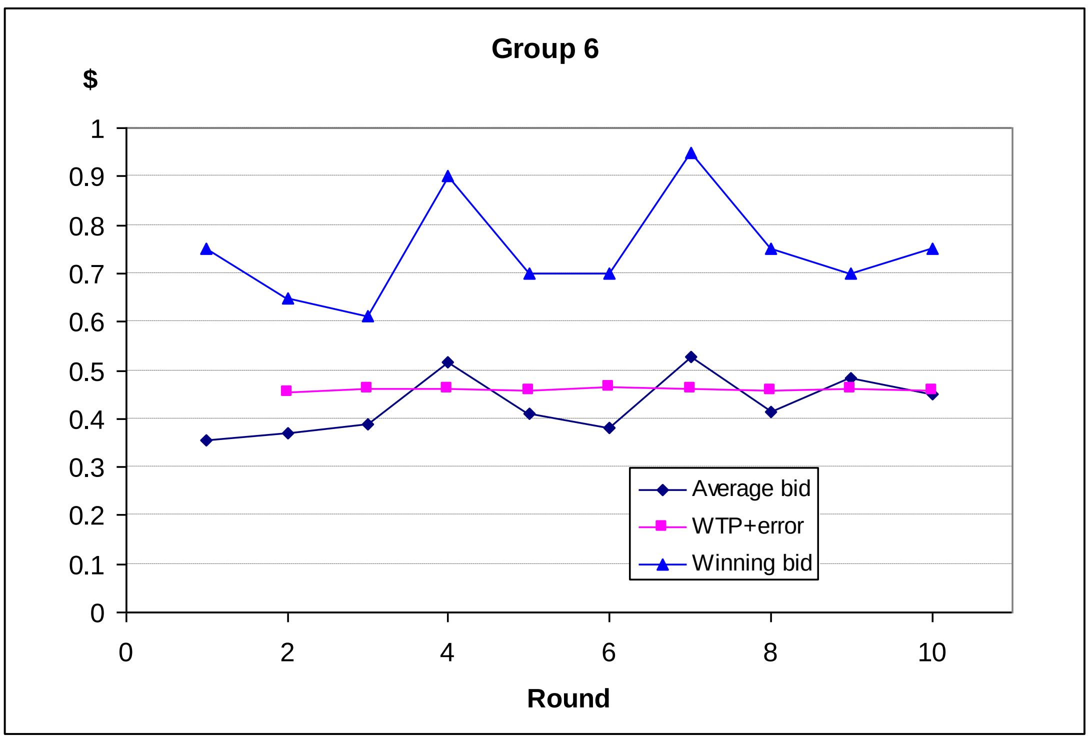
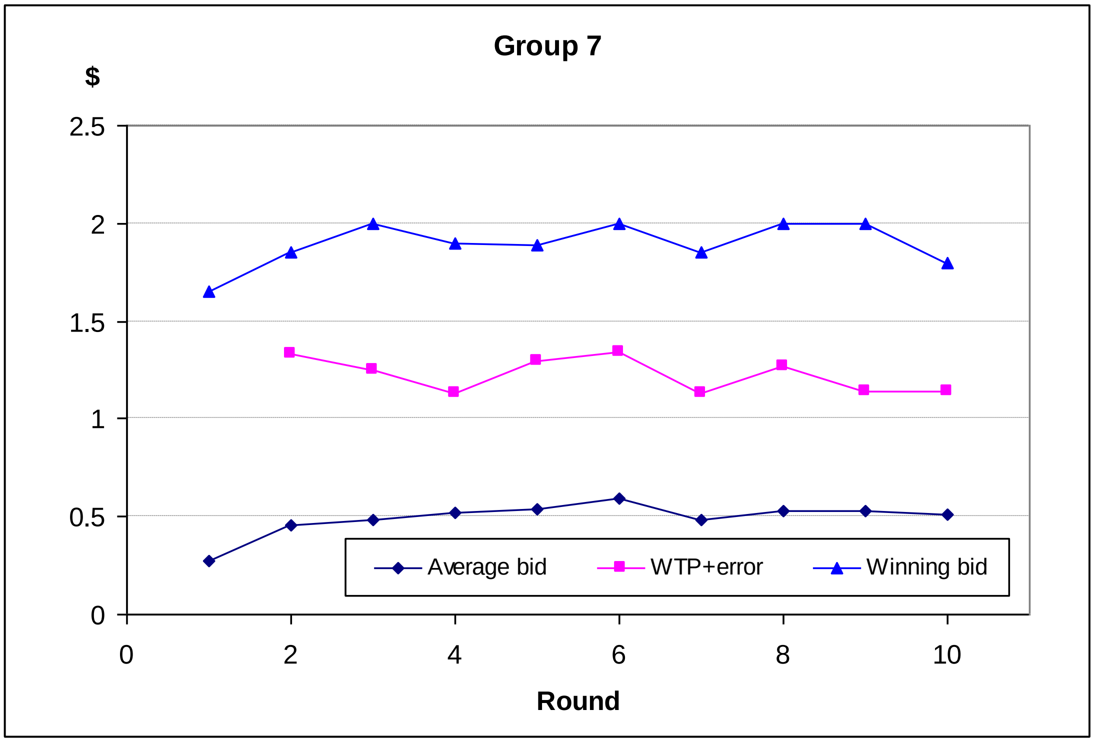


Figure 11. Continued



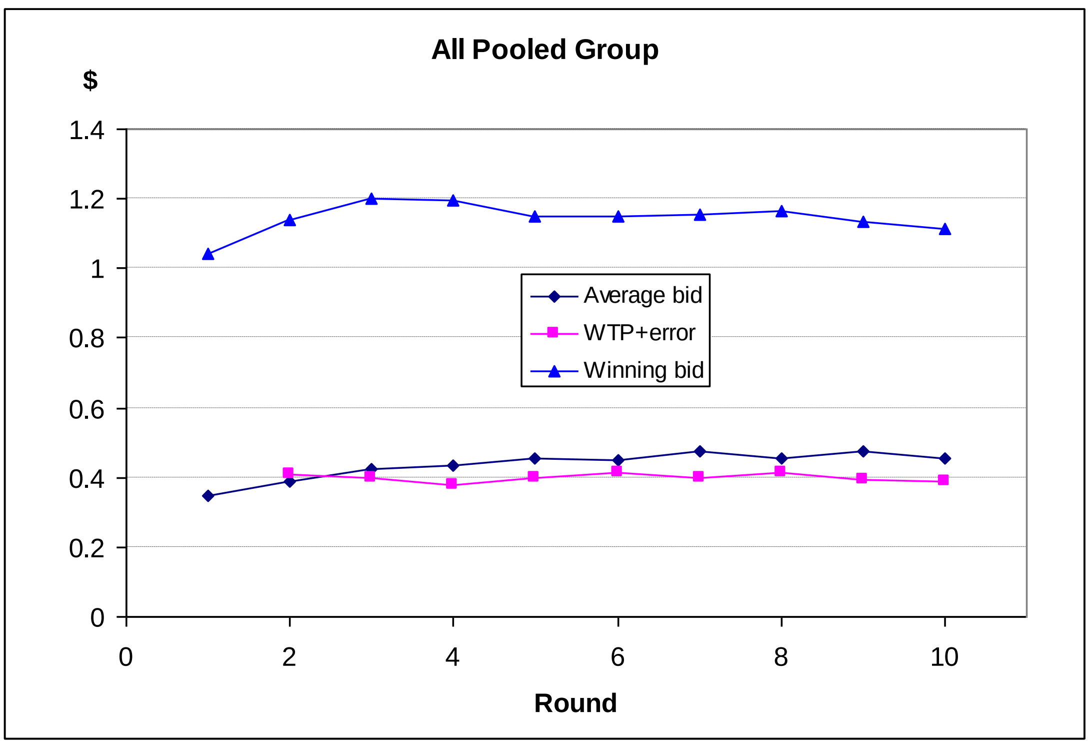


Figure 11. Continued

APPENDIX B

TABLES

Table 1. Test Results of Functional Form

A. Equation by equation test (RESET test, H_0: no omitted variable)

Model A,	***F* (p-value)**	**Model B,**	***F* (p-value)**
Korean beef		**Korean beef**	
Type 1	1.45 (0.2360)	Type 1	1.80 (0.1515)
Type 2	1.77 (0.1591)	Type 2	1.72 (0.1684)
Type 3	1.75 (0.1636)	Type 3	1.73 (0.1655)
Pork		**Pork**	
Type 1	1.74 (0.1646)	Type 1	<u>2.77 (0.0455)</u>
Type 2	1.89 (0.1379)	Type 2	2.14 (0.0992)
Type 3	1.88 (0.1402)	Type 3	2.12 (0.1026)
Chicken		**Chicken**	
Type 1	0.89 (0.4483)	Type 1	0.18 (0.9073)
Type 2	<u>2.81 (0.0450)</u>	Type 2	2.06 (0.1097)
Type 3	<u>2.75 (0.0485)</u>	Type 3	2.03 (0.1140)
U.S. beef			
Type 1	1.01 (0.3919)		
Type 2	1.82 (0.1508)		
Type 3	2.02 (0.1181)		

* Underline means omitted variable bias is suspected at the 5% significance level.

Table 1. Continued

B. Results of joint equation comparison among types

Model A		**Type I**		**Type II**		**Type III**	
		w/ ρDS	**w/o ρDS**	**w/ ρDS**	**w/o ρDS**	**w/ ρDS**	**w/o ρDS**
Equation (10)	H_0: ρ=0	χ^2=43.04 (0.1133)	-	χ^2=44.86 (0.0816)	-	χ^2=47.35 (0.0505)	-
	BIC	-1807.52	-1925.57	-1825.51	-1941.59	-1813.99	-1928.10
Equation (11)	H_0: ρ=0	χ^2=18.63 (0.0680)	-	χ^2=18.57 (0.0692)	-	χ^2=18.06 (0.0802)	-
	BIC	-1797.87	-1913.05	-1783.75	-1898.98	-1770.15	-1886.33

Model B		**Type I**		**Type II**		**Type III**	
		w/ ρDS	**w/o ρDS**	**w/ ρDS**	**w/o ρDS**	**w/ ρDS**	**w/o ρDS**
Equation (10)	H_0: ρ=0	χ^2=14.22 (0.8934)	-	χ^2=18.67 (0.6653)	-	χ^2=18.48 (0.6772)	-
	BIC	-1363.55	-1554.47	-1384.25	-1569.09	-1374.41	-1560.09
Equation (11)	H_0: ρ=0	χ^2=18.73 (0.6617)	-	χ^2=18.17 (0.6956)	-	χ^2=17.97 (0.7078)	-
	BIC	-1368.09	-1545.28	-1358.06	-1535.77	-1348.96	-1526.79

* BIC = $-2lnL + klnN$ (L: maximized log-likelihood, k: number of parameters estimated, N: sample size)

Table 2. Test Results of Normality

A. Equation by equation test (H_0: The error term of each equation follows normal distribution)

	Skew-ness	Kurto-sis	D'Agostino (χ^2)	Shapiro-Wilk(Z)	Shapiro-Francia(Z)
Model A					
Kor. beef	-0.5195	3.7621	7.38 (0.0250)	1.116 (0.1323)	1.427 (0.0767)
Pork	0.4267	3.7746	6.19 (0.0453)	0.928 (0.1768)	1.276 (0.1010)
Chicken	-0.3781	3.6264	2.27 (0.3219)	-0.110 (0.5436)	0.558 (0.2883)
U.S. beef	0.6393	5.3309	14.64 (0.0007)	2.478 (0.0066)	2.701 (0.0035)
Model B					
Kor. beef	-0.3704	3.8041	6.80 (0.0335)	1.566 (0.0586)	1.706 (0.0440)
Pork	0.3875	3.8597	7.30 (0.0260)	1.526 (0.0635)	1.699 (0.0447)
Chicken	-0.0492	4.0731	5.20 (0.0744)	2.494 (0.0063)	2.544 (0.0055)

* The numbers in parenthesis are p-values.
* Underline means the null hypothesis is rejected at the 5% significance level.

B. Joint equation test (H_0: The mean/variance of Mahanalobis distance and calculated χ^2 value are same)

	Model A	**Model B**
Mean (*t*)	-0.05 (0.957)	-0.03 (0.973)
Variance (*F*)	1.55 (0.009)	1.36 (0.029)

* The numbers in parenthesis are p-values.
* Underline means the null hypothesis is rejected at the 5% significance level.

Table 3. Test Results of Endogeneity

A. Weak (under) identification test of instrumental variables

Shea's Partial R^2 (from auxiliary regression of potential endogenous variables)				**Kleibergen-Paap LM (χ^2)** (H_0: Under identified)
Model A		**Model B**		
$ln(P_{Korean\ beef})$	0.8697	$ln(P_{Korean\ beef})$	0.7950	**Model A** (p-value)
$ln(P_{pork})$	0.9143	$ln(P_{pork})$	0.8732	30.242 (0.0015)
$ln(P_{chicken})$	0.7353	$ln(P_{chicken})$	0.6242	
$ln(P_{US\ beef})$	0.6989	$ln(X/P^*)$	0.8808	**Model B** (p-value)
$ln(X/P^*)$	0.9017			37.989 (0.0000)

B. Hansen's Over identification test of instrumental variables (H_0: IVs are independent of error term)

Model A	**Hansen's J** (p-value)	**Model B**	**Hansen's J** (p-value)
Korean beef	6.553 (0.7668)	Korean beef	6.871 (0.6506)
Pork	6.430 (0.7780)	Pork	6.865 (0.6511)
Chicken	6.632 (0.7597)	Chicken	7.249 (0.6112)
U.S. beef	6.781 (0.7459)		

C. Durbin-Wu-Hausman test of endogeneity (H_0: IVs are exogenous)

Model A	χ^2 (p-value)	**Model B**	χ^2 (p-value)
Korean beef	0.098 (0.9998)	Korean beef	0.089 (0.9990)
Pork	0.004 (1.0000)	Pork	0.079 (0.9992)
Chicken	0.031 (1.0000)	Chicken	0.070 (0.9994)
U.S. beef	0.164 (0.9995)		

Table 4. Test Results of Homoskedasticity and Independence

A. Equation by Equation test

	Breuch-Pagan χ^2 (p-value) (H_0: constant variance)	**ARCH LM χ^2 (p-value) (H_0: no ARCH)**	**Breusch-Godfrey χ^2 (p-value) (H_0: no autocorrelation)**	**Ljung-Box Q χ^2 (p-value) (H_0: white noise)**
Model A				
Kor. beef	6.10 (0.0135)	2.891 (0.0891)	5.798 (0.0160)	64.962 (0.0075)
Pork	3.67 (0.0554)	11.337 (0.0008)	2.234 (0.1350)	39.918 (0.4739)
Chicken	7.93 (0.0049)	2.340 (0.1261)	14.434 (0.0001)	53.794 (0.0713)
U.S. beef	7.38 (0.0066)	0.154 (0.6943)	5.952 (0.0147)	23.312 (0.9837)
Model B				
Kor. beef	18.13 (0.0000)	15.752 (0.0001)	5.005 (0.0253)	86.438 (0.0000)
Pork	10.97 (0.0009)	12.573 (0.0004)	3.454 (0.0631)	69.576 (0.0026)
Chicken	32.96 (0.0000)	18.993 (0.0000)	31.711 (0.0000)	131.61 (0.0000)

* Underline means the rejection of null hypothesis at the 5% significance level.

B. Joint equation test (Multivariate Ljung-Box Q test, H_0: white noise)

Model A: χ^2 (p-value)	**Model B: χ^2 (p-value)**
516.1696 (0.9999)	326.3972 (0.8977)

Table 5. Wald Test Results of Homogeneity and Symmetry

	H_0: Homogeneity (χ^2)	**H_0: Symmetry (χ^2)**
Model A	39.02 (0.0000)	109.61 (0.0000)
Model B	39.72 (0.0000)	124.72 (0.0000)

* The numbers in parenthesis are p-values.

Table 6. Summary Statistics of Expenditure Share for Each Korean Meat

	Mean	Standard Deviation	Min.	Max.
Model A				
Korean beef	0.3281611	0.0784879	0.1681645	0.5067226
Pork	0.5508403	0.0886962	0.3668760	0.7688179
Chicken	0.0893455	0.0228878	0.0471182	0.1576779
U.S. beef	0.0316532	0.0155512	0.0000022	0.0822078
Sum	1			
Model B				
Korean beef	0.3238172	0.0802179	0.1681653	0.5321102
Pork	0.5894983	0.0867627	0.3852371	0.7698209
Chicken	0.0866846	0.0243384	0.0393559	0.1633450
Sum	1			

Table 7. Non-linear Wald Test Results of Separability for Korean Meat Demand

H_0	χ^2	p-value
Model A		
Korean beef can be aggregated with others	21269.17	0.0000
Pork can be aggregated with others	71201.94	0.0000
Chicken can be aggregated with others	72793.64	0.0000
U.S. beef can be aggregated with others	8917.75	0.0000
Meat group is separable	62985.78	0.0000
Model B		
Korean beef can be aggregated with others	6350.14	0.0000
Pork can be aggregated with others	3112.52	0.0000
Chicken can be aggregated with others	6740.76	0.0000
Meat group is separable	9781.58	0.0000

Table 8. Estimated Model Evaluation of Korean Meat Demand

	# of obs	RMSE	R^2	χ^2 (p-value)	BIC
Model A					
Kor. beef	116	0.0305379	0.8437	643.7 (0.0000)	
Pork	116	0.0285483	0.8955	994.4 (0.0000)	-1941.593
Chicken	116	0.0061336	0.9276	1485.3 (0.0000)	
U.S. beef	116	0.0057217	0.8632	731.9 (0.0000)	
Model B					
Kor. beef	156	0.0328122	0.8316	770.4 (0.0000)	-1569.086
Pork	156	0.0288459	0.8888	1246.3 (0.0000)	
Chicken	156	0.0065527	0.9270	1982.4 (0.0000)	

* BIC = $-2lnL + klnN$ (L: maximized log-likelihood, k: number of parameters estimated, N: sample size)

Table 9. Model Estimation Results for Korean Meat Demand

A. Model A

i	Kor. beef	Pork	Chicken	U.S. beef
α_i	1.0472490	0.3523931	0.4900749**	-0.8897163***
δ_{2i}	-0.8465808	0.7887561	-0.4810409	0.5388663
δ_{3i}	-0.0274064***	0.0139311*	0.0087498***	0.0047255***
$\gamma_{i,kor}$	0.0177420	-0.0563418***	0.0105842**	0.0280157***
$\gamma_{i,pork}$	-0.2184505***	0.2681400***	-0.0360316***	-0.0136579**
$\gamma_{i,chk}$	-0.1044988**	0.0218927	0.0911540***	-0.0085480
$\gamma_{i,usb}$	0.0561442***	-0.0544046***	-0.0199214***	0.0181818***
$\varnothing_{2i,kor}$	0.0883516	-0.0325575	0.0108232	-0.0666174*
$\varnothing_{2i,pork}$	0.0675684	-0.0763873	-0.0324237	0.0412426*
$\varnothing_{2i,chkk}$	0.1638852	-0.2088813*	-0.0245436	0.0695397***
$\varnothing_{2i,usb}$	-0.0646244*	0.0719658**	0.0151384**	-0.0224798***
β_i	0.0812664	-0.0774265	-0.0417998***	0.0379589***
τ_{2i}	-0.0785835	0.0736939	0.0407024***	-0.0358127***
θ_{i2}	-0.0401499**	0.0437011***	-0.0000700	-0.0036211
θ_{i3}	-0.0800347***	0.0830582***	0.0083785***	-0.0114020***
θ_{i4}	-0.0724747***	0.0699389***	0.0137181***	-0.0111823***
θ_{i5}	-0.0563995***	0.0370905***	0.0279005***	-0.0085915***
θ_{i6}	-0.0568842***	0.0224763	0.0413816***	-0.0069738**
θ_{i7}	-0.0702580***	0.0202505	0.0606558***	-0.0106483***
θ_{i8}	-0.0450274***	0.0217531	0.0330829***	-0.0098086***
θ_{i9}	0.0134122	-0.0193608	0.0080313***	-0.0020827
θ_{i10}	-0.0999039***	0.0987087***	0.0139306***	-0.0127354***
θ_{i11}	-0.0825826***	0.0858749***	0.0097282***	-0.0130206***
θ_{i12}	-0.0622835***	0.0623865***	0.0128424***	-0.0129455***

* Model A: See Equation (15) on page 14. D_{1t} is zero for Model A.

*, **, *** means the estimate is significant at the 10%, 5%, 1% level respectively.

Table 9. Continued

B. Model B

i	Kor. beef	Pork	Chicken
α_i	1.6418980	-1.0402110	0.3983126*
δ_{1i}	-4.5113260**	5.3912830***	-0.87995836**
δ_{2i}	-1.2288080	1.4630500	-0.2342410
δ_{3i}	-0.0232718**	0.0139190*	0.0093528***
$\gamma_{i,kor}$	0.0323894	-0.0405443*	0.0081549
$\gamma_{i,pork}$	-0.2070550***	0.2482374***	-0.0411824***
$\gamma_{i,chk}$	-0.0649958	-0.0162156	0.0812114***
$\varnothing_{1i,kor}$	0.1965634*	-0.1758636*	-0.0206998
$\varnothing_{1i,pork}$	-0.0734495	0.0095764	0.0638730***
$\varnothing_{1i,chkk}$	0.2021180***	-0.1337605*	-0.0683575***
$\varnothing_{2i,kor}$	0.0388415	-0.0303126	-0.0085291
$\varnothing_{2i,pork}$	0.0154812	0.0200907	-0.0355719*
$\varnothing_{2i,chkk}$	0.1803556	-0.1780101*	-0.0023455
β_i	0.0450606	-0.0073771	-0.0376835***
τ_{1i}	0.0845448	-0.1408896	0.0563449***
τ_{2i}	-0.0416242	0.0047195	0.0369047***
θ_{i2}	-0.0589710***	0.0550871***	0.0038839
θ_{i3}	-0.1034252***	0.0931296***	0.0102956***
θ_{i4}	-0.0861582***	0.0711678***	0.0149904***
θ_{i5}	-0.0703978***	0.0407963***	0.0296015***
θ_{i6}	-0.0659184***	0.0242767*	0.0416418***
θ_{i7}	-0.0806626***	0.0181767	0.0624858***
θ_{i8}	-0.0595505***	0.0255376**	0.0340129***
θ_{i9}	0.0132430	-0.0218182*	0.0085752***
θ_{i10}	-0.1097711***	0.0952493***	0.0145218***
θ_{i11}	-0.0933860***	0.0833277***	0.0100583***
θ_{i12}	-0.0649988***	0.0532024***	0.0117964***

* Model: See Equation (15) on page 14.

*, **, *** means the estimate is significant at the 10%, 5%, 1% level respectively.

Table 10. Test Results of BSE Effects on the Korean Meat Market

Null hypothesis (for all *i, j*)	**χ^2 (p-value)**	**Result (5% significance level)**
Model A		
H_0: $\delta_{2i}= 0$	4.30 (0.2306)	Accepted
H_0: $\phi_{2ij} = 0$	63.78 (0.0000)	Rejected
H_0: $\tau_{2i}= 0$	24.47 (0.0000)	Rejected
H_0: All of the above	338.29 (0.0000)	Rejected
Model B		
H_0: $\delta_{1i} = 0$	26.49 (0.0000)	Rejected
H_0: $\delta_{2i} = 0$	1.23 (0.5399)	Accepted
H_0: $\phi_{1ij} = 0$	48.41 (0.0000)	Rejected
H_0: $\phi_{2ij} = 0$	11.25 (0.0809)	Accepted
H_0: $\tau_{1i} = 0$	19.04 (0.0001)	Rejected
H_0: $\tau_{2i} = 0$	12.06 (0.0024)	Rejected
H_0: $\delta_{1i} = \phi_{1ij} = \tau_{1i} =0$	119.73 (0.0000)	Rejected
H_0: $\delta_{2i} = \phi_{2ij} = \tau_{2i} =0$	20.64 (0.0238)	Rejected
H_0: All of the above	138.18 (0.0000)	Rejected

Table 11. Estimated Korean Meat Demand Elasticities

i	Marshallian Price Elasticities of Demand(ε_{ij})				Expenditure Elasticity(η_i)
Model A	*j*: Kor. beef	Pork	Chicken	U.S. beef	
D_1=D_2=0 (-2003.12)					
Kor. beef	-1.02720160	-0.80209195	-0.34056304	0.16324859	1.24764190
	(0.0000)	(0.0000)	(0.0075)	(0.0041)	(0.0000)
Pork	-0.05615737	-0.43579087	0.05230254	-0.09431734	0.85944094
	(0.1216)	(0.0000)	(0.4612)	(0.0029)	(0.0000)
Chicken	0.27199182	-0.14557591	0.06204153	-0.20816137	0.53215561
	(0.0000)	(0.2667)	(0.5094)	(0.0000)	(0.0001)
U.S. beef	0.49154647	-1.09205880	-0.37719464	-0.46355386	2.19921260
	(0.0001)	(0.0016)	(0.1280)	(0.0000)	(0.0000)
D_1=0,D_2=1(2007.4-)					
Kor. beef	-0.67938555	-0.46428415	0.18023677	-0.02610037	1.00817550
	(0.2761)	(0.2201)	(0.6497)	(0.8007)	(0.0000)
Pork	-0.15916540	-0.64815896	-0.33885525	0.03209531	0.99322552
	(0.6468)	(0.0021)	(0.1252)	(0.5772)	(0.0000)
chicken	0.24363271	-0.75942037	-0.25336563	-0.05314479	0.87717092
	(0.5965)	(0.0065)	(0.3868)	(0.4860)	(0.0000)
U.S. beef	-1.24177160	0.83411985	1.92081700	-1.13793310	1.06780300
	(0.3059)	(0.2571)	(0.0128)	(0.0000)	(0.0000)
Model B	*j*: Kor. beef	Pork	Chicken		
D_1=D_2=0 (-2003.12)					
Kor. beef	-0.94503692	-0.72145064	-0.21278008		1.13915450
	(0.0000)	(0.0002)	(0.1089)		(0.0000)
Pork	-0.06472541	-0.57152355	-0.02642272		0.98748589
	(0.0412)	(0.0000)	(0.6802)		(0.0000)
Chicken	0.23484581	-0.21881633	-0.02545559		0.56527992
	(0.0000)	(0.1270)	(0.7971)		(0.0001)
D_1=1,D_2=0(-2007.3)					
Kor. beef	-0.42256202	-1.10218560	0.38876088		1.40024240
	(0.1387)	(0.0064)	(0.0686)		(0.0000)
Pork	-0.28566091	-0.41438902	-0.23261086		0.74848667
	(0.0382)	(0.0337)	(0.0240)		(0.0000)
Chicken	-0.214429354	0.13485407	-0.87037727		1.21527940
	(0.3138)	(0.6547)	(0.0000)		(0.0000)
D_1=0,D_2=1(2007.4-)					
Kor. beef	-0.78346371	-0.59786678	0.35533003		1.01061210
	(0.1752)	(0.0322)	(0.2630)		(0.0000)
Pork	-0.11873886	-0.54216211	-0.32908554		0.99549189
	(0.6705)	(0.0001)	(0.0318)		(0.0000)
Chicken	-0.00140638	-0.88014623	-0.08941862		0.99101502
	(0.9974)	(0.0000)	(0.7057)		(0.0000)

* The numbers in parenthesis are p-values.

Table 12. Estimated Model evaluation

	R^2	RMSE	BIC	
Model 1	0.4217	0.0567800	-1095.166	* Non time-varying * OLS
Model 2	0.6509	0.0450476	-1277.018	* Linearly time-varying * NLS
Model 3	0.7893	0.0351298	-1459.046	* 2nd order time-varying * NLS
Model 4	0.8342	0.0312004	-1544.876	* 3rd order time-varying * NLS

* BIC = $-2\ln L + k\ln N$ (*L*: maximized log-likelihood, *k*: number of parameters estimated, *N*: sample size)

Table 13. Estimation Results of Model 1 and Model 4

	Model 1		Model 4
a	16.5962 (0.000)	a_0	17.414330000 (0.144)
		a_1	0.700864000 (0.000)
		a_2	-0.000021500 (0.972)
		a_3	-0.000005600 (0.001)
b	0.1809 (0.000)	b_0	-0.594947900 (0.000)
		b_1	0.005711800 (0.032)
		b_2	-0.000026300 (0.054)
		b_3	0.000000043 (0.039)
c	-0.1797 (0.000)	c_0	0.850802100 (0.000)
		c_1	-0.011020800 (0.000)
		c_2	0.000051400 (0.000)
		c_3	-0.000000076 (0.000)
d=-b-c	-0.0012 (0.872)		
e	0.1839 (0.000)	e_0	-0.193611500 (0.769)
		e_1	0.043158400 (0.000)
		e_2	-0.000045400 (0.200)
		e_3	-0.000000214 (0.008)
m_2	-0.0948 (0.000)	m_2	-0.0930 (0.000)
m_3	-0.0151 (0.210)	m_3	-0.0180 (0.034)
m_4	-0.0623 (0.000)	m_4	-0.0643 (0.000)
m_5	-0.0404 (0.002)	m_5	-0.0471 (0.000)
m_6	-0.0760 (0.000)	m_6	-0.0807 (0.000)
m_7	-0.0583 (0.000)	m_7	-0.0574 (0.000)
m_8	-0.0515 (0.000)	m_8	-0.0642 (0.000)
m_9	-0.1006 (0.000)	m_9	-0.1084 (0.000)
m_{10}	-0.0499 (0.000)	m_{10}	-0.0644 (0.000)
m_{11}	-0.0554 (0.000)	m_{11}	-0.0698 (0.000)
m_{12}	-0.0091 (0.420)	m_{12}	-0.0195 (0.038)

* Model 1, Model 4: See Equation (31) on page 42.

* The numbers in parenthesis are p-values.

Table 14. Various Changes in Inputs of U.S. Natural Gas Production (1987-2009)

Year	Average Product of Labor Index in Oil and Gas Extraction Industry (2000=100)	Average Product of Capital Index in Petroleum and Coal Production Industry (2000=100)	Number of Employees in Oil and Gas Extraction Industry (Thousand)	Number of Gas and Gas Condensate Wells	Number of Crude Oil and Natural Gas Rotary Rigs
1976			156.5		1,658
1977			165.0		2,001
1978			177.0		2,259
1979			192.0		2,177
1980			218.6		2,909
1981			253.1		3,970
1982			264.5		3,105
1983			255.6		2,232
1984			251.9		2,428
1985			244.7		1,980
1986			216.6		964
1987	67.071	89.325	198.0		936
1988	67.664	91.738	194.5		936
1989	63.743	92.583	191.0	262,483	869
1990	63.380	93.288	190.2	269,790	1,010
1991	65.374	92.110	191.0	276,987	860
1992	68.278	92.811	182.2	267,014	721
1993	70.953	94.397	170.9	282,152	754
1994	73.267	93.321	162.4	291,773	775
1995	79.764	92.437	151.7	298,541	723
1996	82.101	92.010	146.9	301,811	779
1997	83.761	94.460	144.1	310,971	943
1998	84.744	97.168	140.8	316,929	827
1999	90.366	97.089	131.2	302,421	625
2000	100.000	100.000	124.9	341,678	918
2001	101.830	98.295	123.7	373,304	1,156
2002	103.671	97.642	121.9	387,772	830
2003	108.944	98.443	120.2	393,327	1,032
2004	93.520	101.674	123.4	406,147	1,192
2005	90.268	99.753	125.7	425,887	1,381
2006	84.023	96.884	134.5	440,516	1,649
2007	81.212	94.818	146.2	452,945	1,768
2008	-	-	160.5	478,562	1,879
2009	-	-	161.6	-	1,089

Table 15. Characteristics of the Seven Groups

	Participants	Number of Participants	Treatment
Group 1	Kenyon Univ. Students	16	Confederate Bidders
Group 2	Kenyon Univ. Students	10	No treatment
Group 3	Kenyon Univ. Students	19	No treatment
Group 4	OSU Students	9	No treatment
Group 5	OSU Students	15	No treatment
Group 6	NC State Univ. Students	11	No treatment
Group 7	NC State Univ. Students	21	Confederate Bidders

Table 16. Average Bid Including Zero Bid and Excluding Zero Bid

Round	1	2	3	4	5	6	7	8	9	10
Group 1										
Ave. bid	0.281	0.314	0.453	0.425	0.508	0.420	0.605	0.578	0.726	0.602
zero bid (%)	25%	19%	13%	13%	19%	19%	13%	13%	19%	25%
Ave.non-zero	0.375	0.387	0.517	0.486	0.625	0.517	0.691	0.661	0.894	0.802
Group 2										
Ave. bid	0.345	0.361	0.385	0.420	0.381	0.310	0.295	0.276	0.271	0.291
zero bid (%)	50%	50%	50%	40%	40%	50%	50%	50%	40%	50%
Ave. non-zero	0.690	0.722	0.770	0.700	0.635	0.620	0.590	0.552	0.452	0.582
Group 3										
Ave. bid	0.267	0.268	0.333	0.339	0.320	0.374	0.419	0.327	0.344	0.399
zero bid (%)	21%	21%	11%	11%	16%	16%	11%	21%	21%	21%
Ave. non-zero	0.338	0.340	0.372	0.379	0.379	0.444	0.468	0.415	0.436	0.505
Group 4										
Ave. bid	0.312	0.296	0.216	0.282	0.306	0.301	0.320	0.321	0.312	0.311
zero bid (%)	22%	0%	11%	0%	0%	0%	0%	0%	0%	0%
Ave. non-zero	0.401	0.296	0.243	0.282	0.306	0.301	0.320	0.321	0.312	0.311
Group 5										
Ave. bid	0.657	0.619	0.590	0.487	0.611	0.586	0.576	0.609	0.522	0.486
zero bid (%)	7%	7%	7%	20%	13%	13%	7%	7%	13%	20%
Ave. non-zero	0.704	0.663	0.632	0.608	0.706	0.676	0.617	0.653	0.602	0.608
Group 6										
Ave. bid	0.356	0.369	0.389	0.517	0.410	0.381	0.529	0.415	0.484	0.450
zero bid (%)	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%
Ave. non-zero	0.436	0.451	0.476	0.632	0.501	0.466	0.647	0.507	0.507	0.550
Group 7										
Ave. bid	0.271	0.452	0.483	0.518	0.542	0.598	0.483	0.533	0.533	0.510
zero bid (%)	24%	24%	19%	19%	19%	19%	24%	24%	24%	24%
Ave. non-zero	0.356	0.594	0.597	0.639	0.670	0.738	0.634	0.700	0.700	0.669

Table 17. Estimation Results of the Third Order Functional Form for Each Group

	Group 1	Group2	Group3	Group 4	Group 5	Group 6	Group 7
a_1	1.4584 (0.003)	-0.0887 (0.651)	0.0614 (0.825)	-0.1960 (0.207)	0.3602 (0.008)	-0.1942 (0.319)	-0.1815 (0.093)
a_2	-2.1333 (0.008)	-0.0710 (0.370)	-0.5857 (0.219)	-0.2177 (0.276)	-0.4042 (0.000)	0.0233 (0.926)	-0.7004 (0.000)
a_3	0.5439 (0.086)	-0.0167 (0.865)	-0.0119 (0.982)	-0.6143 (0.382)	-0.2948 (0.000)	-0.4274 (0.384)	0.1202 (0.035)
b_1	-1.1082 (0.599)	0.5026 (0.046)	0.1985 (0.171)	-0.1202 (0.056)	0.0915 (0.561)	-0.0276 (0.846)	0.5057 (0.015)
b_2	0.0203 (0.587)	-0.0949 (0.033)	-0.0302 (0.251)	0.0222 (0.047)	-0.0033 (0.907)	0.0103 (0.691)	-0.0882 (0.019)
b_3	-0.0010 (0.616)	0.0051 (0.033)	0.0015 (0.314)	-0.0012 (0.047)	-0.0004 (0.810)	-0.0007 (0.606)	0.0047 (0.024)
c_0	0.6409 (0.375)	-0.4055 (0.709)	-0.3652 (0.380)	-0.3233 (0.464)	0.4725 (0.529)	1.7761 (0.015)	1.1784 (0.010)
c_1	0.3480 (0.262)	0.5585 (0.025)	0.5865 (0.002)	0.0268 (0.689)	0.0162 (0.898)	0.9120 (0.002)	-0.1169 (0.417)
c_2	-0.0010 (0.019)	0.0008 (0.474)	-0.0004 (0.366)	0.0001 (0.183)	-0.0005 (0.538)	0.0003 (0.243)	0.0001 (0.606)
c_3	0.3214 (0.010)	0.2526 (0.427)	0.0976 (0.173)	-0.1166 (0.105)	0.0083 (0.965)	0.0549 (0.555)	0.0318 (0.598)
c_4	0.0837 (0.629)	-0.1592 (0.576)	0.0614 (0.525)	0.2695 (0.050)	-0.0330 (0.868)	-0.6065 (0.023)	-0.0601 (0.402)

* The numbers in parenthesis are p-values

* Model: See Equation (36) (d=0) on page 54.

Table 18. Comparison of BIC for Each Functional Form

*** Group 1**

B* \ A*	0	1	2	3
0	181.32	154.90	**134.07**	136.17
1	169.90	155.61	137.94	140.11
2	174.36	160.27	142.86	144.94
3	179.43	164.88	147.60	149.66

*** Group 2**

B \ A	0	1	2	3
0	77.737	59.685	63.721	67.980
1	79.339	**57.306**	61.769	66.223
2	83.167	61.785	66.235	70.693
3	85.714	62.599	66.312	70.784

*** Group 3**

B \ A	0	1	2	3
0	**80.172**	87.407	86.329	94.198
1	81.113	90.732	89.120	94.236
2	84.807	94.864	92.655	97.797
3	89.784	99.231	96.780	101.92

*** Group 4**

B \ A	0	1	2	3
0	-70.25	**-147.6**	-144.3	-140.2
1	-67.10	-144.3	-140.3	-136.3
2	-62.68	-139.9	-135.9	-131.9
3	-59.91	-138.1	-135.0	-131.3

*** Group 5**

B \ A	0	1	2	3
0	265.39	117.87	116.23	**91.709**
1	269.41	122.70	120.72	96.286
2	274.42	126.56	122.15	93.076
3	278.47	130.57	126.47	97.923

*** Group 6**

B \ A	0	1	2	3
0	-9.446	**-11.81**	-7.351	-3.979
1	-9.536	-8.889	-4.497	-0.708
2	-6.096	-5.370	-1.013	2.775
3	-1.524	-1.014	3.311	7.102

*** Group 7**

B \ A	0	1	2	3
0	280.17	211.85	184.93	**180.81**
1	281.63	216.72	188.33	190.54
2	282.23	221.50	192.52	195.49
3	286.51	226.02	192.00	195.46

*** All pooled group**

B \ A	0	1	2	3
0	985.08	616.24	620.48	**522.15**
1	981.22	621.81	626.57	523.36
2	982.85	623.72	628.79	523.68
3	989.62	630.04	672.67	527.25

* BIC = $-2lnL + klnN$ (L: maximized log-likelihood, k: number of parameters estimated, N: sample size)
* 'A' means the order of bidding error and 'B' means the order of trend.
* The numbers in bold mean the lowest BIC.

Table 19. Estimated Coefficients of Selected Functional Form

	Group 1	**Group 2**	**Group 3**	**Group 4**	**Group 5**	**Group 6**	**Group 7**	**All Group**
a_1	0.7130 (0.002)	0.0398 (0.671)	-	-0.3724 (0.000)	0.2816 (0.044)	-0.3268 (0.007)	-0.2311 (0.032)	0.0423 (0.457)
a_2	-0.8162 (0.000)	-	-	-	-0.4246 (0.000)	-	-0.7218 (0.000)	-0.1202 (0.000)
a_3	-	-	-	-	-0.2846 (0.000)	-	0.1473 (0.008)	-0.1430 (0.000)
b_1	-	-0.0268 (0.006)	-	-	-	-	-	-
c_0	0.7101 (0.235)	0.2798 (0.818)	0.8898 (0.000)	-0.5270 (0.159)	0.7324 (0.248)	1.9606 (0.007)	2.0856 (0.000)	0.9526 (0.003)
c_1	0.1923 (0.498)	0.6759 (0.016)	-0.0002 (0.689)	0.0289 (0.635)	0.0065 (0.955)	0.9759 (0.001)	-0.0843 (0.561)	0.2105 (0.003)
c_2	-0.0008 (0.056)	0.0010 (0.474)	0.1031 (0.244)	0.0002 (0.101)	-0.0004 (0.597)	0.0003 (0.279)	0.0001 (0.786)	0.0000 (0.985)
c_3	0.2755 (0.019)	0.3076 (0.392)	0.1055 (0.373)	-0.1062 (0.099)	0.0107 (0.937)	0.0392 (0.686)	0.0308 (0.613)	0.1369 (0.039)
c_4	0.0372 (0.822)	-0.1882 (0.571)	-0.3258 (0.416)	0.2767 (0.025)	-0.0171 (0.924)	-0.6643 (0.016)	-0.0734 (0.310)	-0.0485 (0.578)
d_2	-	-	-	-	-	-	-	-0.7303 (0.000)
d_3	-	-	-	-	-	-	-	-0.6248 (0.000)
d_4	-	-	-	-	-	-	-	-0.6176 (0.000)
d_5	-	-	-	-	-	-	-	-0.4425 (0.000)
d_6	-	-	-	-	-	-	-	-0.5682 (0.000)
d_7	-	-	-	-	-	-	-	0.1945 (0.078)

* The numbers in parenthesis are p-values

* Model : See Equation (36) on page 54.

Table 20. Estimated Willingness to Pay (WTP) and Average Actual Bid

Round		1	2	3	4	5	6	7	8	9	10	Mean	Std.
Group 1	$\overline{BD}_t$	0.281	0.314	0.453	0.425	0.508	0.420	0.65	0.578	0.726	0.602	0.491	0.139
	BW_t	1.650	0.700	1.700	1.650	1.660	1.660	1.650	1.650	1.650	1.650	1.662	0.002
	$\hat{WTP}_t$	-	0.633	0.631	0.680	0.699	0.700	0.707	0.731	0.701	0.644	0.680	0.036
Group 2	$\overline{BD}_t$	0.345	0.361	0.385	0.420	0.381	0.310	0.295	0.276	0.271	0.291	0.334	0.052
	BW_t	0.500	1.000	1.250	1.150	1.050	0.750	0.800	0.800	0.700	0.760	0.876	0.230
	$\hat{WTP}_t$	-	0.232	0.230	0.232	0.229	0.225	0.222	0.220	0.247	0.215	0.228	0.009
Group 3	$\overline{BD}_t$	0.267	0.268	0.333	0.339	0.319	0.374	0.419	0.327	0.344	0.399	0.339	0.050
	BW_t	0.600	0.600	0.750	0.750	0.650	0.690	0.710	0.670	0.690	0.700	0.681	0.053
	$\hat{WTP}_t$	-	0.270	0.274	0.274	0.272	0.272	0.276	0.270	0.270	0.270	0.272	0.002
Group 4	$\overline{BD}_t$	0.312	0.296	0.216	0.282	0.306	0.301	0.320	0.321	0.321	0.311	0.298	0.031
	BW_t	0.500	0.500	0.400	0.400	0.410	0.410	0.450	0.450	0.400	0.400	0.432	0.041
	$\hat{WTP}_t$	-	0.341	0.307	0.345	0.346	0.346	0.345	0.345	0.345	0.346	0.341	0.013
Group 5	$\overline{BD}_t$	0.657	0.619	0.590	0.487	0.611	0.586	0.576	0.609	0.522	0.486	0.574	0.058
	BW_t	1.000	1.050	1.000	1.020	1.050	1.050	1.030	1.080	1.000	0.050	1.033	0.028
	$\hat{WTP}_t$	-	0.540	0.527	0.480	0.505	0.523	0.531	0.540	0.500	0.470	0.513	0.026

Table 20. Continued

Round		1	2	3	4	5	6	7	8	9	10	Mean	Std.
Group 6	$\overline{BD}_t$	0.356	0.369	0.389	0.517	0.410	0.381	0.529	0.415	0.484	0.450	0.430	0.062
	BW_t	0.750	0.650	0.610	0.900	0.700	0.700	0.950	0.750	0.700	0.750	0.746	0.105
	$\hat{WTP}_t$	-	0.455	0.461	0.462	0.459	0.465	0.461	0.457	0.460	0.456	0.460	0.003
Group 7	$\overline{BD}_t$	0.271	0.452	0.483	0.518	0.542	0.598	0.483	0.533	0.533	0.510	0.492	0.087
	BW_t	1.650	1.850	2.000	1.900	1.890	2.000	1.850	2.000	2.000	1.800	1.894	0.114
	$\hat{WTP}_t$	-	1.336	1.251	1.129	1.292	1.344	1.129	1.267	1.142	1.137	1.225	0.091
All Pooled Group	$\overline{BD}_t$	0.350	0.389	0.422	0.434	0.434	0.447	0.476	0.456	0.476	0.454	0.436	0.040
	BW_t	1.042	0.137	1.201	1.200	1.151	1.152	1.155	1.165	1.137	1.116	1.145	0.012
	$\hat{WTP}_t$	-	0.408	0.399	0.377	0.400	0.413	0.400	0.416	0.395	0.386	0.399	0.012

* $\overline{BD}_t$: average actual bid, BW_t : winning bid, $\hat{WTP}_t$: estimated true willingness to pay

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