AN ANALYSIS ON AGRICULTURAL MARKET BEHAVIOR

A Dissertation

by

CHUL CHOI

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,	David A. Bessler
Committee Members,	David J. Leatham
	Gabriel Power
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ABSTRACT

An Analysis on Agricultural Market Behavior. (August 2010)

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Chair of Advisory Committee: Dr. David A. Bessler

This dissertation is concerned with (i) how to model an agricultural market, (ii) how to analyze the impacts of a certain event (i.e. animal disease outbreak) on the market, and (iii) what are the relationships between different markets. The research on the first two issues will focus on the US beef market, and the impact of the bovine spongiform encephalopathy (BSE) outbreak (Dec. 2003) on the US beef market will be analyzed. For the third issue, a multinational meat market will be considered, which includes three countries (Korea, US, and UK) and three meat products (beef, pork, and poultry). Their market movements will be compared, considering the impacts of the major animal disease outbreaks: BSE, foot and mouth disease (FMD), and avian influenza (AI).

Based on the properties of an agricultural product (longer cycle of production and perishability) and the extensive empirical results, it is concluded that a recursive model is appropriate for modeling an agricultural market. A variety of structural change tests are applied to reveal that the change due to the BSE event still lies in an allowable range of the prediction error. For the comparisons between market movements, some multivariate statistical methods such as canonical correlation analysis (CCA) and principal component analysis (PCA) are used, and the main finding is that the knowledge about the threat of BSE to human health played an important role in changing people's attitude towards an animal disease event.

DEDICATION

Be joyful in hope, patient in affliction, faithful in prayer.

(Romans 12:12)

This dissertation is dedicated to:

my parents, Moojeon Choi and Soondong Kim;

my father-in-law, Hoonsei Choi;

my wife, Young Eun;

my daughters, Dayeon and Dajeong;

my neighbors, Aaron and Ruby G. Lewis;

in memory of my mother-in-law, Insoon Jang.

ACKNOWLEDGEMENTS

I would like to thank my advisory committee chair, Dr. David A. Bessler for his encouragement and inspiring guidance throughout the study of this dissertation. I should like to extend my grateful thanks to the members of the committee, Dr. David J. Leatham, Dr. Gabriel Power, and Dr. Samiran Sinha for their precious comments and questions, which made this dissertation improved. Dr. Leatham encouraged me to continue studying in the Ph.D. program when I had completed my master's degree and also helped me with my study plan.

The teaching assistantship from the department of agricultural economics not only supported my study but also provided me with invaluable experiences of teaching and communicating with students. This research was also supported by a project with the Foreign Animal and Zoonotic Disease Center (FAZD) at Texas A&M University.

Finally, I thank Dr. Duchwan Ryu for his helpful comments on the statistical analyses, and Emily K. Seawright for her review of the entire dissertation and comments for editing.

NOMENCLATURE

1989Q1	1st Quarter of 1989
2SLS	Two Stage Least Squares
3SLS	Three Stage Least Squares
ADL	Autoregressive Distributed Lag
AEH	Adaptive Expectation Hypothesis
AI	Avian Influenza
AIC	Akaike Information Criterion
AIDS	Almost Ideal Demand System
$AR(p)$	Autoregressive Process of Order p
$ARMA(p,q)$	Autoregressive Moving Average Process of Order (p,q)
BEA	Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
BSE	Bovine Spongiform Encephalopathy
CCA	Canonical Correlation Analysis
$CI(d)$	Cointegrated of Order d
CPI	Consumer Price Index
Cov	Covariance
CUSUM	Cumulative Sums (of the Recursive Residuals)
CUSUMSQ	Cumulative Sums of Squares (of the Recursive Residuals)
DAG	Directed Acyclic Graph
DEFRA	Department for Environment, Food and Rural Affairs
DGP	Data Generating Process
E	Expectation
ERS	Economic Research Service
FIML	Full Information Maximum Likelihood

FMD	Foot and Mouth Disease
HQ	Hannan-Quinn (Criterion)
$I(d)$	Integrated of Order d
iid	Independent and Identically Distributed
ILS	Indirect Least Squares
KR	Korea (the Republic of)
LR	Likelihood Ratio
MANOVA	Multivariate Analysis of Variance
$MA(q)$	Moving Average Process of Order q
MIFFAF	Ministry for Food, Agriculture, Forestry and Fisheries
MSE	Mean Squared Error
NAFTA	North American Free Trade Agreement
NASS	National Agricultural Statistics Service
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
RSS	Residual Sum of Squares
SC	Schwarz Criterion
SUR	Seemingly Unrelated Regression
UK	United Kingdom
US	United States
USDA	United States Department of Agriculture
Var	Variance
VAR	Vector Autoregressive (Process)
$VAR(p)$	Vector Autoregressive Process of Order p
vCJD	Variant Creutzfeldt-Jakob Disease
VECM	Vector Error Correction Model

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CHAPTER I
INTRODUCTION

Undoubtedly, one of the central roles of modern economics is to explain a market phenomenon through a specific model. However, a market phenomenon is so complicated or indefinite that it may be impossible to completely model its nature. For this reason, many theories exist with different perspectives, even for the exact same phenomenon. Thus an economic model is usually a simplified version of a complex reality. A well defined model constitutes an economic theory, which involves statements or hypotheses that are mostly testable using observable data. The very empirical analysis belongs to the area of econometrics.

This dissertation is primarily concerned with three main topics: (i) modeling an agricultural market (especially for meat products), (ii) analyzing the impacts of a certain event or shock (i.e. animal disease outbreak) on the market, and (iii) comparing market movements due to different types of events. The first two issues will be analyzed sequentially because they are related to each other. The complete analysis has two main parts: (i) to build an appropriate economic model for a meat market and to estimate the specified model, and (ii) to apply some statistical methods to detect and characterize a possible structural change (i.e. significant changes in the parameters) due to an animal disease event. The former is basically relying on the traditional economic theories of market and expectation formation (i.e. AEH). The latter involves extensive tests for structural change. These two parts will focus on the US beef market. For the third issue, multinational markets, which consist of three countries (Korea, UK, and US) and three meat products (beef, pork, and poultry), will be considered. In particular, some multivariate statistical methods will be applied for comparisons between different markets.

This dissertation follows the format and style of *Journal of Agricultural Economics*.

Obviously, the phenomenon to be analyzed is the way that market participants (i.e. consumers and producers) respond to an animal disease outbreak. Their responses (in aggregate terms) are reflected in the market demand or supply to determine a new equilibrium status. The observable data from a market is, in fact, a set of equilibrium points determined by the market mechanism. In the following chapter, I will discuss the general issues related to using market data and other problematic issues in the market analysis. In particular, the background of the econometric model will be emphasized in comparison with the traditional demand system (i.e. Rotterdam and AIDS) approaches. From the discussion, a set of general assumptions relevant to the analytical work in the remaining chapters will be made. Additional assumptions may be added in the particular settings of each chapter. As in any other econometric research, four major steps are involved in each analysis: (i) specifying the system of relationships that is believed to have produced the observed data, (ii) finding out whether these relationships can be identified, (iii) performing the statistical analysis, and lastly (iv) interpreting the results.

In Chapter III, the US beef market will be modeled. An agricultural product, like beef, typically has two common properties that make it distinguishable from other economic goods. First, it is perishable. Second, it has a relatively longer cycle of production. For example, the cattle industry has a production cycle of approximately three-years[1]. Thus the basic model proposed for beef market can be applicable to other agricultural products with minor modifications. Two basic models will be proposed in terms of a simultaneous equations system: a recursive model and an interdependent model. As explained in detail later in this dissertation, the data frequency impacts the recursiveness of a system. Since it is, a priori, not clear that using quarterly data is enough for a recursive model, considering both models would be advantageous for the purpose of comparing their empirical results and determining which is most appropriate.

Chapter IV focuses on the analysis of structural changes. Various statistical meth-

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[1] In terms of breeding stock. Refer to Rosen et al. (1994).

ods have been developed to detect and test for a structural change in linear regression. Additionally, some statistical techniques are applicable to cases where break points are not known. This dissertation, however, focuses on the structural change with a known break point. Again, the central problem is to analyze the impacts of a certain event, which is already known, on the market. This chapter is devoted entirely to the US beef market. For this analysis, market data was collected for the US beef industry. During the sample period[2], two notable events occurred that most likely affected the market. One is the enforcement of the NAFTA in January 1994, and the other is the BSE (also known as Mad Cow Disease) outbreak in December 2003. Even though more emphasis is placed on the BSE case, comparing the consequences of the two events would provide meaningful implications. A priori, the hypotheses of this dissertation are that there is a significant structural change in the US beef market due to the BSE event and that consumers become more sensitive to a price change after the event.

Chapter V is devoted to the analysis of multinational markets, which includes three countries (Korea, UK and US), three kinds of meat products (beef, pork and poultry), and three types of animal diseases (AI, BSE and FMD). Although an analysis of the single market has been the main focus of this research thus far, further consideration of multinational markets will provide more informative conclusions for market impacts from specified events. The primary purpose of the analysis is to ascertain whether the major animal disease events considered had similar impacts on the related markets. To a large extent, therefore, the methodology and scope for the chapter are different from those of the preceding chapters.

Generating a set of common variables is very crucial to comparing the impacts of the three animal diseases. Additionally, the relationship between price and quantity will play an important role in accounting for the impact of an animal disease outbreak on the market. The analysis will be twofold: (i) to identify the similarity (or concordance)

[2] Chapter III and chapter IV use quarterly time series from 1989Q1 to 2008Q4.

of the market movements, and (ii) to identify the changes in the variance structures of the markets. The former will be analyzed by the CCA and the latter by the PCA. Using these approaches, the hypotheses of interest will be tested.

Finally, the primary research questions and their answers will be summarized in Chapter VI and an overall conclusion of the research results generated from this study will be provided.

CHAPTER II

PROBLEMATIC ISSUES

The first issue to be addressed is how to interpret observations on market prices and quantities in terms of market equilibria. For the purposes of this research, this type of data will be called 'market equilibrium data' or 'market data' in short.[3] In the demand or market analysis literature, most research has been oriented toward the demand system approaches. The Rotterdam model, AIDS or other variants of those seem to be the mainstream of market analysis. However, these models originate from consumer theory and therefore do not consider supply, the other side of a market. Obviously, the demand system approaches are primarily concerned with the demand side. Nonetheless, some researchers often apply them to market data, which can be justified only in a restricted situation.

The structure of a market can be described by two forces, demand and supply. Market data is determined by the interaction between demand and supply. Figure 2.1

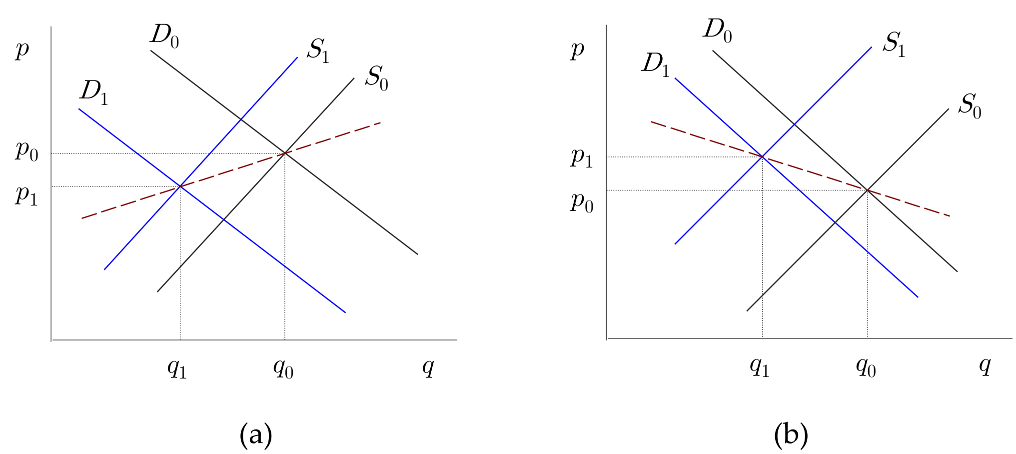


Figure 2.1 Relative shifts of demand (D) and supply (S)

[3] Strictly speaking, this view is based on the assumption that a market attains equilibrium at all times.

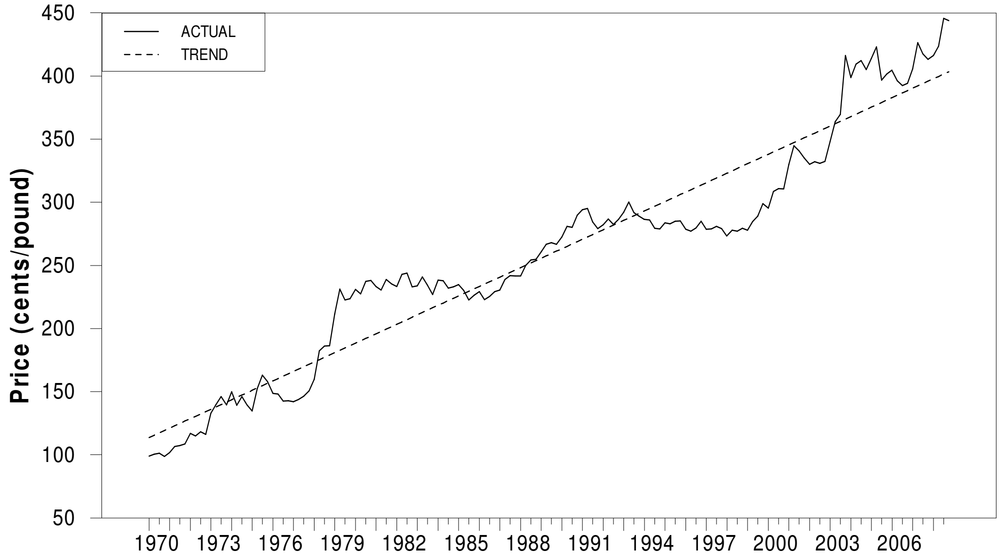
shows that the observed market price (p) and quantity (q) may be quite different even when demand and supply shift in the same directions, respectively. In both diagrams, the demand curves shift downward, while the supply curves shift upward. The only difference is that the demand curve shifted relatively more in Figure 2.1 (a) and the supply curve shifted relatively more in Figure 2.1 (b). However, each scenario resulted in the different consequences. That is, the market price decreased in Figure 2.1 (a), but increased in Figure 2.1 (b). Thus the observed data points (p_0, q_0) and (p_1, q_1) scarcely tell us about the shifts of the demand and supply. In other more different cases[4], differing scenarios of demand and supply shifts can make the observations on market prices and quantities more difficult to interpret. An extreme case is when the demand stays the same but supply alone shifts, where the observed data points still differ. Consumer survey data, which is different from market data by nature, would be more appropriate for demand system approaches. However, not considering the supply and using market data for a demand system only may produce misleading results. Further, demand system approaches, to a large extent, depend on the completeness of an individual consumption bundle which includes various goods or categorized items. The bundle should be able to account for the total expenditures as a whole. Considering these problems for a single good of interest and for its market data given, I suggest a system of simultaneous equations, where both demand and supply are involved.

When using market data, further problems still remain. A data point observed from a market originally consists of a nominal price and aggregate quantity. For analytical purposes, however, they are often converted into a real price and per capita quantity, respectively. This can be subdivided into two issues: (i) how to deal with inflation, and (ii) whether consumers are homogeneous. These are, in fact, very delicate problems. As such, they will be discussed separately with careful consideration.

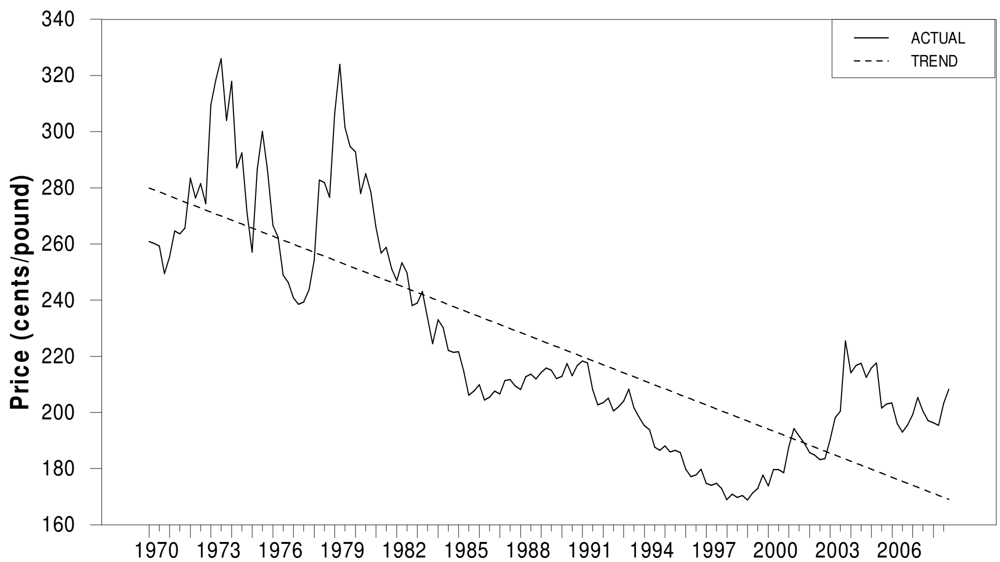
The first problem is related to money illusion[5], which has been a controversial issue

[4] Refer to Ferguson and Maurice (1978, pp. 49-52).

[5] It refers to the tendency of people to think of money in nominal, rather than real, terms.



(a)



(b)

Figure 2.2 US beef retail prices in (a) nominal and (b) real[6] terms

[6] Generated using CPI-US city average (1982~84=100).

in economics. Figure 2.2 shows that the nominal and real prices of US beef differ considerably in their time trends and fluctuations. Therefore, which one to use for an empirical analysis is an important issue.

One basic question addresses whether consumers respond to nominal or real price changes. While it seems resonable that they would respond to both of them, it is likely that their response depends on the frequency of consumption.[7] To be specific, suppose that an individual consumes beef and a durable good[8] (e.g. television set, automobile or so on). In a general sense, the individual consumes beef at least once a month, while the purchase of a television set likely occurred years before. Thus the high frequency of beef consumption would make the individual sensitive to a nominal price change rather than to a real price change. This does not simply mean that real price is less important,

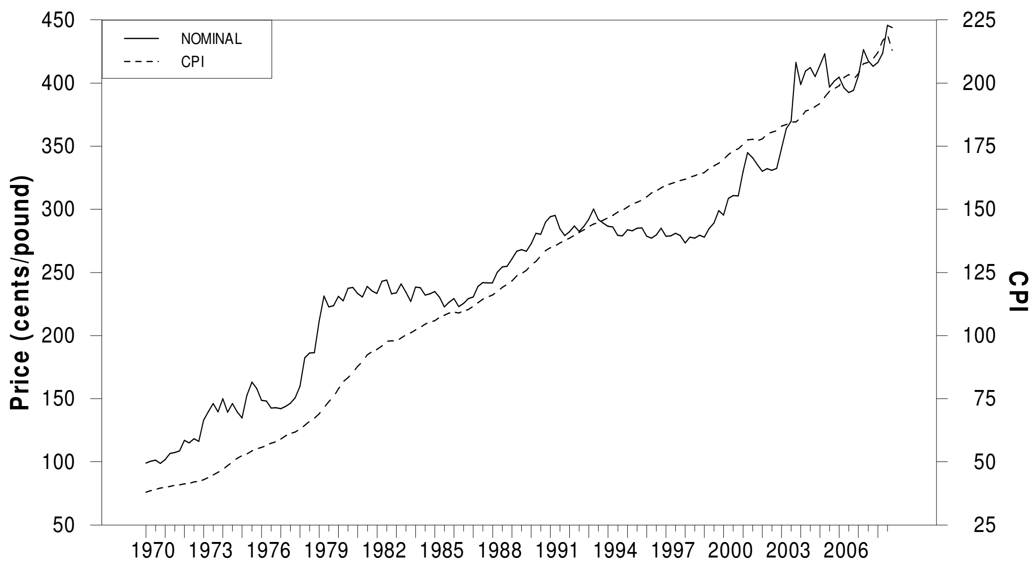


Figure 2.3 Nominal price of beef and CPI

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[7] Here I provide this argument without any further empirical evidence. To verify it is beyond the scope of this dissertation. Maybe there are some previous researches on this topic even though I do not refer to any of them.

[8] In fact, the consumption of a durable good lasts for its longer lifetime.

as it changes in small increments for a short period of time (e.g. one month). Suppose that both beef price and CPI have risen by 5% for a very short time. There is no change in the real price of beef; however, people would likely not react according to the unchanged real price.

Figure 2.3 shows that the graph of CPI is nearly a straight line and looks like the linear time trend of the nominal price series. As illustrated in Figure 2.2, the nominal price seems to be relatively stable[9] around the linear time trend, while the real price fluctuates irregularly. One further problem of using the real price is that it can be susceptible to the price changes in other goods which may be unrelated to beef. This is because a real price is conceptually a relative price.[10] As a result, the original price movement determined by the market mechanism may be distorted. Even the linear time trend of

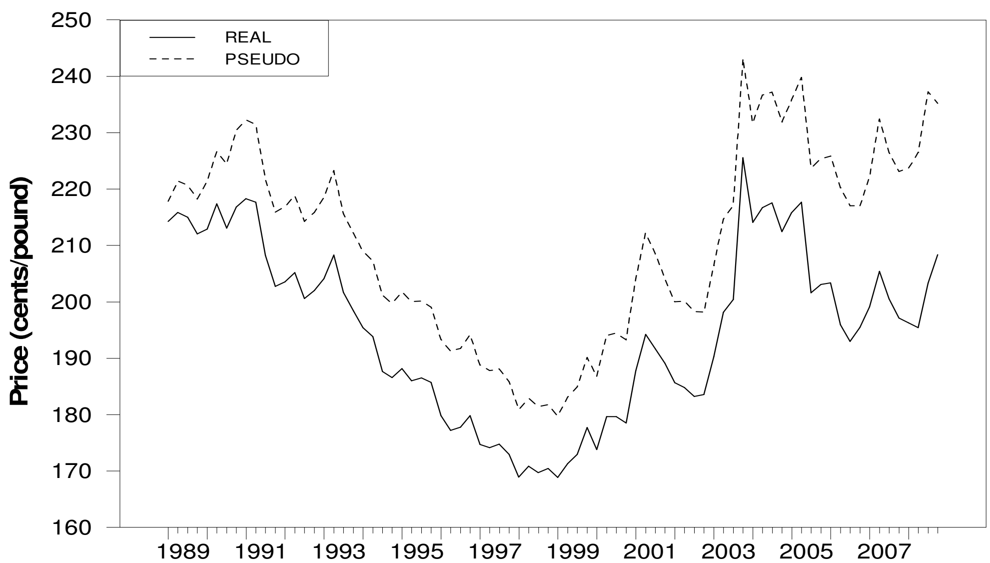

Figure 2.4 Real and pseudo real prices of beef (1989Q1 to 2008Q4)

[9] For now, I do not mean by this that the nominal price series is trend stationary.

[10] For instance, suppose that CPI is the price of some imaginary good. Then the ratio of nominal beef price to CPI yields the real price of beef, which is a relative price.

the nominal price can generate a pseudo series,[11] which we can synchronize with the real price series. This is shown in Figure 2.4 above. While these are some problems of using real price data, the length of sample period is also important in ascertaining which data is more relevant. For example, the analyses in the following two chapters will be based on the US beef market data from 1989Q1 to 2008Q4, which has a total of 80 observations. For such a time span (i.e. 20 years or less), it would be more justifiable to use nominal data.

The second problem of using market data is the heterogeneity of consumers. In general, as time goes on, an economy grows with a larger population and greater income. Accordingly, beef consumption would show an increasing pattern over time. Figure 2.5 shows that the US beef consumption series has an overall increasing trend and distinct seasonal component. Many researchers prefer to use per capita consumption instead of

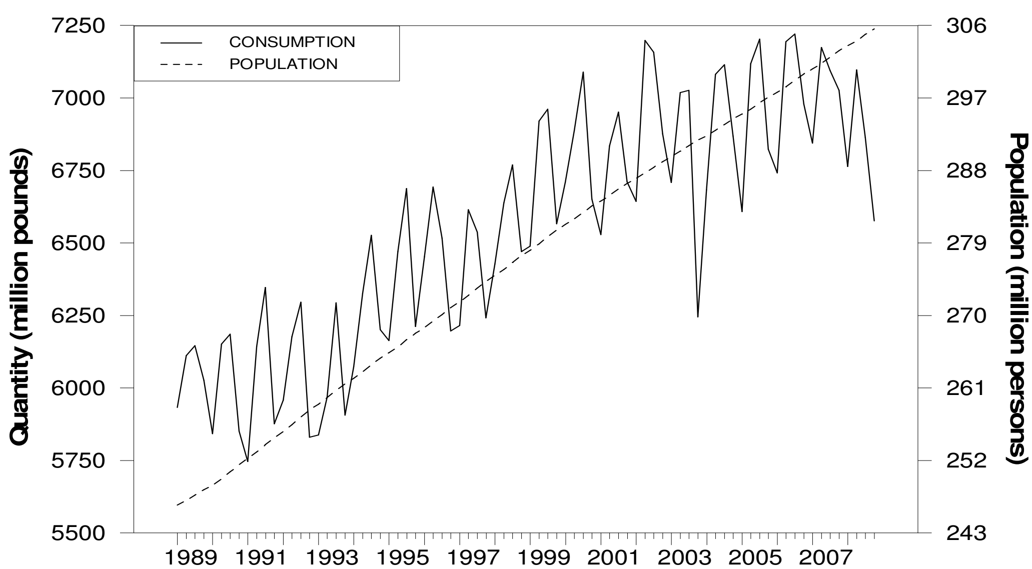

Figure 2.5 US beef consumption and population (1989Q1 to 2008Q4)

[11] This can be obtained by substituting the fitted series from the trend line for the actual CPI series.

aggregate consumption. Its underlying assumption is that consumers are homogeneous and therefore, an individual can represent the whole population. Even if this assumption is accepted, it is more plausible to divide the total consumption by the beef-consuming population, not by the total population. Beef consumption patterns must be different according to the demographic characteristics. For example, if some age groups (e.g. under 10 years old) are excluded from the total population, the slope of the trend line will be smaller than that shown in Figure 2.5. Intuitively, per capita consumption should be bounded above because of physical limitations, and may be bounded below too. This is shown in Figure 2.6, where the per capita consumption is defined as the total consumption divided by the total population. Since the total consumption and population have a linearly increasing time trend in common, the resulting series (i.e. per capita consumption) becomes detrended and stationary. In terms of integration, such a series is said to be $I(0)$. In Figure 2.6, the graph shows an abrupt decline at 2003Q4 and exhibits a decreasing pattern afterwards. However, it does not affect the stationarity of

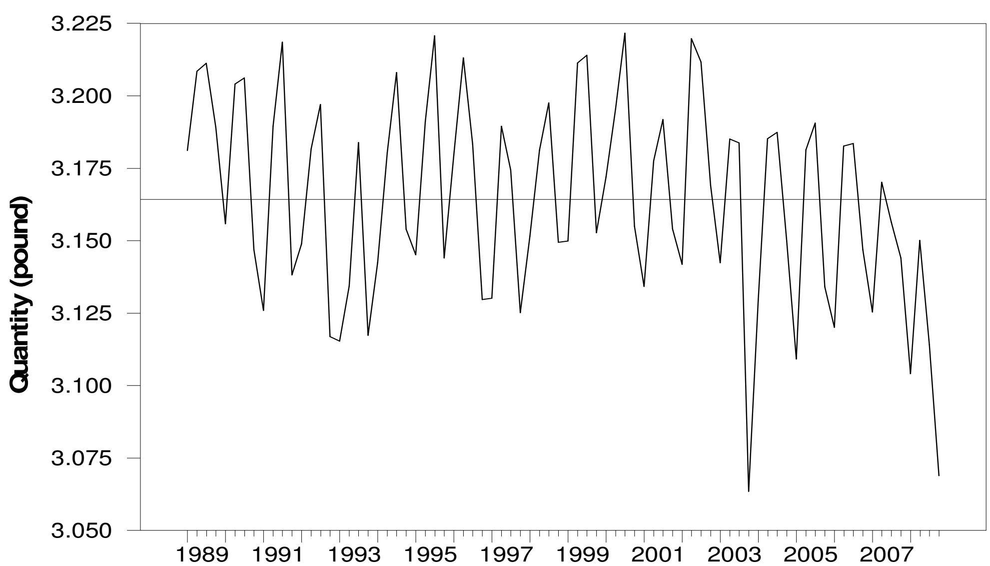

Figure 2.6 Per capita consumption of beef (1989Q1 to 2008Q4)

the per capita consumption series. For a unit root test, the Dickey-Fuller test statistic is -6.559 and the critical value at a 1% level is -3.539. Thus, the null hypothesis of a unit root process is rejected at the 1% level. Now suppose a linear regression:

$$q \sim constant, p, y, u,^{12}$$

where q is quantity, p is price, y is income, and u is a disturbance term. If we are given all the nominal, real, aggregate, and per capita data, there are four combinations exist for the regression: (i) nominal and aggregate, (ii) nominal and per capita, (iii) real and aggregate, and lastly (iv) real and per capita. Combinations (i) and (iv) are more meaningful cases, and will be examined further in this research. The $I(1)$ variables of aggregate consumption as q, nominal price as p, and nominal income as y all have an increasing trend. On the other hand, per capita consumption as q is $I(0)$, while real price as p and real per capita income as y are $I(1)$. As shown in Figure 2.7, both the aggregate

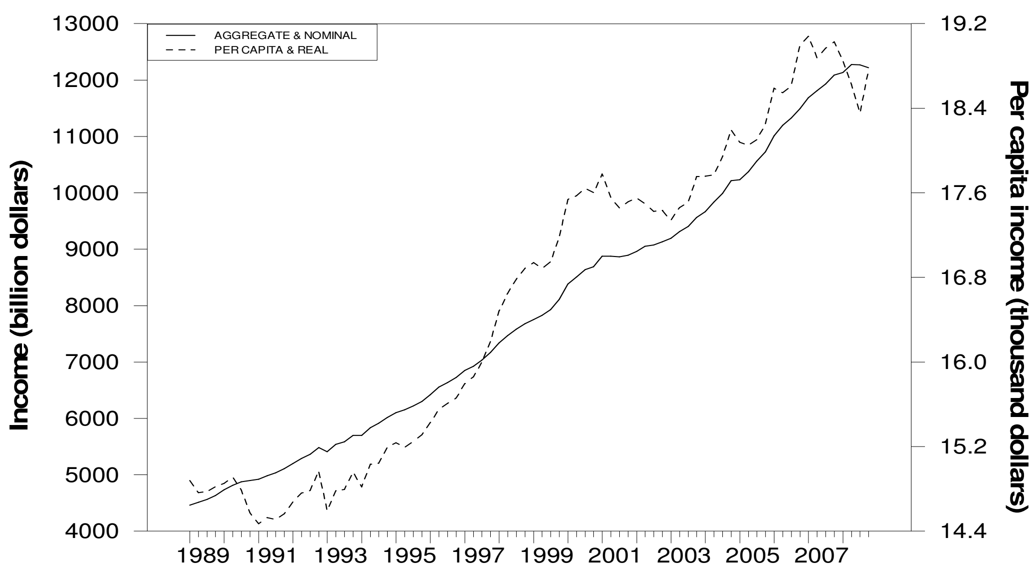

Figure 2.7 Aggregate nominal and per capita real incomes (1989Q1 to 2008Q4)

[12] The notation '$\sim$' is simply used to separate the dependent variable (q) from the regressors and disturbance term, which usually come in the righthand side of a regression equation.

nominal and per capita real income series are nonstationary. Thus, if the case (iv) is chosen, the linear combination of price (p) and income (y) should be stationary; in other words, p and y are cointegrated. However, the cointegration test[13] indicates that there exists no cointegrating vector. Also, the model using (iv) gives a very poor estimation result. For these reasons, I will use the market data consisting of nominal prices and aggregate quantities. The analyses in the following two chapters will be concerned with the behavior of the whole population as a single consumer.

[13] Based on Johansen's procedure, the cointegrating rank is 0. For the details of the Johansen procedure, refer to Enders (2004, pp. 354-366).

CHAPTER III

MODELS FOR AGRICULTURAL MARKETS

3.1 Preliminaries

In the preceding chapter, some problematic issues were mentioned of using market data. Since this research is concerned with the market phenomena which involve the nominal prices and total quantities consumed in a country, the market will be regarded as if there were two participants, namely aggregate consumer and aggregate supplier. Furthermore, if market data is used, both demand and supply should be simultaneously considered even if the demand side is of primary interest. The establishment of a basic model, to a large extent, depends on which type of data is available for the analysis. With the US beef market data given, I will construct a system of simultaneous equations, in which the market mechanism operates.

A market can be represented by a system of the demand, supply and equilibrium equations. The basic model[14] is given by

$$q_t^D = \beta_0 + \beta_1 p_t + \beta_2 y_t + u_t, \tag{3.1a}$$

$$q_t^S = \gamma_0 + \gamma_1 p_t^e + \gamma_2 z_t + v_t, \tag{3.1b}$$

$$q_t^D = q_t^S = q_t, \tag{3.1c}$$

where q_t^D is quantity demanded, q_t^S is quantity supplied, and p_t is price at time t. There are two exogenous variables y_t and z_t (one in each equation), which stand for income and input (i.e. feed) price, respectively. Theoretically, the derivation of (3.1a) and (3.1b) is based on the consumer theory and producer theory, respectively.[15] Despite the fact

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[14] This model will be later extended to other different versions.

[15] The demand function $q = D(p, r, y)$, where r is the vector of other prices, is derived from the consumer's utility maximization condition, and the supply function $q = S(p, z)$ is derived from the producer's profit maximization condition. r is omitted in (3.1a) because the coefficients were not significant.

that this is a time series model, it is assumed that the disturbance terms u_t and v_t are spherical, that is,

$$u \sim N\left(0, \sigma_u^2 I_T\right) \text{ and } v \sim N\left(0, \sigma_v^2 I_T\right),$$

where $u = (u_1, \cdots, u_T)$, $v = (v_1, \cdots, v_T)$, and I_T is an identity matrix of order T. Note that the supply equation has p_t^e as a predetermined variable, which denotes the expectation of price at time t. The underlying assumption is that quantity supplied depends on the expected price (p_t^e) rather than the actual price (p_t) at time t. It seems quite reasonable on the grounds that most agricultural products, including meat, are perishable and have a longer production cycle.

The assumption about expectation formation plays an important role in the model. Simply, if $p_t^e = p_{t-1}$, then the above system becomes the traditional cobweb model. Klein (1974)[16] refers to the cobweb model as a typical example of a recursive system, which will be discussed later. Alternatively, p_t^e can be considered as a linear function of the previous values of p_t:

$$p_t^e = a_1 p_{t-1} + a_2 p_{t-2} + \cdots + a_h p_{t-h} + b = \sum_{j=1}^{h} a_j p_{t-j} + b. \tag{3.2}$$

Thus (3.1b) can be written as

$$q_t^S = \gamma_0 + \gamma_1\left(\sum_{j=1}^{h} a_j p_{t-j} + b\right) + \gamma_2 z_t + v_t = \zeta_0 + \sum_{j=1}^{h} \zeta_j p_{t-j} + \gamma_2 z_t + v_t, \tag{3.3}$$

where $\zeta_0 = \gamma_0 + \gamma_1 b$ and $\zeta_j = \gamma_1 a_j$ $(j = 1, \cdots, h)$. This is a finite distributed lag scheme. However, further problems still remain. First, how can the finite lag length (h) be determined? A large lag length will result in fewer degrees of freedom. Second, if p_t is regarded as a random variable, how can the h random explanatory variables (i.e. p_{t-j} for $j = 1, \cdots, h$) be treated in the equation? In fact, p_t is an endogenous variable in the system, so that p_t and its lagged variables are stochastic. Third, apart from the randomness of the explanatory variables, multicollinearity may lead to imprecise estimation due to

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[16] See p. 199.

the generally high correlation of the lagged variables. The standard errors of the coefficients also tend to be large in the presence of multicollinearity. In the following sections, a variety of models and econometric methods will be considered when approaching these problems.

Another alternative method of defining p_t^e is to formulate it in terms of adaptive expectations. The expectation formation process suggested by Nerlove (1958a) can be represented by

$$p_t^e = p_{t-1}^e + \lambda\left(p_{t-1} - p_{t-1}^e\right) = (1-\lambda)p_{t-1}^e + \lambda p_{t-1} \text{ for } 0 < \lambda \leq 1. \tag{3.4a}$$

$\lambda = 0$ is excluded from (3.4a) because it is a trivial case that expectations stay the same at all times. When $\lambda = 1$, the ordinary cobweb model results. According to Nerlove (1958b), λ in (3.4a) can be interpreted as the elasticity of expectations, which was originally defined by Hicks (1946)[17] as the ratio of the proportional rise in expected future prices of a commodity to the proportional rise in its current price . Now using the lag operator (e.g. $L^j x_t = x_{t-j}$), (3.4a) can be represented by

$$p_t^e = \frac{1-\theta}{1-\theta L} p_{t-1} \text{ for } 0 \leq \theta < 1, \tag{3.4b}$$

where $\theta = 1 - \lambda$. This can also be written as

$$p_t^e = (1-\theta)\sum_{j=1}^{\infty} \theta^{j-1} p_{t-j} \text{ for } 0 \leq \theta < 1. \tag{3.4c}$$

Putting (3.4b) into (3.1b), we have

$$q_t^S = \gamma_0(1-\theta) + \gamma_1(1-\theta)p_{t-1} + \gamma_2 z_t - \gamma_2\theta z_{t-1} + \theta q_{t-1}^S + v_t - \theta v_{t-1}. \tag{3.5a}$$

On the other hand, putting (3.4c) into (3.1b) yields

$$q_t^S = \gamma_0 + \gamma_1(1-\theta)\sum_{j=1}^{\infty} \theta^{j-1} p_{t-j} + \gamma_2 z_t + v_t. \tag{3.5b}$$

We can see that (3.5b) is very similar to (3.3), except for the infinite summation. Each of (3.5a) and (3.5b) has advantages and disadvantages which are referred to above. Still, it

[17] See p. 205.

is worth mentioning that (3.5a) is an autoregressive scheme with a moving average disturbance term $(v_t - \theta v_{t-1})$ and a lagged dependent variable (q_{t-1}^S) that is correlated with the disturbance term. Note that $Cov\left(q_t^S, v_t\right) \neq 0$ implies $Cov\left(q_{t-1}^S, v_t - \theta v_{t-1}\right) \neq 0$.

3.2 Recursive Model

A model is said to be recursive[18] if there exists an ordering of the endogenous variables and an ordering of the equations such that the ith equation can be considered to describe the determination of the value of the ith endogenous variable during period t as a function of the predetermined variables and of the endogenous variables of index less than i. If a model is not recursive, it is said to be interdependent.[19]

The basic model represented by (3.1a) through (3.1c) can now be restated in a condensed structural form:

$$p_t = \beta_0 + \beta_1 q_t + \beta_2 y_t + u_t, \tag{3.6a}$$

$$q_t = \gamma_0 + \gamma_1 p_t^e + \gamma_2 z_t + v_t, \tag{3.6b}$$

where p_t and q_t are reflecting the equilibrium price and quantity at each time period because the equilibrium equation has been omitted in this model. A remarkable thing is that the demand equation is given by an inverse demand function, where the price is dependent. Thus, strictly speaking, the system of (3.6a) and (3.6b) is quite different from that of (3.1a) through (3.1c). In particular, the coefficients and disturbance term of (3.6a) should be distinguished from those of (3.1a), although the same notation is preserved. The relationships established by the model can be described by a DAG as follows.

$$\begin{array}{ccccccc}
 & z_t & & y_t & & & \\
 & \searrow & & \searrow & & & \\
p_t^e & \rightarrow & q_t & \rightarrow & p_t & \rightarrow & p_{t+1}^e \cdots \\
 & \nearrow & & \nearrow & & & \\
 & v_t & & u_t & & &
\end{array}$$

[18] Refer to Malinvaud (1980, pp. 605-608).

[19] There can be further classifications for this situation. Refer to Kmenta (1986, pp. 659-660).

In this model, the ordering of the variables is q_t and then p_t. The ordering of the equations is supply (3.6b) and then demand (3.6a). The omitted equilibrium equation would have come between the supply and demand equations. Again, this ordering is justifiable considering the properties of an agricultural product as stated above.

A recursive model assumes that the disturbance terms are uncorrelated with each other, namely $Cov(u_t, v_t) = 0$. This is an important assumption for the recursiveness along with the triangular form[20] of the coefficients of endogenous variables. Then, from (3.6b),

$$Cov(q_t, u_t) = E\left[\left(\gamma_0 + \gamma_1 p_t^e + \gamma_2 z_t + v_t\right)u_t\right] = 0.$$

Thus estimating each equation separately will be relevant. However, if the disturbance terms are correlated with each other, the equations of the model should not be considered separately, as they are related to each other. In that case, an alternative method is to estimate (3.6b) first and then substitute the fitted $\hat{q}_t$ for q_t in (3.6a). Since $\hat{q}_t$ is a linear combination of p_t^e and z_t, which are both uncorrelated with u_t, the resulting estimators will be consistent. This is called a single-equation method. However, a more usual approach is the SUR method, which utilizes the full information contained in the model. As a matter of fact, the possibility that the disturbance terms are mutually correlated cannot be ruled out, even though the equations have different dependent variables. Based on the separate estimation results, the correlation between the residuals ($\hat{u}_t$ and $\hat{v}_t$) will be computed. If the correlation is close enough to zero, the separation would be justifiable.

From the structural form, the reduced-form equation with respect to p_t is given by

$$p_t = \beta_0 + \beta_1\gamma_0 + \beta_1\gamma_1 p_t^e + \beta_2 y_t + \beta_1\gamma_2 z_t + \omega_t, \tag{3.7a}$$

where $\omega_t = u_t + \beta_1 v_t$. The estimation of (3.7a) will provide useful information because

[20] This means that the coefficients of endogenous variables take the form of a triangular matrix as in $\begin{pmatrix} 1 & -\beta_1 \\ 0 & 1 \end{pmatrix}\begin{pmatrix} p_t \\ q_t \end{pmatrix} = \begin{pmatrix} \beta_0 + \beta_2 y_t + u_t \\ \gamma_0 + \gamma_1 p_t^e + \gamma_2 z_t + v_t \end{pmatrix}$.

the coefficients of the reduced-form equations summarize the comparative static results of the model. If u_t and v_t are contemporaneously uncorrelated with each other, the disturbance term ω_t will have

$$E(\omega_t) = E(u_t + \beta_1 v_t) = 0,$$

$$Var(\omega_t) = Var(u_t + \beta_1 v_t) = \sigma_u^2 + \beta_1^2 \sigma_v^2.$$

Even though u_t and v_t are spherical disturbance terms, ω_t may not be spherical[21] unless

$$Cov(\omega_t, \omega_j) = 0 \text{ for } t \neq j.$$

Putting (3.4b) into (3.7a),

$$p_t = \delta_0 + \delta_1 p_{t-1} + \beta_2 y_t + \delta_2 y_{t-1} + \delta_3 z_t + \delta_4 z_{t-1} + \omega_t - \theta \omega_{t-1}, \tag{3.7b}$$

where $\delta_0 = (\beta_0 + \beta_1 \gamma_0)(1-\theta)$, $\delta_1 = \beta_1 \gamma_1 (1-\theta) + \theta$, $\delta_2 = -\beta_2 \theta$, $\delta_3 = \beta_1 \gamma_2$, and $\delta_4 = -\beta_1 \gamma_2 \theta$. From the reduced-form equation, either (3.7a) or (3.7b), we can see that

$$\frac{\partial p_t}{\partial y_t} = \beta_2,$$

which is the same as the partial derivative of the structural equation (3.6a) with respect to y_t. This is because the two structural equations in a recursive model are regarded as separate. Therefore, a proper estimation of (3.7a) or (3.7b) would yield the same estimate of β_2 as that of (3.6a). In general, however, the coefficient β_2 of the structural equation is quite different from that of the reduced-form equation. In this model, for example, the former is concerned with a demand shift due to income change, while the latter with a change in equilibrium price.

I will also consider a variant[22] of the above recursive model, which is

$$q_t = \beta_0 + \beta_1 p_t + \beta_2 y_t + u_t, \tag{3.8a}$$

$$q_t = \gamma_0 + \gamma_1 p_t^e + \gamma_2 z_t + v_t. \tag{3.8b}$$

As in the previous model, p_t and q_t are reflecting the equilibrium price and quantity at

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[21] The variance-covariance matrix is $E(ww^\top) = E[(u+\beta_1 v)(u+\beta_1 v)^\top] = E(uu^\top) + \beta_1 E(uv^\top) + \beta_1 E(vu^\top) + \beta_1^2 E(vv^\top)$, where $E(uu^\top) = \sigma_u^2 I_T$ and $E(vv^\top) = \sigma_v^2 I_T$.

[22] Although this belongs to an interdependent model, it is, in a sense, in the middle of the two categories.

time t. The only difference is that (3.8a) is a quantity-dependent (having the quantity as a dependent variable) demand equation, while (3.6a) is a price-dependent (having the price as a dependent variable) demand equation. Haynes and Stone (1985) argue that in many markets, quantity tends to be demand-determined in the short run but price tends to be supply-determined. Their simple model is represented by

$$q_t = \beta - \sum_{j=0}^{\infty} \phi_j p_{t-j} \text{ (demand)},$$

$$p_t = \gamma + \sum_{j=0}^{\infty} \psi_j q_{t-j} \text{ (supply)}.$$

On the other hand, Eales and Unnevehr (1993) argue that quantity supplied is likely to be predetermined because meats are perishable and are produced with a long biological lag; therefore quantity-dependent models may be inappropriate. Their test results indicate that beef quantity could be predetermined. However, the system of (3.8a) and (3.8b) can provide some advantages as an alternative model. First, it is a benchmark that is comparable with the hypothetical model. Quite often uncertainty exists concerning whether or not a model is a true model; however, statistical techniques can help determine the best model among the alternatives. The encompassing principle, for example, is applicable to these two non-nested empirical models (i.e. price-dependent and quantity-dependent). Second, the system of (3.8a) and (3.8b) can be extended to a disequilibrium model if the equilibrium condition is replaced with an inventory equation. In fact, a disequilibrium model is more agreeable in terms of flexibility and reality because there exist, to some extent, excess demands or supplies in the market.

The alternative model looks like a recursive system, but it is not. We cannot make such orderings as in the previous model, even when $Cov(u_t, v_t) = 0$. Although a separate estimation of (3.8b) is legitimate, (3.8a) cannot be estimated separately from (3.8b) as long as both equations are bound in the system. The essential aspect of this system is the endogeneity of p_t in (3.8a). The reduced form equation with respect to p_t is

$$p_t = \frac{-\beta_0 + \gamma_0}{\beta_1} + \frac{\gamma_1}{\beta_1}p_t^e - \frac{\beta_2}{\beta_1}y_t + \frac{\gamma_2}{\beta_1}z_t - \frac{1}{\beta_1}u_t + \frac{1}{\beta_1}v_t, \tag{3.9}$$

provided that $\beta_1 \neq 0$. Thus we can see that $Cov(p_t, u_t) \neq 0$ and $Cov(p_t, v_t) \neq 0$; in other words, p_t is endogenous. Let $w = u - v$. Then, under $Cov(u_t, v_s) = 0$, $w \sim N\left(0, \left(\sigma_u^2 + \sigma_v^2\right)I_T\right)$. Further, using (3.4b), (3.9) can be written as

$$p_t = \frac{-\beta_0 + \gamma_0}{\beta_1}(1-\theta) + \left\{\frac{\gamma_1}{\beta_1}(1-\theta) + \theta\right\}p_{t-1} - \frac{\beta_2}{\beta_1}\phi(L)y_t + \frac{\gamma_2}{\beta_1}\phi(L)z_t - \frac{1}{\beta_1}\phi(L)w_t,$$

where $\phi(L) = 1 - \theta L$ and $0 \le \theta < 1$. This regression equation now includes a lagged dependent variable and $MA(1)$ disturbance term. Furthermore, since p_{t-1} and w_{t-1} are correlated, an appropriate instrument for p_{t-1} is needed for consistency. Thus consider $\hat{p}_{t-1}$ as a linear combination of 1, y_{t-1} and z_{t-1}.[23]

The supply equation (3.6b) or (3.8b) with adaptive expectation formation cannot be directly estimated because it has a lagged dependent variable and $MA(1)$ disturbance term. One possible approach is the so-called approximate maximum likelihood estimation. Following the procedure by Johnston (1984)[24], the supply equation can be written as

$$q_t = r_0 x_{0,t} + \gamma_0 x_{1,t} + \gamma_1 x_{2,t} + \gamma_2 x_{3,t} + v_t, \tag{3.10}$$

where $x_{0,t} = \theta^t$, $x_{1,t} = (1-\theta)\left(1 + \theta + \cdots + \theta^{t-1}\right)$, $x_{2,t} = (1-\theta)p_t{*}$, and $x_{3,t} = z_t - \theta^t z_0$. Note that $p_t{*} = p_{t-1} + \theta p_{t-2} + \cdots + \theta^{t-1}p_0$. For more details, refer to Appendix A.1.

3.3 Interdependent Model

The susceptibility of the basic model to a change in the unit of time (e.g. monthly to quarterly, or quarterly to yearly) is another issue that must be taken into consideration. Fox (1968)[25] discussed this issue, distinguishing a 'derived model' from a 'basic model'.

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[23] The linear combination is given by $\hat{p}_t = -1.7703 + 0.4493 y_t + 0.0932 z_t$ and the correlation between p_t and $\hat{p}_t$ is 0.88.

[24] See pp. 368-370.

In general, a complete model explicitly incorporates all the actions of every individual and introduces time in that sufficiently short periods correspond to the actions of the subjects. This is called a basic model, which is always recursive. A derived model, in contrast to a basic model, is an aggregated and gross approximation of reality. The availability of data often determines the unit of time selected as well as the degree of aggregation, which introduces arbitrary elements into the model. These elements may be responsible for the interdependent nature of many derived models. In this regard, the longer the unit of time in the model, the more simultaneous relationships will be found. In the proposed model, q_t is a flow variable and p_t is considered as an average price over the time period t. Thus, if a quarter is not a short enough time unit for a recursive model, introducing p_t^e into the basic model may be irrelevant. The price elasticity of demand (supply) varies with the amount of time given to the consumers (suppliers) in responding to a price change. In general, the long run demand (supply) is more elastic than the short run demand (supply). In this case, a recursive model becomes inappropriate and an interdependent model can substitute. In a similar fashion to (3.6a) and (3.6b), an interdependent model can be written as

$$p_t = \beta_0 + \beta_1 q_t + \beta_2 y_t + u_t, \tag{3.11a}$$

$$q_t = \gamma_0 + \gamma_1 p_t + \gamma_2 z_t + v_t. \tag{3.11b}$$

Since the structural equations (3.11a) and (3.11b) are just-identified, the ILS method will be applicable and give the same estimates as the 2SLS method. However, these methods are applicable only if the disturbance terms are uncorrelated. Using Cramer's rule, the reduced form equations are given by

$$p_t = \frac{\beta_0 + \beta_1\gamma_0}{1-\beta_1\gamma_1} + \frac{\beta_2}{1-\beta_1\gamma_1} y_t + \frac{\beta_1\gamma_2}{1-\beta_1\gamma_1} z_t + \frac{1}{1-\beta_1\gamma_1} u_t + \frac{\beta_1}{1-\beta_1\gamma_1} v_t, \tag{3.12a}$$

$$q_t = \frac{\gamma_0 + \beta_0\gamma_1}{1-\beta_1\gamma_1} + \frac{\beta_2\gamma_1}{1-\beta_1\gamma_1} y_t + \frac{\gamma_2}{1-\beta_1\gamma_1} z_t + \frac{\gamma_1}{1-\beta_1\gamma_1} u_t + \frac{1}{1-\beta_1\gamma_1} v_t. \tag{3.12b}$$

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[25] See p. 411.

If the disturbance terms are correlated, namely $Cov(u_t, v_t) \neq 0$, it is more desirable to use a full information estimation technique (i.e. 3SLS and FIML), which has the effect of improving efficiency.

In the same manner as the preceding subsection, an alternative model in a similar form to (3.8a) and (3.8b) will also be considered. That is,

$$q_t = \beta_0 + \beta_1 p_t + \beta_2 y_t + u_t, \tag{3.13a}$$

$$q_t = \gamma_0 + \gamma_1 p_t + \gamma_2 z_t + v_t. \tag{3.13b}$$

The reduced form equations are

$$p_t = \frac{\beta_0 - \gamma_0}{\gamma_1 - \beta_1} + \frac{\beta_2}{\gamma_1 - \beta_1} y_t - \frac{\gamma_2}{\gamma_1 - \beta_1} z_t + \frac{1}{\gamma_1 - \beta_1} u_t - \frac{1}{\gamma_1 - \beta_1} v_t, \tag{3.14a}$$

$$q_t = \frac{\beta_0 \gamma_1 - \beta_1 \gamma_0}{\gamma_1 - \beta_1} + \frac{\beta_2 \gamma_1}{\gamma_1 - \beta_1} y_t - \frac{\beta_1 \gamma_2}{\gamma_1 - \beta_1} z_t + \frac{\gamma_1}{\gamma_1 - \beta_1} u_t - \frac{\beta_1}{\gamma_1 - \beta_1} v_t. \tag{3.14b}$$

Now that the system is interdependent, the partial derivative of the structural equation (3.13a) with respect to y_t is different from that of the reduced form equation (3.14a). As mentioned above, the former is concerned with a demand shift due to income change, while the latter with a change in equilibrium price.

3.4 Estimation

3.4.1 Data

The data set consists of the quarterly times series of the following variables spanning from 1989Q1 to 2008Q4 (a total of 80 observations). The data series and their sources are summarized below.

- Beef, pork and poultry prices (cents/pound, retail): ERS, USDA
- Beef consumption (million pounds, carcass weights): ERS, USDA
- Beef import and export (million pounds, carcass weights): ERS, USDA
- Personal income (million dollars): US Bureau of Economic Analysis (BEA)
- Population (million persons): US Census Bureau

- Corn price (dollars/bushel): NASS, USDA
- Hay price (dollars/ton): NASS, USDA
- CPI (US city average, 1982~84=100): US Bureau of Labor Statistics (BLS)

For feed price (z_t), corn and hay prices are used to make a composite price index in the following manner. First, each individual price index is generated, based on the average price between 1982 and 1984. Second, the weighted average (i.e. 70% of corn price and 30% of hay price) of the two price indices is computed.

The original data series are changed into logarithms. Thus, by using the logarithmic variables, the regression equation is represented in a log-linear form. Each coefficient means an elasticity, which is constant at any point.

3.4.2 Estimation of Recursive Model: Supply

Although the demand equation is of primary interest, the supply equation will be considered first, as it comes first in the ordering of the recursive model. Before considering the supply equation under the AEH, I will estimate the supply equation of the traditional cobweb model with $p_t^e = p_{t-1}$, as well as a benchmark equation with $p_t^e = p_t$ for comparison. An important thing about the quantity (beef consumption) series is that there is a distinct seasonal pattern as illustrated in Figure 2.5. Thus introducing seasonal dummies into the demand and supply equations will give a better result. Including three dummies s_2 (2nd quarter), s_3 (3rd quarter) and s_4 (4th quarter), the estimated supply equation of (3.6b) and (3.8b) is

$$\begin{array}{llllllll} \hat{q}_t = & 7.3053 & + \, 0.2822p_{t-1} & - \, 0.0373z_t & + \, 0.0493s_{2,t} & + \, 0.0512s_{3,t} & - \, 0.0008s_{4,t} \\ & (0.0000) & (0.0000) & (0.1445) & (0.0003) & (0.0002) & (0.9515) \end{array} \tag{3.15}$$

$$\overline{R}^2 = 0.6013, \; d = 0.3149.$$

The goodness of fit given by the adjusted coefficient of determination ($\overline{R}^2$) is relatively weak. Considering the p-values in parentheses, the intercept and price coefficients are significant even at a 1% level, while the input (z_t) coefficient is not significant even at a

10% level. The low Durbin-Watson statistic (d) indicates that the disturbances may be positively autocorrelated[26] of order 1. So the overall result of the estimation looks poor. However, the signs of the price and input coefficients are in accordance with the basic producer theory. That is, the quantity supplied has a positive relationship with price and a negative relationship with input price. With $p_t^e = p_t$, on the other hand, Equation (3.6b) and (3.8b) is estimated as

$$\underset{}{\hat{q}_t} = \underset{(0.0000)}{7.3519} + \underset{(0.0000)}{0.2709 p_t} - \underset{(0.1979)}{0.0337 z_t} + \underset{(0.0009)}{0.0459 s_{2,t}} + \underset{(0.0001)}{0.0544 s_{3,t}} - \underset{(0.9434)}{0.0009 s_{4,t}} \tag{3.16}$$

$$\overline{R}^2 = 0.57883,\ d = 0.4381.$$

This result is very similar to the previous one, but no better. Note that the correlation between p_t and p_{t-1} is 0.9879. Since both results suffer from the low d statistics, it may be better to estimate them with $AR(1)$ adjustments, such that

$$v_t = \rho_v v_{t-1} + \varepsilon_{v,t},$$

where $\varepsilon_{v,t}$ is white noise. Allowing for the serial correlation among the disturbances modifies the regression equation. Equation (3.6b) and (3.8b) are altered to

$$q_t = (1-\rho_v)\gamma_0 + \gamma_1 p_t^e - \rho_v \gamma_1 p_{t-1}^e + \gamma_2 z_t - \rho_v \gamma_2 z_{t-1} + \rho_v q_{t-1} + \varepsilon_{v,t}.$$

Table 3.1

Estimation of the supply equations[27] with $AR(1)$ adjustments

Supply I	$constant$	p_{t-1}	z_t	v_{t-1}	$\overline{R}^2$	d
	7.5654 (0.0000)	0.2098 (0.0025)	−0.0041 (0.9039)	0.8542 (0.0000)	0.8849	2.4902
Supply II	$constant$	p_t	z_t	v_{t-1}	$\overline{R}^2$	d
	11.6362 (0.0000)	−0.4855 (0.0000)	−0.0142 (0.6508)	0.9942 (0.0000)	0.9126	2.8586

† p-values in parentheses

26 Some authors distinguish autocorrelation from serial correlation; in this research, these terms have the same meaning.

27 *Supply I* stands for the supply equation with $p_t^e = p_{t-1}$, *Supply II* for the supply equation with $p_t^e = p_t$, and later on *Supply III* for the supply equation with adaptive expectation formation.

Table 3.1 shows the estimation results using the maximum likelihood search method for ρ. Although the previous results (without $AR(1)$ adjustments) hinted that there could be no differences between substituting p_{t-1} and p_t for p_t^e, these results now differentiate between them. That is, the substitution of p_t for p_t^e becomes even more inferior (not plausible). The input coefficients of both equations are not significant. More important is the sign of the price coefficient. In *Supply II*, it is changed to negative, which is expected in a demand equation. Since the supply equation with $p_t^e = p_{t-1}$ maintains the positive sign of the price coefficient, but does not with $p_t^e = p_t$ does not, a recursive model may be appropriate for an agricultural product such as beef. Still, it is premature and further evidence is needed.

When examining the d statistics, the results show that the $AR(1)$ adjustments have not necessarily settled the serial correlation problem. According to the d table,[28] $d_L = 1.5031$ and $d_U = 1.7712$, when $n = 79$ and $K = 6$.[29] Thus the d statistic of *Supply I* still belongs to the indecisive area, while that of *Supply II* belongs to the negative autocorrelation area. A further notable thing is that the intercepts and price coefficients of *Supply I* with and without the $AR(1)$ adjustment are not so different.

Now consider the supply equation under the AEH. As mentioned before, it cannot be estimated directly from (3.6b) or (3.8b), but (3.10). To estimate (3.10), θ should be predetermined. For this, the procedure proposed by Leamer (1983), which is a cross validation method, will be followed. This seeks to minimize

$$P = g(\theta; Q_1, Q_2, X_1, X_2) = (Q_1 - X_1c_2)^\top (Q_1 - X_1c_2) + (Q_2 - X_2c_1)^\top (Q_2 - X_2c_1), \quad (3.17)$$

where Q_i is a vector of quantities, X_i is a matrix of explanatory variables, and c_i is a vector of parameter estimates for the ith part of the data. Thus, from the data given, P for θ in $[0, 1)$ can be computed.[30] Figure 3.1 shows how P varies with θ. The penalty (P) is

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[28] Refer to Appendix E.

[29] Each equation has 6 regressors ($K = 6$) including the intercept and seasonal dummy variables. Due to the inclusion of an $AR(1)$ disturbance term, the number of usable observations is 79 ($n = 79$).

[30] Refer to Appendix A.2 for the detailed computation.

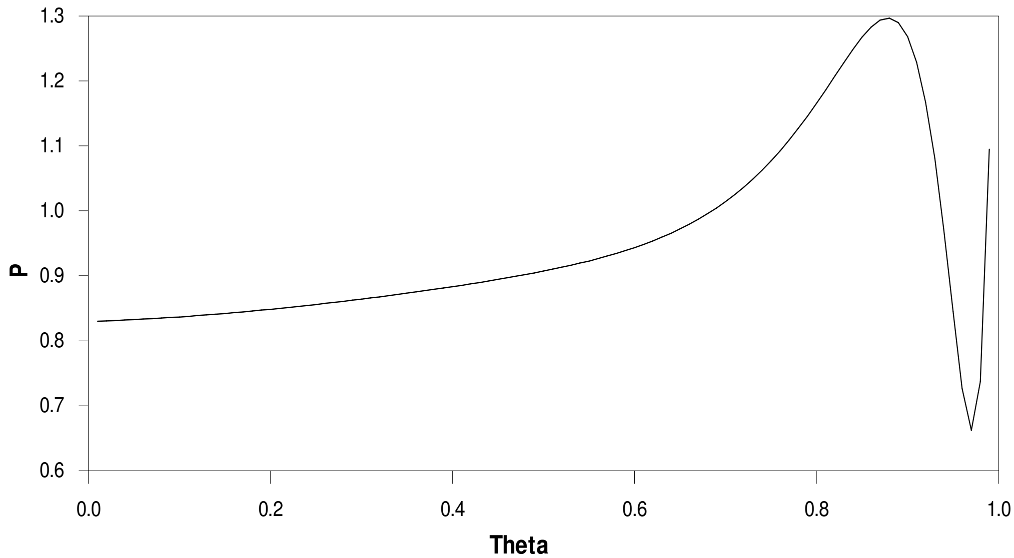


Figure 3.1 Graph of $P = g(\theta; Q_1, Q_2, X_1, X_2)$

minimized at $\theta = 0.97$. This is a useful method when there is no theory about choosing θ. However, it is not easy to explain the result theoretically, as pointed out in Leamer (1983).

Having done this, the next step is to generate relevant variables in (3.10) and estimate it using the OLS method. Table 3.2 displays the estimation result obtained indirectly from (3.10). Compared to the previous results, especially to the one of $Supply\ I$ with an $AR(1)$ adjustment, this result seems to be very plausible. The only drawback is the relatively low d statistic. However, as the estimation with an $AR(1)$ adjustment did not settle the problem, there remains no need for such an adjustment. In fact, the serial

Table 3.2

Estimation of the supply equation under the adaptive expectation hypothesis

	$constant$	p_t^e	z_t	$\overline{R}^2$	d
$Supply\ III$	7.9617 (0.0000)	0.1850 (0.0114)	−0.0396 (0.0302)	0.8653	0.9667

† p-values in parentheses

correlation problem is frequent, especially when using time series data. There are some different reasons for the problem. The disturbance terms reflect omitted variables that may change slowly over time. Additionally, the disturbance at a certain observation may be related to the disturbances at nearby observations. Another possibility is that the smoothing of data may result in an averaging of the disturbance terms over several periods. Of course, misspecification of a model (i.e. the exclusion of relevant variables) is a general cause of serial correlation.

One of the most important properties of a good estimator is efficiency, which may be harmed by the serial correlation problem. In the estimation result of *Supply III*, the estimators of the key parameters (i.e. the intercept and price coefficients) have relatively smaller variances[31] and the estimates are not so different from those of *Supply I* with an $AR(1)$ adjustment. Hence, the serial correlation problem is less serious than in the first estimation results (*Supply I* and *Supply II* without an $AR(1)$ adjustment). Therefore, the

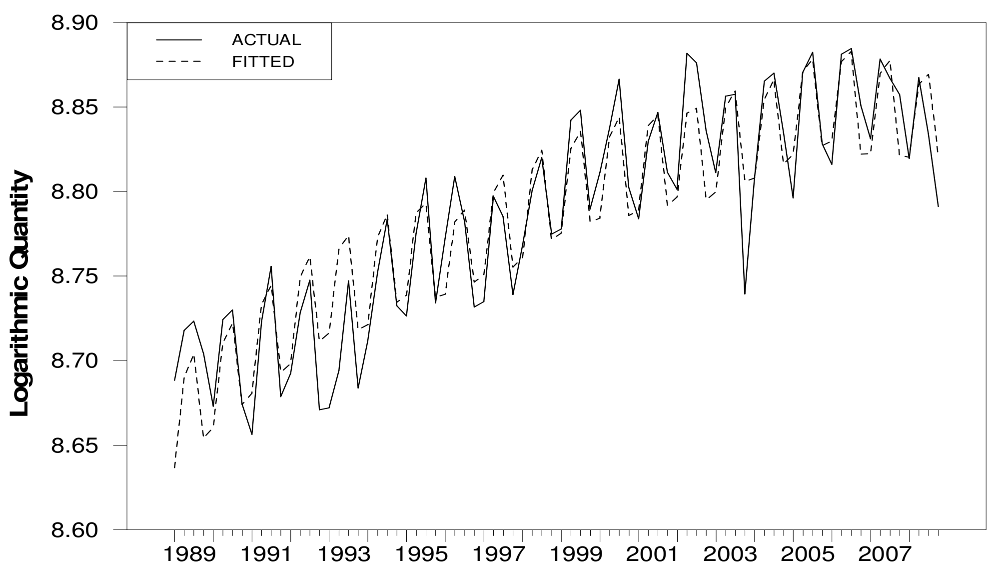


Figure 3.2 Actual and fitted quantities of *Supply III*

[31] This does not mean that σ_v^2 is smaller, but that $Var\left(\hat{\gamma}_k\right)$ is smaller for $k = 0, 1$.

result of *Supply III* for the supply equation of a recursive model will be used. Figure 3.2 tells how well *Supply III* fits the actual quantity series.

There are some implications worth mentioning from the above results. First, the quantity supplied has a positive relationship with the expected price and the elasticity is less than 1 (inelastic). This is a common property of agricultural products because it is not easy to control production in response to some change in market conditions. This is also closely related to the elasticity of expectation, which will be discussed later in this dissertation. Second, the quantity supplied has a negative relationship with the input price but the elasticity is very small. This means that beef suppliers are less sensitive to input price changes. Third, there are obvious seasonal shifts in the intercept. Figure 3.3 below illustrates the changes. The intercepts in the first and fourth quarters are γ_0, which is the original level of the supply curve ($S_{1,4}$). In the second and third quarters, it shifts to the right (S_2 and S_3,respectively). The lengths of $\overline{AB}$ and $\overline{AC}$ are the same as the coefficients of the second and third seasonal dummy variables, respectively. As to the seasonal changes, the estimation results of the three supply equations agree with each other very closely. According to the estimation result of *Supply III*, $\overline{AB}= 0.0485$ and $\overline{AC}= 0.0528$. Lastly, since $\lambda = 1-\theta$, the elasticity of expectations (λ) is 0.03. It implies

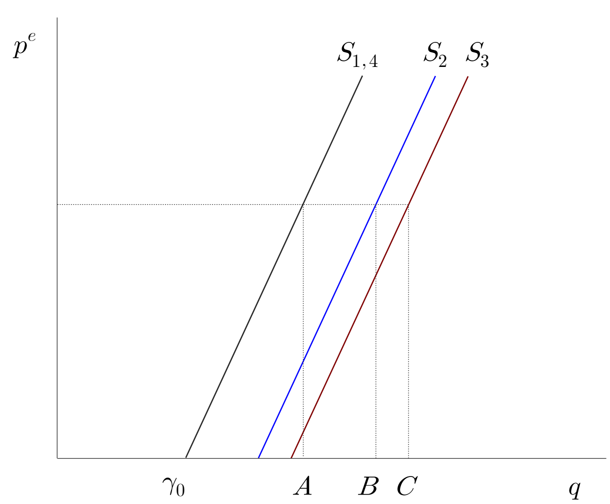


Figure 3.3 Seasonal changes in supply

that people's expectations are not so sensitive to actual price changes. This is analogous to the fact that the supply is price-inelastic, that is, the price elasticity (in an absolute value) is less than 1. Note that the estimated price elasticity is 0.1850 from Table 3.2. Of course, there might arise a criticism about the constancy of the parameter λ (or θ) over time; this issue is addressed in Chapter IV. However, it can still be regarded as an approximate indication of the elasticity of expectations over the time period being analyzed.

3.4.3 Estimation of Recursive Model: Demand

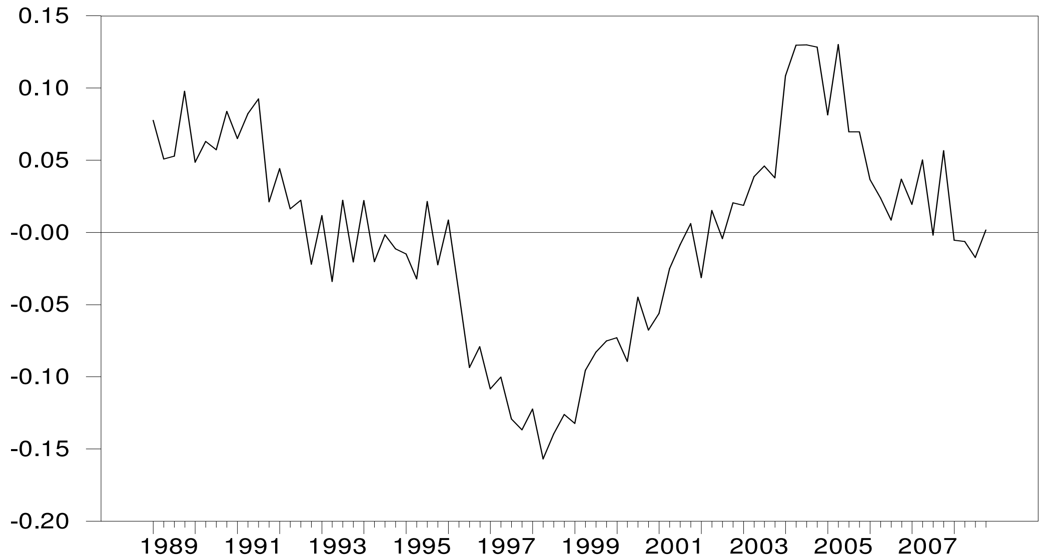
A more careful approach is required to estimate the demand equation for the reasons mentioned below. First, the demand equation contains two endogenous variables (p_t and q_t) in contrast to the supply equation, which has only one. As mentioned before, an additional assumption, $Cov(u_t, v_t) = 0$, is needed for a recursive model so that the endogeneity of q_t may be taken away from (3.6a). Thus the assumption should be justified. Second, the estimation may be very sensitive to a functional form change. There have been disputes between researchers about the functional form of an agricultural demand equation. For instance, (3.6a) is quite different from (3.8a). Even if the recursive model is justified, looking into the alternative functional form such as (3.8a) will provide an informative background for further study.

First, (3.6a) and (3.8a) will be estimated by OLS as if they were a single equation. The estimated demand equation of (3.6a) is given by

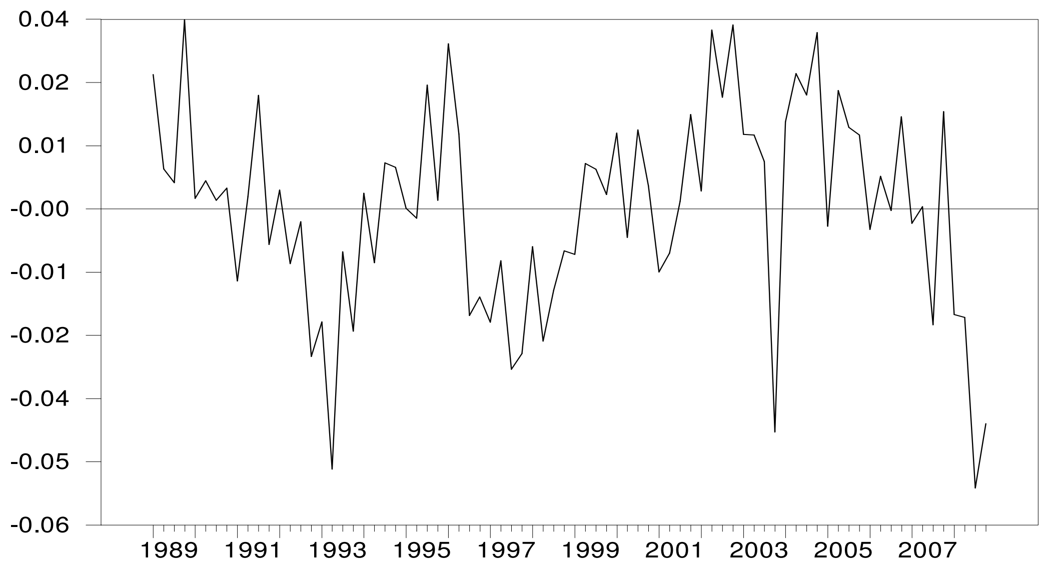
$$\begin{aligned} \hat{p}_t = \; & \underset{(0.0002)}{8.9440} - \underset{(0.0000)}{1.7797}q_t + \underset{(0.0000)}{0.7840}y_t + \underset{(0.0015)}{0.0946}s_{2,t} + \underset{(0.0019)}{0.0977}s_{3,t} + \underset{(0.9459)}{0.0016}s_{4,t} \end{aligned} \tag{3.18}$$

$$\overline{R}^2 = 0.8084, \; d = 0.2086.$$

The explanatory power of the regression is moderate. Considering the p-values, most coefficients are statistically significant even under a 1% level. The negative sign of the quantity coefficient is in accordance with the law of demand, and the positive sign of the income coefficient implies that beef is a normal good. This result is also pursuant to



(a)



(b)

Figure 3.4 Residual series of (a) $Demand\,I$ and (b) $Demand\,II$[32]

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32 $Demand\,I$ stands for the inverse (price-dependent) demand equation, and $Demand\,II$ for the ordinary (quantity-dependent) demand equation.

common sense. The only fly in the ointment is a low Durbin-Watson statistic (d). Since $d = 0.2086$ is far less than $d_L = 1.5031$ ($n = 79$, $K = 6$), it indicates a positive first-order autocorrelation in the disturbance term. This is illustrated very clearly in Figure 3.4 (a). Furthermore, the presence of autocorrelation deteriorates the efficiency of the estimators; however, the estimators are still unbiased and consistent. Thus, if a serial correlation is the only problem that remains, whether or not to accept the model would be a hard question to answer.

On the other hand, the estimated demand equation of (3.8a) is

$$\begin{array}{rcccccc} \hat{q}_t = & 5.7445 & -\ 0.1340 p_t & +\ 0.2393 y_t & +\ 0.0481 s_{2,t} & +\ 0.0541 s_{3,t} & -\ 0.0006 s_{4,t} \\ & (0.0000) & (0.0000) & (0.0000) & (0.0000) & (0.0000) & (0.9229) \end{array} \tag{3.19}$$

$$\overline{R}^2 = 0.9031,\ d = 1.1099.$$

The result of this demand estimation is more plausible than the previous one in all aspects (i.e. the explanatory power of the regression, d statistic, and p-values). Even if the d statistic belongs to the positive first-order autocorrelation region, the pattern of (b) is distinct from that of (a) in Figure 3.4. Also, this equation instantly gives the price and income elasticities, the coefficients of p_t and y_t, respectively. The price elasticity of 0.1340 does not match that of (3.6a), which is 1/1.7797=0.5619. As stated before, however, (3.8a) could not be estimated separately from the supply equation because it has an endogenous variable (p_t) on the righthand side. Thus special treatments are needed for this equation and will be discussed later in this research. Another positive result of the demand estimation is that the inclusion of the income variable (y_t) does make the demand equation identifiable. The only difference between (3.16) and (3.19) is that they include different exogenous variables, income (y_t) and input (z_t), respectively. The resulting parameter estimates are all desirable, which means that the signs of the coefficients all comply with basic economic theories. This compliance is another clue to the recursiveness of the system given by (3.6a) and (3.6b). Finally, the correlation between the residuals should be checked. Table 3.3 below summarizes the covariances and correlations computed for all the possible combinations. Since the residuals are very small in

Table 3.3

Covariances and correlations between residuals[33]

Residuals		$\hat{v}_I$	$\hat{v}_{II}$	$\hat{v}_{III}$
$\hat{u}_I$	*covariance*	-0.0014	-0.0013	0.0003
	correlation	-0.5021	-0.4681	0.1760
$\hat{u}_{II}$	*covariance*	0.0003	0.0003	0.0004
	correlation	0.3853	0.4319	0.8311

their value, the covariances are also small. Thus the correlation coefficients are more useful for the purpose of comparison. The residual series are, to some extent, correlated with each other. However, the combination of *Demand I* and *Supply III* gives a very small correlation coefficient, which is 0.1760. Considering all the facts discovered up to this point, the system of *Demand I* and *Supply III* can therefore be considered as a recursive model.

Since (3.18) and (3.19) have the serial correlation problem in common, remedial procedures are necessary. The low d statistics indicate that the disturbances are generated by the first-order autoregressive scheme. As done before, the disturbance term is determined by

$$u_t = \rho_u u_{t-1} + \varepsilon_{u,t},$$

where $\varepsilon_{u,t}$ is white noise. Putting this into Equation (3.6a), it is now modified to

$$p_t = (1 - \rho_u)\beta_0 + \beta_1 q_t - \rho_u \beta_1 q_{t-1} + \beta_2 y_t - \rho_u \beta_2 y_{t-1} + \rho_u p_{t-1} + \varepsilon_{u,t}.$$

Table 3.4 shows the estimation results using the maximum likelihood search method for ρ. At a glance, the result of *Demand I* seems to be improved, while that of *Demand II* is not so much different from the previous one. However, an important difference exists between the two results of *Demand I*. The price and income elasticities of demand have been become more elastic, while the intercept has slightly increased. In particular, the

33 $\hat{u}_I$ is from (3.18), $\hat{u}_{II}$ from (3.19), $\hat{v}_I$ from (3.15), $\hat{v}_{II}$ from (3.16), and $\hat{v}_{III}$ from the estimation of (3.10) in Appendix A.1.

Table 3.4

Estimation of the demand equations with $AR(1)$ adjustments

$Demand\,I$	$constant$	q_t	y_t	u_{t-1}	$\overline{R}^2$	d
	3.6206 (0.0445)	−0.6620 (0.0000)	0.5033 (0.0000)	0.9651 (0.0000)	0.9842	2.0001
$Demand\,II$	$constant$	p_t	y_t	u_{t-1}	$\overline{R}^2$	d
	5.6995 (0.0000)	−0.2102 (0.0000)	0.2698 (0.0000)	0.5362 (0.0000)	0.9216	2.4234

† p-values in parentheses

price elasticity of demand has changed from inelastic ($1/1.7797 = 0.5619 < 1$) to elastic ($1/0.6620 = 1.5106 > 1$). This change is more serious than the income elasticity change from ($0.7840/1.7797 = 0.4405$) to ($0.5033/0.6620 = 0.7603$). The two results of $Demand\,II$ show a similar pattern of changes but not so severe. Compared to the parameter estimates of $Demand\,II$, the drastic changes in the elasticities of $Demand\,I$ make the relevance of the $AR(1)$ adjustment rather questionable.

To sum up the findings, the system of $Demand\,I$ and $Supply\,III$ is ideal for a recursive model, but the demand equation suffers from serial correlation in disturbances. Additionally, an $AR(1)$ adjustment does not settle the problem in a desirable way.[34] Strictly speaking, the system of $Demand\,II$ and $Supply\,III$ is not regarded as a recursive model. If the endogeneity of p_t can be appropriately managed, however, it may be an alternative model to the recursive model.

3.4.4 *Complementary Results to Recursive Model*

Thus far, results have shown a recursive model as ideal for an agricultural product, especially for meat products with which this study is concerned. Strictly speaking, the system of (3.8a) and (3.8b) is not a recursive model. However, it is possible to estimate

34 Although the autocorrelation problem is not completely settled, a certain level of autocorrelation is allowed in this study, based on the results of the suggested remedial procedures. Even with this problem, a least squares estimator is still unbiased, while it is not efficient.

the supply equation separately and then to estimate the demand equation in the relation to the supply equation using an instrument variable method. Thus, in some sense, such a model is considered to be in between recursive and interdependent. In (3.8a), an instrument for p_t is needed for consistency, regardless of $Cov(u_t, v_t) = 0$. As such, the 2SLS estimation method is considered. However, the reduced form equation (3.9) is difficult to estimate because of its complicated specification (i.e. lagged dependent variable and $MA(1)$ disturbance term). Furthermore, some coefficients are given in a complex of parameters, which makes the estimation even harder. Instead, the endogeneity problem will be settled using alternative methods.

The first alternative is to use (3.4c) instead of (3.4b). The coefficients are written as

$$a_1 = (1-\theta), a_2 = (1-\theta)\theta, \cdots, a_h = (1-\theta)\theta^{h-1}, \cdots \tag{3.20}$$

The infinite sum of the coefficients are given by

$$(1-\theta)\sum_{j=1}^{\infty}\theta^{j-1} = 1 \text{ for } 0 \leq \theta < 1.$$

Since the optimal estimate of θ is 0.97, the a's can be computed, resulting in the series

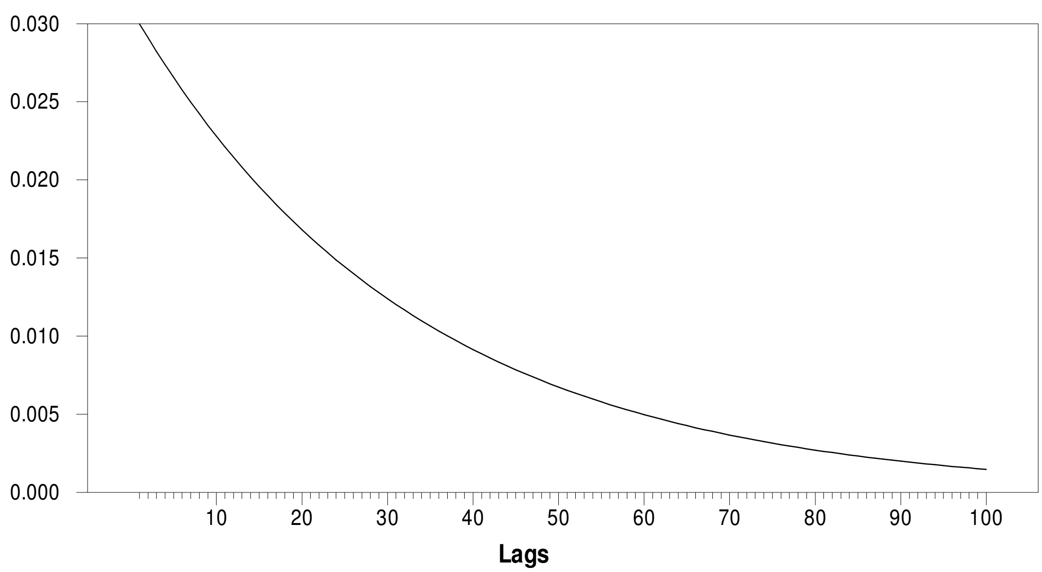


Figure 3.5 The graph of a's

decreasing slowly, as illustrated in Figure 3.5. In fact, it exhibits a long memory process. The smaller θ is, the more rapidly the graph decreases. Thus, for the extreme of $\theta = 0$, the graph becomes a vertical line on the first lag. Therefore, a large value of θ implies that the suppliers' price expectations may not be sensitive to a sudden price change. With the value of θ given, it is possible to generate p_t^e using (3.4c). However, more price data is needed for such a large time lag. The time span for the price series will be expanded by adding 76 more sample points of nineteen years before the current sample period. The price series now spans 39 years (156 observations) from 1970Q1 to 2008Q4. Even with the extended sample period, it is not possible to completely reflect the effects of the lagged price coefficients under $\theta = 0.97$. Figure 3.6 shows how many lags are needed to explain the total price effects. For example, 75% of the total effects can be explained by approximately 46 lags. 76 lags (19 years) can explain approximately 90%. Thus, p_t^e can be approximated using (3.2) and (3.20):

$$p_t^e \simeq a_1 p_{t-1} + a_2 p_{t-2} + \cdots + a_h p_{t-h} + b = \sum_{j=1}^{h} (1-\theta)\theta^{j-1} p_{t-j} + b. \tag{3.21}$$

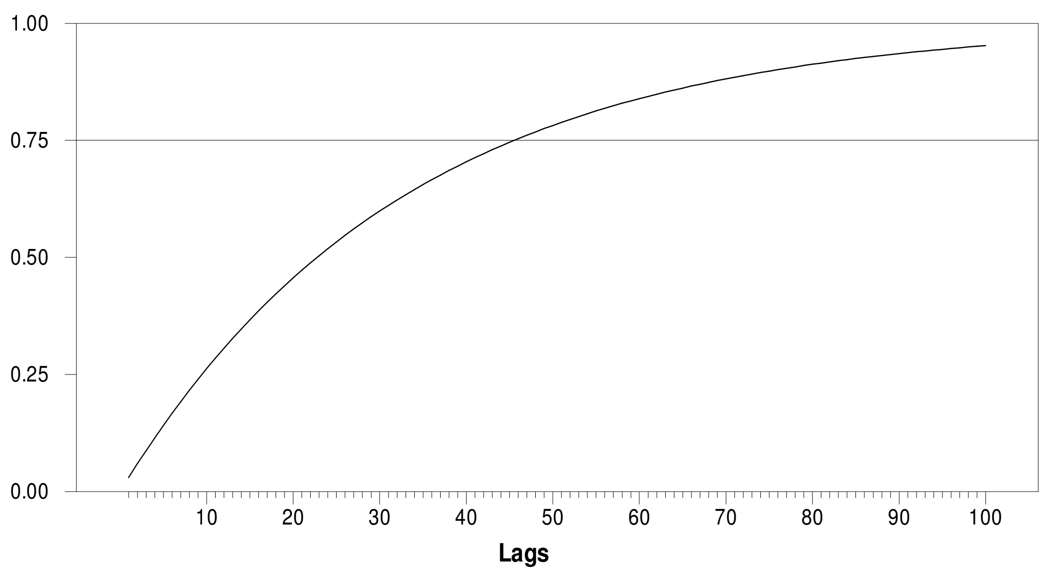


Figure 3.6 The graph of the cumulative sums of a's

Simply, h can be the number of the additional sample points; that is, $h = 76$. For b, the initial condition must be established; for example, $p^e_{1989Q1} = p_{1989Q1}$. Thus, the first period of the effective sample is 1989Q1 as was in the previous sample. Additionally, b will be given a certain value. Finally, we can generate a series of p^e_t from 1989Q1 to 2008Q4. Using this series of p^e_t, the estimated supply equation of (3.6b) or (3.8b), also referred to as $Supply\ IV$, is

$$\underset{}{\hat{q}_t} = \underset{(0.0000)}{6.5980} + \underset{(0.0000)}{0.4350 p^e_t} - \underset{(0.0000)}{0.0796 z_t} + \underset{(0.0000)}{0.0506 s_{2,t}} + \underset{(0.0000)}{0.0523 s_{3,t}} - \underset{(0.5820)}{0.0047 s_{4,t}}$$

$$\overline{R}^2 = 0.8251,\ d = 0.7601.$$

This result may be compared to that of $Supply\ III$ because they both are based on the AEH. Table 3.5 below summarizes the estimation result of $Supply\ IV$ with an $AR(1)$ adjustment. Compared to the results of $Supply\ I$ and $Supply\ II$ in Table 3.1, this result is more plausible in many aspects. The input coefficient is now significant at a 10% level. A notable difference between the estimation results of $Supply\ I$ and $Supply\ IV$ is that the price coefficient of $Supply\ IV$ is greater than that of $Supply\ I$, in which it is assumed that $p^e_t = p_{t-1}$. This is because p^e_t in $Supply\ IV$ is represented explicitly as a linear combination of the lagged prices and therefore may have a larger effect on the dependent variable. p^e_t in $Supply\ III$ is also a linear combination of the lagged prices; however, the underestimated price coefficient may be the result of including a nuisance parameter. Figure 3.7 shows how well the estimated quantity of $Supply\ IV$ fits the actual quantity series. Overall, p^e_t in $Supply\ IV$ appears to be more relevant than p_{t-1} in the traditional

Table 3.5

Estimation of $Supply\ IV$ with an $AR(1)$ adjustment

	$constant$	p^e_t	z_t	v_{t-1}	$\overline{R}^2$	d
$Supply\ IV$	6.7316 (0.0000)	0.3884 (0.0000)	−0.0501 (0.0789)	0.6535 (0.0000)	0.8908	2.3695

† p-values in parentheses

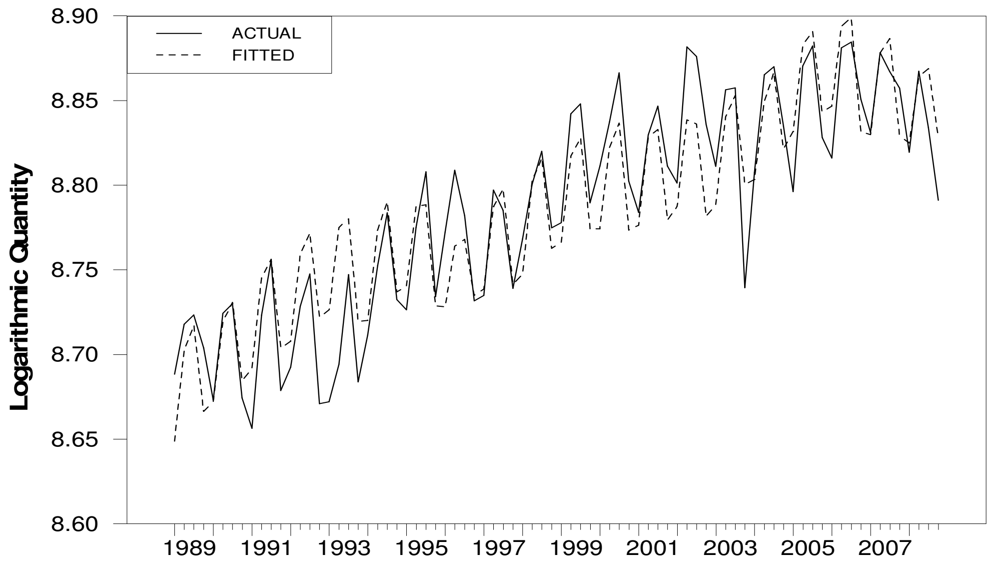


Figure 3.7 Actual and fitted quantities of $Supply\,IV$

cobweb model. Furthermore, (3.21) can be used to reestimate θ at a different level of h. For different values of θ in $[0,1)$, the series of p_t^e can be generated in a similar manner as done above. In the second stage, the regression of the supply equation given by (3.1b) would be performed. Then the penalty (e.g. RSS) would be computed to find the optimal θ such that the penalty is minimized. Although the concept is simple, this procedure is time-consuming and as a result will not be pursued in this study.

For the estimation of demand equations in relation to the supply equation, $Supply\,I$ and $Supply\,IV$ will be considered. As referred to before, it is always possible to estimate each equation separately in a recursive system. However, the recursiveness may not hold. One reason for this is that the disturbance terms are correlated with each other; $Cov(u_t, v_t) \neq 0$. Another reason is that the demand equation has a quantity-dependent functional form such as (3.8a). As long as the demand and supply equations are considered to constitute a system, there arises an endogeneity problem in Equation (3.8a), no matter the relation between u_t and v_t. After all, both cases result in an endogeneity problem. For the system of (3.6a) and (3.6b), if $Cov(u_t, v_t) \neq 0$,

$$Cov(q_t, u_t) = E\big[(\gamma_0 + \gamma_1 p_t^e + \gamma_2 z_t + v_t)u_t\big] \neq 0.$$

In (3.6a), therefore, q_t is correlated with the disturbance term. For the system of (3.8a) and (3.8b), we have

$$p_t = \frac{1}{\beta_1}\big(-\beta_0 + \gamma_0 + \gamma_1 p_t^e - \beta_2 y_t + \gamma_2 z_t - u_t + v_t\big).$$

Also, p_t in (3.8a) is correlated with the disturbance term, that is, $Cov(p_t, u_t) \neq 0$. Because of this problem, we may not expect the consistency of an estimator. However, it can be settled by using an appropriate instrument for the endogenous variable. For instance, the linear combination of p_t^e, y_t, and z_t can be thought of as an instrument for q_t in (3.6a), or $Demand\,I$. Similarly, the linear combination of p_t^e, y_t, and z_t can be thought of as an instrument for p_t in (3.8a), or $Demand\,II$. Now that two different representations of p_t^e[35] have been introduced (based on the traditional cobweb model and the AEH, respectively), each representation must be examined to determine which one more accurately fits the actual data series. By regressing q_t on p_{t-1}, y_t, z_t and seasonal dummies,

$$\begin{array}{lllllll} \hat{q}_t = 5.8672 & -\ 0.0878 p_{t-1} & +\ 0.2252 y_t & -\ 0.0362 z_t & +\ 0.0484 s_{2,t} & +\ 0.0547 s_{3,t} & -\ 0.0021 s_{4,t} \\ \quad\ (0.0000) & (0.0033) & (0.0000) & (0.0053) & (0.0000) & (0.0000) & (0.7472) \end{array}$$

$$\overline{R}^2 = 0.9014,\ d = 1.3765.$$

Substituting $\hat{q}_t$ for q_t in (3.6a), the estimated demand equation ($Demand\,I$) is

$$\begin{array}{llllll} \hat{p}_t = 32.3447 & -\ 5.6996 q_t & +\ 1.4750 y_t & +\ 0.2770 s_{2,t} & +\ 0.3086 s_{3,t} & -\ 0.0027 s_{4,t} \\ \quad\ (0.0000) & (0.0000) & (0.0000) & (0.0000) & (0.0000) & (0.8768) \end{array} \tag{3.22}$$

$$\overline{R}^2 = 0.8933,\ d = 0.3486.$$

Still, this result suffers from a low d statistic. The price elasticity is $1/5.6996 = 0.1755$ and the income elasticity is $1.4750/5.6996 = 0.2588$. Surprisingly, this result is more similar to (3.19) than to (3.18), even though the former is based on a different functional form, $Demand\,II$. In the same manner, regressing p_t on p_{t-1}, y_t, and z_t gives

[35] From now on, p_{t-1} will denote the expected price in the traditional cobweb model and p_t^e will simply denote the expected price under the AEH.

$$\hat{p}_t = \underset{(0.1500)}{-0.1959} + \underset{(0.0000)}{0.9495p_{t-1}} + \underset{(0.0703)}{0.0296y_t} + \underset{(0.7228)}{0.0056z_t}$$

$$\overline{R}^2 = 0.9758,\ d = 2.0116.$$

Substituting $\hat{p}_t$ for p_t in (3.8a), the estimated demand equation ($Demand\,II$) is

$$\hat{q}_t = \underset{(0.0000)}{5.7809} - \underset{(0.0005)}{0.1127p_t} + \underset{(0.0000)}{0.2292y_t} + \underset{(0.0000)}{0.0465s_{2,t}} + \underset{(0.0000)}{0.0552s_{3,t}} - \underset{(0.8953)}{0.0009s_{4,t}} \tag{3.23}$$

$$\overline{R}^2 = 0.8921,\ d = 1.2477.$$

This result is even more similar to (3.19). The elasticities are slightly less than those of (3.19) in their absolute values. Thus, the presumption can be made that the actual demand equation may be approximated by estimating (3.8a) alone, without consideration of the endogeneity problem. However, more evidence is needed.

Figure 3.8 (a) and Figure 3.8 (b) show how well the estimated demand equations fit the actual data series, price and quantity, respectively. In Figure 3.8 (a), the estimated demand equation overstates the prices for the period of three years from 1995 to 1997, but on the whole, fits the actual price series well. On the other hand, the same procedure can be replicated with p_t^e in place of p_{t-1}. By regressing q_t on p_t^e, y_t, z_t and seasonal dummies, the following equation results:

$$\hat{q}_t = \underset{(0.0000)}{5.7213} - \underset{(0.0034)}{0.2956p_t^e} + \underset{(0.0000)}{0.3052y_t} - \underset{(0.2894)}{0.0164z_t} + \underset{(0.0000)}{0.0475s_{2,t}} + \underset{(0.0000)}{0.0545s_{3,t}} - \underset{(0.9230)}{0.0006s_{4,t}}$$

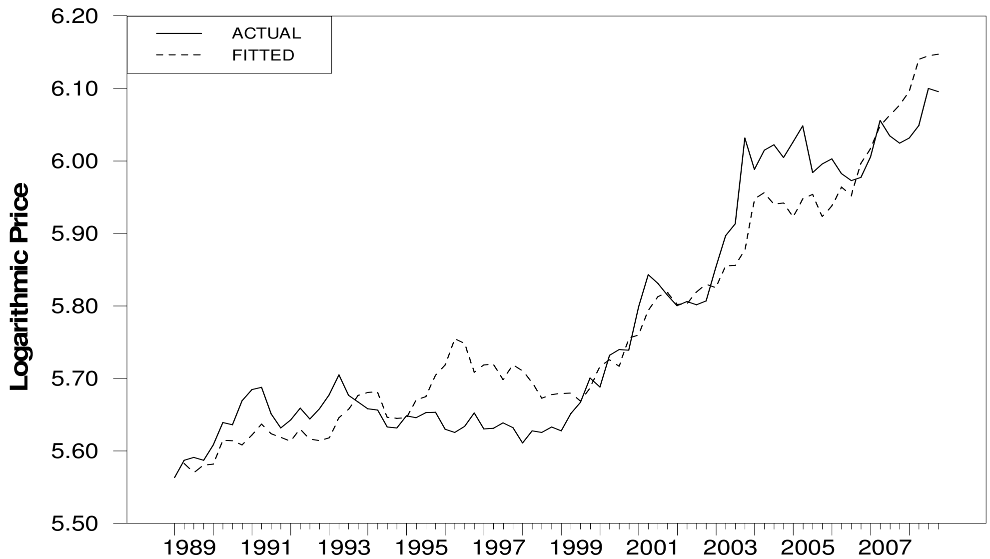
$$\overline{R}^2 = 0.9013,\ d = 1.3179.$$

Substituting $\hat{q}_t$ for q_t in (3.6a), the estimated demand equation ($Demand\,I$) is

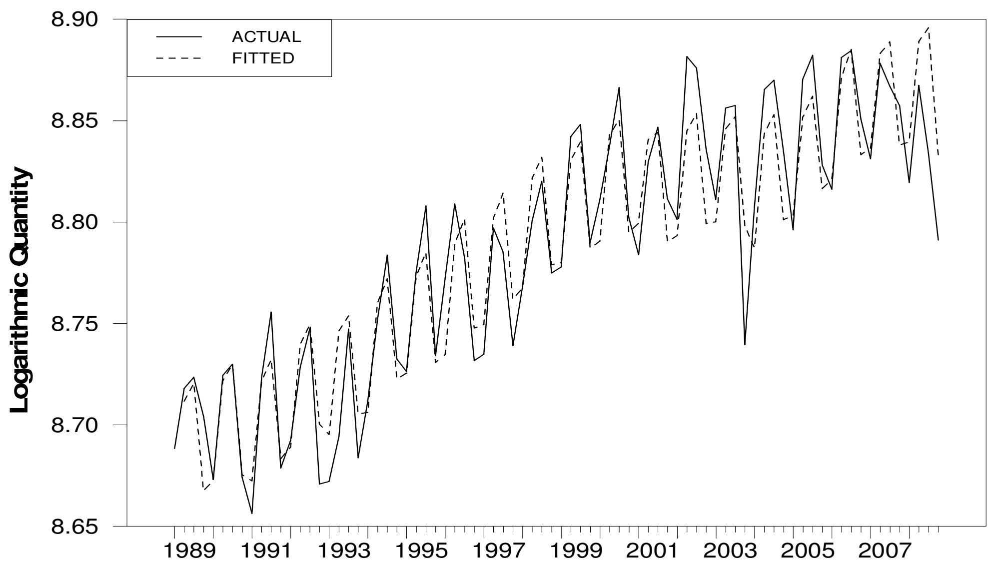
$$\hat{p}_t = \underset{(0.0006)}{17.1421} - \underset{(0.0002)}{3.1530q_t} + \underset{(0.0000)}{1.0261y_t} + \underset{(0.0006)}{0.1585s_{2,t}} + \underset{(0.0008)}{0.1716s_{3,t}} + \underset{(0.9973)}{0.0001s_{4,t}} \tag{3.24}$$

$$\overline{R}^2 = 0.7926,\ d = 0.1204.$$

The explanatory power of regression and d statistic are lower for (3.24) than in (3.22). The price elasticity of demand is now $1/3.1530 = 0.3172$ and the income elasticity is $1.0261/3.1530 = 0.3254$; both are more elastic than the elasticities from (3.22). Regressing



(a)



(b)

Figure 3.8 Estimated demand equations using p_{t-1}, y_t and z_t:

(a) $Demand\,I$ and (b) $Demand\,II$

p_t on p_t^e, y_t, and z_t gives

$$\begin{aligned}\hat{p}_t = &-0.4348 &+ 1.3520p_t^e &- 0.0953y_t &- 0.0311z_t \\ &(0.2538) &(0.0000) &(0.3632) &(0.5124)\end{aligned}$$

$$\overline{R}^2 = 0.8038,\ d = 0.1358.$$

Substituting $\hat{p}_t$ for p_t in (3.8a), the estimated demand equation ($Demand\ II$) is

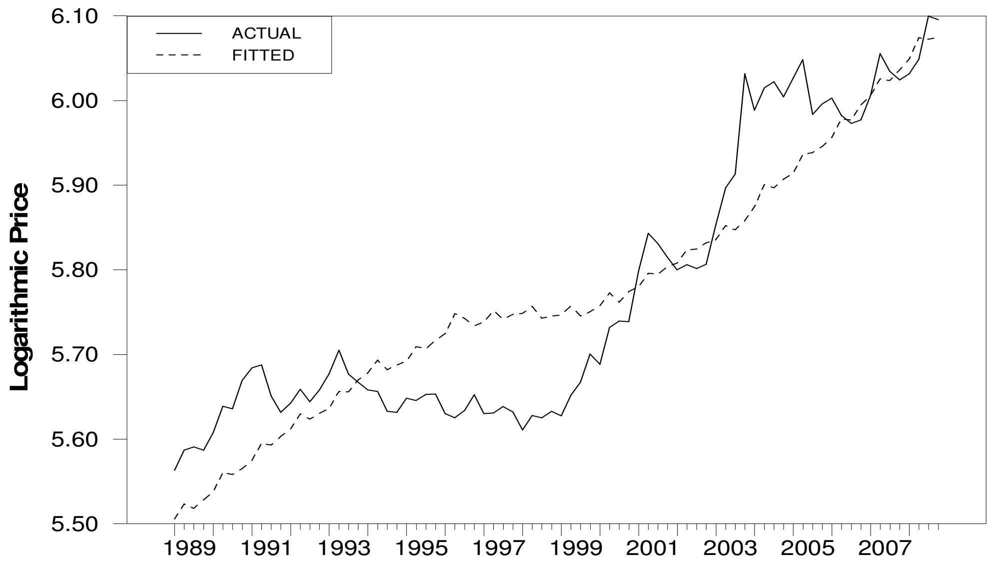
$$\begin{aligned}\hat{q}_t = &\ 5.5047 &- 0.2779p_t &+ 0.3069y_t &+ 0.0463s_{2,t} &+ 0.0549s_{3,t} &+ 0.0005s_{4,t} \\ &(0.0000) &(0.0000) &(0.0000) &(0.0000) &(0.0000) &(0.9440)\end{aligned} \tag{3.25}$$

$$\overline{R}^2 = 0.8991,\ d = 1.2751.$$

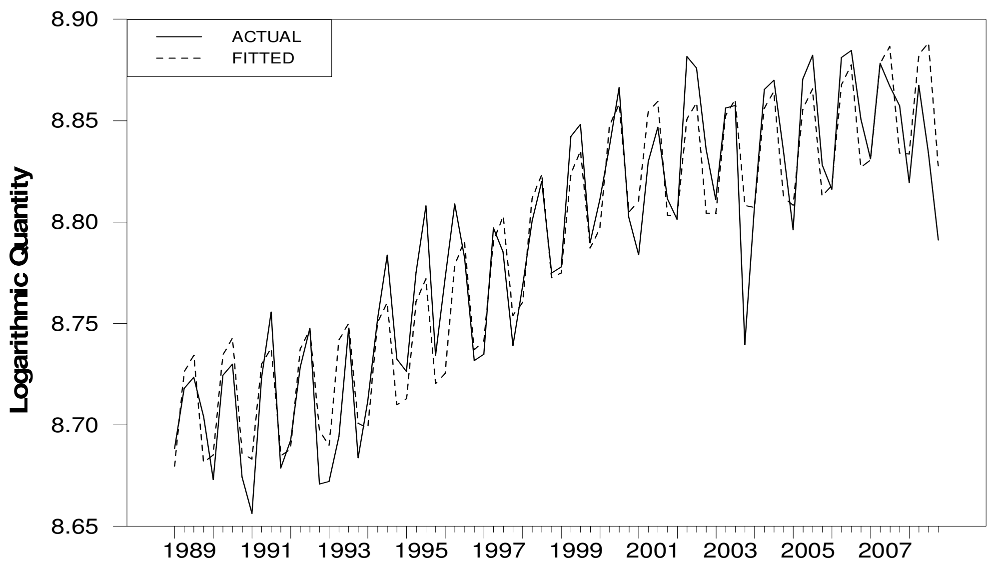
This result of (3.25) appears better than that of (3.24) in many aspects. As mentioned before, the functional form of (3.24) does not seem to be appropriate for a demand equation in this study. Overall, the results of (3.24) and (3.25) are inferior to those of (3.22) and (3.23), which becomes more clear when comparing Figure 3.8 and Figure 3.9. In particular, since p_t^e is irrelevant as an instrument for p_t, the estimated demand equation of (3.24) shown in Figure 3.9 (a) reflects only the time trend of the actual price series. Intuitively, consumers would respond to the current price rather than to previous prices. Therefore, substituting a linear combination of the previous prices (i.e. p_t^e) for p_t is not plausible. However, p_{t-1} is very closely related with p_t and, at the same time, can be considered not to be related with u_t.[36] For this reason, (3.22) and (3.23) produce a better result than (3.24) and (3.25).

In conclusion, the system of (3.6a) and (3.6b) is well defined as a recursive model for an agricultural product, especially for beef. If an endogeneity problem arises, it can be settled using the instrument variable method. The usual set of instruments includes the first lagged price, income and input price. An alternative model is the system of (3.8a) and (3.8b). This is not a recursive system; however, it is possible to estimate the supply equation separately and then the demand equation using the instrument variable methods. In particular, the estimation of (3.8a) alone yields a very similar result to

[36] In fact, this is the condition of a good instrument variable.



(a)



(b)

Figure 3.9 Estimated demand equations using p_t^e, y_t and z_t:

(a) $Demand\,I$ and (b) $Demand\,II$

(3.22) and (3.23), which are considered the most agreeable results. This fact supports the argument that an agricultural market can be analyzed with a recursive model in which supply is determined by the expected price and demand by the current price. Further, this separateness of the demand equation (3.8a) lays the foundation for the analysis in Chapter IV, where the tests for structural change are based on the single equations of demand and supply.

Figure 3.10 below illustrates how the market price and quantity are determined in a recursive model. For example, suppose that the demand and supply equations are given by $q = D(p)$ and $q = S(p^e)$. Further, assume that there are no changes in the parameters and exogenous variables (i.e. income and input price). For $t = 1$, producers supply q_1 according to their expected price p_1^e. Thus, the supply curve at $t = 1$ becomes the vertical line S_1 and the market is closed at (p_1, q_1). For the next period, the producers make price expectations according to (3.4a) and may have p_2^e. At $t = 2$, they will supply q_2 with supply curve S_2 and the market will close at (p_2, q_2). Now that $p_2^e = p_2$, p_3^e will stay the same and the market will attain a stable equilibrium at this point unless other things change. In fact, the demand and supply may be affected by many unpredictable factors,

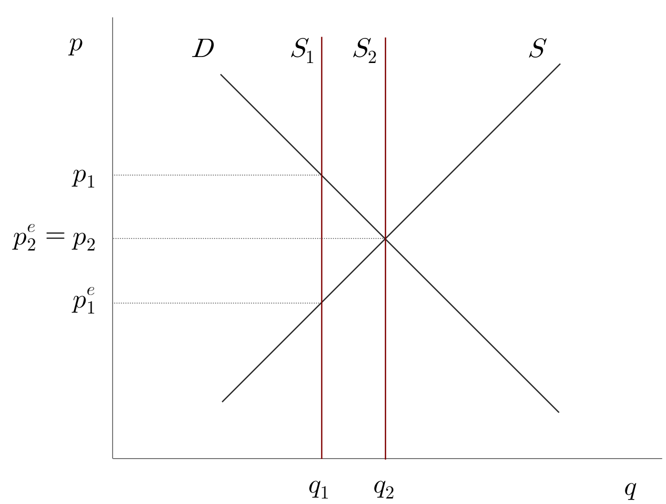


Figure 3.10 Market mechanism in a recursive model

such as weather conditions and disease outbreaks. As long as these factors are not explicitly considered in a model, they must be included in the disturbance terms (i.e. u_t and v_t). Additionally, it may take a long time to move to (p_2, q_2) starting from (p_1, q_1). Such a stable point is often referred to as a long run equilibrium. Of course, the market is in equilibrium at each point, as shown above. In reality, however, other conditions hardly remain constant, which results in shifts of the demand and supply curves. The new curves follow the same rule as illustrated in Figure 3.10.

Time frequency is very important for market analysis with a recursive model. If each observation has a longer time unit (i.e. yearly), the data may not be appropriate for a recursive model. This matter has already been discussed in the previous section, quoting from Fox (1968). Based on the findings, the estimation result of (3.8a) alone closely represents the true demand relationships for an appropriate unit of time data. This background knowledge is crucial in analyzing the structural changes in the market.

3.4.5 Estimation of Interdependent Model

As mentioned before, the interdependence between the demand and supply equations may be affected by the unit of time selected in a model. It is not clear that a quarter is short enough for the system to be considered a recursive model. Rosen et al. (1994) suggest approximately three-year cycles for the production and consumption of beef. While the data may be more appropriate for a recursive model, using the data for an interdependent model will provide an insight as to how the system of linear equations works as both models.

Two types of estimation methods exist for a system of linear equations. One method is the limited information method (also know as single-equation method) and the other is the full information method (also known as system method). The limited information approach estimates one equation at a time, using the information limited to the estimated equation. In contrast, the full information approach estimates the entire system at the same time, using all information available in each equation. In this study, both methods will be applied: the 2SLS for the limited information approach and the 3SLS for the full information approach. According to Klein (1974)[37], in the context of a simultaneous system, a single-equation method may be less sensitive to specification error in the sense that the correctly specified parts of the system may not be affected appreciably by the specification errors in another part.

Two interdependent models are considered in this study. One is given by (3.11a) and (3.11b), or the system of $Demand\,I$ and $Supply\,II$. The other is given by (3.13a) and (3.13b), or the system of $Demand\,II$ and $Supply\,II$. Note that $Supply\,I$ and $Supply\,III$ will not be considered. First, the reduced form equations are given by the regression of each endogenous variable on the exogenous variables. There are two endogenous variables, p_t and q_t, and two exogenous variables, y_t and z_t in each system; thus, there are two reduced form equations (one for each endogenous variable). As mentioned before, these reduced form equations are useful for comparative statics, which are concerned with the effect of a change in one or more of the exogenous variables on the equilibrium point. The reduced form equation with respect to p_t is

$$\begin{aligned}\hat{p}_t = & -\underset{(0.0003)}{1.7703} + \underset{(0.0000)}{0.4493}y_t + \underset{(0.0559)}{0.0932}z_t\end{aligned} \tag{3.26a}$$

$$\overline{R}^2 = 0.7687,\ d = 0.1157.$$

The reduced form equation with respect to q_t is

$$\hat{q}_t = \underset{(0.0000)}{6.0241} + \underset{(0.0000)}{0.1834}y_t - \underset{(0.1317)}{0.0310}z_t \tag{3.26b}$$

$$\overline{R}^2 = 0.7214,\ d = 1.6763.$$

Even if the above results are not strong in terms of the goodness of fit, d statistic and significance level, the signs of the coefficients are all plausible and agreeable. That is, an increase in income would raise both equilibrium price and quantity ($\partial p/\partial y > 0$ and $\partial q/\partial z > 0$) because it makes the demand curve shift upward, as shown in Figure 3.11 (a).

[37] See p. 150.

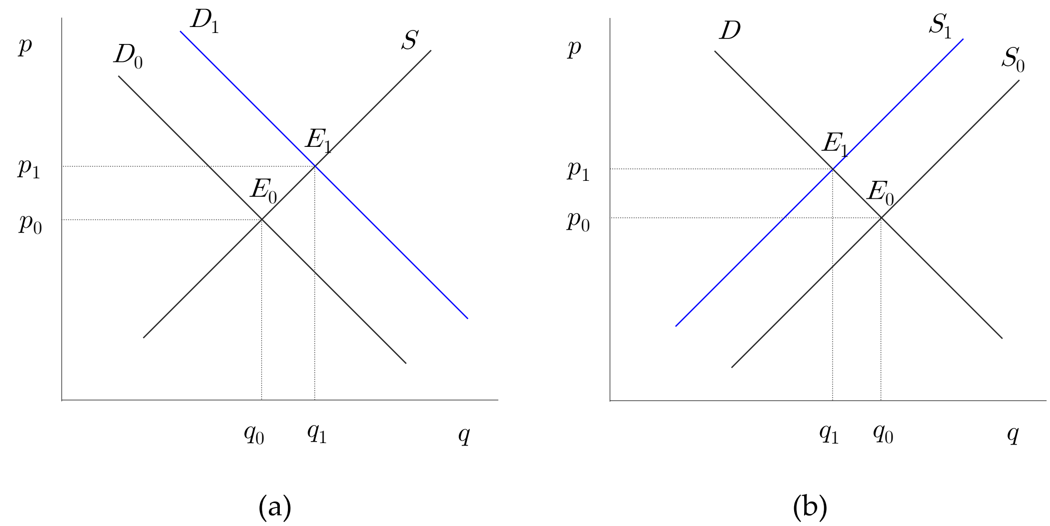


Figure 3.11 Movements of equilibrium by the changes in (a) y and (b) z

On the other hand, an increase in input price would raise equilibrium price ($\partial p/\partial y > 0$) but lower equilibrium quantity ($\partial q/\partial z < 0$) because it makes the supply curve shift upward, as shown in Figure 3.11 (b). The shifts of the demand and supply curves are explained by the structural equations, while the movements of the equilibrium point are shown by the reduced form equations.

Table 3.6 summarizes the estimation results by the 2SLS method. Since each system is estimated by the single-equation approach, the estimated equation of $Supply\,II$ does not change. The system of $Demand\,I$ and $Supply\,II$ does not seem to be a relevant model because the result of the inverse demand equation is very poor. The signs and magnitudes of the coefficients are reasonable. The intercept and quantity coefficients are significant at the 10% level; however they are not significant at the 5% level. Additionally, the result suffers from a very low d statistic. Thus, in the analysis of the US beef market, an inverse (or price-dependent) demand equation does not seem to be a relevant specification, which can also be concluded from the findings in the previous subsections. Furthermore, most of the empirical results consistently do not meet the inverse demand specification.

Table 3.6

Estimation of the system by 2SLS

$Demand\,I$	$constant$	q_t	y_t	$\overline{R}^2$	d
	16.2331 (0.0954)	−2.9884 (0.0660)	0.9971 (0.0008)	0.7596	0.1116
$Supply\,II$	$constant$	p_t	z_t	$\overline{R}^2$	d
	6.7474 (0.0000)	0.4151 (0.0000)	−0.0833 (0.0000)	0.8905	1.1751

$Demand\,II$	$constant$	p_t	y_t	$\overline{R}^2$	d
	5.1644 (0.0000)	−0.4792 (0.0009)	0.4018 (0.0000)	0.8905	1.1751
$Supply\,II$	$constant$	p_t	z_t	$\overline{R}^2$	d
	6.7474 (0.0000)	0.4151 (0.0000)	−0.0833 (0.0000)	0.8905	1.1751

† p-values in parentheses

Table 3.7 shows the estimation results using the 3SLS method. Since it is a system method in which all the equations are simultaneously considered, the method of estimation yields the same parameter estimates for the system of $Demand\,I$ and $Supply\,II$. That is, the price and income elasticities of $Demand\,I$ are the same as those of $Demand\,II$. The parameter estimates are also very close to those of the 2SLS. Compared to the estimation results of the recursive model, the price elasticity (in an absolute value) and the income elasticity are much larger than in the recursive system. This difference occurs

Table 3.7

Estimation of the system by 3SLS

$Demand\,II$	$constant$	p_t	y_t	$\overline{R}^2$	d
	5.1592 (0.0000)	−0.4823 (0.0305)	0.4031 (0.0001)	0.7403	0.2799
$Supply\,II$	$constant$	p_t	z_t	$\overline{R}^2$	d
	6.7473 (0.0000)	0.4152 (0.0000)	−0.0831 (0.0045)	0.5309	0.4290

† p-values in parentheses

because an interdependent model considers the time unit allocated to the model as long enough for interaction between demand and supply to occur. The estimation results reinforce the fundamental notion that the long run demand and supply are more elastic[38] than the short run demand and supply. Considering the time frequency of the given data and the overall estimation results, the US beef market can be best analyzed using a recursive or triangular system. As mentioned above, these findings are the foundations for the analysis in the following chapter, where the tests for structural change are based on the single equations of demand and supply.

One further thing to be mentioned is the range of price elasticity from the other related researches. Based on the data and model specifications used, the price elasticities may be quite different from each other. For example, Fox (1968) estimated the single demand equation for the US beef market from 1949 to 1960 to obtain -0.7525, and further estimated the system of demand and supply for the US beef market from 1922 to 1941 to obtain -1.0329. Eales and Unnevehr (1993) estimated the AIDS for the US beef market from 1962 to 1989 using SUR and 3SLS to obtain -0.573 and -0.850, respectively. Peterson and Chen (2005) estimated the price elasticities of US beef demand and domestic beef (Wagyu) demand in Japan to obtain -0.0929 and -1.8965, respectively. Burton and Young (1996) estimated the UK beef market from 1961 to 1993 to obtain a long-run price elasticity of -1.522. Piggott and Marsh (2004) estimated the US beef market from 1982 to 1999 to obtain -0.907. In this study, the price elasticities were estimated -0.1340 from (3.19), -0.1755 from (3.22), and -0.1127 from (3.23). Thus the average of these three elasticities are close to the lower bound, -0.0929, which is the price elasticity of demand for US beef in Japan.

[38] This means a price elasticity.

CHAPTER IV

STRUCTURAL CHANGE

4.1 Preliminaries

An important assumption underlying the linear regression model is that the parameters (β's and γ's) are time invariant. However, it is more realistic to assume that those parameters are changeable over time with different regimes. This view is not to regard the parameters as time-dependent variables (i.e. β_t and γ_t with a time subscript) but rather to allow the parameters to take different values according to each regime (i.e. an animal disease outbreak in this chapter). Of course, the latter can be considered as a particular case of the former in that

$$\beta_t = \begin{cases} \beta^{(1)} & t < \tau \\ \beta^{(2)} & t > \tau \end{cases} \text{ and } \gamma_t = \begin{cases} \gamma^{(1)} & t < \tau \\ \gamma^{(2)} & t > \tau \end{cases} \text{ for a break point } \tau.$$

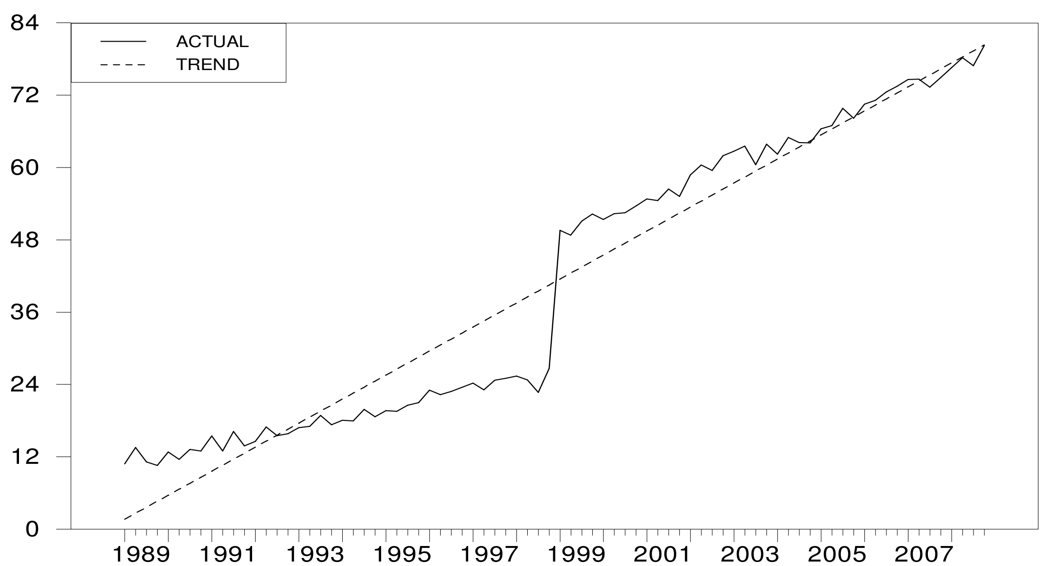


Figure 4.1 Changes in the intercept and slope of $\{x_t\}$

Figure 4.1 shows an example series $\{x_t\}$[39] where the intercept and slope change at a certain time point (i.e. 1999Q1). Even though a trend line can be fitted over the whole period, it is not the best way of representing the series in this case. If the break point can be detected, the entire sample can be split into two subsamples and then the trend can be estimated over each subperiod. On the other hand, the differences (i.e. parameter instabilities) between the subsamples can be seen in each equation by simply introducing a dummy variable.

While the break point is already known in this particular analysis, the primary concern is to find a structural change in the US beef demand due to an animal disease outbreak (i.e. a BSE case in December 2003). However, detecting a break point without any prior knowledge of an event and determining whether the detected break coincides with the event of interest is meaningful in the comparison of the main event results with those of another possible break. Since the US beef market data from 1989Q1 to 2008Q4 is used in this study, the enforcement of NAFTA in January 1994 could be considered a regime-switching event.

Based on the findings in Chapter III, a single demand equation given by (3.8a) will be used for the study in this chapter. The inverse demand equation is not appropriate for the analysis of structural change due to the poor estimation result in terms of the low goodness of fit and d statistic, which may negatively affect the tests for structural change.

Over the decades, various methods of detecting and testing for structural change have been proposed. In the example illustrated in Figure 4.1, the structural change in the trend is easy to detect by analyzing the graph. In general, a distinct change is more difficult to identify if other related variables are present. Thus, statistical methods are needed to address these problems. In the following section, a review of the popular methods used in the applied econometric literature will be presented.

[39] This series is generated in the following manner: $x_t = 10 + 0.4t + \epsilon_t$ for $t \leq 1998Q4$ and $x_t = 15 + 0.8t + \epsilon_t$ for $t > 1998Q4$, where $\epsilon_t \sim N(0, 1)$.

4.2 Tests for Parameter Constancy

4.2.1 Chow Test

The Chow test was popularized by Chow (1960) and concerns the equality of two regression equations based on splitting the entire sample. Assuming that a probable break point (τ) is known, the sample can be divided into two subsamples with n_1 and n_2 observations, respectively. The subsample sizes, n_1 and n_2, need not be the same. For each subsample i, then, (3.1a) can be written as

$$q_t^D = \beta_0^{(i)} + \beta_1^{(i)} p_t + \beta_2^{(i)} y_t + u_t^{(i)} \text{ for } i = \begin{cases} 1 & t < \tau \\ 2 & t \geq \tau \end{cases}. \tag{4.1}$$

It is assumed that $u_t^{(1)}$ and $u_t^{(2)}$ are independently distributed with $N(0, \sigma^2)$. If they have different variances, the Chow test will not be applicable. The null hypothesis is

$$H_0 : \beta_k^{(1)} = \beta_k^{(2)} \text{ for } k = 0, 1, 2.$$

The test statistic is

$$T = \frac{(RSS_R - RSS_U)/K}{RSS_U/(n - 2K)} \sim F_{K,\, n-2K}, \tag{4.2a}$$

where RSS_R is the residual sum of squares of the pooled sample, RSS_U is given by the sum of RSS_1 and RSS_2, K is the number of parameters (or restrictions), and $n = n_1 + n_2$. This test statistic is applicable only if $n_2 > K$. If $n_2 \leq K$, the suggested test statistic is

$$T^* = \frac{(RSS_R - RSS_1)/n_2}{RSS_1/(n_1 - K)} \sim F_{n_2,\, n_1 - K}. \tag{4.2b}$$

Note that the Chow test tends to reject the null hypothesis more often than it ought to. Additionally, it may suffer from a lowered degrees of freedom with a small subsample size. Furthermore, when examining a particular parameter (i.e. price elasticity), the revision of the above test statistics will be more complicated. For these reasons, a dummy variable is used to separate two subsamples in a single equation. In a sense, this is very analogous to the difference between an F-test and t-test in a linear regression.

The separate estimates for the two subsamples can be described in terms of dummy variables. Now (3.1a) can be written as

$$q_t^D = \beta_0^{(1)} + \beta_0 d_t + \beta_1^{(1)} p_t + \beta_1 d_t p_t + \beta_2^{(1)} y_t + \beta_2 d_t y_t + u_t, \tag{4.3}$$

where

$$d_t = \begin{cases} 0 & t < \tau \\ 1 & t \geq \tau \end{cases}.$$

(4.3) has $2K$ coefficients to be estimated over the whole sample. The null hypothesis corresponding to the above one is

$$H_0 : \beta_0 = \beta_1 = \beta_2 = 0.$$

However, a variety of hypotheses can be tested with ease. For instance, a t-test on β_1 will test whether the price coefficient stays the same over the whole period. Compared to the Chow test, the t-test based on dummy variables is more convenient for adding or dropping a restriction. Using this test can save more degrees of freedom, especially when the sample size is not large enough.

4.2.2 Recursive Estimation

The Chow test, as well as the dummy variable approach, assumes that the break points are known. Even if they are not known, it is possible to detect a break point by looking at the graph of recursively estimated parameters. The idea is very simple. If an extraordinary parameter estimate at a particular time point is observed, the presumption can be made that a structural break occurred at that time.

From now on, the basic model is represented using matrices. Let $x_t = (1, p_t, y_t)^\top$ and $\boldsymbol{\beta}_t = (\beta_{0,t}, \beta_{1,t}, \beta_{2,t})^\top$. Then, (3.1a) can be written as

$$q_t^D = x_t^\top \boldsymbol{\beta}_t + u_t \text{ for } t = 1, \cdots, T. \tag{4.4}$$

Note that the coefficient vector $\boldsymbol{\beta}_t$ has a time subscript, as it is now assumed to be time-dependent. The null hypothesis of no structural change (constancy) consists of the restrictions for both of the coefficients and the disturbance variances;

$$H_0 : \begin{array}{l} \boldsymbol{\beta}_0 = \boldsymbol{\beta}_1 = \cdots = \boldsymbol{\beta}_T = \boldsymbol{\beta} \\ \sigma_0 = \sigma_1 = \cdots = \sigma_T = \sigma. \end{array} \tag{4.5}$$

Under H_0, the least squares estimator of $\boldsymbol{\beta}$, using the first r ($\geq K$) observations only, is given by

$$\hat{\boldsymbol{\beta}}_r = \left(X_r^\top X_r\right)^{-1} X_r^\top Q_r,^{40}$$

where,

$$X_r = \begin{pmatrix} x_1^\top \\ \vdots \\ x_r^\top \end{pmatrix} \text{ and } Q_r = \begin{pmatrix} q_1 \\ \vdots \\ q_r \end{pmatrix}.$$

Given an additional observation, it becomes

$$X_{r+1} = \begin{pmatrix} X_r \\ x_{r+1}^\top \end{pmatrix} \text{ and } Q_{r+1} = \begin{pmatrix} Q_r \\ q_{r+1} \end{pmatrix}.$$

Thus the least squares estimator of $\boldsymbol{\beta}$, using the first $r+1$ observations, is given by

$$\hat{\boldsymbol{\beta}}_{r+1} = \left(X_{r+1}^\top X_{r+1}\right)^{-1} X_{r+1}^\top Q_{r+1}. \tag{4.6a}$$

According to Kmenta (1986),[41] the equivalent recursive estimator is

$$\hat{\boldsymbol{\beta}}_{r+1} = \hat{\boldsymbol{\beta}}_r + \frac{\left(X_r^\top X_r\right)^{-1} x_{r+1}}{1 + x_{r+1}^\top \left(X_r^\top X_r\right)^{-1} x_{r+1}} \left(q_{r+1} - x_{r+1}^\top \hat{\boldsymbol{\beta}}_r\right). \tag{4.6b}$$

In terms of the Kalman filter, (4.6b) explains how to calculate the estimates sequentially as new observations become available. That is, the updated estimator $\hat{\boldsymbol{\beta}}_{r+1}$ is equal to the sum of the previous estimator $\hat{\boldsymbol{\beta}}_r$ and an adjustment factor, which is proportional to the prediction disturbance ($q_{r+1} - x_{r+1}\hat{\boldsymbol{\beta}}_r$). The vector of proportionality is also known as smoothing vector.

In addition to the parameter constancy, the instability of disturbance variances is another useful indicator of a structural change. In fact, this instability is a violation of one of the basic assumptions underlying the Chow test; that is, the disturbance terms have the same variance. Intuitively, however, it is probable that some distributional properties (i.e. variance) of the disturbance terms are changed in a different regime. In

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[40] Note that $\hat{\boldsymbol{\beta}}_r$ is different from $\hat{\boldsymbol{\beta}}_t$. The latter simply means the estimator at time t.

[41] See pp. 423-424.

this perspective, the updated RSS is given by

$$RSS_{r+1} = RSS_r + \frac{q_{r+1} - x_{r+1}^\top \hat{\boldsymbol{\beta}}_r}{1 + x_{r+1}^\top \left(X_r^\top X_r\right)^{-1} x_{r+1}}. \tag{4.7}$$

Although no particular tests are explicitly involved in this study, looking into the mentioned statistics will provide a convenient way of monitoring the stability of the model being analyzed.

4.2.3 CUSUM and CUSUMSQ Tests

The smoothing vector in the last term of (4.6b) can be decomposed into two parts, one of which is very closely related to the so-called recursive residuals. That is,

$$\frac{\left(X_r^\top X_r\right)^{-1} x_{r+1}}{\sqrt{1 + x_{r+1}^\top \left(X_r^\top X_r\right)^{-1} x_{r+1}}} \times \frac{q_{r+1} - x_{r+1}^\top \hat{\boldsymbol{\beta}}_r}{\sqrt{1 + x_{r+1}^\top \left(X_r^\top X_r\right)^{-1} x_{r+1}}}.$$

The recursive residuals defined by

$$w_r = \frac{q_r - x_r^\top \hat{\boldsymbol{\beta}}_{r-1}}{\sqrt{1 + x_r^\top \left(X_{r-1}^\top X_{r-1}\right)^{-1} x_r}} \text{ for } r = K+1, \cdots, T. \tag{4.8}$$

Using this equation, Brown et al. (1975) proposed the CUSUM test statistic

$$W_r = \sum_{j=K+1}^{r} \frac{w_j}{s} \text{ for } r = K+1, \cdots, T, \tag{4.9}$$

where s is the sample standard deviation determined by

$$s^2 = \frac{1}{T-K} \sum_{t=1}^{T} \hat{u}_t^2.$$

Further, they showed that the distribution of W_r can be approximated by the normal distribution $N(0, r-K)$ and $Cov(W_r, W_j) = min(r, j) - K$ under the null hypothesis (4.5). Thus the critical region is given by

$$|W_r| > c_\alpha = a(T-K)^{\frac{1}{2}} + 2a(r-K)(T-K)^{-\frac{1}{2}}, \tag{4.10}$$

where a is determined by the size α of the test. For $\alpha = 0.01$ and $\alpha = 0.05$, $a = 1.143$ and $a = 0.948$, respectively. Harvey (1989)[42] refers to this as a useful procedure for detecting structural change and provides some applications. A formal assessment of the CUSUM plot is obtained by determining whether it crosses either of two predefined significance lines drawn above and below the horizontal axis ($W_r = 0$). The equations of these lines is given by (4.10). Brown et al. (1975) also proposed the CUSUMSQ test statistic as a useful complement to the CUSUM test statistic, especially when the departure from constancy of the coefficients is not systematic. The test statistic is

$$V_r = \frac{\sum_{j=K+1}^{r} w_j^2}{\sum_{j=K+1}^{T} w_j^2} \text{ for } r = K+1, \cdots, T. \tag{4.11}$$

Under H_0, it has a beta distribution with parameters $(r-K)/2$ and $(T-r)/2$, so that its mean is $(r-K)/(T-K)$.

4.2.4 Sequential F-test

This is a test method that uses the test statistic T^* in (4.2b) sequentially. The procedure is very similar to that of the CUSUM test. The test statistic is given by

$$F_r = \frac{(RSS_r - RSS_{r-1})/1}{RSS_{r-1}/(r-K-1)} \sim F_{1,\, r-K-1} \text{ for } r = K+2, \cdots, T, \tag{4.12}$$

where RSS_r is the residual sum of squares based on the first r observations, and RSS_{r-1} is defined in the same way. Note that an additional subsample has only one observation (i.e. $n_2 = 1$).

4.3 Test Results

4.3.1 Chow Test

In this analysis, it is assumed that the structural break points are known. In fact, there were two major events that may have affected the US beef market during the sample

[42] See p. 257 and pp. 402-408.

period (1989Q1 to 2008Q4). One is the enforcement of NAFTA in January 1994 and the other is a BSE outbreak in December 2003. The Chow test, the most basic test for parameter constancy, will be performed for these two events and the results will be compared.

Under the null hypothesis of no structural break, the Chow test statistic for the first case (NAFTA) is

$$T_1(6,68) = 2.3737 \ \ (0.0385), \tag{4.13a}$$

where the number in the last parentheses is a significance level. Thus the null hypothesis is rejected at the 5% level, but is not rejected at the 1% level. For the second case (BSE), the test statistic is

$$T_2(6,68) = 3.9675 \ \ (0.0018). \tag{4.13b}$$

Even under 1% level, the null hypothesis is rejected. Although this test tends to reject the null hypothesis more than it has to, rejection is not frequent. For an arbitrary point (i.e. 1992Q2), the statistic is 1.1262 and the significance level is 0.3566, which leads to failure in rejecting the null hypothesis even at the 10% level. The Chow test results suggest that there were structural breaks for both cases. As seen by the formula in (4.2a), however, the test statistic tends to increase as the total sample size (n) increases. The subsample sizes may be different according to the location of a break point. The first case comes in 1994Q1 and the second one in 2003Q4. For the NAFTA case, $n_1 = 20$ and $n_2 = 60$.[43] For the BSE case, $n_1 = 59$ and $n_2 = 21$.[44] Furthermore, a longer subperiod might include another unknown break point. For the purpose of comparison, it is more reasonable to take the subsamples of the same size for both cases. Thus 40 observations will be used for the first case and 42 observations for the second case.[45] Their sample sizes are not exactly the same, but the difference is negligible. With these samples, the test results could be changed.

For the NAFTA case, the revised test statistic is given by

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[43] 20 observations from 1989Q1 to 1993Q4, and 60 observations from 1994Q1 to 2008Q4.

[44] 59 observations from 1989Q1 to 2003Q3, and 21 observations from 2003Q4 to 2008Q4.

[45] 40 observations from 1989Q1 to 1998Q4, and 42 observations from 1998Q3 to 2008Q4.

$$T_1(6,28) = 1.9579 \;\; (0.1061). \tag{4.14a}$$

Under this statistic, the null hypothesis is not rejected, even at a 10% level. For the BSE case, on the other hand, the revised test statistic is

$$T_2(6,30) = 5.6512 \;\; (0.0005). \tag{4.14b}$$

The null hypothesis of no structural change is still rejected even at a 1% level. These modified results agree with intuition.

The enforcement of NAFTA was an anticipated event. This agreement was not expected to affect beef consumers' taste or any other factors related to beef demand. If imported beef had changed the US consumers' preferences, the impact should have been reflected as a structural change. In Figure 4.2, however, beef imports show a rather stable pattern during the sample period of 1989Q1 to 1998Q4. In contrast, beef exports begin increasing rapidly from 1994Q1. Thus this situation may have affected the supply side, but not the demand side. The movements of the price and quantity after the event also support this scenario. In Figure 2.2 (a), the price begins to decrease gradually from

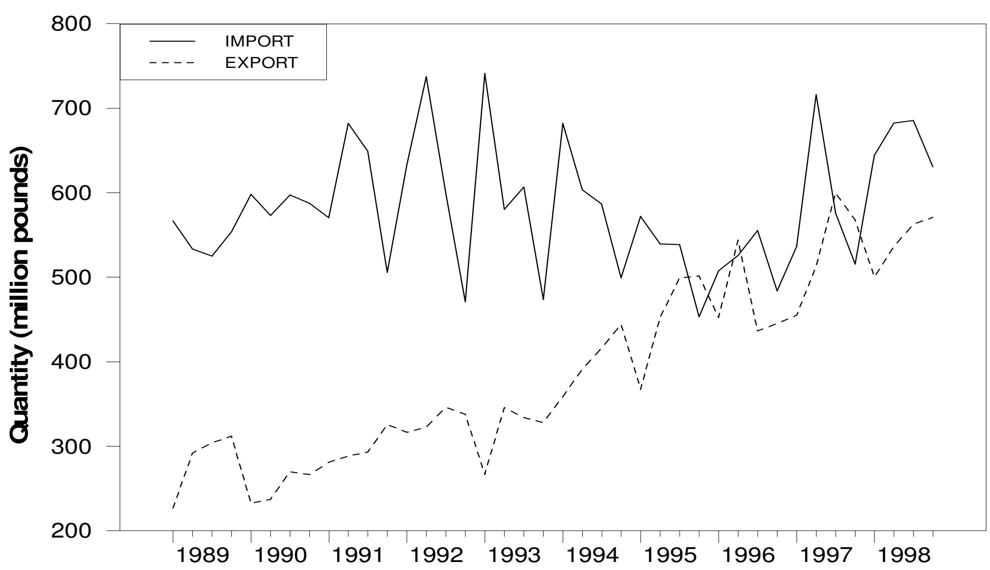

Figure 4.2 Import and export of beef in the US (1989Q1 to 1998Q4)

1994. In Figure 2.5, at the same time, the quantity continues to grow with a typical seasonal pattern. This is a general consequence of the case that demand remains constant but supply increases (i.e. shifts to the right). For the BSE case, however, it turned out that there was a structural change before and after the event. Intuitively, the unexpected event would have at least affected beef demand, or more likely, both demand and supply. The BSE outbreak is a very important issue that may have altered consumers' preferences by a substantial degree. It is generally believed that the BSE is also fatal to human health.[46] Thus another question to be addressed later in this research is whether or not the BSE outbreak had a long run impact.

To see if the demand curve shifted after those events, the intercept and price coefficients of the demand equation were examined. While the Chow test concerns the stability of all coefficients jointly, the parameters need to be considered separately. As stated before, this can be accomplished by using the method based on dummy variables. Thus (4.3) can be rewritten as

$$q_t = \beta_0^{(1)} + \beta_0 d_{j,t} + \beta_1^{(1)} p_t + \beta_1 d_{j,t} p_t + \beta_2^{(1)} y_t + \beta_2 d_{j,t} y_t + u_t{}^{47}, \tag{4.15a}$$

where $j = 1$ for NAFTA and $j = 2$ for BSE. Table 4.1 summarizes the estimation results.

The advantage of using dummy variables is that the impacts of the events on each coefficient of the demand equation can be seen. Looking at the table, it is also clear why the Chow test rejected the null hypothesis for both events; in each equation, at least one coefficient related to the dummy variable is significant. For example, in the NAFTA case, the coefficient of $d_{1,t}$ is significant even at a 1% level, but those of $d_{1,t}p_t$ and $d_{1,t}y_t$ are not significant even at a 10% level. Therefore, the intercept was lowered, while the price and income coefficients did not change. In the BSE case, the intercept increased, the price coefficient decreased, and the income coefficient did not change. These results

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[46] In 1996, UK scientists announced a suspected link between BSE in cattle and vCJD in humans. Many scientists suspect that humans contract vCJD by ingesting the causative agent in products made from brain, spinal cord, or other infective tissues from BSE-infected cattle.

[47] For the purpose of estimation, seasonal dummy variables are added to this equation, although they are not explicitly included.

Table 4.1

Structural changes in demand equations

NAFTA	$constant$	$d_{1,t}$	p_t	$d_{1,t}p_t$	y_t	$d_{1,t}y_t$
	8.6447 (0.0000)	−2.7621 (0.0040)	−0.3022 (0.0967)	0.1892 (0.3045)	0.1127 (0.2278)	0.1103 (0.2555)
	$\overline{R}^2 = 0.9148$			$d = 1.2503$		
BSE	$constant$	$d_{2,t}$	p_t	$d_{2,t}p_t$	y_t	$d_{2,t}y_t$
	5.5140 (0.0000)	3.6682 (0.0001)	−0.0807 (0.0606)	−0.4409 (0.0014)	0.2346 (0.0000)	−0.0635 (0.2390)
	$\overline{R}^2 = 0.9211$			$d = 1.3705$		

† p-values in parentheses

agee with those from (4.13a) and (4.13b), respectively. However, due to the differences in sample size, they still suffer from the problem that a longer subperiod may include another unknown break point and therefore the test results may be meaningless. To cope with this problem, the estimation procedure will be replicated with the subsample sizes equaled, as done before.

Even with this adjustment, another problem remains. Due to the reduced sample sizes, there may not be adequate degrees of freedom. Intriligator (1978)[48] suggests the idea of associating a dummy variable applies with all coefficients; this is equivalent to dividing the sample into two subsamples. However, the dummy variable can be applied to some of the coefficients, particularly the intercept and price coefficients, so that the number of coefficients estimated may be reduced. Further, it is shown that the income coefficient did not change for both cases. Omitting the $d_{1,t}y_t$ term, therefore, (4.15a) can be reduced to

$$q_t = \beta_0^{(1)} + \beta_0 d_{j,t} + \beta_1^{(1)} p_t + \beta_1 d_{j,t} p_t + \beta_2 y_t + u_t. \tag{4.15b}$$

Note that (4.15b) assumes the constancy of the income coefficient and also uses reduced samples (i.e. 40 observations for NAFTA and 42 observations for BSE). The estimation

[48] See p. 195.

results are summarized in Table 4.2. As expected from the results of (4.14a) and (4.14b), the NAFTA event did not change the intercept or the slope of the demand curve; the demand curve stays the same. In contrast, the BSE event changed both of them. The notable difference between Table 4.1 and Table 4.2 is the intercept of the first demand equation (NAFTA). Because the coefficients of $d_{1,t}$ and $d_{1,t}p_t$ are insignificant even at the 10% level, the conclusion is reached that there was no structural change before and after the NAFTA event.

Furthermore, the price coefficient of the second equation (BSE) is insignificant. This means that the price elasticity was zero (perfectly inelastic) before the BSE event. The perfectly inelastic characteristic of the equation appears to have been caused by the inclusion of the $d_{2,t}p_t$ term, which makes p_t less important. Considering the results of Table 4.1 and Table 4.2 together, the conclusion can be drawn that there was a structural change before and after the BSE event; that is, the intercept was lifted up and the price elasticity (in an absolute value) was increased after the event. This means that consumers actually became more sensitive to a price change due to the BSE outbreak, which is a reasonable consequence. If more information is provided about the supply side, it is possible to account for the actual price and quantity movements before and after the events.

Table 4.2

Structural changes in demand equations with the subsample sizes equaled

NAFTA	$constant$	$d_{1,t}$	p_t	$d_{1,t}p_t$	y_t
	8.7425 (0.0000)	2.3327 (0.2602)	−0.2542 (0.0163)	−0.4072 (0.2659)	0.0888 (0.0299)
	$\overline{R}^2 = 0.9063$			$d = 1.8130$	
BSE	$constant$	$d_{2,t}$	p_t	$d_{2,t}p_t$	y_t
	5.8459 (0.0000)	3.1216 (0.0000)	−0.0477 (0.3750)	−0.5219 (0.0000)	0.2019 (0.0001)
	$\overline{R}^2 = 0.7876$			$d = 1.4944$	

† p-values in parentheses

As for the supply equation, however, the same procedure for determining structural changes is not applicable because the equation is estimated using variables created under the assumption that the key parameter θ is constant over the entire period. Two supply equations, $\mathit{Supply\,III}$ and $\mathit{Supply\,IV}$, are used in the context of a recursive model. Even though the former is more reliable because of its rather solid theoretical foundation, the latter is more flexible and will be used for this analysis. To make it more deliberate, a two-step procedure will be followed. First, the dummy variable method is applied to $\mathit{Supply\,III}$ with the restriction that the coefficients of $x_{0,t}$, $x_{1,t}$ and $x_{3,t}$ in (3.10) are all constant. Of course, it is implicitly assumed that θ is constant over time. In fact, $x_{0,t}$ and $x_{1,t}$ are artificial variables generated by θ, and $x_{3,t}$ is the variable related to the input price, of which the coefficient is very small or is sometimes insignificant at a 5% level. It is not relevant to relate a dummy variable to the artificial variables. Thus, including a dummy variable, (3.10) can be rewritten as

$$q_t = r_0 x_{0,t} + \gamma_0 x_{1,t} + \gamma_1^{(1)} x_{2,t} + \gamma_1 d_{j,t} x_{2,t} + \gamma_2 x_{3,t} + v_t.\text{[49]} \tag{4.16}$$

Since $x_{2,t}$ is generated from the price series, a significant value of γ_1 means a change in

Table 4.3

Structural changes in $\mathit{Supply\,III}$[50]

NAFTA	$x_{0,t}$	$x_{1,t}$	$x_{2,t}$	$d_{1,t}x_{2,t}$	$x_{3,t}$
	8.6691 (0.0000)	7.5725 (0.0000)	0.2457 (0.0001)	0.0226 (0.0000)	−0.0606 (0.0002)
	$\overline{R}^2 = 0.9063$			$d = 1.4050$	
BSE	$x_{0,t}$	$x_{1,t}$	$x_{2,t}$	$d_{2,t}x_{2,t}$	$x_{3,t}$
	8.6357 (0.0000)	6.7508 (0.0000)	0.4085 (0.0082)	−0.0058 (0.0966)	−0.0510 (0.0088)
	$\overline{R}^2 = 0.8686$			$d = 0.9370$	

† p-values in parentheses

49 For estimation, I added seasonal dummy variables to this equation.

50 I used the whole sample, not the reduced one.

the slope of the supply curve. The price coefficient of the first supply equation (NAFTA) also changed, as shown in Table 4.3, while that of the second one (BSE) is not significant at the 5% level. Intuitively, the NAFTA event is likely to have affected the supply side, considering the fact that beef exports notably increased after the event; this is shown in Figure 4.2. At the same time, beef production also increased rapidly, as shown in Figure 4.3. Thus the results in Table 4.3 provide a further restriction on each supply equation. For the first equation (NAFTA), only the input price coefficient is constant. For the second equation (BSE), the price and input price coefficients are constant. Under these restrictions obtained from the first stage, the dummy variable method is further applied to $\mathit{Supply\,IV}$ in the second stage. The estimation results are summarized in Table 4.4. In a sense, this approach might yield incorrect results, as it is based on the test result of a non-nested supply equation (i.e. $\mathit{Supply\,III}$). However, there are further evidences supporting these results. The graph of beef production shown in Figure 4.3 provides insight into the results of this approach. First, the NAFTA event caused a structural change in

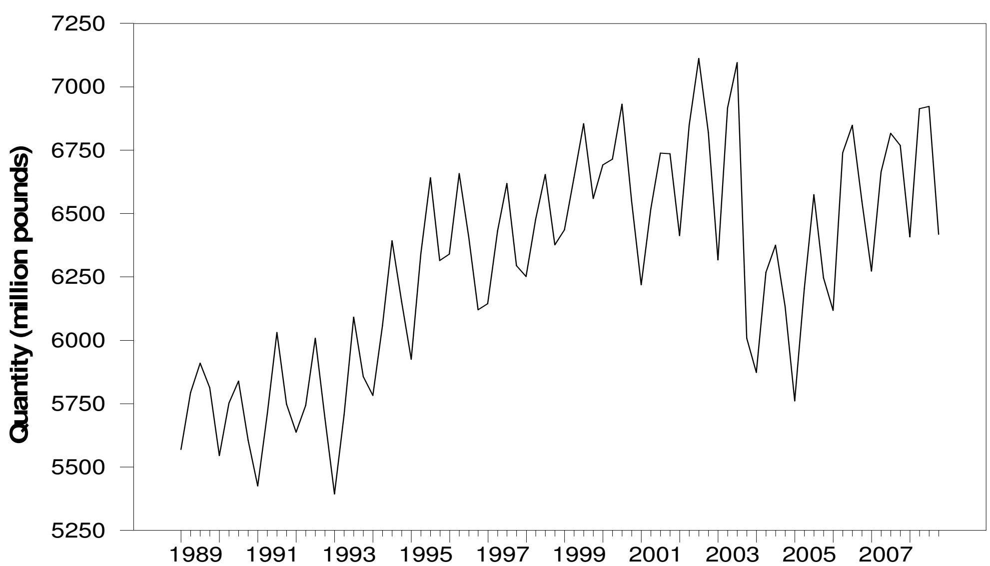


Figure 4.3 US beef production

Table 4.4

Structural changes in $Supply\,IV$[51]

NAFTA	$constant$	$d_{1,t}$	p_t^e	$d_{1,t}p_t$	z_t
	8.7701 (0.0000)	−3.8399 (0.0013)	−0.0124 (0.8628)	0.6769 (0.0011)	−0.0044 (0.8563)
	$\overline{R}^2 = 0.8809$			$d = 1.8188$	
BSE	$constant$	$d_{2,t}$	p_t^e	$d_{2,t}p_t$	z_t
	6.4682 (0.0000)	−0.0363 (0.0182)	0.4564 (0.0002)	$n.a.$	−0.0744 (0.0037)
	$\overline{R}^2 = 0.7045$			$d = 1.4193$	

† p-values in parentheses

the supply equation. Table 4.3 and Table 4.4 agree that the price elasticity increased after the event. In that period, the actual production and exports were steadily increasing, as shown in Figure 4.2 and Figure 4.3. Thus it is likely that the supply curve shifted to the right. Further, according to Table 4.4, the intercept (on the quantity axis) decreased (i.e. $d_{1,t} < 0$). Such a shift of the supply curve is depicted in Figure 4.4 (a), namely $S_0 \rightarrow S_1$. On the other hand, the BSE event also caused a structural change in the supply equation, but only for the intercept. From the previous estimation result in Table 4.3, it is assumed that the slope does not change (i.e. $d_{2,t}p_t = 0$). According to Table 4.4, only a small change in the intercept occurred due to the BSE event; however, Figure 4.3 shows a considerable decrease in production after the event. Therefore, the supply curve most likely shifted horizontally to the left as illustrated in Figure 4.4 (b).

In summary, the NAFTA event brought about a structural change in supply only, while the BSE event caused a change in both demand and supply. Considering all the findings from the study, the market phenomena (or behaviors) can be described in Figure 4.4. The graphs are drawn for a relatively longer period of time,[52] not for a unit time (i.e. a quarter). Thus, the price and quantity may be regarded as an average price

[51] I used a reduced sample with the subsample sizes equaled.

[52] According to the data length, it is approximately 20 quarters (or 5 years).

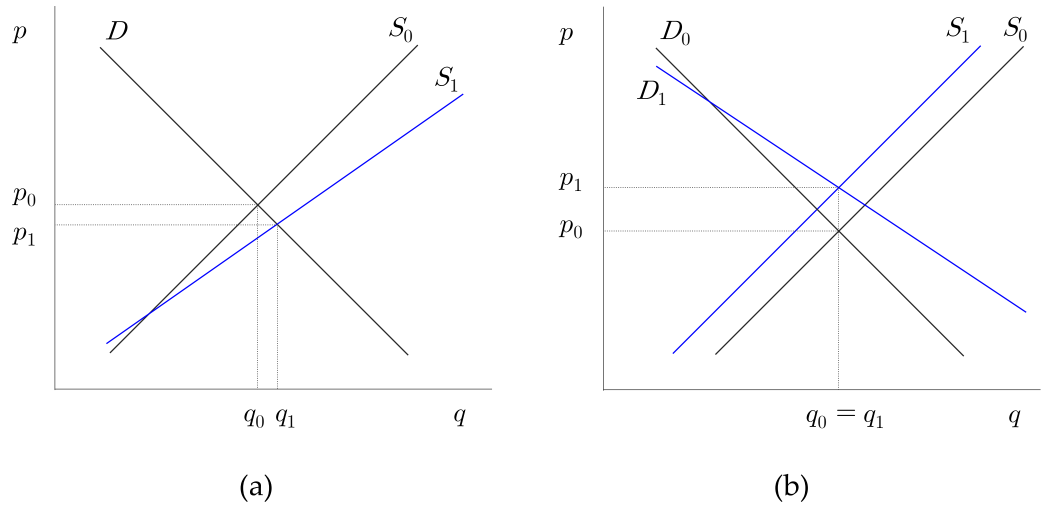


Figure 4.4 Impacts of (a) NAFTA and (b) BSE on the US beef market

and quantity during the period. At the beginning, the properties of market data were emphasized, which consists of equilibrium prices and quantities. Figure 2.2 (a) shows that the price gradually decreases after the NAFTA event and increases after the BSE event. As seen in Figure 2.5, the quantity continues to increase after the NAFTA event and remains rather stable after the BSE event. All these situations are exactly congruent with the market consequences illustrated in Figure 4.4.

The reason for the increase in the demand for beef, even after the BSE outbreak, remains uncertain. Some account for this market consequence (i.e. price increase and quantity decrease) by assuming a situation occurred similar to that presented in Figure 2.1 (b). At this moment, it is also not clear whether the market consequence of the BSE event is a general situation. This will be the main question of the following chapter, where the multinational market phenomena due to animal disease outbreaks will be examined.

4.3.2 CUSUM and CUSUMSQ Tests

Up to this point, the structural changes due to the known events have been analyzed. Since the Chow test tends to reject the null hypothesis too frequently, it is desirable to check if the events coincide with the break points detected by other methods. So these tests can be useful complements to the Chow test. The results of the recursive estimation are closely related to those of CUSUM test because they are all based on prediction errors. Since the tests are somewhat sensitive to degrees of freedom, seasonal dummies will not be used in the demand equation. First, Figure 4.5 shows the recursive residuals computed by (4.8). The dotted lines are the upper and lower bounds of the 95% confidence interval, which are derived from a normal distribution. The graph shows that the recursive residual fell beyond the lower bound at the time of the BSE case (i.e. 2003Q4), while it remains within the 95% confidence interval at the time of the NAFTA case. This agrees with the Chow test result that the NAFTA event did not cause a structural change in the demand for beef. Intuitively, NAFTA was an anticipated event and thus, no sudden change in the residuals was a natural occurrence. In contrast, BSE was an unexpected shock to the market and the recursive residual fell outside the interval. This implies that there occurred a significant change in the demand at least temporarily. This also agrees with the Chow test result. However, the CUSUM and CUSUMSQ plots

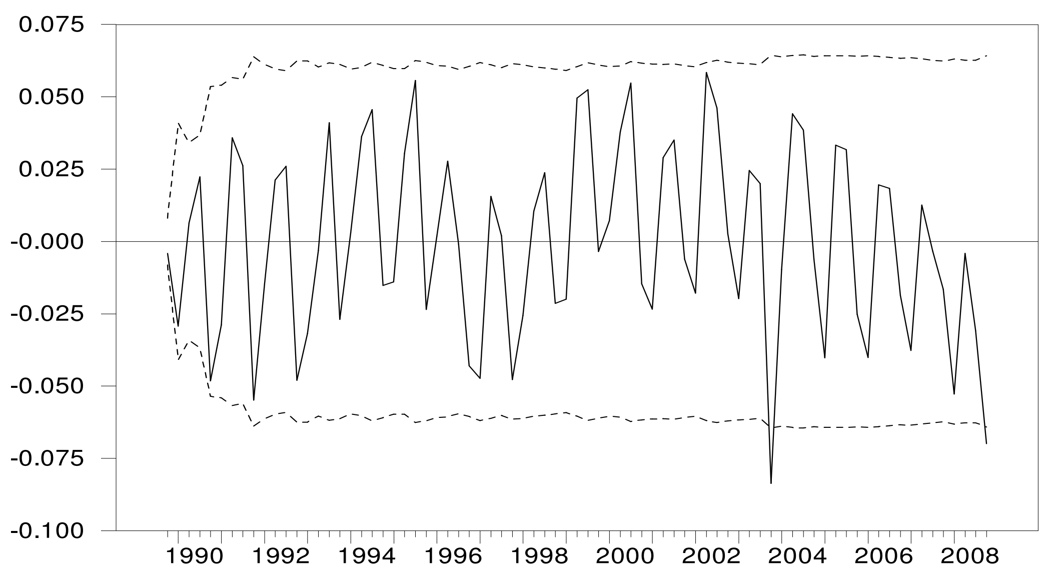
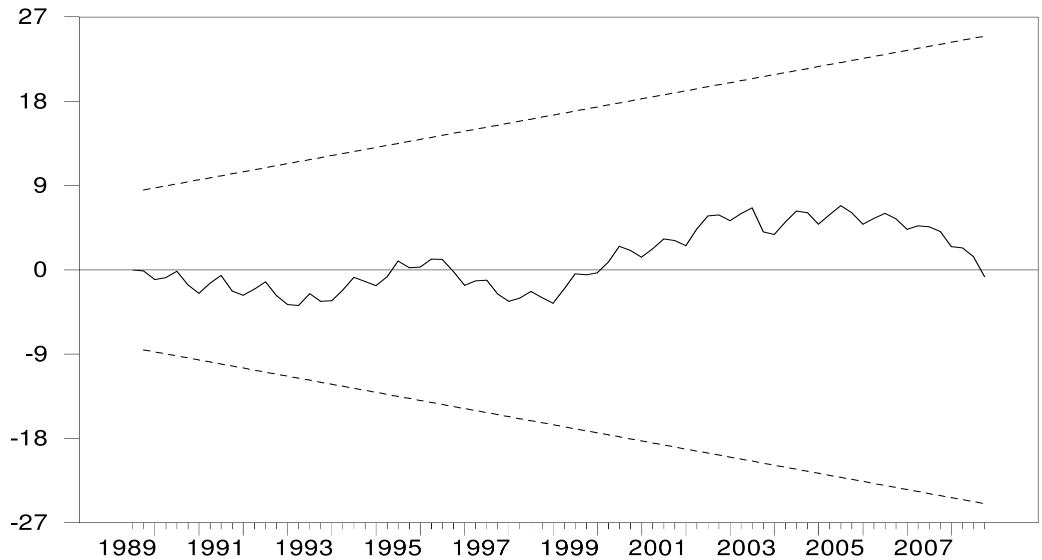
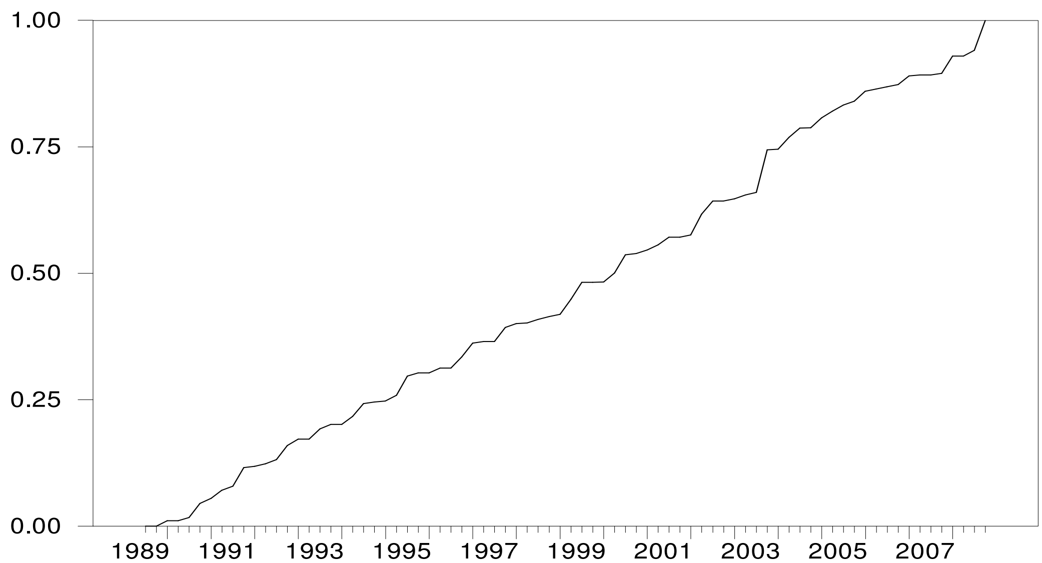


Figure 4.5 Plot of recursive residuals



(a)



(b)

Figure 4.6 Plots of (a) CUSUM and (b) CUSUMSQ in Figure 4.6 do not indicate a structural change even for the BSE case. Throughout the sample period, the CUSUM statistics computed by (4.9) remain inside the 95% intervals which are given by (4.10). Both CUSUM and CUSUMSQ results imply that there was no structural break during the sample period. Obviously, the patterns that these graphs show are somewhat unusual after the BSE event, but not to the extent that the null hypothesis of no structural change can be rejected.

4.3.3 Sequential F-test

Figure 4.7 illustrates the sequential F-statistics computed by (4.11). The statistic reaches the maximum ($F_{2003Q4} = 1.79$) at the time of the BSE event; however, the critical value at this point is $F(1, 55) = 4.0162$ at the 5% level. Therefore, it leads to the conclusion that there was no structural change during the sample period. This result agrees with those of the CUSUM and CUSUMSQ.

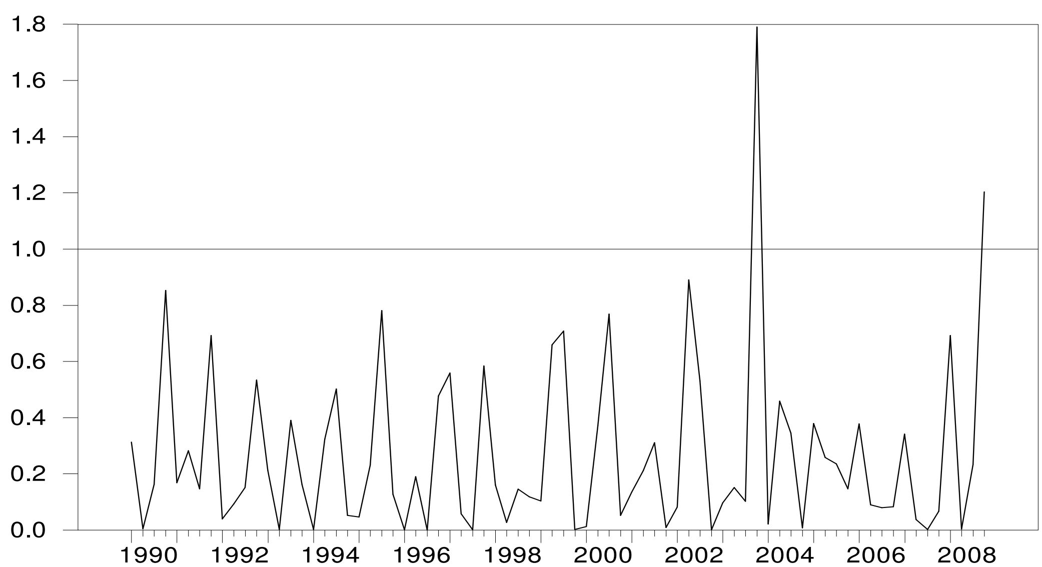


Figure 4.7 Plot of sequential F-statistics

4.3.4 Implications

The CUSUM and other related tests give a different result from that of the Chow test. Of course, it is obvious that the BSE event caused a significant change in the market structure at least in the short run, as described in Figure 4.4 (b). Its impact on the market is much stronger than that of the NAFTA event. However, it is still questionable whether it lasted for a longer period of time. The CUSUM and CUSUMSQ tests, as well as the sequential F-test, indicate that the market impact was not influential enough to cause a distinct structural change in the long run. In other words, such an impact still lies in the allowable range in terms of prediction error. This implication can also be supported by the experimental results shown in Appendix B.

CHAPTER V

MULTINATIONAL MEAT MARKETS

5.1 Preliminaries

This chapter will be devoted to the exploration of the multinational meat markets consisting of three kinds of meat products (i.e. beef, pork and poultry) of three countries (i.e. Korea, US and UK). The selection of these countries satisfies the standard of diversification (i.e. Korea from Asia, US from North America, and UK from Europe). Moreover, the countries are known to have been affected by the major animal disease outbreaks. The primary purpose of this study is to ascertain whether the events had similar impacts on the markets. To a large extent, therefore, this chapter is separate from the previous chapters in its scope and methodology.

Since this analysis is concerned with comparisons between the countries as well as between the meat products, generating a set of common variables is very crucial to this purpose. A market-based approach has been applied to the analysis of the US beef market in previous chapters, emphasizing that market data consists of the equilibrium prices and quantities. In a similar way, the relationship between price and quantity will play an important role in accounting for the impact of an animal disease outbreak on the market. As shown in Figure 2.1, a shift of demand or supply causes a movement of the equilibrium point, which involves a change in either price, quantity, or both. Hence, for the purpose of comparison, examining the changes in the variables (i.e. price and quantity) can provide meaningful information.

The data has two categories: country and meat type. Each data point is two-dimensional: price and quantity. Based on the data structure, different countries, as well as different meat types, can be compared. This study is more concerned with the comparison between countries. However, the pattern of market movement differs according to countries and meat types. Figure 5.1 shows the market movement for each country and meat type, which also represents the long-run relationship between price and quantity. Since this analysis uses nominal price and aggregate quantity variables, a positive relationship is expected in the long run. At a glance, the US and Korean data conform to this expectation, while the UK data shows an irregular pattern for all the meat types. Considering the fact that the UK has suffered much from major animal disease outbreaks (e.g. BSE 1996 and FMD 2001), such irregularity might look possible.

There are many reasons for the market movements. Most common are the changes in income and input price, which were explicitly considered in previous chapters. They

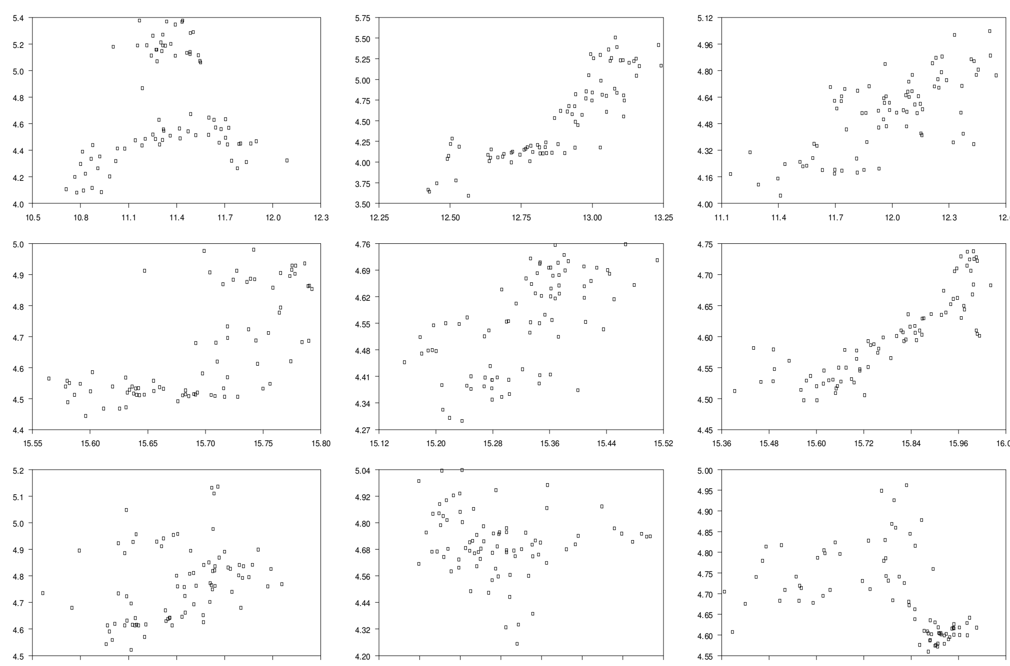


Figure 5.1 Bivariate scatter diagrams of price and quantity[53]

[53] This is a 3×3 set of scatter diagrams. Each row stands for a country (i.e. 1=KR, 2=US, 3=UK) and each column for a meat type (i.e. 1=beef, 2=pork, 3=poultry). In each diagram, the logarithmic price and quantity are on the vertical and horizontal axes, respectively. A more detailed diagram is provided in Appendix C.

also depend on changes in taste and weather. In addition, policy changes and animal disease outbreaks are other possible reasons. Even though an exact reason for a certain movement is difficult to determine, an abrupt change in price or quantity can be attributed to an unexpected shock to the market, such as an animal disease outbreak. For this reason, differencing the original series is an advantageous method of generating new data series appropriate for this particular analysis.

Let P_t and Q_t be the original price and quantity. Then the logarithmic price (p_t) and quantity (q_t) are defined as

$$p_t = \ln P_t \text{ and } q_t = \ln Q_t.$$

Then their first differences are

$$\Delta p_t = p_t - p_{t-1} = \ln\left(\frac{P_t}{P_{t-1}}\right) \text{ and } \Delta q_t = q_t - q_{t-1} = \ln\left(\frac{Q_t}{Q_{t-1}}\right). \tag{5.1}$$

The original variables have a trend component, which can be removed by differencing. In fact, the series generated by (5.1) are mean-reverting (i.e. detrended). However, these new series still reflect seasonal effects. Since this research uses quarterly time series data, an adjustment for seasonality may be necessary; in fact, such an adjustment played an important role in estimating demand and supply equations in Chapter III. Making appropriate adjustments will improve the data quality for this particular study. Thus, the final data series should be generated by (i) removing the seasonal components from the original variables, (ii) taking logarithms, and (iii) differencing. It is possible to obtain a mean-reverting series using (ii) and (iii) only. However, it is quite different from the series generated using (i), (ii), and (iii). The difference between them is shown in Figure 5.2. Both series are generated from the US beef quantity time series; the upper one using (ii) and (iii), while the lower one using (i), (ii), and (iii). The impact of the BSE event appears to be more outstanding in the lower graph. Further, a distinct pattern of increasing volatility can also be seen in the lower graph, but not in the upper graph. Even a single graph of an adjusted time series contains so much useful information. This is the reason for using the series generated by (5.1) with seasonal adjustments for the original

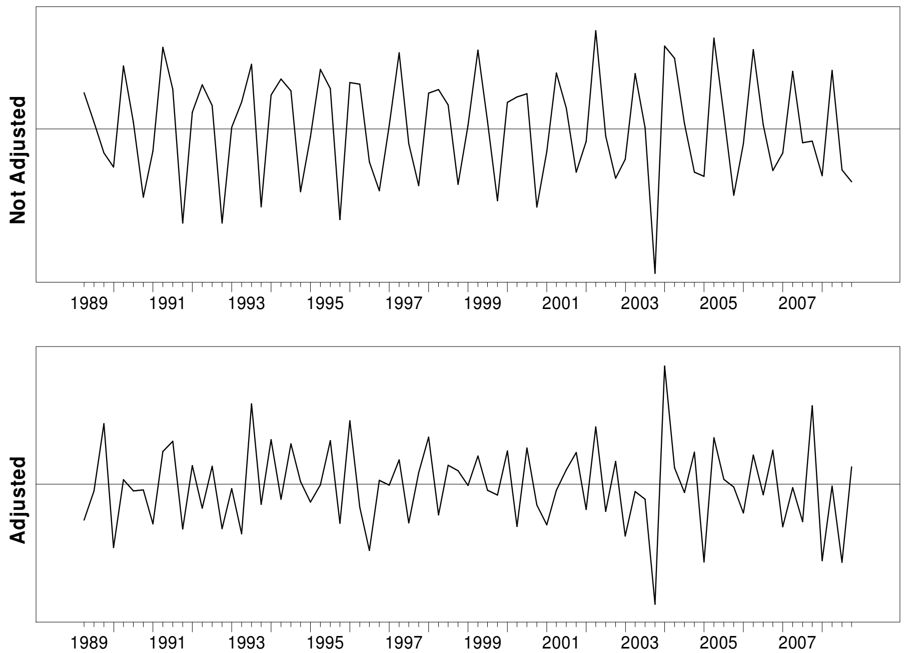


Figure 5.2 Effect of seasonal adjustment

series (i.e. P_t and Q_t). The seasonal adjustment is also important for the comparison between two subsamples which have different starting points; for example, one may begin in the first quarter of a year, while the other in the fourth quarter of a year.

To some extent, market behavior can be accounted for by market movement, which is represented by a bivariate series of price and quantity changes (i.e. Δp_t and Δq_t, respectively) on a two-dimensional plane. After the original data is adjusted, the resulting data series has appropriate properties for applying multivariate statistical methods such as CCA and PCA. First, each series has no autocorrelation; $Cov(\Delta p_t, \Delta p_s) = 0$ and $Cov(\Delta q_t, \Delta q_s) = 0$ for $t \neq s$. Second, each series is normally distributed; $\Delta p_t \sim N(0, \sigma_p^2)$ and $\Delta q_t \sim N(0, \sigma_q^2)$. Finally, the bivariate series is also normally distributed:

$$x_t = (\Delta p_t, \Delta q_t)^\top \sim iid\, N(0, \Sigma), \tag{5.2}$$

where Σ is a 2×2 variance-covariance matrix. The final property (5.2) is, in fact, implying the other properties; the reverse does not generally hold. As mentioned above, there may be a possibility that some series does not have a constant variance throughout the sample period; for example, the series in Figure 5.2 exhibits a distinct change in volatility after the BSE event. Still, (5.2) holds for each of the subsamples divided by the break point; in this case, the data series in the first subsample follows $N(0, \Sigma_1)$ and the data series in the second subsample follows $N(0, \Sigma_2)$.

A change in volatility can be explained more easily for a univariate case and the explanation simply can be extended to a bivariate case. For example, the US beef quantity series can be divided into two subsamples before and after the BSE event; the first subsample spans from 1989Q2 to 2003Q3 and the second subsample spans from 2003Q4 to 2008Q4. Although the original series starts from 1989Q1, the first difference of the series starts from 1989Q2, losing the first observation. The first subsample has 58 observations ($n_1 = 58$) and the second subsample has 21 observations ($n_2 = 21$). Further, it is assumed that the first subsample is distributed with $N(0, \sigma_1^2)$ and the second subsample is distributed with $N(0, \sigma_2^2)$. Then, under the null hypothesis of $\sigma_1^2 = \sigma_2^2$, the F-ratio (i.e. a ratio of sample variances, S_1^2 and S_2^2) can be computed and compared to the critical value at a particular significance level. In this case, the test statistic is given by

$$F = \frac{S_2^2}{S_1^2} = 2.6275 > 1.7575 = F_{20,57}(\alpha = 0.05).$$

Thus the null hypothesis is rejected at a 5% level and it is concluded that the two subsamples have a different variance. The graphs of all the univariate series are presented in Appendix D.

Finally, the analysis is twofold: the canonical correlation analysis and the principal component analysis. In this study, the former is concerned with the comparison between countries, while the latter is concerned with the comparison between meat types. These two approaches can be applied extensively to testing a variety of hypotheses of interest. Also, these analyses will provide more information about the equality of impacts of the disease events. The history of the animal disease outbreaks is summarized below.

- July 1988: BSE (UK)
- March 1996: BSE (UK), announcement of the suspected link between BSE in cattle and vCJD in humans
- February 2001: FMD (UK)
- May 2002: FMD (Korea)
- December 2003: AI (Korea)
- December 2003: BSE (US)
- November 2003 and February 2004: AI (US)

5.2 Canonical Correlation Analysis

The correlation coefficient (or simply, correlation) measures the strength or degree of linear association between two variables. For two series x_t and y_t, the correlation ρ_{xy} is given by

$$\rho_{xy} = \frac{S_{xy}}{S_x S_y},[54]$$

where

$$S_{xy} = \frac{1}{T}\sum_{t=1}^{T}(x_t - \bar{x})(y_t - \bar{y}), \tag{5.3}$$

$$S_x = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t - \bar{x})^2} \text{ and } S_x = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t - \bar{x})^2}, \tag{5.4}$$

where $\bar{x}$ and $\bar{y}$ are the sample means. For any two perfectly synchronized series, the correlation is 1.[55] For any two perfectly opposite series, the correlation is -1. Thus the

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[54] This is a sample correlation. Conventionally, ρ is reserved for a population correlation, but it is used for a sample correlation here.

[55] Suppose $x_t = (-1)^t$ and $y_t = a(-1)^t + b$ for $a > 0$. When T is an even number, $S_{xy} = a$ from (5.3), and $S_x = 1$ and $S_y = a$ from (5.4). Finally, $\rho_{xy} = 1$ from (5.3).

correlation can be regarded as an indicator of synchronization of two series. For example, see Figure 5.3, which illustrates the beef quantity time series of Korea and US. Of course, they are difference variables; they look different on the whole. However, suppose that the two series are resampled for the period of 2003Q4 to 2008Q4. The correlation between them is then 0.6563, a very significant correlation value, compared to the overall correlation of -0.1628. This relationship can also be measured and tested using rank correlation such as Kendall's tau or Spearman's rho.[56] For the same data, the null hypothesis of independence is rejected at the 5% level, based on both tests.

As already known, the US BSE outbreak comes in 2003Q4. Korea is one of the major beef importing countries from the US. Thus the event may have affected Korea' beef market, with one time (i.e. quarter) lead. In fact, Korea banned the beef import from the

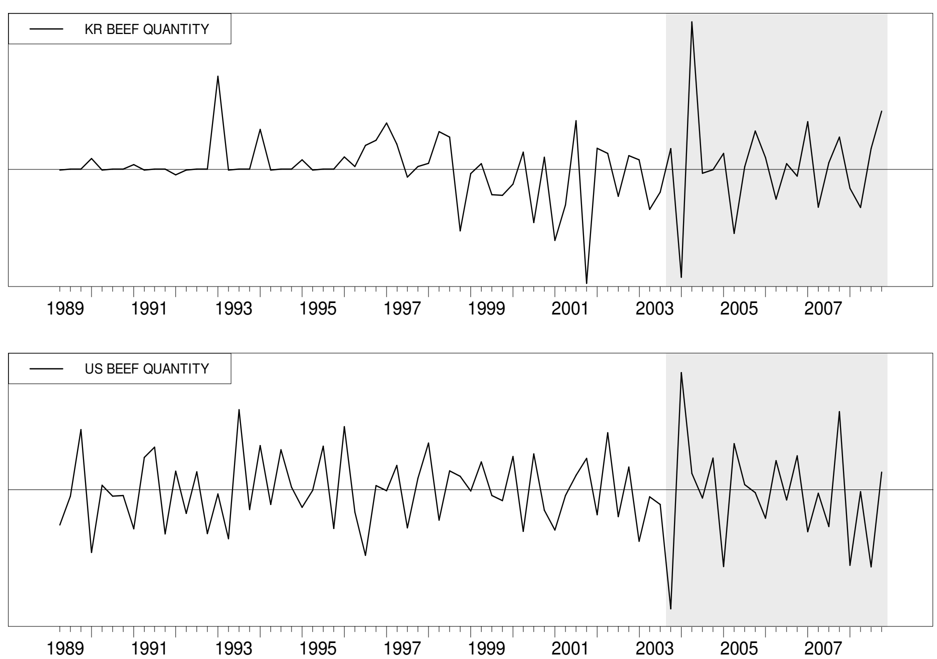

Figure 5.3 Synchronization of two series

56 For the computations of the statistics and test procedures, refer to Blalock (1972, pp. 415-421).

US after the event and food safety became an important issue. However, this correlation is reflecting just one side of market movement. Market movement can be described by both price and quantity. This is the reason that CCA is introduced.

The canonical correlation measures the strength of the overall relationships between the linear composites of the predictor and criterion sets of variables. According to Mardia et al. (1979)[57], an x-set denotes the predictor set and a y-set denotes the criterion set. In the previous example, the US market data is the predictor and the Korea market data is the criterion set. Thus it is possible to examine how much of the market movement in the US accounts for that of Korea, and how much they are alike. In fact, multiple regression analysis is a special case of canonical correlation analysis, in which an x -set have K variables (regressors) and a y-set has only one dependent variable. This analysis is based on the assumption that the movements of any two markets may be similar to each other when they are contemporaneously affected by the same event.[58]

Let x and y be two-dimensional random vectors, and μ and υ the respective means. Then the variance-covariance matrices are defined as

$$\Sigma_{11} = E\big[(x-\mu)(x-\mu)^\top\big],$$

$$\Sigma_{22} = E\big[(y-\upsilon)(y-\nu)^\top\big],$$

$$\Sigma_{12} = \Sigma_{21}^\top = E\big[(x-\mu)(y-\nu)^\top\big].$$

Now consider two linear combinations $a^\top x$ and $b^\top y$. The correlation between them is given by

$$\rho(a,b) = \frac{a^\top \Sigma_{12} b}{\big(a^\top \Sigma_{11} a b^\top \Sigma_{22} b\big)^{1/2}}. \tag{5.5}$$

Thus the correlation varies with different values of a and b. In this research, the vectors show the structure of the market movements, as x and y are sets of the variables that

[57] See p. 281.

[58] If this is linked to an analysis on herding behavior, it will be a meaningful research topic. As in financial world, there may be some contagious effect and herding behavior. Seeing that others do not consume meat because of an animal disease outbreak, one might decide not to consume meat either.

represent the shifts of market equilibria, as shown in (5.2). The next step is to find vectors a and b such that (5.5) is maximized. Since (5.5) does not depend on the scaling of a and b, it is equivalent to

$$\max_{a,\, b} \quad a^\top \Sigma_{12} b \tag{5.6a}$$

$$s.t. \quad a^\top \Sigma_{11} a = b^\top \Sigma_{22} b = 1. \tag{5.6b}$$

The Lagrange function to this maximization problem is

$$\mathcal{L} = a^\top \Sigma_{12} b - \frac{1}{2}\nu_1\left(a^\top \Sigma_{11} a - 1\right) - \frac{1}{2}\nu_2\left(b^\top \Sigma_{22} b - 1\right), \tag{5.7}$$

where ν_1 and ν_2 are Lagrange multipliers. Differentiating $\mathcal{L}$ with respect to a, b, ν_1 and ν_2 gives the following first-order conditions:

$$\frac{\partial \mathcal{L}}{\partial a} = \Sigma_{12} b - \lambda_1 \Sigma_{11} a = 0, \tag{5.8a}$$

$$\frac{\partial \mathcal{L}}{\partial b} = \Sigma_{12}^\top a - \lambda_2 \Sigma_{22} b = 0, \tag{5.8b}$$

$$\frac{\partial \mathcal{L}}{\partial \nu_1} = a^\top \Sigma_{11} a - 1 = 0, \tag{5.8c}$$

$$\frac{\partial \mathcal{L}}{\partial \nu_2} = b^\top \Sigma_{22} b - 1 = 0. \tag{5.8d}$$

From the above conditions, it can be easily seen that

$$\nu_1 = \nu_2 = a^\top \Sigma_{12} b,$$

which is the correlation between $a^\top x$ and $b^\top y$. Now let ν denote the correlation. The first-order conditions (5.8a) and (5.8b) can be represented in a matrix equation:

$$\begin{pmatrix} -\nu\Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & -\nu\Sigma_{22} \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix} = 0. \tag{5.9}$$

For a solution satisfying the constraints of (5.6b), it should hold that

$$\begin{vmatrix} -\nu\Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & -\nu\Sigma_{22} \end{vmatrix} = 0. \tag{5.10}$$

By the theorem[59], the rth canonical correlation between x and y is the rth largest root of

(5.10).

Finally, the CCA yields the vectors $a = (a_1, a_2)$ and $b = (b_1, b_2)$, which satisfy the maximization conditions, and the canonical correlations. These vectors play an important role in determining the similarity of market movements. If they are in the same direction (i.e. $a_i b_i > 0$ for $i = 1, 2$)[60] and the largest canonical correlation is significant, it is concluded that the two markets move together.

5.3 Principal Component Analysis

Up to this point in this chapter, the method for comparing the market movements of different countries due to animal disease events has been discussed. However, the domestic meat markets of a country are also important. For example, three meat markets exist according to the kinds of meat, all of which are related to each other. In general, they are assumed to be substitutes. Let p be a vector of beef, pork and poultry price changes, and μ and Σ be the mean vector and covariance matrix, respectively. Now consider the following transformation:

$$p \to z = \Gamma^\top (p - \mu), \tag{5.11}$$

where Γ is orthogonal and satisfies $\Gamma^\top \Sigma \Gamma = \Lambda$, where Λ is diagonal and its eigenvalues are $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$. Then the ith ($i = 1, 2, 3$) principal component of p is defined as the ith element of z, that is

$$z_i = \gamma_i^\top (p - \mu), \tag{5.12}$$

where γ_i is the ith column of Γ. Under the assumption that $p \sim N(0, \Sigma)$, (5.12) is reduced to $z_i = \gamma_i^\top p$. Further, the principal component has the following properties:

$$E(z_i) = 0 \text{ for } i = 1, 2, 3,$$

[59] See Anderson (2003, p. 495).

[60] Since the variables are scale-invariant, a weak condition for market co-movement can be deduced; that is, $\langle a, b \rangle = a^\top b = b^\top a > 0$, in which one of price and quantity changes dominates the other.

$$Var(z_i) = \gamma_i^{\top} \Sigma \gamma_i = \lambda_i \text{ for } i = 1, 2, 3,$$

$$Cov(z_i, z_j) = \gamma_i^{\top} \Sigma \gamma_j = 0 \text{ for } i \neq j,$$

$$Var(z_1) \geq Var(z_2) \geq Var(z_3) \geq 0.$$

Thus the idea of PCA is to find γ_i such that z_i and z_j are uncorrelated and the variances of z_i ($i = 1, 2, 3$) are maximized.[61] This idea of maximizing some variance-type quantity subject to certain constraints (orthogonality of linear composites) is very similar to that of the CCA.

5.4 Empirical Results

5.4.1 Canonical Correlation Analysis

To apply the CCA to the comparison between the impacts of an animal disease outbreak on the different markets, the following cases are considered.

- Case 1: UK BSE (1988Q3) and UK BSE (1996Q1) on beef markets
- Case 2: UK BSE (1996Q1) and UK FMD (2001Q1) on beef markets
- Case 3: UK BSE (1996Q1) and US BSE (2003Q4) on beef markets
- Case 4: UK FMD (2001Q1) and US BSE (2003Q4) on beef markets
- Case 5: US BSE (2003Q4) and KR indirect impact (2004Q1) on beef markets
- Case 6: KR AI (2003Q4) and US AI (2003Q4) on poultry markets
- Case 7: KR AI (2003Q4) and UK indirect impact (2003Q4) on poultry markets
- Case 8: US AI (2003Q4) and UK indirect impact (2003Q4) on poultry markets

Almost all samples have a total of 20 observations (5 years). Considering the time intervals between the events, a larger sample size is not attainable without making some periods overlapped. In particular, Case 1 has 24 observation, but the time of the event occurrence is beyond the sample period beginning from 1989Q2. Thus, three observations (i.e. 1988Q3, 1988Q4, and 1989Q1) are missing. Even if the data were available and in-

[61] For more details, refer to Mardia et al. (1979, pp. 214-215).

cluded in the analysis, the results would not make a significant difference. The CCA results of the eight cases are summarized in Table 5.1 below. Since x and y are 2×1 vectors, two canonical correlations are computed. The first canonical correlation is the largest (main) one. Furthermore, the tests of significance of all canonical correlations are given by Wilks' lamda and L-H trace.[62] The null hypothesis of each test is that there is no correlation between the bivariate series x and y. Note that correlation is basically for a linear relationship between the variables; this fact is also the same for CCA. If the correlation coefficient between two market movements is close enough to 1, the markets can be considered to move together. Further, it means that people's reactions are homogeneous between the markets.

As mentioned earlier, the analysis of Case 1 bears the problem of lacking the first three observations. However, the missing portion is not crucial and thus the results can

Table 5.1

Results of canonical correlation analysis

	canonical corr.	obs.	Wilks' lamda	L-H trace	decision on market reaction
Case 1	0.2704 0.1546	24	0.9047 (0.7262)	0.1034 (0.7422)	different
Case 2	0.7848 0.0106	20	0.3841 (0.0034)	1.6032 (0.0011)	same
Case 3	0.3106 0.1202	20	0.8905 (0.7518)	0.1214 (0.7677)	different
Case 4	0.5671 0.2913	20	0.6208 (0.0970)	0.5668 (0.1022)	different
Case 5	0.7037 0.2034	20	0.4840 (0.0177)	1.0239 (0.0123)	same (weak)
Case 6	0.3695 0.1975	20	0.8298 (0.5452)	0.1987 (0.5690)	different
Case 7	0.1744 0.0292	20	0.9688 (0.9712)	0.0322 (0.9740)	different
Case 8	0.3997 0.2428	20	0.7907 (0.4237)	0.2528 (0.4501)	different

† p-values in parentheses

62 Lawley-Hotelling trace criterion. See Anderson (2003, pp. 328-329).

still be considered as meaningful. This case analysis is concerned with the comparison between the market movements due to the BSE events in the same country (i.e. UK). One notable issue related to this case is that the first BSE event occurred before the announcement of a suspected link between BSE in cattle and vCJD in humans, while the second BSE occurrence coincided with the announcement. Therefore, if the two patterns of market behavior are similar, it can be concluded that people reacted to the BSE events in a similar way, regardless of the knowledge about the threat of BSE to human health. However, the CCA result indicates that the market reactions to these two BSE events were different (i.e. people actually reacted differently), and further it is implied that the knowledge regarding the threat of BSE played an important role in changing people's general attitude towards the animal disease.

The question of Case 2 is whether the two different events (i.e. BSE and FMD) in the same country (i.e. UK) caused homogeneous market reactions. Since BSE is known to be harmful to human health but FMD is not, it is expected, a priori, that the two market movements should be different. Surprisingly, however, the result is that the market reactions are the same. This tendency of co-movement is so strong that the null hypothesis of no correlation may be rejected even at a 1% level. Thus, it can be concluded that (UK) people were deeply concerned about FMD and reacted in a similar way to the BSE outbreak, although there was no scientific evidence that FMD threatened human health in the same manner as BSE.

The question of Case 3 is whether the same type of animal disease events (i.e. BSE) in two different countries (i.e. UK and US) caused homogeneous market reactions. Since the knowledge about the threat of BSE was available at the times of both BSE outbreaks, it is expected, a priori, that the two market movements should be similar. However, it turns out that the market reactions were different. A relatively longer time interval between the two events (i.e. 1996Q1 and 2003Q4) and some different market characteristics between the countries are possible reasons for the different market movements.

The question of Case 4 is very similar to that of Case 3. Only difference is that Case

4 is concerned with different animal disease events (i.e. FMD and BSE). The largest canonical correlation (0.5671) is relatively large. At the 10% significance level, the two statistics (i.e. Wilks' lamda and L-H trace) lead to different conclusions. In spite of the relatively high correlation, the vectors are not in the same direction. Finally, it is concluded that the market reactions are different.

The result of Case 5 was, to some extent, well anticipated from the previous correlation analysis for the univariate series (i.e. quantity change). Considering price change and quantity change simultaneously, the two bivariate series are also closely correlated, which means that the two markets move together. However, the vectors are not in the same direction and satisfy the weak condition (i.e. a positive inner product of the vectors). The markets weakly move together. Replicating the same procedure for the periods before the event, the CCA gives a very small correlation. Thus, it can be concluded that the BSE outbreak in the US also affected the Korea's beef market.

Case 6 to Case 8 are related to each other. The AI event was serious in Korea, but was less so in the US, where the impacts were local and restrictive. Thus it is expected that these two cases are not highly correlated. In other words, the similarity of the market movements is not necessary. The results agree with these presumptions. Case 6 is concerned with the relationship between Korea and US poultry markets, where the AI events actually occurred at approximately the same time. The results indicate that the patterns of market behavior are different from each other. On the other hand, no such event occurred in the UK at that time. Therefore, the three poultry markets exhibit their own patterns of market behavior, which are different from each other.

5.4.2 Principal Component Analysis

The variance structure of market prices can be examined by PCA. Table 5.2 shows how PCA decomposes the total variation into the principal components. Since p is a three-dimensional vector, namely $p^\top = (\Delta p_1, \Delta p_2, \Delta p_3)$[63], there are three components. The first two components can explain more than 75% of the total variation, as shown in Table 5.2.

Table 5.2

Results of principal component analysis for (a) Korea, (b) US, and (c) UK

(a)

Components	*eigenvalue*	*eigenvector*			*proportion*	*cumulative*
z_1	1.3585	0.5565	0.6984	0.4501	0.4528	0.4528
z_2	0.9829	−0.6199	−0.0116	0.7846	0.3276	0.7805
z_3	0.6586	0.5531	−0.7156	0.4265	0.2195	1.0000

(b)

Components	*eigenvalue*	*eigenvector*			*proportion*	*cumulative*
z_1	1.5702	0.6214	0.6249	0.4726	0.5234	0.5234
z_2	0.8361	−0.3475	−0.3209	0.8811	0.2787	0.8021
z_3	0.5937	0.7023	−0.7117	0.0178	0.1979	1.0000

(c)

Components	*eigenvalue*	*eigenvector*			*proportion*	*cumulative*
z_1	1.3816	0.5169	0.5603	0.6472	0.4605	0.4605
z_2	0.8945	0.7671	−0.6388	−0.0596	0.2982	0.7587
z_3	0.7239	0.3800	0.5273	−0.7600	0.2413	1.0000

One interest thing is that the general market movement may be represented by the first principal component (z_1), which is a weighted linear combination of the price changes (i.e. Δp_1, Δp_2, and Δp_3). In the same context, Tsay (2005)[64] call the first principal component a market component. For example, pork is the most popular meat in Korea. The average quantities (in logarithms) are $q_1 = 11.33$, $q_2 = 12.88$, and $q_3 = 11.97$. In terms of market share, pork takes approximately 35.60% out of the total quantity. Further, the unit price of pork is quite lower than that of beef. From (5.12), the first principal component (z_1) is represented by

$$z_1 = \gamma_1^\top p = c_1 \Delta p_1 + c_2 \Delta p_2 + c_3 \Delta p_3,$$

[63] The subscripts mean the meat types (i.e. 1=beef, 2=pork, 3=poultry).

[64] See p. 424.

where $\gamma_1 = (c_1, c_2, c_3)^\top$. Thus the variance of the principal component is

$$Var(z_1) \simeq c_1^2\, Var(\Delta p_1) + c_2^2\, Var(\Delta p_2) + c_3^2\, Var(\Delta p_3),$$

where the covariance terms are omitted because their values are very small in this particular example. From Table 5.2 (a), the elements of the eigenvector for the first principal component are $c_1 = 0.5565$, $c_2 = 0.6984$, and $c_3 = 0.4501$. The relatively large coefficient (c_2) of pork price change (Δp_2) indicates that, to some extent in Korea, pork price movement can represent the price movement of the entire market, which includes all of the three meat types. In the other two countries (US and UK), the differences between the coefficients of beef and pork price changes are relatively small. In fact, the differences between beef and pork prices, as well as the differences between their market shares, are relatively small in the countries.[65]

PCA can also be applied to identifying a change in the variance structure of market

Table 5.3

Results of principal component analysis for the US market (a) before and (b) after the BSE event

(a)

Components	*eigenvalue*	*eigenvector*			*proportion*	*cumulative*
z_1	1.5607	0.5980	0.6349	0.4891	0.5202	0.5202
z_2	0.8338	−0.4815	−0.2033	0.8525	0.2779	0.7982
z_3	0.6055	0.6407	−0.7453	0.1842	0.2018	1.0000

(b)

Components	*eigenvalue*	*eigenvector*			*proportion*	*cumulative*
z_1	1.7007	0.6703	0.6430	0.3704	0.5669	0.5669
z_2	0.8975	−0.1717	−0.3513	0.9204	0.2992	0.8661
z_3	0.4018	−0.7220	0.6805	0.1251	0.1339	1.0000

65 For the US, $q_1 = 15.69$, $q_2 = 15.32$, and $q_3 = 15.79$ in logarithms. For the UK, $q_1 = 13.20$, $q_2 = 12.95$, and $q_3 = 13.66$ in logarithms.

prices due to an event. For example, consider the market impact of the BSE outbreak in the US. Table 5.3 shows the PCA results before and after the event. The weight on beef (c_1) increased, as shown by the difference in values from Table 5.3 (a) to Table 5.3 (b) (i.e. 0.5980 $\rightarrow$ 0.6703). Thus a larger portion of the total market variance is explained by the variance of beef price change. It also implies that the BSE event increased the volatility of beef price change. This change in volatility is highly noticeable from Figure 5.4, which shows that the series becomes rather unstable and the range of price change becomes greater after the BSE event (2003Q4). A larger variance in price difference also implies the instability of the market. That is, the BSE event made the market price more changeable.

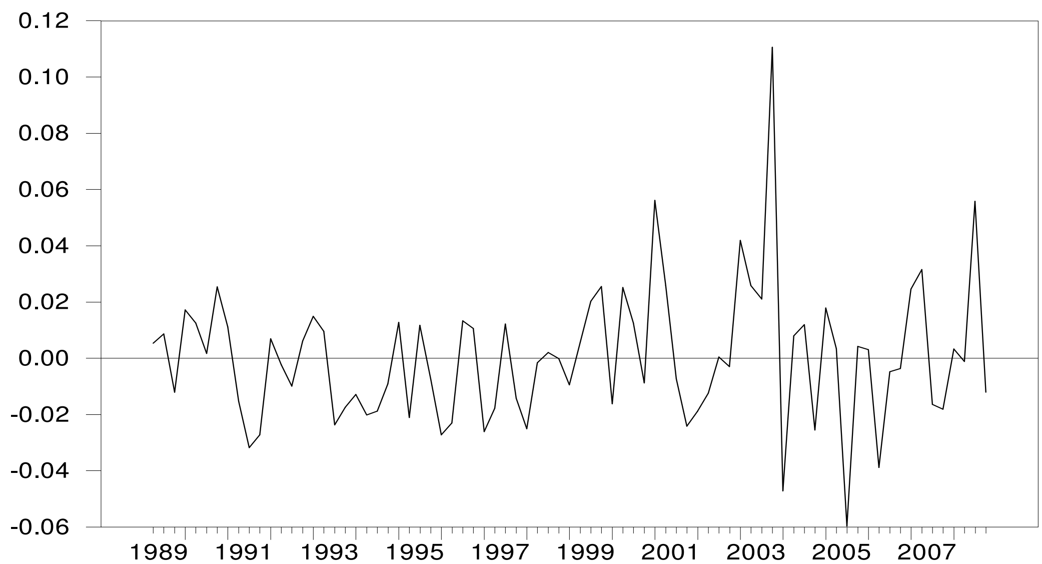

Figure 5.4 US beef price change

CHAPTER VI

SUMMARY AND CONCLUSIONS

This dissertation is concerned with three major questions: (i) how to model an agricultural market, (ii) how to analyze the impacts of a certain event (or shock) on the market, and lastly (iii) what are the relationships between different markets. The first two issues, which are discussed in Chapter III and Chapter IV, focused on the US beef market; the last chapter focused on the multinational meat markets.

There are various approaches to modeling an agricultural market. Emphasizing the properties of market data, a system of simultaneous equations was arranged as a recursive model to consider both demand and supply. In this model, the quantity supplied is determined by the expected price and feed price. Using quarterly data, the recursive model can account for the actual market very well.

Structural change in the US beef market was analyzed with the framework of the recursive model. The entire sample period (i.e. 1989Q1 to 2008Q4) contained two possible break points: the enforcement of NAFTA (1994Q1) and the BSE outbreak (2003Q4). The former is an anticipated policy change, while the latter is an unexpected shock to the market. Using the proposed model for the US beef market, the shifts of demand and supply due to those events were estimated. Further, the results of this study showed that the estimated shifts can explain the actual movements of the market price and quantity. However, the structural change still lies in the allowable range of the prediction error in view of other structural change test methods, which do not assume a known break point.

To determine the relationship between different markets, multivariate analysis methods such as CCA and PCA were applied to the market data. The applicability of these methods, by and large, depends on the properties of the data used for the analysis. In most cases, multivariate time series methods, such as VAR and VECM, are more prevalent because of the characteristics of time series data. To capture the market movements, however, a bivariate series, i.e. (p_t, q_t), was generated using a special transformation procedure. The variables identified were found to be normally distributed and have a zero autocorrelation.

It is important for economists to understand the impact of animal disease on market price and quantity, and how these evolve over time. This study entertained the hypothesis that effects could depend on whether the disease event was related to human health (or death) or not. Based on the findings through CCA, the knowledge of the suspected link between BSE in cattle and vCJD in humans played an important role in changing people's attitude toward an animal disease event. However, people are concerned about FMD as well as BSE. The PCA also showed the general structure of market variance and the changes in volatility due to some animal disease events.

Finally, the CCA and PCA are applied to test for a variety of hypotheses of interest. Even though they are not discussed in this dissertation, those approaches can be extensively applied to other empirical researches. Instead of using the difference variables, it is possible to generate other new variables through some special transformation. For example, the polar transformation will be useful in more precisely capturing the direction and extent of market movement. The application of PCA to identifying a change in volatility is somewhat analogous to the structural change test discussed in Chapter IV. However, there are some differences between them. The PCA approach in this chapter does not provide a test statistic. In the future, there should be more research on the application of PCA and how to interpret the results.

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APPENDIX A.1

MATHEMATICAL DERIVATION OF THE SUPPLY EQUATION

(3.5a) can be written as

$$q_t = \xi_0 + \xi_1 p_{t-1} + \gamma_2(z_t - \theta z_{t-1}) + \theta q_{t-1} + v_t - \theta v_{t-1},$$

where $\xi_0 = \gamma_0(1-\theta)$, $\xi_1 = \gamma_1(1-\theta)$, and the equilibrium quantity q_t substitutes for q_t^S. By letting $r_t = q_t - v_t$,

$$r_t = \xi_0 + \xi_1 p_{t-1} + \gamma_2 z_t - \gamma_2 \theta z_{t-1} + \theta q_{t-1} - \theta v_{t-1}. \qquad \text{(A.1)}$$

From (A.1), we can obtain

$$r_t - \theta r_{t-1} = q_t - v_t - \theta(q_{t-1} - v_{t-1}) = \xi_0 + \xi_1 p_{t-1} + \gamma_2 z_t - \gamma_2 \theta z_{t-1}.$$

Or equivalently,

$$r_t = \theta r_{t-1} + \xi_0 + \xi_1 p_{t-1} + \gamma_2(z_t - \theta z_{t-1}). \qquad \text{(A.2)}$$

Repeated substitution for r's in (A.2) yields

$$r_1 = \theta r_0 + \xi_0 + \xi_1 p_0 + \gamma_2(z_1 - \theta z_0)$$

$$r_2 = \theta r_1 + \xi_0 + \xi_1 p_1 + \gamma_2(z_2 - \theta z_1)$$

$$\vdots$$

and therefore we have

$$r_t = \theta^t r_0 + \xi_0(1 + \theta + \cdots + \theta^{t-1}) + \xi_1(p_{t-1} + \theta p_{t-2} + \cdots + \theta^{t-1} p_0) + \gamma_2(z_t - \theta^t z_0).$$

Note that r_0 is a nuisance parameter. Since $q_t = r_t + v_t$, we finally have

$$q_t = \theta^t r_0 + \xi_0(1 + \theta + \cdots + \theta^{t-1}) + \xi_1 p_t^* + \gamma_2(z_t - \theta^t z_0) + v_t,$$

where $p_t^* = p_{t-1} + \theta p_{t-2} + \cdots + \theta^{t-1} p_0$. With the original parameters, it becomes

$$q_t = \theta^t r_0 + \gamma_0(1-\theta)(1 + \theta + \cdots + \theta^{t-1}) + \gamma_1(1-\theta) p_t^* + \gamma_2(z_t - \theta^t z_0) + v_t. \qquad \text{(A.3)}$$

If θ can be predetermined in (A.3), we can rewrite it as

$$q_t = r_0 x_{0,t} + \gamma_0 x_{1,t} + \gamma_1 x_{2,t} + \gamma_2 x_{3,t} + v_t, \qquad \text{(A.4)}$$

where $x_{0,t} = \theta^t$, $x_{1,t} = (1-\theta)(1+\theta+\cdots+\theta^{t-1})$, $x_{2,t} = (1-\theta)p_t{}^*$, and $x_{3,t} = z_t - \theta^t z_0$.

For example, if $\theta = 0.97$, the estimation result of (A.4) is

$$\hat{q}_t = \underset{(0.0000)}{8.6333x_{0,t}} + \underset{(0.0000)}{7.9617x_{1,t}} + \underset{(0.0114)}{0.1850x_{2,t}} - \underset{(0.0302)}{0.0396x_{3,t}} + \underset{(0.0000)}{0.0485s_{2,t}} + \underset{(0.0000)}{0.0528s_{3,t}} - \underset{(0.6741)}{0.0032s_{4,t}}$$

$$\overline{R}^2 = 0.8653,\ d = 0.9667.$$

APPENDIX A.2

SEARCHING FOR THE OPTIMAL THETA

- R program code for finding the optimal θ

```
md <- read.table("data.csv",sep=",",header=TRUE)
q1 <- md$lnq[77:116]       # quantities for period 1
q2 <- md$lnq[117:156]      # quantities for period 2
A <- diag(1,40,40)
p1 <- md$lnp1[76:115]      # prices for period 1
p2 <- md$lnp1[116:155]     # prices for period 2
s <- rep(c(1,0,0,0),11)    # create seasonal dummies, s1~s4
s1 <- s[5:44]
s2 <- s[4:43]
s3 <- s[3:42]
s4 <- s[2:41]
serial <- 1:40
p_stat <- rep(NA,99)       # define P series
thetas <- rep(NA,99)       # define Theta series
for (k in 1:99) {          # make a loop for 99 iterations
theta <- k/100
x0 <- theta^serial         # x0~x3 regressors for period 1
y0 <- x0                   # y0~y3 regressors for period 2
x1 <- (1-theta)*cumsum(theta^(serial-1))
y1 <- x1
x3 <- md$lnz[77:116]-theta^serial*md$lnz[76]
y3 <- md$lnz[117:156]-theta^serial*md$lnz[116]
for (i in 1:40) {          # make a procedure for x2 computation
  for (j in 1:i) {
    A[i,j] <- theta^(i-j)
  }
}
x2 <- (1-theta)*A%*%p1
y2 <- (1-theta)*A%*%p2
lm(q1~x0+x1+x2+x3-1)               # linear regression 1
lm(q2~y0+y1+y2+y3-1)               # linear regression 2
result1 <- lm(q1~x0+x1+x2+x3+s2+s3+s4-1)
result2 <- lm(q2~y0+y1+y2+y3+s2+s3+s4-1)
c1 <- result1$coefficients         # coefficients for period 1
c2 <- result2$coefficients         # coefficients for period 2
X <- cbind(x0,x1,x2,x3,s2,s3,s4)
Y <- cbind(y0,y1,y2,y3,s2,s3,s4)
p_stat[k] <- t(q1-X%*%c2)%*%(q1-X%*%c2)+t(q2-Y%*%c1)%*%(q2-Y%*%c1)
thetas[k] <- theta
}
cbind(thetas,p_stat)
min(p_stat)                        # find the minimum P
plot(thetas,p_stat,type="l",xlab=substitute(theta),ylab="P")
```

Table A.2

Computation result: table of θ and penalty (P)

θ	P	θ	P	θ	P
0.01	0.8305183	0.34	0.8716623	0.67	0.9873153
0.02	0.8310330	0.35	0.8735503	0.68	0.9956680
0.03	0.8316010	0.36	0.8754728	0.69	1.0047095
0.04	0.8322218	0.37	0.8774310	0.70	1.0145001
0.05	0.8328949	0.38	0.8794262	0.71	1.0251028
0.06	0.8336195	0.39	0.8814605	0.72	1.0365813
0.07	0.8343951	0.40	0.8835360	0.73	1.0489990
0.08	0.8352210	0.41	0.8856554	0.74	1.0624165
0.09	0.8360965	0.42	0.8878221	0.75	1.0768879
0.10	0.8370207	0.43	0.8900399	0.76	1.0924558
0.11	0.8379930	0.44	0.8923132	0.77	1.1091446
0.12	0.8390125	0.45	0.8946474	0.78	1.1269505
0.13	0.8400784	0.46	0.8970483	0.79	1.1458280
0.14	0.8411898	0.47	0.8995229	0.80	1.1656711
0.15	0.8423459	0.48	0.9020789	0.81	1.1862881
0.16	0.8435457	0.49	0.9047252	0.82	1.2073678
0.17	0.8447884	0.50	0.9074718	0.83	1.2284345
0.18	0.8460730	0.51	0.9103299	0.84	1.2487902
0.19	0.8473986	0.52	0.9133122	0.85	1.2674419
0.20	0.8487643	0.53	0.9164327	0.86	1.2830141
0.21	0.8501692	0.54	0.9197071	0.87	1.2936513
0.22	0.8516124	0.55	0.9231529	0.88	1.2969221
0.23	0.8530931	0.56	0.9267894	0.89	1.2897548
0.24	0.8546103	0.57	0.9306381	0.90	1.2684581
0.25	0.8561634	0.58	0.9347226	0.91	1.2289287
0.26	0.8577515	0.59	0.9390688	0.92	1.1672180
0.27	0.8593741	0.60	0.9437055	0.93	1.0807336
0.28	0.8610305	0.61	0.9486640	0.94	0.9705001
0.29	0.8627203	0.62	0.9539785	0.95	0.8450863
0.30	0.8644431	0.63	0.9596863	0.96	0.7270190
0.31	0.8661987	0.64	0.9658282	0.97	0.6627189
0.32	0.8679870	0.65	0.9724481	0.98	0.7371969
0.33	0.8698081	0.66	0.9795934	0.99	1.0949803

APPENDIX B

STRUCTURAL CHANGES IN EXPERIMENTAL SERIES

Consider two artificial time series $\{c_{1,t}\}$ and $\{c_{2,t}\}$, which are determined by

$$c_{1,t} = \begin{cases} 15 + 0.8t + \varepsilon_t & (t \geq 1999Q1) \\ 10 + 0.4t + \varepsilon_t & (otherwise) \end{cases}, \tag{C.1}$$

$$c_{2,t} = \begin{cases} 50 + 0.4t + \varepsilon_t & (t = 1999Q1) \\ 10 + 0.4t + \varepsilon_t & (otherwise) \end{cases}. \tag{C.2}$$

Both series span from 1989Q1 to 2008Q4 (a total of 80 observations), which is the same sample period as the data used for the main analyses. In fact, $\{c_{1,t}\}$ in (C.1) is the same as the series in Figure 4.1. I replicated the same procedure as done in Chapter IV. Below are the results.

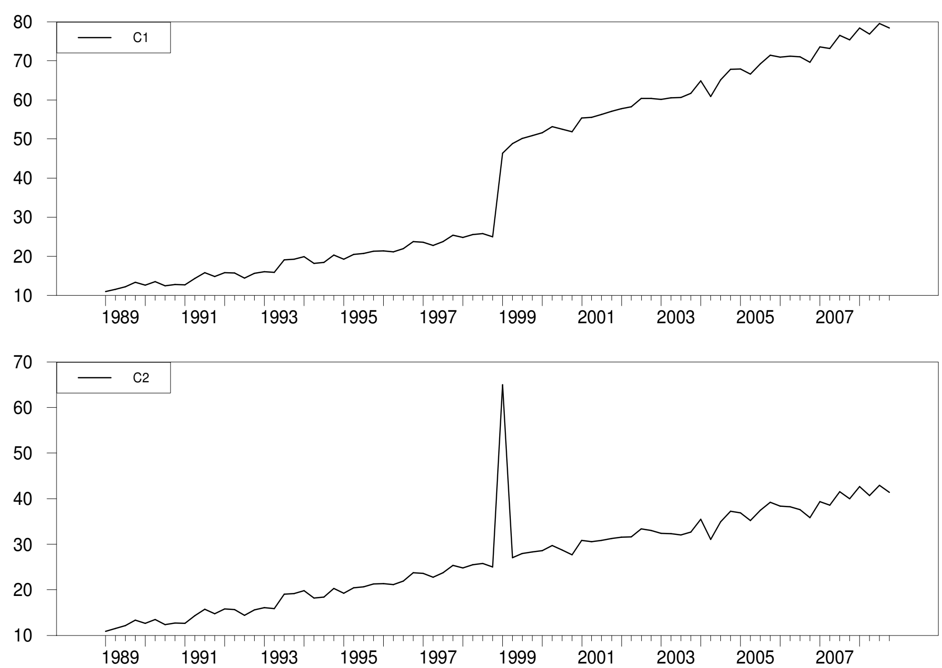

Figure B.1 Graphs of $\{c_{1,t}\}$ and $\{c_{2,t}\}$

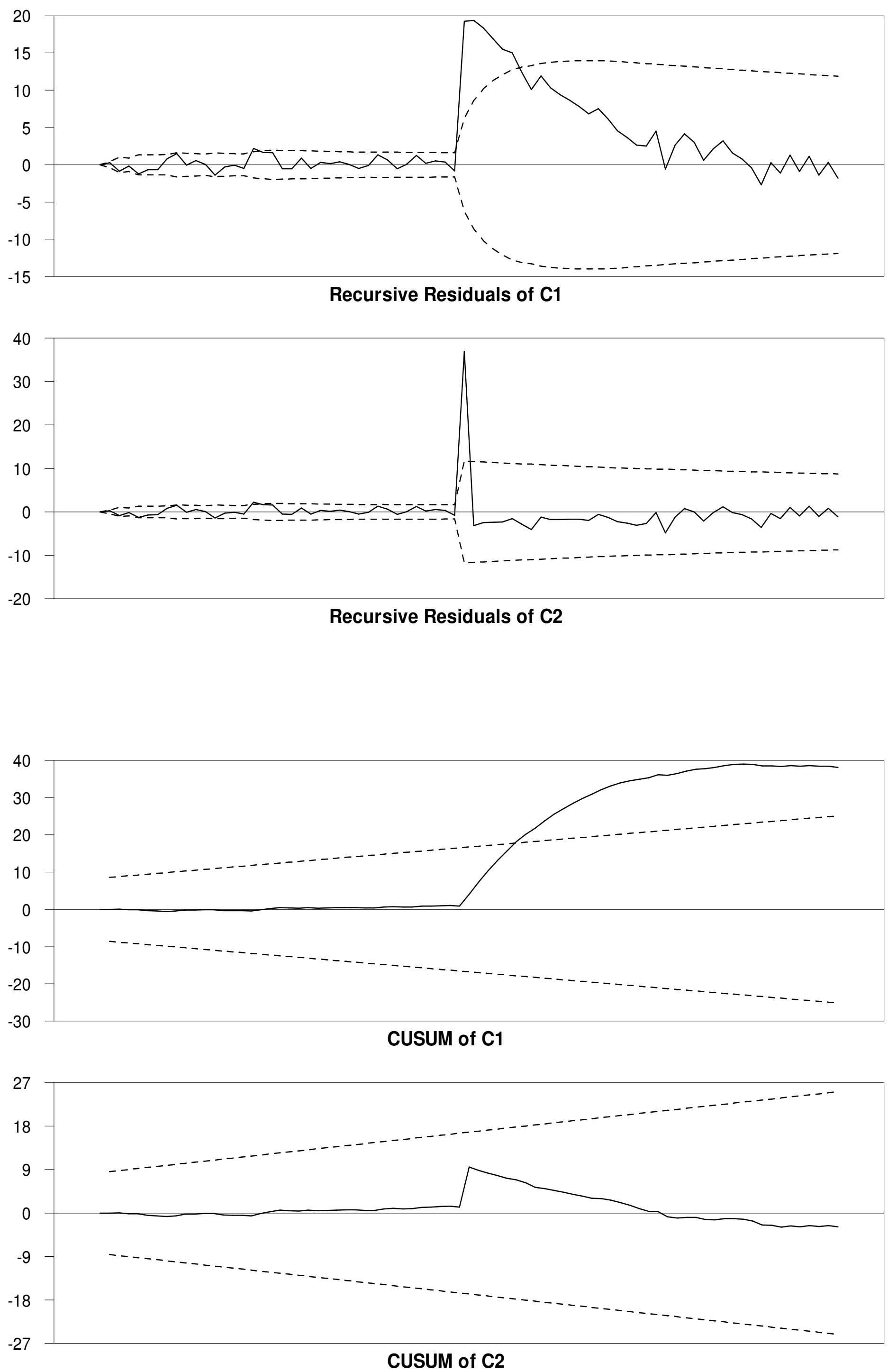

Figure B.2 Recursive residuals and CUSUM of $\{c_{1,t}\}$ and $\{c_{2,t}\}$

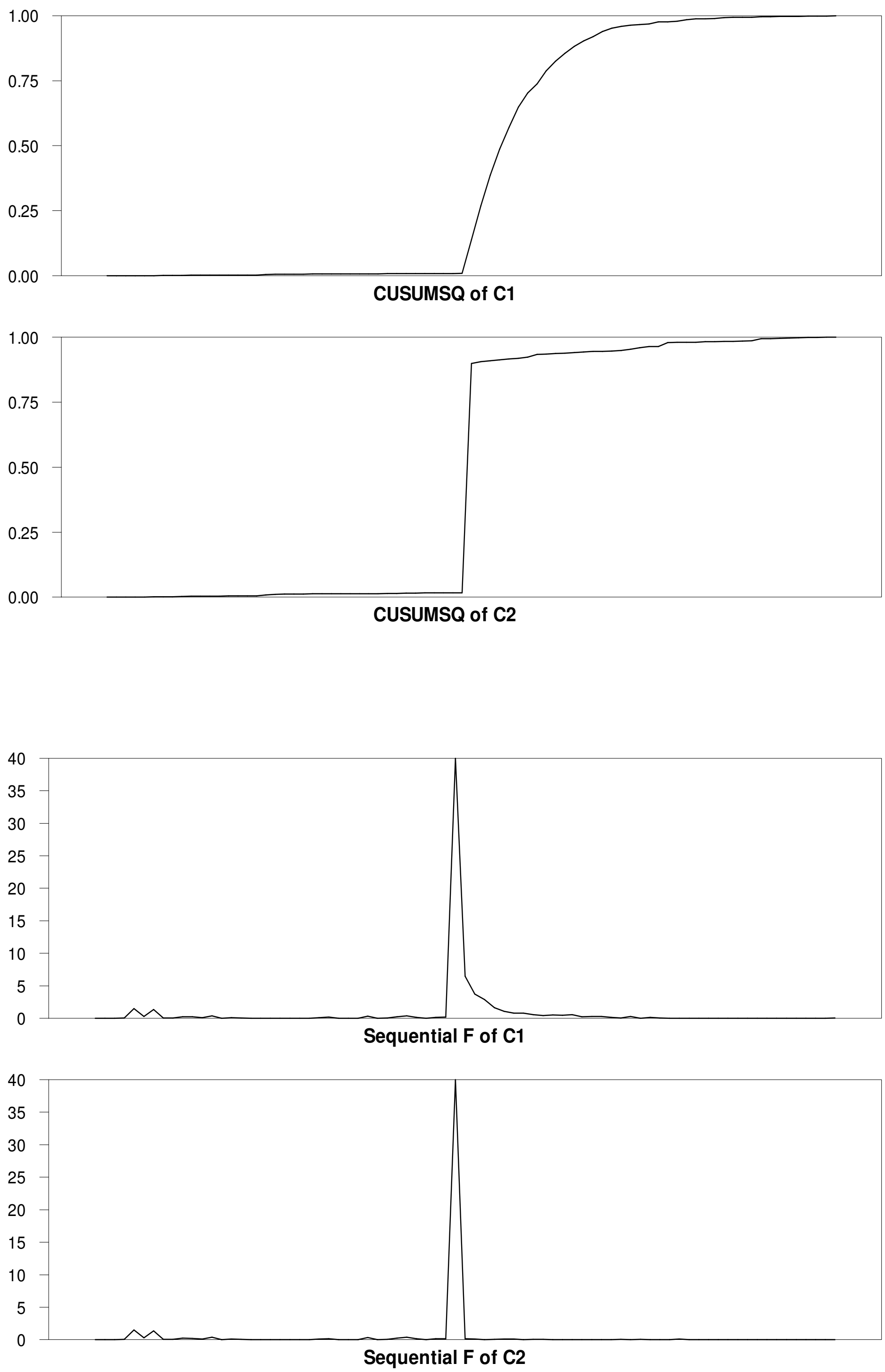

Figure B.3 CUSUMSQ and sequential F-statistics of $\{c_{1,t}\}$ and $\{c_{2,t}\}$

- RATS program code for the procedure

```
CALENDAR 1989 1 4
ALLOCATE 2008:4
SET TREND = T
SET EE = %RAN(1)
SET C1 1989:1 1998:4 = 10+0.4*TREND+EE
SET C1 1999:1 2008:4 = 15+0.8*TREND+EE
SET C2 1989:1 1998:4 = 10+0.4*TREND+EE
SET C2 1999:1 1999:1 = 50+0.4*TREND+EE
SET C2 1999:2 2008:4 = 10+0.4*TREND+EE
SPGRAPH(VFIELDS=2,HFIELDS=1)
GRA(KEY=UPLEFT) 1
# C1
GRA(KEY=UPLEFT) 1
# C2
SPGRAPH(DONE)
** RECURSIVE ESTIMATION **
DOFOR S = C1 TO C2
RLS(SEHIST=SEHIST,COHIST=COHIST,SIGHIST=SIGHIST,CSUM=CUSUM,CSQUARED=
CUSUMSQ) S 1989:01 2008:04 %S('RR'+%L(S))
# CONSTANT TREND
SET %S('UPPER'+%L(S)) = 1.96*SIGHIST
SET %S('LOWER'+%L(S)) = -1.96*SIGHIST
COMPUTE RSTART = %REGSTART()+%NREG
** CUSUM TEST **
SET %S('CUSUM'+%L(S)) = CUSUM/SQRT(%SEESQ)
SET %S('UP'+%L(S)) RSTART 2008:04 =
0.948*SQRT(%NDF)*(1+2*(TREND-RSTART+1)/%NDF)
SET %S('LO'+%L(S)) RSTART 2008:04 = -1*%S('UP'+%L(S))
** CUSUMSQ TEST **
SET %S('CUSUMSQ'+%L(S)) = CUSUMSQ/CUSUMSQ(2008:04)
** SEQUENTIAL F-TEST **
SET %S('SEQF'+%L(S)) = (T-RSTART)*(CUSUMSQ-CUSUMSQ{1})/CUSUMSQ{1}
SET %S('SEQFCV'+%L(S)) RSTART+1 * =
%S('SEQF'+%L(S))/%INVFTEST(0.05,1,T-RSTART)
END DOFOR S
** RECURSIVE RESIDUAL PLOT **
SPGRAPH(VFIELDS=2,HFIELDS=1)
DOFOR S = C1 TO C2
GRAPH(NOTICK,HLABEL='Recursive Residuals of '+%L(S),PATTERNS) 3
# %S('RR'+%L(S))
# %S('UPPER'+%L(S))
# %S('LOWER'+%L(S)) / 2
END DOFOR S
SPGRAPH(DONE)
** CUSUM PLOT **
SPGRAPH(VFIELDS=2,HFIELDS=1)
DOFOR S = C1 TO C2
GRAPH(NOTICK,HLABEL='CUSUM of '+%L(S),PATTERNS) 3
# %S('CUSUM'+%L(S))
# %S('UP'+%L(S))
# %S('LO'+%L(S)) / 2
END DOFOR S
```

```
SPGRAPH(DONE)
** CUSUMSQ PLOT **
SPGRAPH(VFIELDS=2,HFIELDS=1)
DOFOR S = C1 TO C2
GRAPH(NOTICK,HLABEL='CUSUMSQ of '+%L(S),PATTERNS) 1
# %S('CUSUMSQ'+%L(S))
END DOFOR S
SPGRAPH(DONE)
** SEQUENTIAL F-STAT **
SPGRAPH(VFIELDS=2,HFIELDS=1)
DOFOR S = C1 TO C2
GRAPH(MAX=40,NOTICK,HLABEL='Sequential F of '+%L(S)) 1
# %S('SEQFCV'+%L(S))
END DOFOR S
SPGRAPH(DONE)
```

APPENDIX C

BIVARIATE SCATTER DIAGRAMS

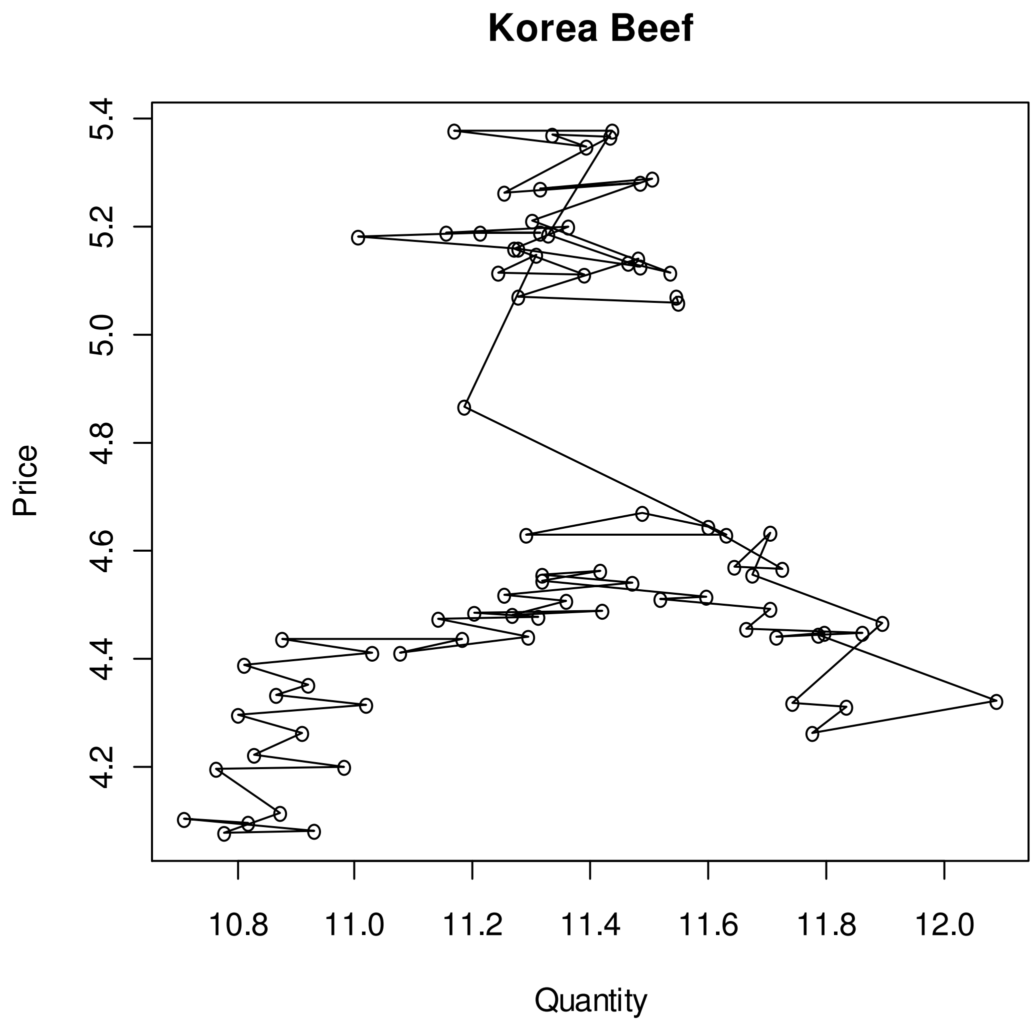

Figure C.1 Scatter plot of price and quantity (Korea beef market)

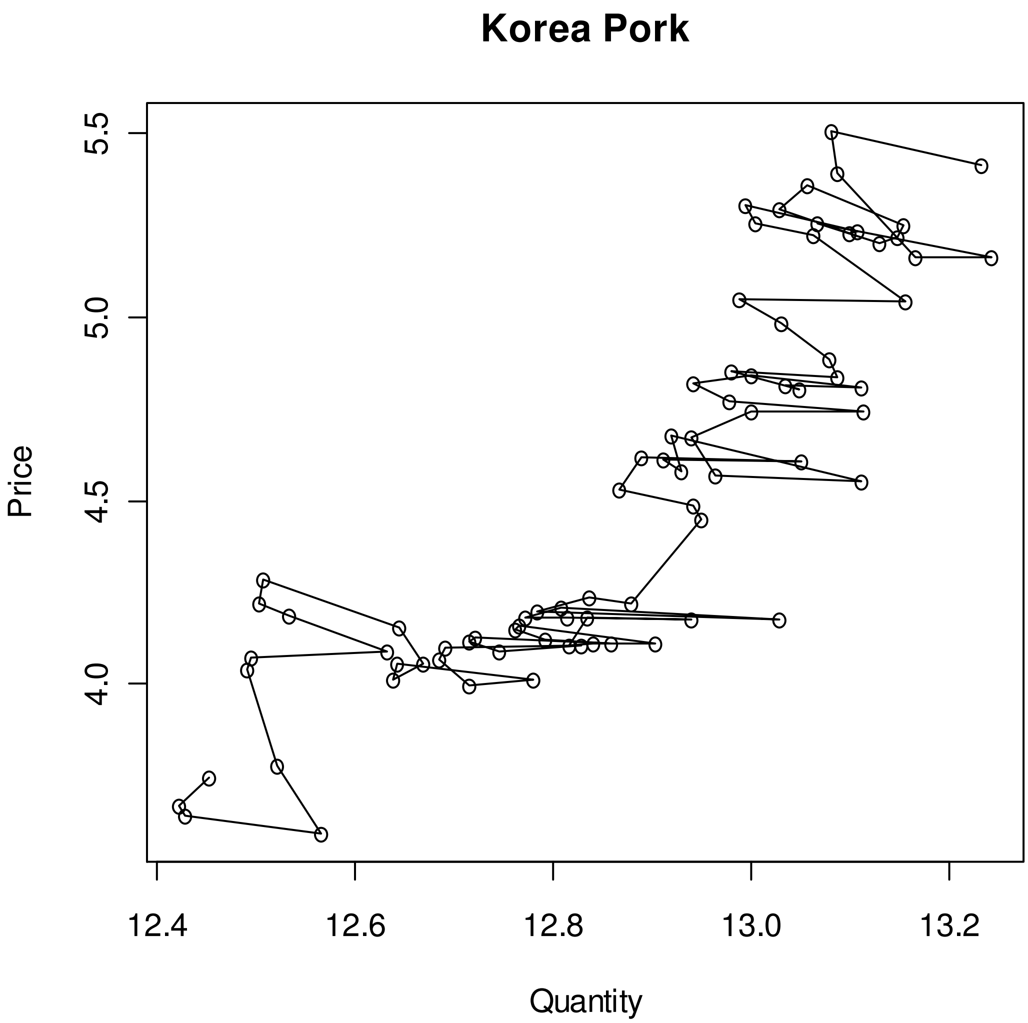

Figure C.2 Scatter plot of price and quantity (Korea pork market)

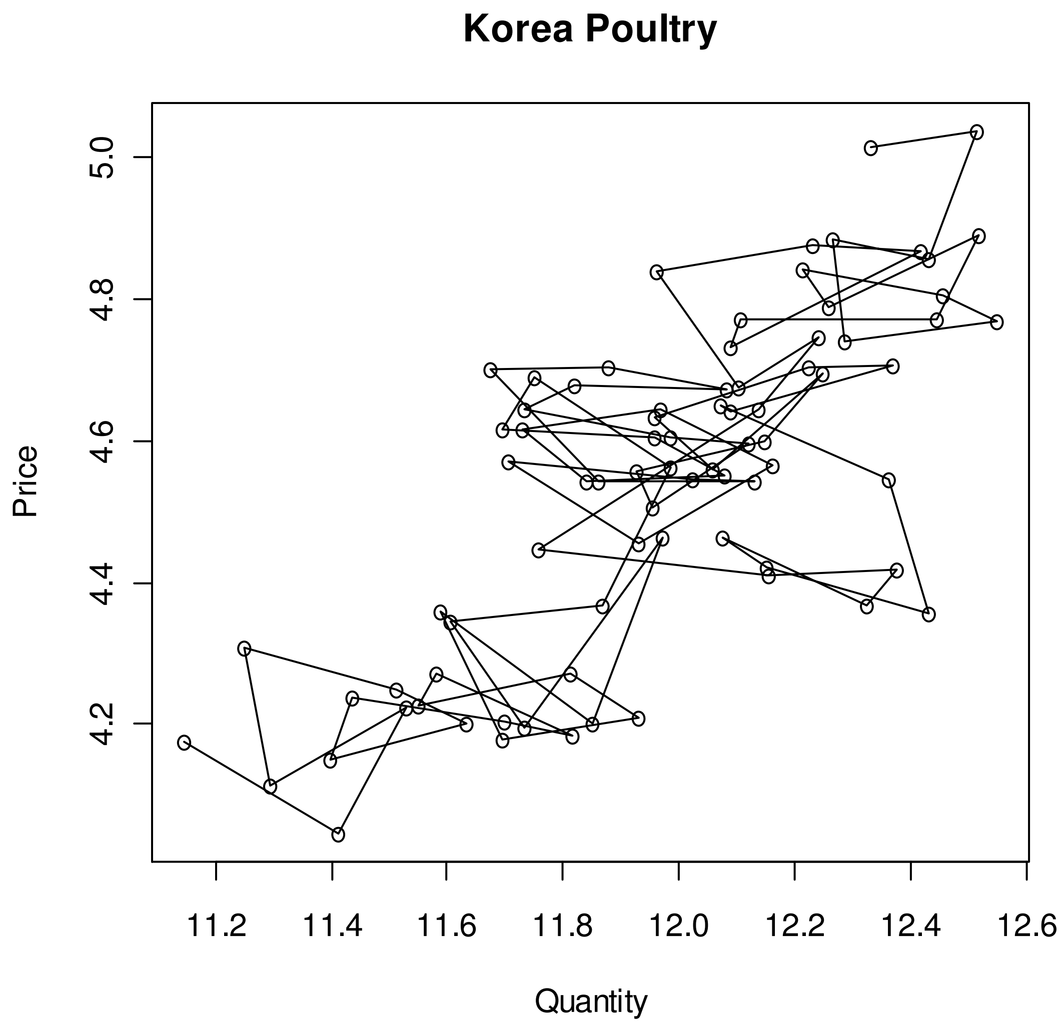

Figure C.3 Scatter plot of price and quantity (Korea poultry market)

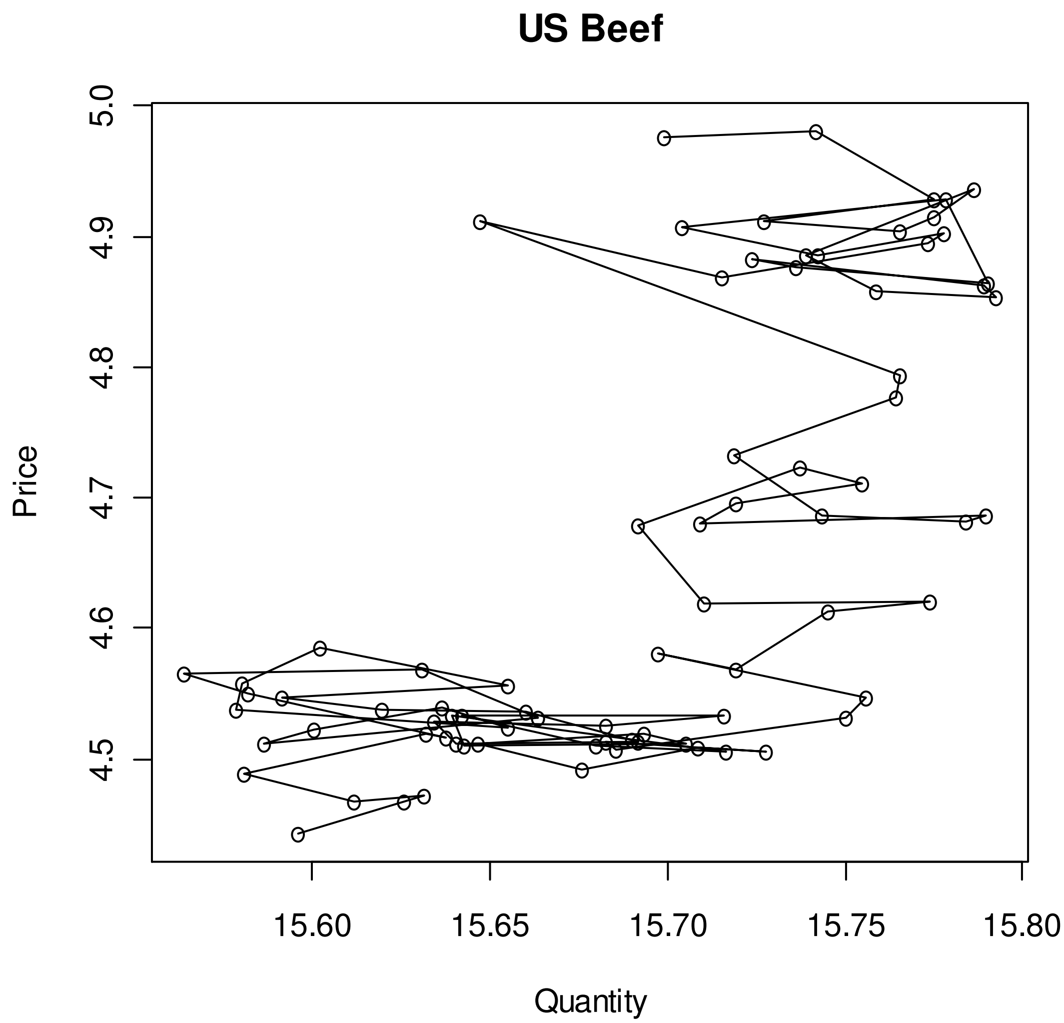

Figure C.4 Scatter plot of price and quantity (US beef market)

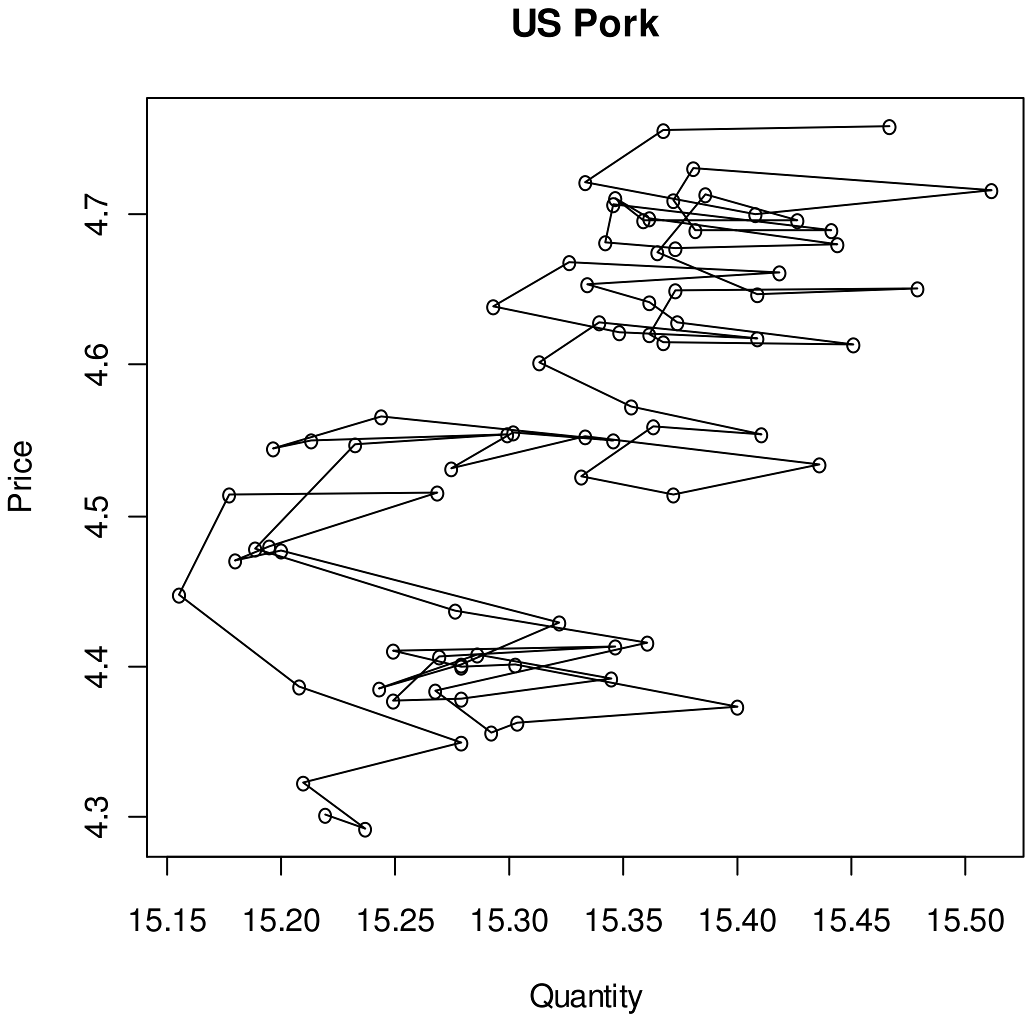

Figure C.5 Scatter plot of price and quantity (US pork market)

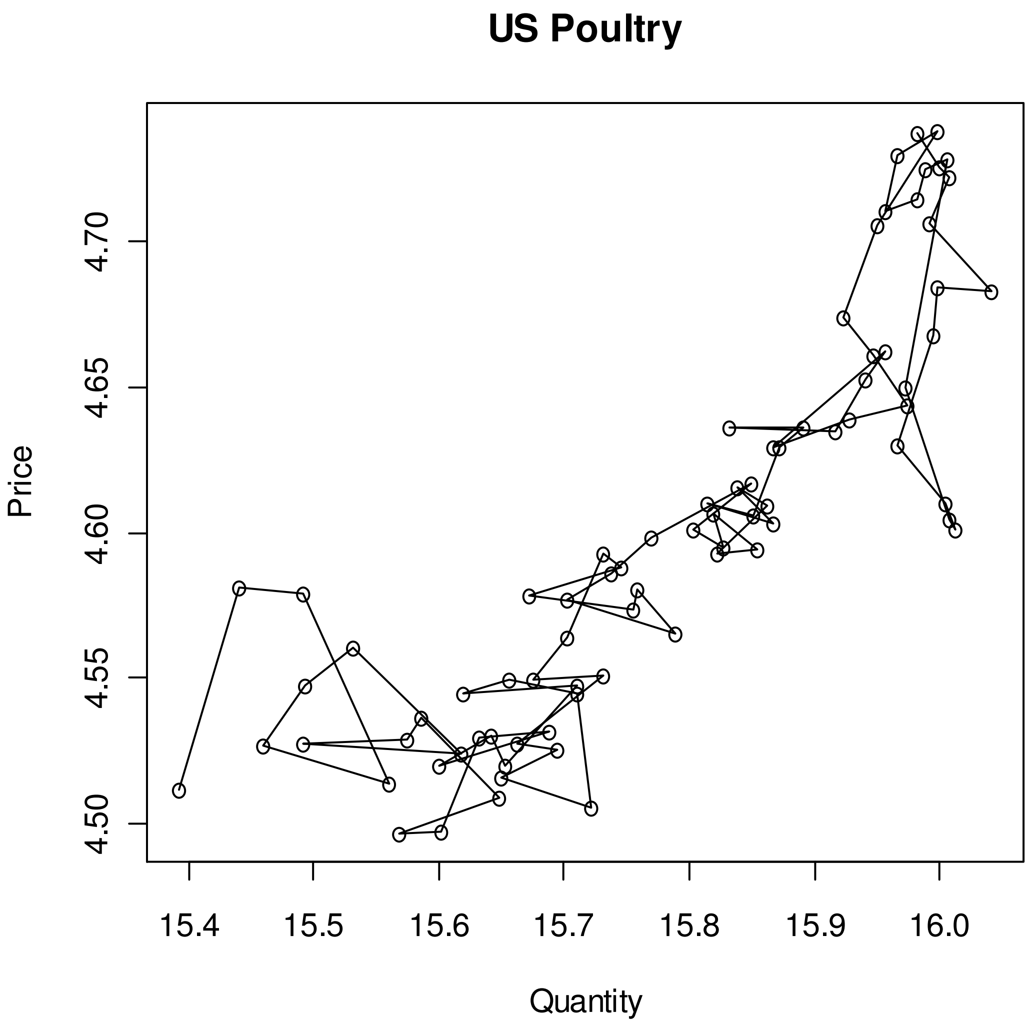

Figure C.6 Scatter plot of price and quantity (US poultry market)

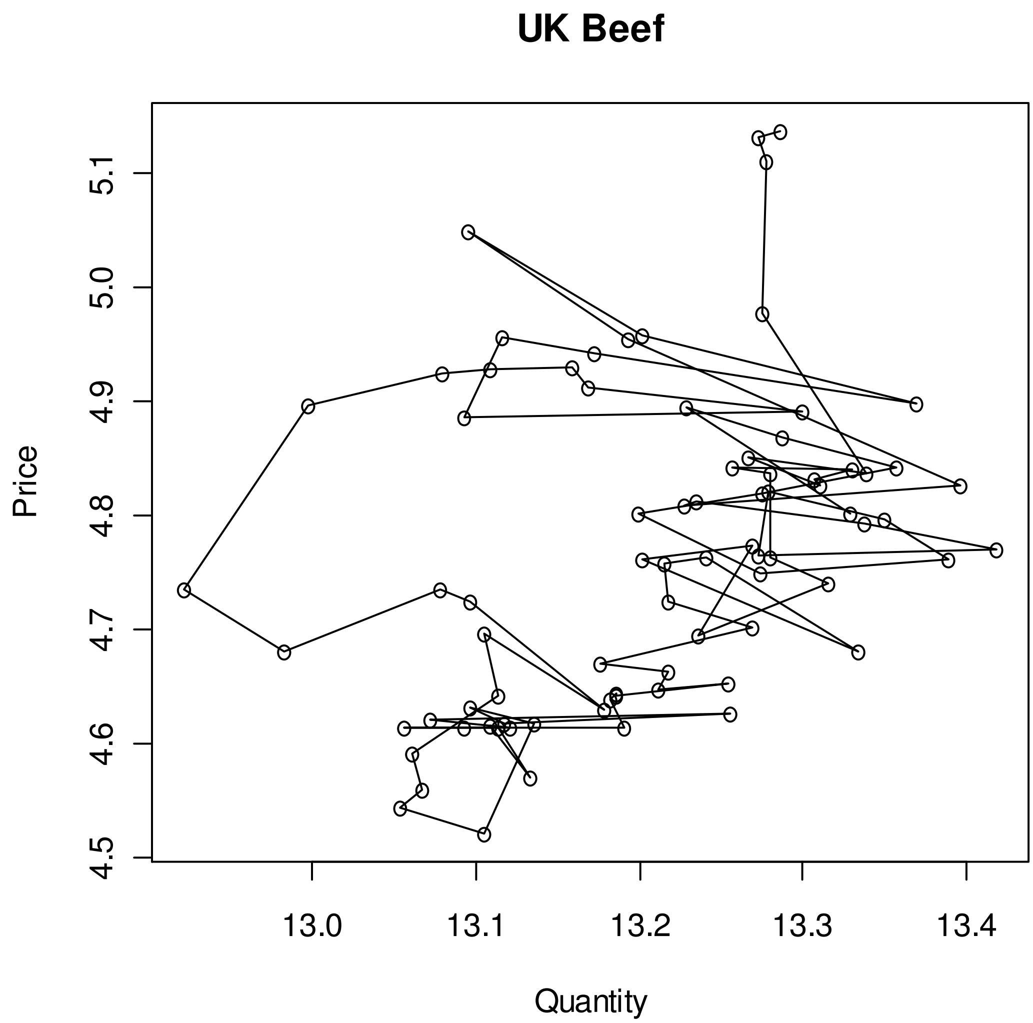

Figure C.7 Scatter plot of price and quantity (UK beef market)

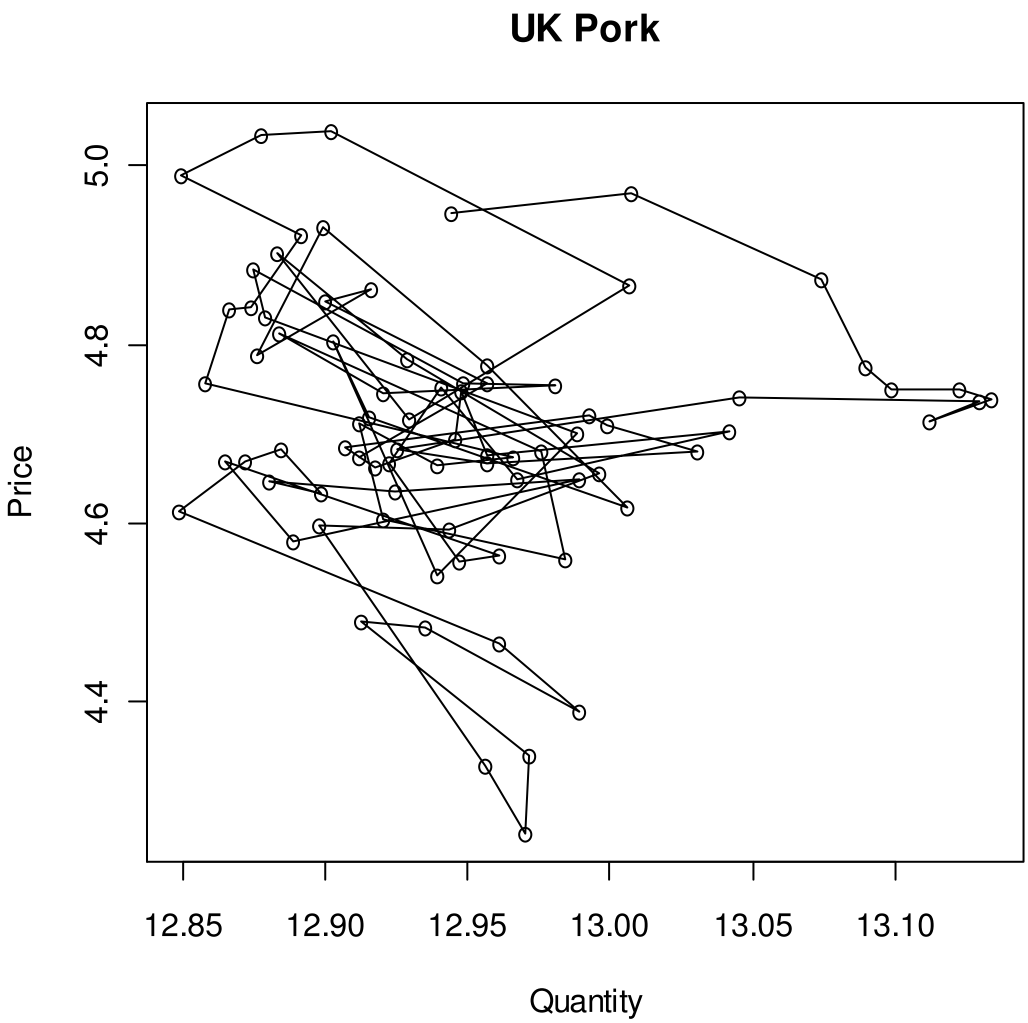

Figure C.8 Scatter plot of price and quantity (UK pork market)

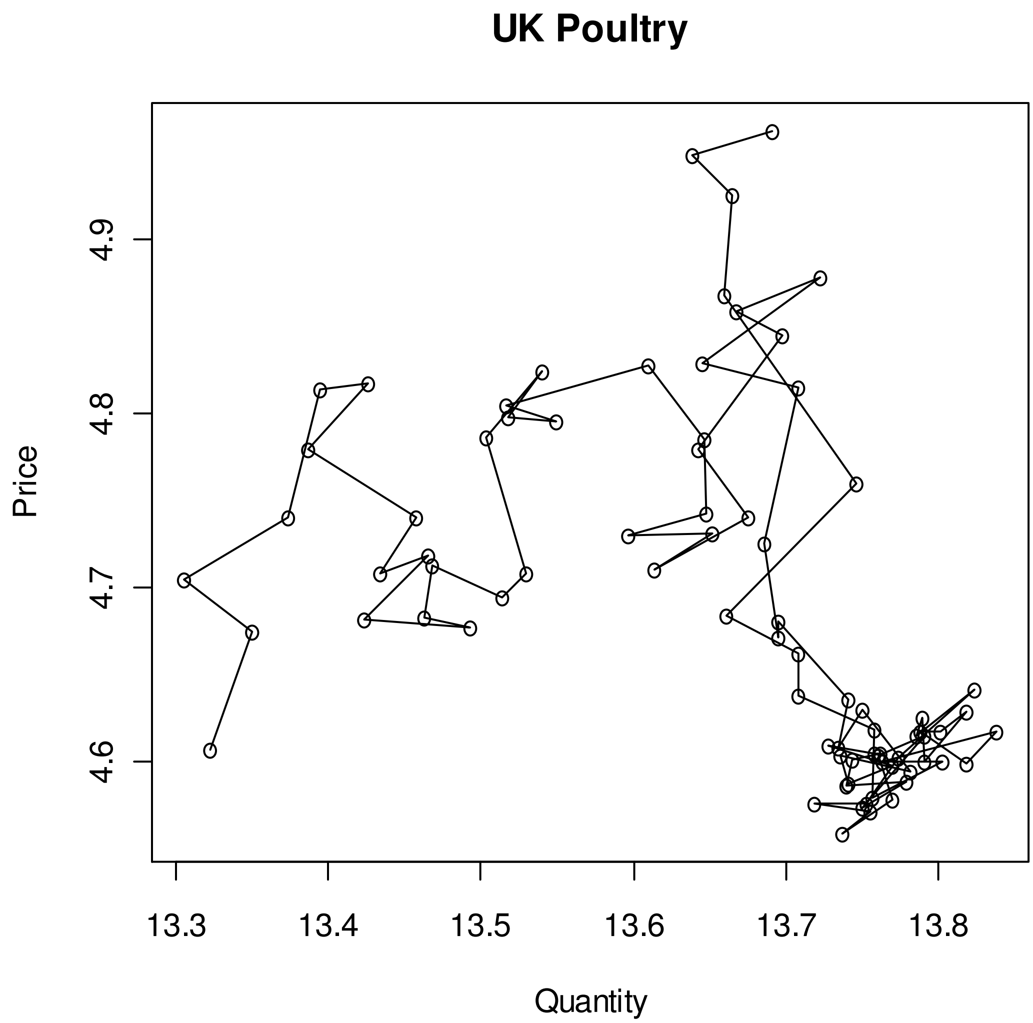

Figure C.9 Scatter plot of price and quantity (UK poultry market)

APPENDIX D

GRAPHICAL RESULTS OF MULTINATIONAL MARKETS

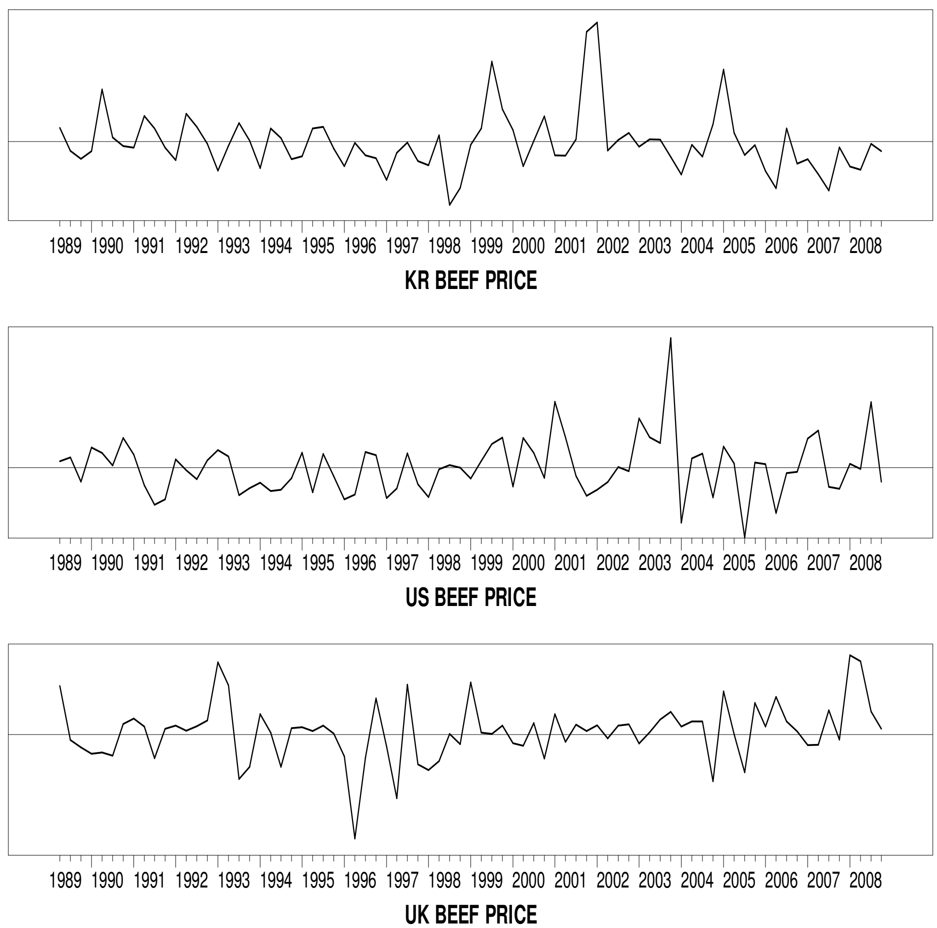

Figure D.1 Differencing beef price series

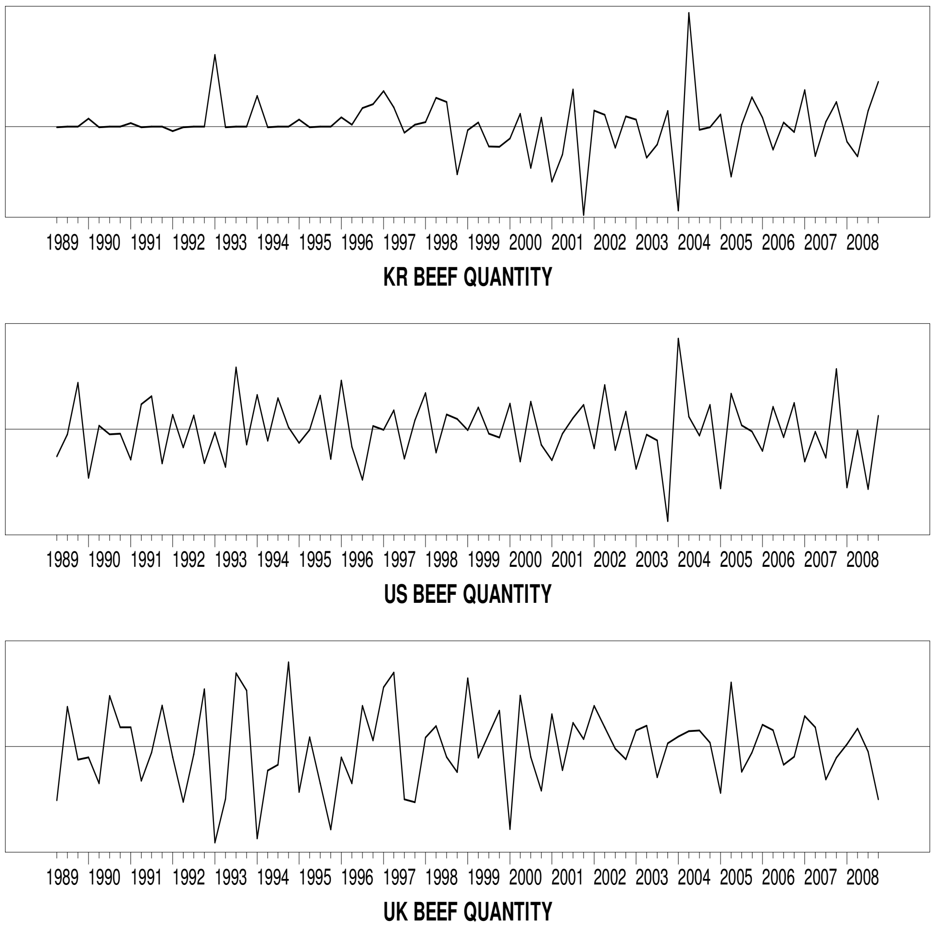

Figure D.2 Differencing beef quantity series

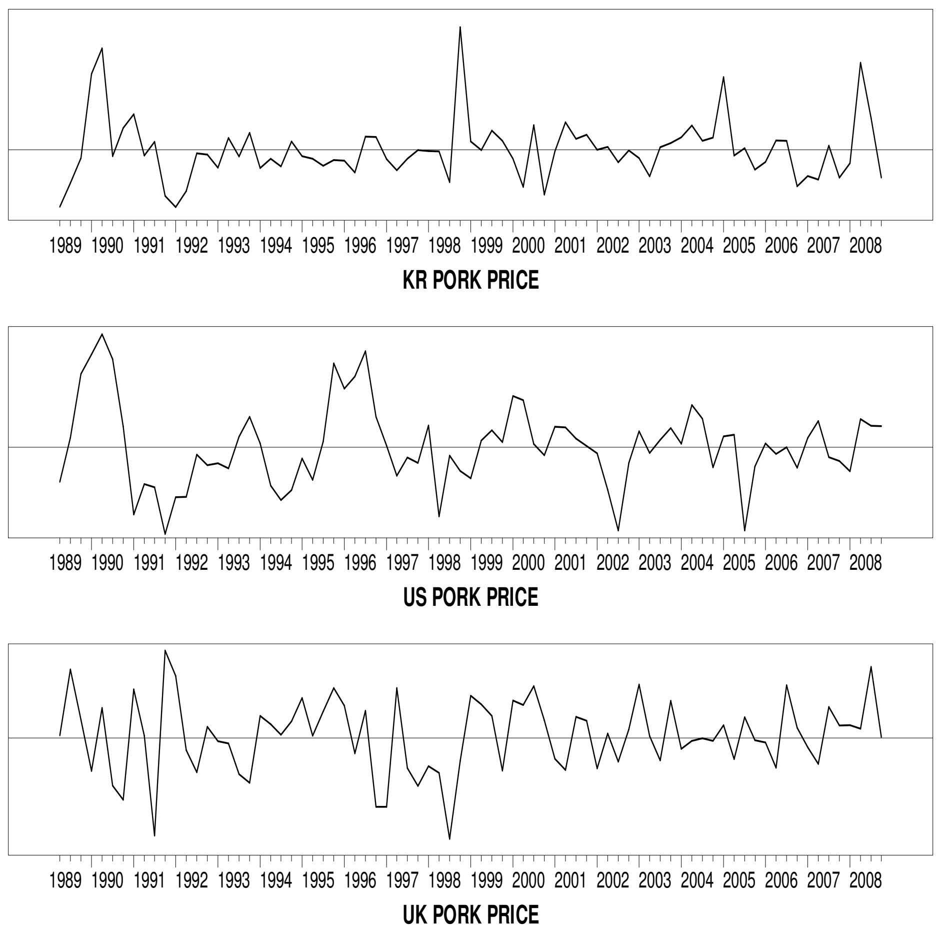

Figure D.3 Differencing pork price series

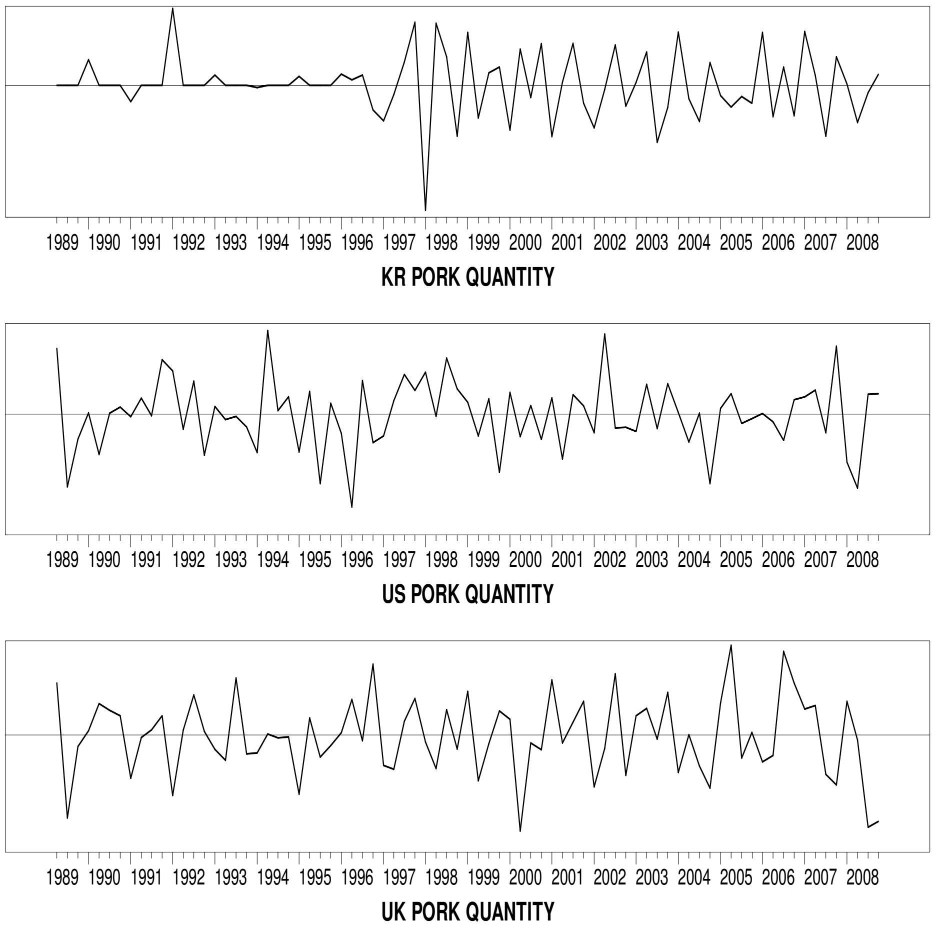

Figure D.4 Differencing pork quantity series

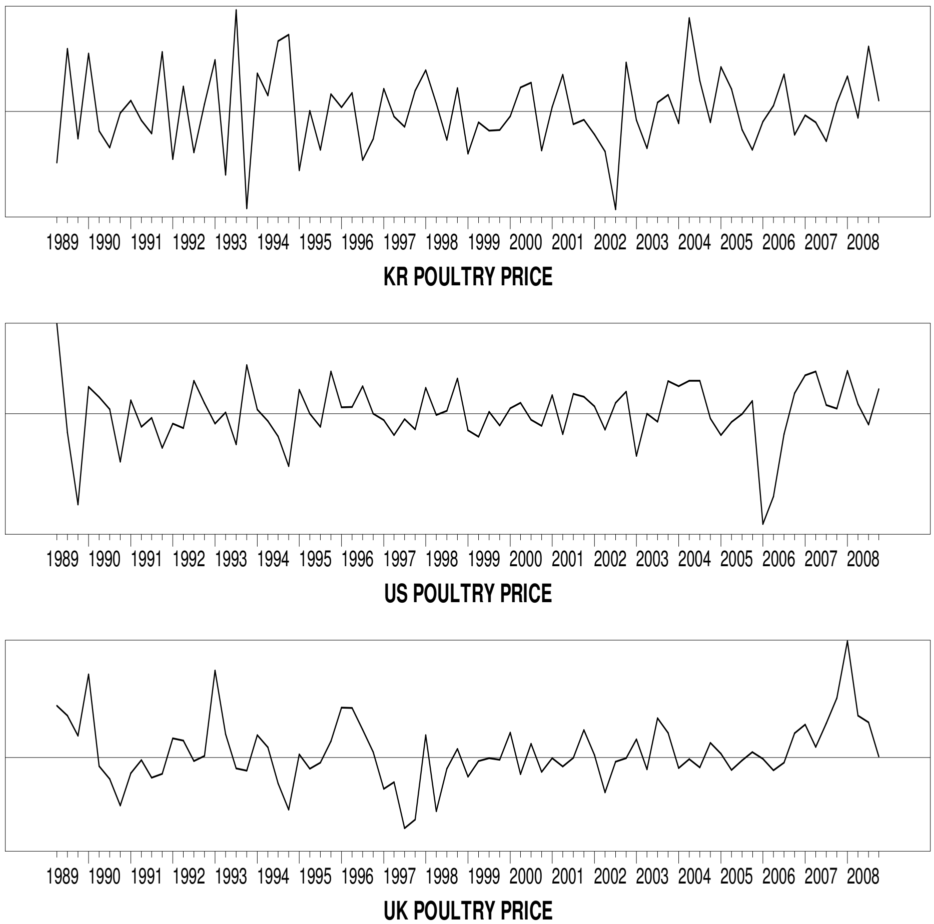

Figure D.5 Differencing poultry price series

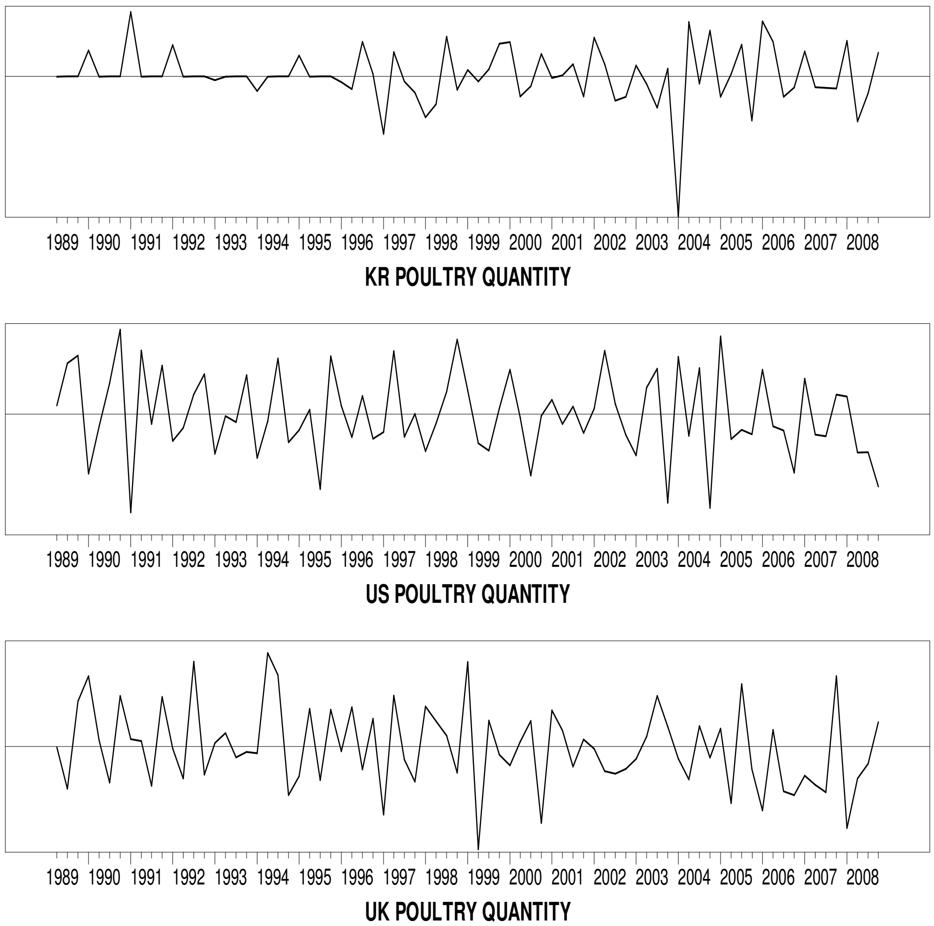

Figure D.6 Differencing poultry quantity series

APPENDIX E

COMPLEMENTARY STATISTIC TABLE

Table E

Critical Values for the Durbin-Watson Test (5% Significance Level)

T	K	d_L	d_U
50	3	1.46246	1.62833
50	6	1.33457	1.77077
50	7	1.29059	1.82203
60	3	1.51442	1.65184
60	6	1.40832	1.76711
60	7	1.37186	1.80817
70	3	1.55422	1.67152
70	6	1.46369	1.76827
70	7	1.43262	1.80245
77	3	1.57710	1.68348
77	6	1.49503	1.77044
77	7	1.46690	1.80102
78	3	1.58010	1.68509
78	6	1.49912	1.77081
78	7	1.47136	1.80093
79	3	1.58304	1.68667
79	6	1.50312	1.77118
79	7	1.47572	1.80086
80	3	1.58592	1.68823
80	6	1.50703	1.77156
80	7	1.47999	1.80081

† K includes intercept

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