

THREE ESSAYS ON APPLIED ECONOMICS

A Dissertation

by

SANG-CHEOL SHIN

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 2008

Major Subject: Agricultural Economics

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ABSTRACT

Three Essays on Applied Economics. (August 2008)

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In this dissertation three essays were presented. In the first two essays we measure the consumer welfare changes caused by U.S. meat price changes. In the third essay the dynamic structure of international gasoline prices using the time series methodology is investigated.

In chapter II, we investigate the U.S. consumer behavior on meat consumption depending on a linear expenditure system (LES), and then we simulate the welfare effects of a set of price changes on the U.S. meat consumption. The simulation results show that the amount of consumer welfare change for each meat is not same across the meats under the same percentage change of price. The simulation results also show that when all the prices are doubled the total amount of CV reaches almost the same amount of current total quarterly expenditures for the three meats.

In chapter III, we apply the compensating variation (CV) approach for the measurement of consumer welfare losses associated with beef price changes. We applied the long-run cointegrating relationship in vector error correction model (VECM) to estimate the Marshallian demand function. Apparently, the use of long-run cointegration in VECM in deriving the direct Marshallian demand function to measure the consumer

welfare change is the first attempt in the literature. This is one of the contributions of the study. The simulation results show that the amount of consumer welfare change for beef is compatible with the one derived from LES methodology.

In chapter IV, an empirical framework to summarize the interdependence of four international gasoline markets (New York, U.S. Gulf Coast, Rotterdam and Singapore) is presented. For that purpose, we employ a structural VECM and directed acyclic graphs (DAGs). To solve the identification problem in structural VECM, we apply DAGs derived from contemporaneous VECM innovations.

The impulse response functions show that the time period in which a shock in a market affects the other market is very short. Forecast error variance decompositions (FEVD) shows that in all markets, except the U.S. Gulf Coast market, current and past shocks in their own market explained the most of the volatility in their own market in the Short-run.

DEDICATION

This dissertation is dedicated to the following people
whose love and encouragement made it possible:

my father, HyunSeok Shin,

my mother YoonDoo Jung.

Without them I would not be where I am today.

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CHAPTER I

INTRODUCTION

The objective of this dissertation is twofold. The first objective is to measure the consumer welfare in U.S. meat consumption. The second is the empirical exploitation of time series methodology. The first objective is pursued in Chapter II and Chapter III, the second objective is pursued in Chapter IV.

Specifically, in chapter II the welfare effects of a set of price changes on U.S. meat consumption is investigated in a multivariate framework. The data are quarterly time series data of beef, pork and chicken. We first investigate consumer behavior using a linear expenditure system (LES) which is consistent with the theory of utility maximization and has been extensively applied for the past several decades as a basis of deriving empirically estimable demand equations. Then we derive a compensating variation (CV) measure based on the LES and empirically evaluate it. Welfare effects examined under price changes for beef, pork and chicken. Further, the welfare effect caused by animal disease is explored.

In chapter III the study investigates the calculation of consumer welfare measures based on recent developments on cointegration and vector error correction models. Based on the U.S. meat consumption data the Marshallian demand function is obtained

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

from the long-run equation of the proposed vector error correction model. Apparently, the use of long-run equation of the VECM in measuring the consumer welfare change is the first attempt in the literature. This is one of the contributions of the study.

In Chapter III the compensating variation (CV) measure is applied to calculate consumer welfare. It is found that the suggested methodology performs well on both theoretical and statistical grounds, as the Marshallian demands from VECM are consistent with the consumer utility maximization. As in Chapter II we simulate the amount of welfare change assuming various levels of changes in beef price, and the estimated welfare changes are found to be consistent with the results obtained from the LES model in Chapter II.

In Chapter IV the price dynamics among four international gasoline markets (Europe, NY, U.S. Gulf Coast and Asia) are investigated. A structural time series approach is applied to establish an empirical framework that summarizes the interdependence of four international gasoline markets. In analyzing the international transmission of gasoline prices the analysis applies directed acyclic graphs (DAG) in identifying a structural vector error correction model. Based on the empirical result from the structural vector error correction model (VECM) the associated impulse response functions (IRF) and forecast error variance decomposition (FEVD) are presented. For an empirical analysis, daily price for the spot FOB gasoline of four international markets are used.

Finally Chapter V presents a brief set of summary and concluding comments that arise across the main results of the prior individual chapters.

CHAPTER II

WELFARE CHANGE MEASUREMENT IN U.S. MEAT CONSUMPTION

Consumers' welfare may increase or decrease when the economic environment changes. Product price changes alter consumers' welfare. The classical measure of welfare change is consumer's surplus (Varian, 1992) which is Marshallian measure of welfare change. But consumer's surplus is not an exact measure of welfare change. Rather the unobservable compensating and equivalent variations are the correct theoretical measures of the welfare impact of changes in prices and income on an individual (Willig, 1976).

Willig (1976) has shown that the Marshallian surplus measure may be close to the EV and CV in certain circumstances, and provides some formulas for the maximum error when Marshallian measures are used to approximate CV and EV. But Hausman (1981, p663) argues that "Even in cases where Willig's approximations hold for the complete compensating variations, the Marshallian deadweight loss can be a very poor approximation for the theoretically correct Hicksian measure of deadweight loss based on the compensated demand curve".

Up to now three types of methodologies were have been suggested to measure the correct amount of consumers' welfare change. One of the possibilities to obtain an appropriate Marshallian demand function is the one suggested by Hausman (1981). In

his work a linear (or quasi-linear) Marshallian demand function is estimated, and then the corresponding expenditure function is recovered by solving a differential equation. But there is an important shortcoming that the method does not allow us to recover the complete expenditure function in case of multiple goods case.

To overcome the shortcomings involved in Hausman (1981) methodology, we may adopt a numerical approximation method to capture the welfare change measurement in a multiple price change situation. The methods suggested by Vartia (1983), Breslaw and Smith (1995), McKenzie and Pearce (1976), etc. are good examples. Such approximation methods are useful when we meet the situation that a closed-form utility or expenditure function is not easily obtained from the estimated demand functions (Irvine and Sims, 1998).

The third method is to use a demand system based on demand theory such as linear expenditure system (LES) or almost ideal demand system (AIDS).

In this study the linear expenditure system (LES) is used to derive welfare change under various price changes for beef, pork, and broilers. LES allows it possible to calculate the welfare change even in the case that multiple prices change. Also no approximation argument is required because indirect utility function and expenditure function are obtained from LES.

Consumer Utility Maximization with Linear Expenditure System

In choosing an optimal consumption level $x = x(p, m)$ the consumers' utility maximization problem is

$$(2-1) \quad \underset{x}{\text{Max}} [U(x(p, m))] \quad \text{s.t.} \quad px = m$$

where U is the consumer's utility function, $x = x(p, m)$ is the vector of the quantity of goods consumed, p is the vector of the prices for x , and m is the level of income expenditures.

Let's assume that the utility function takes the following functional form.

$$(2-2) \quad U = \sum_{j=1}^n \mathbf{b}_j \ln(x_j - r_j)$$

where x_j denotes the consumption of the j -th good, r_j is the minimum required quantities or committed consumption for the j -th good, \ln is the natural logarithm.

The utility function in Eq. (2-2) is a special case of an additive demand system (Powell, 1974). In this study, we assume that meats are directly, weakly separable¹ from other goods. The β 's are the demand elasticities of utility and are all non-negative, and we restrict \mathbf{b} 's sum across j to unity (Deaton and Muellbauer (1980), Creedy (1998))².

¹ Moschini et al. (1994) provides some supports for commonly used weak separability assumptions about food and meat demand.

² Eq. (2-3) and $\sum \mathbf{b}_j = 1$ satisfy the theoretical restrictions of adding-up, homogeneity, and symmetry (Deaton and Muellbauer, 1980).

The Marshallian demand function resulting from the consumer's utility maximization subject to the budget constraint $m = \sum_j p_j x_j$ is represented as

$$(2-3) \quad x_j = r_j + \frac{\mathbf{b}_j}{p_j} \cdot \left[m - \sum_{k=1}^n p_k r_k \right], \quad j = 1, \dots, n \quad k = 1, \dots, n.$$

where p_j is the price of the j -th good.

By multiplying p_j on both sides of Eq. (2-3) we can convert the demand function into the expenditure form as

$$(2-4) \quad p_j x_j = p_j r_j + \mathbf{b}_j \cdot \left[m - \sum_{k=1}^n p_k r_k \right], \quad j = 1, \dots, n \quad k = 1, \dots, n.$$

Although Eq. (2-4) is non-linear in the parameters \mathbf{b} and r , the expenditure on each good is linear in all prices and income, thus this demand system is commonly called the Linear Expenditure System (LES) (Silberberg and Suen, 2001). From the mathematical perspective there is no need to place restrictions on the sign of r_j 's, but usually we restrict the r_j 's to be positive because these parameters are often interpreted as minimum required quantities. Deaton and Muellbauer (1980) gives a good interpretation of Eq. (2-4) stating "the committed expenditures $p_j r_j$ are bought first, leaving a residual, *supernumerary expenditure* $m - \sum_k p_k r_k$, which is allocated between the goods in the fixed proportions \mathbf{b}_j ."

Now let us turn our attention to the calculation of compensating variation. By substituting Eq. (2-3) into Eq. (2-2) we get the indirect utility function

$$(2-5) \quad V(p, m) = \ln \left[\left(m - \sum_k p_k r_k \right) \cdot \prod_{k=1}^n \left(\frac{b_k}{p_k} \right)^{b_k} \right]$$

By the duality of the consumer theory we can set $V(p, m) = U$ and rearrange terms to yield the expenditure function

$$(2-6) \quad E(p, U) = \exp(U) \cdot \prod_{k=1}^n \left(\frac{b_k}{p_k} \right)^{-b_k} + \sum_k p_k r_k$$

where $\exp(\cdot)$ is the exponential function.

For the expenditure function, $E(p, U)$, to be concave (i) all b_k 's should be non-negative, and (ii) $x_k \geq r_k$ must hold for all k (Deaton and Muellbauer, 1980). If the restrictions do not hold, $E(p, U)$ is not concave, thus we can not derive Eq. (2-3) from the constrained utility maximization.

A common measure of change in consumer welfare brought about by a change in price is willingness to pay. When a consumer is free to adjust his/her consumption bundle variation is the appropriate measure of consumer's willingness to pay. On the contrary, surplus is the appropriate measure when a person is not free to adjust his/her consumption bundle (Foster and Just, 1989). We assume that there's no information delay which interrupts the adjustment of a consumer's consumption bundle, thus variation is the appropriate analytical tool in measuring a consumer's welfare change.

In this study we employ compensating variation (CV) in measuring a consumer's welfare change. CV asks what income change would be necessary in order to keep the individual on at the initial utility for after the price change (Varian, 1992).

To estimate compensating variation we employ a method suggested by Hausman (1981). Given that consumption is represented by $x = x(p, m)$, CV, in terms of the indirect expected utility function, is defined by

$$(2-7) \quad V(p^1, m^0 + CV) = V(p^0, m^0) = U^0$$

where U^0 is the initial utility level.

By duality, CV can be represented more explicitly in terms of the expenditure function,

$$(2-8) \quad CV = E(p^1, U^0) - E(p^0, U^0) = E(p^1, U^0) - m^0$$

The CV in Eq. (2-8) is positive if the price rises, but is negative if the price falls. From Eq. (2-6) and (2-8) we get the following formula for compensating variation (CV)

$$(2-9) \quad CV = E(p^1, U^0) - E(p^0, U^0) = \left(\sum_j p_j^1 r_j^1 + U^0 \cdot \prod_{j=1}^n \left(\frac{b_j}{p_j^1} \right)^{-b_j} \right) - m^0$$

Data

The time periods included in the analysis are the 40 quarters from 1st quarter 1995 to 4th quarter 2004. Data used in this study consist of quarterly per capita consumption, expenditure and price series for beef, pork and chicken. Per capita consumption data for beef, pork and chicken (broiler) were obtained from the 'supply, utilization, and per capita consumption' tables in the Red Meat Yearbook. The price series were derived using the per capita consumption data and the data of per capita expenditures on beef, pork and broilers. Quarterly per capita expenditures of beef, pork and broilers were taken

from the 'expenditures per person for red meat' tables in the Red Meat Yearbook. Income data are the combined expenditures on beef, pork and broiler.

All quantity variables are measured in retail weight and are represented in pounds consumed per capita. All price variables are represented in dollars per pound and are found by dividing per capita expenditures by quantities. All prices and the total meat expenditure measure are converted to 2004 real dollars using the consumer price index (CPI) and are expressed respectively in dollars per pound and dollars. The CPI was obtained from the Bureau of Labor Statistics, U.S. Department of Labor is the U.S. city average for all items, not seasonally adjusted, 1982-84=1. Table 2-1 describes the data used for analysis.

Table 2-1. Data Description Used for LES Regression (2004 Real Money Value)

	Mean	Standard Deviation	Minimum	Maximum
Price beef	3.50	0.28	3.19	4.26
Price pork	2.78	0.11	2.50	2.93
Price broiler	1.74	0.05	1.64	1.84
Quantity beef	16.66	0.55	14.96	17.55
Quantity pork	12.70	0.67	11.33	14.09
Quantity broiler	18.93	1.41	16.46	21.84
Expenditure	126.44	6.16	117.16	144.46

(note) The unit of price is dollars per pound (\$/lb), the unit of income is dollars per quarter per person, and the unit of quantity is pounds (lb) per quarter per person.

(source) <http://usda.mannlib.cornell.edu/usda/ers/94006/supplyanduse.xls>
<http://usda.mannlib.cornell.edu/usda/ers/94006/misc.xls>

Estimation of U.S. Meat Consumption

The commodities included in the demand system are beef, pork and chicken. The final demand system to be estimated is composed of the following three equations

$$(2-10) \quad x_{jt} = r_{jt} + (\mathbf{b}_j / p_{jt}) \cdot [(m_t - \sum_{k=1}^3 p_{kt} r_k)] + \mathbf{e}_{jt}, \quad j = 1, 2, 3$$

where j is the commodity index and covers beef, pork and chicken, t indexes time, \mathbf{e}_{jt} is the error term for commodity j in period t .

The three demand functions in Eq. (2-10) can be estimated separately or as a system. In this study the equations are estimated in a system. This is done because it allows us to include substitution effects between the meats. A shock in a certain meat market is not limited to the change of its own price but also affects the prices of other meats. That is to say, if we want to estimate the welfare change caused by a price change of a certain meat we also have to include the welfare changes caused by the price changes of other meats. For empirical estimation, following Hudson *et al.* (2003), we use three equations associated with beef and pork in Eq. (2-10). The LES meat demand system is estimated using a three-stage least squares (3SLS) procedure in which the spot price of west Texas intermediary (WTI) crude oil (really or is this a typo) and the 3 month Treasury bill rate are used as instrumental variables.

The regression results of Eq. (2-10) are reported in Table 2-2. For the validity of the estimation we checked two conditions for the concavity of $E(p,U)$ presented in section 2.2. First, the \mathbf{b} 's are all non-negative. Second, $x_j - r_j$ are all positive for all

periods where j indexes beef, pork, and chicken. The minimum value of $x_j - r_j$ for beef, pork and chicken are 12.73, 2.69 and 6.80 respectively, which mean that all $x_j - r_j$ values are positive for all observations.

Table 2-2. Estimation Results of Linear Expenditure System

	Beef		Pork		Chicken	
	value	t-stat.	value	t-stat.	value	t-stat.
r	2.2278	0.0554	8.6345	0.8811	9.6552	1.4019
b	0.6474	0.8328	0.1438	0.2611	0.2088	0.7429
Log Likelihood	0.41709					

(note) β 's are the demand elasticities of utility, r 's are the minimum required quantities or committed consumption for each commodity

Table 2-3. Compensated Price and Expenditure Elasticities from Linear Expenditure System

	Beef price	Pork price	Broiler price	Expenditure
Beef quantity	-0.3054	0.1246	0.1808	1.4075
Pork quantity	0.2061	-0.2726	0.0665	0.5160
Broiler quantity	0.3153	0.0700	-0.3854	0.8049

Compensated and expenditure elasticities are given in Table 2-3. Table 2-3 shows that the compensated own-price elasticities are all negative, but the compensated cross-price elasticities are all positive which shows that Hicksian substitution effects are dominant among the three meats. The expenditure elasticities range widely from 0.5160 for pork to 1.4075 for beef.

Evaluation of Welfare Change Using Compensating Variation

The CV is calculated by inserting the estimated coefficients into the Eq. (2-9). In measuring the CV we use the average of the expenditures from January 2004 to December 2004 as the base level of expenditures. That is, $E(p^0, U^0) = m^0$ is the average of quarterly (per capita) amount spent for the three meats during 2004. Our data show $E(p^0, U^0) = m^0$ is \$126.44 per quarter per person in 2004 current dollars.

Table 2-4. Simulation Results of CV Measurement for a Single Price Change

Price	Beef			Pork			Chicken			CV sum
Change	CV	U.S.	Ratio	CV	U.S.	Ratio	CV	U.S.	Ratio	
1%	0.53	0.16	0.42	0.30	0.09	0.24	0.28	0.08	0.22	1.11
10%	5.68	1.70	4.49	3.43	1.03	2.71	3.19	0.96	2.52	12.30
20%	11.26	3.38	8.90	6.82	2.05	5.39	6.32	1.90	5.00	24.40
30%	16.69	5.01	13.20	10.15	3.04	8.03	9.36	2.81	7.40	36.20
40%	22.00	6.60	17.40	13.41	4.02	10.61	12.32	3.70	9.74	47.74
50%	27.20	8.16	21.51	16.63	4.99	13.15	15.21	4.56	12.03	59.04
60%	32.30	9.69	25.54	19.80	5.94	15.66	18.04	5.41	14.26	70.13
70%	37.30	11.19	29.50	22.93	6.88	18.14	20.81	6.24	16.46	81.04
80%	42.21	12.66	33.39	26.03	7.81	20.58	23.53	7.06	18.61	91.77
90%	47.05	14.11	37.21	29.09	8.73	23.01	26.20	7.86	20.72	102.34
100%	51.81	15.54	40.98	32.12	9.64	25.41	28.84	8.65	22.81	112.77

(note) CV is \$ per person per quarter.

(note) U.S. is CV for U.S. total assuming the population is 300 million. Units are billion dollars.

(note) Ratio (%) = CV / m^0

Table 2-4 presents the simulated compensating variation estimates when the price changes occurred for the individual meats only. For example, when there's 100% change in beef price, the per capita CV for a consumer is \$51.81/quarter which represents the minimum amount the consumer has to be compensated. The money values in the second columns of each meat represents the total amount of CV for the U.S. as a whole, which are calculated assuming total U.S. population of 300 million people, and is expressed in billion dollars. The ratio column represents the percentage share of CV to average quarterly expenditure for the three meat groups in 2004. From Table 2-4 we can see that the amount of consumers' welfare change for each meat is not same across the meats under the same percentage change of prices.

Table 2-5 presents the simulated CV compensating variation estimates when there are the same percentage changes for all meats. When the prices become doubled at the same time the per capita CV amounts to \$126.34 per quarter, and that takes equals 99.92% of the quarterly average expenditures on the three meats in 2004. This means that the amount of CV caused by price change is approximately equal to the current money expenditures on meat.

We find that the estimated CVs in Table 2-5 are larger than the sum of the individual CVs for beef, pork and broilers in Table 2-4 (i.e. the CV in the last column in Table 2-4) at each level of price changes. This means that the more the number of commodities with in price changes the more the consumer utility decrease under the situation that consumer budgets are fixed. Also this tells us that estimating welfare

change using a demand system is more desirable than estimating welfare change using the separate single demand equation.

Table 2-5. Amount of Combined CV with Same Percentage Change for All Meats

Price change	CV (\$/person/quarter)	U.S. (\$/quarter)	CV to Expenditure Ratio (%)
1%	1.21	0.36	0.96
10%	12.59	3.78	9.96
20%	25.23	7.57	19.95
30%	37.87	11.36	29.95
40%	50.50	15.15	39.94
50%	63.14	18.94	49.94
60%	75.78	22.73	59.94
70%	88.42	26.53	69.93
80%	101.06	30.32	79.93
90%	113.70	34.11	89.92
100%	126.34	37.90	99.92

Application of CV Measurement on the Rift Valley Fever Case

In this section we apply the prior methodologies to estimate the welfare changes caused by a simulated disease outbreak based on internal data to the National Center for Foreign Animal and Zoonotic Disease Defense. Data were drawn from a project on the vulnerability of U.S. agriculture to the outbreak of a zoonotic disease. These data give points from a cumulative distribution function of total animal impact where the 5% gives

the event scope at the lower end of the impact distribution at the 5% percentile while 95% is at the higher end. In addition an assumption was made about disease policy regarding the culling of infected animals and the possibility of them being placed in the meat supply. In this study we use the data derived with the extreme assumptions that infected animals were maximally disposed of and could not enter the meat supply.

Table 2-6. Simulated Amount of Combined CV on the Rift Valley Fever Case

	Simulated price changes for feedlot animals for slaughter (%)			Welfare change		
	Beef	Hogs	Broilers	CV (\$/person)	Ratio (%)	U.S. CV (\$bill)
5%	6.40	-0.90	0.70	3.55	2.81%	1.07
10%	10.80	-0.90	0.70	6.05	4.78%	1.81
20%	18.30	-0.90	0.70	10.23	8.09%	3.07
30%	29.60	-0.90	0.70	16.39	12.97%	4.92
40%	42.20	-0.90	0.70	23.07	18.25%	6.92
50%	46.90	-0.90	0.70	25.52	20.18%	7.66
60%	51.80	-0.90	0.70	28.04	22.18%	8.41
70%	57.30	-0.90	0.70	30.85	24.40%	9.25
80%	67.10	-0.90	0.70	35.78	28.30%	10.73
90%	84.30	-0.90	0.70	44.22	34.98%	13.27
95%	118.00	-0.90	0.70	60.13	47.55%	18.04

In Table 2-6 the last three columns are the estimated welfare changes caused by the animal disease outbreak. In calculating the CV measures, we assume that consumer prices of meats change at the same rate with the price changes for animals for slaughter.

Under the scenario the per capita CV ranges from \$3.55 to \$60.13 per quarter. The ratio column represents the percentage share of CV to average quarterly expenditure for the three meat groups in 2004.

Conclusion

In this study we derived the consumer welfare change using the compensating variation approach with respect to U.S. meats consumption data. We extended our interest to measure the consumer welfare change in U.S. meats consumption instead of limiting our interest in exploiting just the U.S. consumers' consumption behavior on meats.

We started by setting a utility function of an additive demand system and derived the Marshallian demand functions for each meat. In getting CV our demand system model (i.e. LES) allowed us to consider substitution effects by including the price and quantity variables of other substitutable goods.

The welfare losses measured in CV were simulated with various levels of price change. The simulation results showed that the amount of consumer welfare change for each meat is not same across the meats under the same percentage change of price. The simulation results also showed that when all the prices are doubled the total amount of CV reaches almost the same amount of current total quarterly expenditures for the three meats. That is to say, so long as meats are concerned, the minimum amount of money to be compensated to make the consumers stay at the prior utility level is approximately

equal to the additional expenditure that is caused by the price changes setting the quantity consumed at current level.

Another interesting fact we showed is that the combined CV with the same rate of price changes in the three meats is larger than the sum of CVs with price changes in individual meats separately. This indicates that it is more preferable to estimate welfare change from a demand system as a whole instead of estimating welfare change through a single demand function separately.

CHAPTER III

CONSUMERS' WELFARE MEASUREMENT IN U.S. BEEF MARKET USING TIME SERIES ANALYSIS

Consumers' welfare may increase or decrease when the economic environment changes. Product price changes alter consumers' welfare. Traditionally, the concept of consumer's surplus was widely used to measure welfare change (Varian, 1992, p.160). But consumer's surplus is not an exact measure of welfare change. Varian (1992, p.160) says that "However, consumer's surplus is an exact measure of welfare change only in special circumstances." Rather the unobservable compensating variation (CV) and equivalent variation (EV) are the correct theoretical measures (Willig, 1976, p.589).

Willig (1976) has shown that the Marshallian surplus measure may be close to the EV and CV in a certain circumstances. But Hausman (1981, p.672) showed that the Marshallian measure provides a very poor approximation to the exact measure of welfare change. Hausman (1981, p.663) also indicated that "the use of Marshallian measure (and Willig's approximation argument) has important shortcomings in measuring deadweight loss".

Usually welfare analysis starts from deriving an appropriate Marshallian demand function which successfully captures the variations in the observed data. But in most cases the obtained Marshallian demand function is not successfully integrated back to an explicit cost function which is required to calculate the consumers' welfare change. To

overcome this integrability problem, economists sometimes use functions which easily generate a complete utility or expenditure function. The linear expenditure system (LES) and the almost ideal demand system (AIDS) are good examples of techniques to avoid the integrability problem. But in using those functions researchers sometimes have to impose restrictions on the demand function parameters, that are not derived from the observed data and thus sometimes do not adequately reflect the data. (Irvine and Sims, 1998, p.314). Further, since the form of demand function derived from LES or AIDS is fixed, researchers are not usually allowed to get an estimation form which best fits the real observed data.

Hausman (1981) suggested a method to measure the correct amount of consumers' welfare change. Hausman estimated a linear Marshallian demand function, and then recovered the corresponding expenditure function by solving a differential equation. Thus, for a single price change case, Hausman's methodology does not cause any problem regarding the integrability condition of demand theory. Also Hausman's method enables researchers to choose an estimating form.

Usually welfare analysis starts from deriving an appropriate Marshallian demand function. But when the variables are non-stationary, it is known that regression models estimated over non-stationary variables give spurious results. Thus for non-stationary variables we are recommended to think in terms of cointegration.

In this chapter we derive welfare change for a single good case assuming a linear Marshallian demand function. For that, we derive the Marshallian demand function from the long-run component of error correction term of VECM. Kaabia and Gil (2001),

Pesaran and Shin (2002) applied the long-run cointegrating relationship to the almost ideal demand systems (AIDS). To our knowledge this is a new development as we could not find a paper in the literature that applied the long-run cointegrating relationships in VECM to derive a direct Marshallian demand function.

Consumer Utility Maximization

In this section we first derive the indirect utility and expenditure function for a single good case assuming a linear Marshallian demand function. Then we discuss the requirements for the parameters to be consistent with the underlying utility maximization principle.

A linear Marshallian demand function be expressed as a function of the form

$$(3-1) \quad x^M = x(p, m) = c + \mathbf{q}p + \mathbf{d}m$$

In Eq. (3-1) p is price, m is income and x is the quantity consumed while c , \mathbf{q} and \mathbf{d} are coefficients to be estimated. From one of the fundamental identities in consumer theory, we know the following holds for some U^*

$$(3-2) \quad V(p(t), m(t)) = U^*$$

where U^* is an initial utility level, $V(p(t), m(t))$ is the indirect utility function, and t indexes time.

Along a path of price change to stay on the indifference curve (Hausman, 1981), we have

$$(3-3) \quad \frac{\partial V}{\partial p(t)} \frac{\partial p}{\partial t} + \frac{\partial V}{\partial m(t)} \frac{\partial m(t)}{\partial t} = 0$$

Rearranging and applying Roy's identity, we get a differential equation to be solved

$$(3-4) \quad \frac{dm}{dp} = c + \mathbf{q}p + \mathbf{d}m$$

With the initial utility level, U , as a constant of integration, the solution to the ordinary differential Eq. (3-4) is given by

$$(3-5) \quad m = U \exp(\mathbf{d}p) - \frac{1}{\mathbf{d}}[\mathbf{q}p + \frac{\mathbf{q}}{\mathbf{d}} + c]$$

Then the corresponding indirect utility function $V(p, m)$ follows from Eq. (3-5) by interchanging the income variable with the utility level.

$$(3-6) \quad V(p, m) = \exp(-\mathbf{d}p) \cdot \left(m + \frac{1}{\mathbf{d}}[\mathbf{q}p + \frac{\mathbf{q}}{\mathbf{d}} + c] \right)$$

The expenditure function associated with the indirect utility function is obtained by inverting Eq. (3-6)

$$(3-7) \quad E(p, U) = U \exp(\mathbf{d}p) - \frac{1}{\mathbf{d}}(\mathbf{q}p + \frac{\mathbf{q}}{\mathbf{d}} + c)$$

The expenditure function, $E(p, U)$, indicates the minimum expenditure needed to achieve utility U at price level p (Silberberg and Suen (2001), Creedy (2007)).

Before proceeding further we have to check the validity of the assumed demand function, and other functions derived from the demand function. The law of demand requires $\mathbf{q} \leq 0$. For the Marshallian demand function to be valid with utility maximization the

substitution term $S = \partial^2 E(p, U) / \partial p = \partial h(p, U) / \partial p$ must be non-positive. Equivalently, using the well known Slutsky decomposition, the substitution term is easily obtained as

$$(3-7) \quad S = \frac{\partial x}{\partial p} + \frac{\partial x}{\partial m} x = \mathbf{q} + \mathbf{d}x = \mathbf{q} + \mathbf{d}(\mathbf{q}p + \mathbf{d}m + c)$$

For utility maximization the indirect utility function must satisfy the following conditions. First, $\mathbf{q} \leq 0$ meaning demand quantity must be non-increasing in price. Second, $\mathbf{d} \geq 0$ meaning demand quantity must be non-decreasing in income. Third, the indirect utility function in Eq. (3-6) must be continuous and homogeneous of degree of zero in prices and income which is given by our *normalization* using consumer price index (CPI) as numeraire. The final condition that $V(p, m)$ must satisfy is quasi concavity which is equivalent to the Slutsky equation condition (Hausman, 1981). In summary, the expenditure function and indirect utility function are valid if the sign conditions $\mathbf{q} \leq 0$ and $\mathbf{d} \geq 0$ hold along with the substitution term condition that $S = \mathbf{q} + \mathbf{d}x^M = \mathbf{q} + \mathbf{d}(\mathbf{q}p + \mathbf{d}m + c) \leq 0$.

Welfare Change Expressed in Compensating Variation

A common measure of change in consumer's welfare brought about by a change in price is willingness to pay. When a consumer is free to adjust his/her consumption bundle then 'variation' measure is the appropriate measure of consumer's willingness to pay. On the contrary, 'surplus' measure is the appropriate measure when a person is not free to adjust his/her consumption bundle (Foster and Just, 1989). We assume that there's no

information delay which interrupts the adjustment of a consumer's consumption bundle, thus 'variation' measure is the appropriate concept in measuring a consumer's welfare change.

In this study we employ compensating variation (CV) in measuring a consumer's welfare change. CV asks what income change would be necessary in order to keep the individual at the initial level utility after the price change (Varian, 1992).

To estimate CV we employ a method suggested by Hausman (1981). Given the optimal solution for a consumer's utility maximization is represented by $x = x(p, m)$, the CV in terms of the indirect expected utility function, is defined by

$$(3-9) \quad V(p^1, m^0 + CV) = V(p^0, m^0) = U^0$$

where U^0 is the initial utility level, p^0 and m^0 are the initial level of price and expenditure, and p^1 is the changed price level.

By duality, CV can be represented more explicitly in terms of the expenditure function,

$$(3-10) \quad CV = E(p^1, U^0) - E(p^0, U^0) = E(p^1, U^0) - m^0$$

The CV in Eq. (3-10) is positive if the price rises, but is negative if the price falls. From Eq. (3-1) and Eq. (3-10) we get the following formula for compensating variation (CV)

$$(3-11) \quad CV = E(p^1, U^0) - E(p^0, U^0) = \left(U^0 \exp(dp^1) - \frac{1}{d} [qp^1 + \frac{q}{d} + c] \right) - m^0$$

Data

The time periods included in the analysis are the 36 quarters from 1st quarter 1996 to 4th quarter 2004. Data used in this study consist of quarterly per capita beef consumption, quarterly per capita disposable income and price series for beef. Per capita consumption data for beef was obtained from the ‘supply, utilization, and per capita consumption’ tables in the Red Meat Yearbook, the U.S. Department of Agriculture (USDA) (<http://usda.mannlib.cornell.edu/usda/ers/94006/supplyanduse.xls>).

The price series for beef were derived using the per capita consumption data and the data of per capita expenditure on beef. Per capita personal disposable income data were derived using the expenditure data and the data for percentage of expenditure on beef to income. Quarterly per capita expenditure on beef and the data for percentage of expenditure on beef to income were taken from the ‘expenditures per person for red meat’ tables in the Red Meat Yearbook (<http://usda.mannlib.cornell.edu/usda/ers/94006/misc.xls>). Table 3-1 describes the data used.

Table 3-1. Data Description (2004 Real Money Value)

	Mean	Standard Deviation	Minimum	Maximum
Price beef	3.50	0.29	3.19	4.26
Quantity beef	16.66	0.56	14.96	17.55
Income	6887.87	329.90	6325.46	7492.86

(note) The unit of price is dollars per pound (\$/lb), the unit of income is dollars per quarter per person, and the unit of quantity is pounds (lb) per quarter per person.

Within these data all quantities are measured in retail weight and are represented in pounds consumed per capita. All price variables are represented in dollars per pound dividing per capita expenditures by quantities. All prices and the total meat expenditure measure are converted to 2004 dollars using the consumer price index (CPI) and are expressed respectively in dollars per pound and dollars. The CPI was obtained from the Bureau of Labor Statistics, U.S. Department of Labor is the U.S. city average for all items, not seasonally adjusted, 1982-84=1.

The Empirical Regression with Vector Error Correction Model

In this section we introduce the vector error correction model (VECM) and derive the Marshallian demand function in Eq. (3-1) from the long-run equation of VECM. It is known that, in case of the presence of unit root, the use of ordinary least squares (OLS) can produce invalid estimation or spurious regression results. Considering that, in this analysis, we employ a vector error correction model (VECM) instead of OLS.

To find the stationarity of each series we establish the order of integration of the individual price series. The test methods for variable stationarity are the augmented Dickey-Fuller (1979) unit root test and the Phillips-Perron (1988) unit root test, based on critical values provided by MacKinnon (1996). We test for a unit root assuming a series is subject to both deterministic trend and intercept. As shown in Table 3-2, price and income data series have unit roots, but the quantity data series does not have unit root at 5% significance level.

Table 3-2. Unit Root Test Results

	Price of beef	Quantity of beef	Per capita income
Augmented Dickey-Fuller	-2.4415 (0.3535)	-4.8466 (0.0023)	-2.9153 (0.1699)
Phillips-Perron	-2.4433 (0.3526)	-7.1716 (<0.0001)	-2.8335 (0.1953)

(note) H_0 : the variable has a unit root. Values are adjusted t-statistics and (p-values).

Now let's consider $(k \times 1)$ random vectors $Y_t = (y_{1t}, \dots, y_{kt})$ and $X_t = (x_{1t}, \dots, x_{kt})$ where y_{it} and x_{it} are $(T \times 1)$ vectors for all $i = 1, \dots, k$. We assume that a data generating process (DGP) of the form $Y_t = \mathbf{m}_t + X_t$, and X_t has a VECM representation of the form $\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{l-1} \Gamma_i \Delta X_{t-i} + \mathbf{e}_t$ where Π is a $(k \times k)$ coefficient matrix. We further assume that the deterministic component (\mathbf{m}_t) is defined as $\mathbf{m}_t = \mathbf{m}_0 + \mathbf{m}_1 t$ where \mathbf{m}_0 and \mathbf{m}_1 are arbitrary $(k \times 1)$ vectors and k is the number of variables included in the vector error correction model (VECM). Different forms of \mathbf{m}_t give different functional forms of VECM. By the way, Dennis et al. (2005) states that "Since a deterministic component such as a constant term is generally needed to account for the units of measurements of the variables, situations where a VECM without any intercept term is justified are exceptional."

Let's briefly discuss the various functional forms of VECMs with different types of \mathbf{m}_t . Lütkepohl (2005) provides three different forms of deterministic terms in VECM. The first case is that the deterministic component is a constant (i.e. $\mathbf{m}_t = \mathbf{m}_0$) and the

constant term is included in the cointegration space. Then data generation process of Y_t has the following VECM representation

$$(3-12) \quad \Delta Y_t = (\Pi, v) \begin{pmatrix} Y_{t-1} \\ 1 \end{pmatrix} + \sum_{i=1}^{l-1} \Gamma_i \Delta Y_{t-i} + \mathbf{e}_t$$

where Π is a $(k \times k)$ matrix, v is a $(k \times 1)$ vector, Γ_i is short-run coefficient matrix with dimension $(k \times k)$, l is the number of lags in level vector autoregression (VAR), \mathbf{e}_t is error term and independent and identically distributed (i.i.d.) with mean zero and covariance matrix Σ_e (i.e. $\mathbf{e}_t \sim iid(0, \Sigma_e)$), and Δ is the difference operator.

The second case is a process with a linear trend (t), that is, $\mathbf{m}_t = \mathbf{m}_0 + \mathbf{m}_1 t$. Then the data generation process of Y_t has the VECM representation

$$(3-13) \quad \Delta Y_t = \mathbf{n}_1 + (\Pi, v_2) \begin{pmatrix} Y_{t-1} \\ t-1 \end{pmatrix} + \sum_{i=1}^{l-1} \Gamma_i \Delta Y_{t-i} + \mathbf{e}_t$$

where v_1 and v_2 are $(k \times 1)$ vectors.

The third case to be considered is that the variables have a linear trend but there is no such term in the cointegrating relation. In other words, the cointegration relations are drifting along a common linear trend. This situation can arise if the trend slope is the same for all variables which have a linear trend (Lütkepohl, 2005). Formally this case occurs if $\mathbf{m} \neq 0$ and $\Pi \mathbf{m} = \mathbf{a} \mathbf{b}' \mathbf{m} = 0$, or, equivalently, if $\mathbf{b}' \mathbf{m} = 0$ or \mathbf{b}' is orthogonal to \mathbf{m} . Here \mathbf{a} and \mathbf{b} are $(k \times r)$ matrices. Then the Eq. (3-13) reduces to

$$(3-14) \quad \Delta Y_t = \mathbf{n}_1 + \Pi Y_{t-1} + \sum_{i=1}^{l-1} \Gamma_i \Delta Y_{t-i} + \mathbf{e}_t$$

The specification of a VECM starts by determining a suitable lag length (Lütkepohl, 2005). To determine lag length we apply the Schwarz information criterion (SIC) to price of beef, quantity of beef and income data and a constant in the model. At two lags the levels VAR gives the lowest SIC statistics. Thus we conclude that the data support vector autoregression (VAR) with two lags, which corresponds to one lagged difference in VECM.

With the various functional forms of VECM in Eq. (3-12), Eq. (3-13) and Eq. (3-14), we determine the cointegrating rank. Remember that at present we do not know the correct form of the deterministic component of the VECM. For the determination of the cointegrating rank we apply the trace test suggested by Johansen (1991, 1992). Table 3-3 gives trace test statistics and corresponding p-values from Eq. (3-12), Eq. (3-13) and Eq. (3-14). The p-values are approximated using the Γ -distribution, see Doornik (1998).

Table 3-3. Trace Test for VECM with Various Types of Deterministic Terms

Cointegration rank	$\mathbf{m}_t = \mathbf{m}_0$		$\mathbf{m}_t = \mathbf{m}_0 + \mathbf{m}_1 t$		$\mathbf{m}_t \neq 0, \mathbf{b}' \mathbf{m}_t = 0$	
	Trace statistic	p-value	Trace statistic	p-value	Trace statistic	p-value
$r = 0$	96.898	<0.001	37.931	0.004	45.628	0.024
$r = 1$	7.119	0.884	6.081	0.689	13.776	0.680
$r = 2$	1.072	0.927	8.121	0.646	5.256	0.568
Log- Likelihood	56.98539		57.50454		57.50525	

For all the cases in Table 3-3, we find that, at $r = 0$, all the p-values are less than 0.05 thus we reject $r = 0$ at 5% significance level. At $r = 1$ the p-values are larger than

0.05, we fail to reject $r=1$ at 5% significance level. Hence we conclude that the trace tests give one cointegrating equation for all vector error correction models.

Based on one cointegration equation (i.e. $r=1$) we determine the type of deterministic component of VECMs. Johansen (1991, 1992) and Lütkepohl (2005) proposed the likelihood ratio (LR) tests for hypotheses regarding the deterministic terms. We employ the likelihood ratio (LR) test in two stages.

First, under the situation that there is a deterministic linear trend in the variables, we test whether the trend is orthogonal to the cointegration relations. A pair of hypotheses is $H_0 : \mathbf{b}'\mathbf{m}_1 = 0$ versus $H_1 : \mathbf{b}'\mathbf{m}_1 \neq 0$. In other words the test checks the model in Eq. (3-13) against the model in Eq. (3-14): that is, Eq. (3-13) is the unrestricted model and Eq. (3-14) is the restricted model. The corresponding LR test follows a $\mathbf{c}^2(r)$ distribution because r zero restrictions are specified in H_0 . With one degree of freedom we get \mathbf{c}^2 statistic of 0.0014 which is less than the critical value 3.84 at 5% significance level. Thus we fail to reject $H_0 : \mathbf{b}'\mathbf{m}_1 = 0$.

Next we test a model with an unrestricted intercept, Eq. (3-14), against the model where no linear trend is present, and, thus the constant can be absorbed into the cointegration relations as in Eq. (3-12): here Eq. (3-14) is unrestricted model and Eq. (3-12) is the restricted model. The hypothesis is $H_0 : \mathbf{m}_1 = 0$ versus $H_1 : \mathbf{m}_1 \neq 0, \mathbf{b}'\mathbf{m}_1 = 0$. The corresponding LR test follows a $\mathbf{c}^2(k-r)$. With $r=1$ and $k=3$ we got \mathbf{c}^2 statistic = 1.0383 which is less than the critical value 5.99 at 5% significance level. Thus we fail to reject $H_0 : \mathbf{m}_1 = 0$. From the above two tests we conclude the suitable deterministic

component for data generating process (DGP) Y_t is $\mathbf{m}_t = \mathbf{m}_0$. Thus we select the Eq. (3-12) as our final VECM.

The term Π in Eq. (3-12) can be decomposed into two parts ($\Pi = ab'$), and the Eq. (3-12) can be represented as

$$(3-15) \quad \Delta Y_t = ab' \begin{pmatrix} Y_{t-1} \\ 1 \end{pmatrix} + \Gamma_i \Delta Y_{t-i} + \mathbf{e}_t$$

where a is a $(k \times r)$ matrix, b is a $((k+1) \times r)$ matrix.

Let's note that we explore the Marshallian demand function from the long-run

$$\text{equation } b' \begin{pmatrix} Y_{t-1} \\ 1 \end{pmatrix} = 0.$$

Based on the one cointegration relation between the three time series variables, we estimated the VECM by maximum likelihood estimation (MLE) following Johansen (1991). The VECM with one lag for endogenous variables and quarterly seasonal dummy variables gives the estimation results in Eq. (3-16).

In Eq. (3-16) the long-run equation was normalized by quantity of beef consumed, and the values in parenthesis are t -statistics. The components in a vector measure the speed of adjustment to restore a long-run equilibrium for the variables in the system, and the vector b gives the estimates of the long-run cointegrating equation. In Eq. (3-16) q_t is the quantity of beef consumed, p_t is the price of beef normalized by consumer price index, m_t is income which is normalized by consumer price index, $quarter_j$ is the dummy variable for j -th quarter, and \mathbf{e}_{it} is the error term for the i -th series equations, respectively.

$$\begin{aligned}
& \begin{pmatrix} \Delta q_t \\ \Delta p_t \\ \Delta m_t \end{pmatrix} = ab' \begin{pmatrix} q_{t-1} \\ p_{t-1} \\ m_{t-1} \\ 1 \end{pmatrix} + \Gamma_1 \begin{pmatrix} \Delta q_{t-1} \\ \Delta p_{t-1} \\ \Delta m_{t-1} \end{pmatrix} + \Phi \begin{pmatrix} quarter_1 \\ quarter_2 \\ quarter_3 \end{pmatrix} + \begin{pmatrix} \mathbf{e}_{qt} \\ \mathbf{e}_{pt} \\ \mathbf{e}_{mt} \end{pmatrix} \\
(3-16) \quad & = \begin{pmatrix} -0.83143 \\ -9.36301 \\ 0.01834 \\ (1.09296) \\ 14.63036 \\ (1.64799) \end{pmatrix} \begin{pmatrix} 1 & 2.29905 & -0.00229 & -11.88518 \\ & (8.15086) & (-8.67366) & (-16.43944) \end{pmatrix} \begin{pmatrix} q_{t-1} \\ p_{t-1} \\ m_{t-1} \\ 1 \end{pmatrix} \\
& + \begin{pmatrix} -0.26679 & -1.15163 & -0.00085 \\ (-1.26116) & (-0.84124) & (-0.48121) \\ -0.00496 & -0.06760 & 0.00004 \\ (-0.12416) & (-0.26136) & (0.12879) \\ -3.19379 & 76.37029 & -0.13879 \\ (-0.15101) & (0.55801) & (-0.78639) \end{pmatrix} \begin{pmatrix} \Delta q_{t-1} \\ \Delta p_{t-1} \\ \Delta m_{t-1} \end{pmatrix} \\
& + \begin{pmatrix} 0.01159 & 0.97352 & 1.19638 \\ (0.05574) & (8.15513) & (4.92199) \\ -0.02283 & 0.02745 & -0.01440 \\ (-0.58089) & (1.21708) & (-0.31365) \\ 26.72934 & 1.98218 & 9.34128 \\ (1.28554) & (0.16609) & (0.38440) \end{pmatrix} \begin{pmatrix} quarter_1 \\ quarter_2 \\ quarter_3 \end{pmatrix} + \begin{pmatrix} \mathbf{e}_{qt} \\ \mathbf{e}_{pt} \\ \mathbf{e}_{mt} \end{pmatrix}
\end{aligned}$$

Table 3-4 presents some test statistics on the innovations (or residuals) from the VECM. The tests are not on individual series but for the multivariate residuals (i.e. for the error system as a whole). The Lagrangian multiplier (LM) test statistics for serial correlation suggested by Godfrey (1988) follows a χ^2 distribution with 9 degrees of freedom.

As shown in Table 3-4 all the p-values are larger than 0.05. Thus we fail to reject H_0 : no serial correlation at lag order 1 (and 2, 3, 4) at 5% significance level. The multivariate LM tests for ARCH show that there are no conditional heteroscedasticity.

Table 3-4. Lagrangian Multiplier Test for Serial Correlation and ARCH Test

	Serial correlation test	ARCH test
	χ^2 statistics (p-values)	χ^2 statistics (p-values)
LM(1)	3.09874 (0.96025)	49.75882 (0.06327)
LM(2)	5.65634 (0.77376)	86.59535 (0.11559)
LM(3)	0.70773 (0.99987)	108.01046 (0.48162)
LM(4)	15.41768 (0.08008)	166.66230 (0.09511)

Once the cointegrating rank and forms of deterministic terms are determined, restrictions on the cointegration space can be tested using a log-likelihood ratio (LR) test. Two hypotheses are of particular interest in this analysis.

The first is the null of long-run exclusion of a series from the cointegration space. That is, we want to test whether a variable belongs to the cointegration space. The null is H_0 : the i -th series is excluded from cointegration space, and the test is asymptotically distributed as $\chi^2(r)$. As shown in Table 3-5, at one cointegration rank, the p-values for the individual series are all less than 0.05. Thus, at 5% significance level, we reject H_0 : the i -th series is excluded from cointegration space. Hence we conclude that all the series belongs to the long-run cointegration space.

Table 3-5. Test of Long-Run Exclusion and Weak Exogeneity

Test	Critical value (5%)	Quantity (q)	Price (p)	Income (m)	Constant
Long-run exclusion	3.841	24.332 (<0.001)	19.637 (<0.001)	26.134 (<0.001)	14.593 (<0.001)
Weak exogeneity	3.841	42.178 (<0.001)	1.158 (0.282)	2.597 (0.107)	-

(note) Values in parentheses are p-values.

We now employ a weak exogeneity test which examines a hypothesis about the rows of a , and tests if any of the variables can be regarded as weakly exogenous when the parameter of interest is b (Dennis et al., 2006). The null is H_0 : the i -th series is weakly exogenous for b , and the test is asymptotically distributed as $c^2(r)$. A weakly exogenous variable does not respond to the perturbations in the cointegration space, that is, a weakly exogenous variable does not respond to restore equilibrium. Table 3-5 suggests that price and income series does not respond to perturbations in the single long-run relation at 5% significance level.

Evaluation of Compensating Variation with Price Change

The stationary relation in the long-run component of error correction term in Eq. (3-15) gives the following functional form for the Marshallian demand function

$$(3-16) \quad Q_t = 11.88518 - 2.29905 P_t + 0.00229 m_t$$

Since the price variable coefficient is negative and the expenditure variable coefficient is positive, all the sign conditions for utility maximization mentioned in

section 3.3 are satisfied. The negative Slutsky equation condition which is equivalent to the quasi-concavity of indirect utility function is also satisfied for all the observations. For all the observations, the Slutsky equation values span from -2.2648 to -2.2589. Eq. (3-1) and Eq. (3-16) give the following formula for CV

$$(3-17) \quad CV = E(p^1, U^0) - E(p^0, U^0) \\ = \left(U^0 \cdot e^{0.00229p^1} - \frac{1}{0.00229} [(-2.29905)p^1 + \frac{(-2.29905)}{0.00229} + 11.88518] \right) - m^0$$

To calculate a CV estimate we use the mean value of expenditures for all period as the base period income. That is, $E(p^0, U^0) = m^0$ is the average quarterly per capita income from 1st quarter 1996 to 4th quarter 2004. The data showed $E(p^0, U^0) = m^0$ is \$6,887.9 per person per quarter in 2004 current money value.

Table 3-6 presents CV estimates for various levels of beef price changes. All the money values are expressed in 2004 current dollars. When there's 100% change in beef price the per capita CV for a consumer is \$54.7/quarter which measures the minimum amount the consumer has to be compensated.

The money values in the third column of Table 3-6 represents the total amount of CV for U.S. as a whole which are calculated assuming total U.S. population as 300 million people and expressed in billion dollars. When the beef price is doubled the U.S. national consumers' welfare loss for beef consumption amounts to \$16.4 billion per quarter. The last column in Table 3-6 represents the percentage share of CV to average quarterly disposable income. When the beef price is doubled consumer welfare loss for beef consumption amounts to 0.79% of the base period income.

Table 3-6. Simulation Results of CV Measurement from VECM

Beef price change	Per capita CV (\$)	U.S. Total CV (\$ Billion)	CV to Income Ratio (%)
1%	0.62	0.19	0.01
10%	6.66	2.00	0.10
20%	13.11	3.93	0.19
30%	19.29	5.79	0.28
40%	25.18	7.55	0.37
50%	30.80	9.24	0.45
60%	36.14	10.84	0.52
70%	41.21	12.36	0.60
80%	45.99	13.80	0.67
90%	50.50	15.15	0.73
100%	54.73	16.42	0.79

Conclusion

In this chapter we applied the compensating variation approach for the measurement of consumer welfare losses associated with beef price changes. We derived the Marshallian demand function from the long-run component of error correction term of VECM. Based on the estimated Marshallian demand function we estimated the compensating variation with various scenarios of price changes. When there is 100% increase in beef price the per capita CV amounted to \$54.73 per quarter which is 0.79% of the disposable income. Apparently, the use of long-run equation of the VECM in deriving the direct Marshallian

demand function to measure the consumer welfare change is the first attempt in the literature. This is one of the contributions of the study.

CHAPTER IV

INTERNATIONAL TRANSMISSION OF GASOLINE PRICES AMONG INTERNATIONAL GASOLINE MARKETS: U.S., EUROPE AND ASIA

In international gasoline markets the petroleum marketers face enormous price risks. Thus investigating the factors which affect price risks in international gasoline markets could be of crucial importance to gasoline market participants. For the gasoline market traders one of the most important factors to be considered is the price of crude oil from which gasoline is refined. And actually most past studies focused on finding the relationship between the volatility of crude oil and the volatility of petroleum products (Lee and Cheng (2007), Chen et al. (2005), Radchenko (2005), Chacra (2002), etc.).

But the previous literatures did not pay much attention to the inter-relationship among the spatially separated international gasoline markets. A price shock in a spatially separated gasoline market can cause serious price risks to a certain gasoline market. Hammoudeh et al. (2003) and Hammoudeh and Li (2004) tried to find the price leadership among the three international gasoline spot markets (NY market, U.S. Gulf market, and Rotterdam market). But Hammoudeh et al. (2003) and Hammoudeh and Li (2004) did not pay any attention to the dynamic relationship between the international gasoline markets.

Considering past research results on the international gasoline markets, we believe that it is worth to investigate the inter-relationship among the spatially separated international gasoline markets. This study presents an empirical framework to summarize the interdependence of four international gasoline markets. Interdependence in both contemporaneous and lagged time is addressed. However our study takes a somewhat different approach from the previous literature. In analyzing the international transmission of gasoline prices this paper applies the directed acyclic graphs (DAG) approach is used as an aid to identifying a structural vector error correction model. Further we investigate the dynamic properties of world-wide gasoline prices.

Data

The four price series of gasoline markets included in this study are the prices in NY, U.S. Gulf Coast, Rotterdam and Singapore. NY, Singapore and Rotterdam markets are the three main hubs of petroleum products markets in each area. And U.S. Gulf Coast is a main petroleum products producing area in U.S. The Rotterdam market is the center for the Northwest European petroleum trade. Asche et al. (2003, p.293) describe “The Rotterdam market is the generic term given to trade in oil products in Northwest Europe and takes its name from the large refining and storage complex in the Antwerp, Rotterdam, and Amsterdam area. Rotterdam prices are generally accepted as a base to price oil products in trade and in internal company transfer throughout Northern Europe”.

The data series are daily conventional gasoline regular spot price (FOB) in the New York Harbor, U.S. Gulf Coast and Rotterdam. For the Singapore market led regular gasoline spot price (FOB) data are used. All prices are cents per gallon. The data series were obtained from the U.S. Department of Energy.

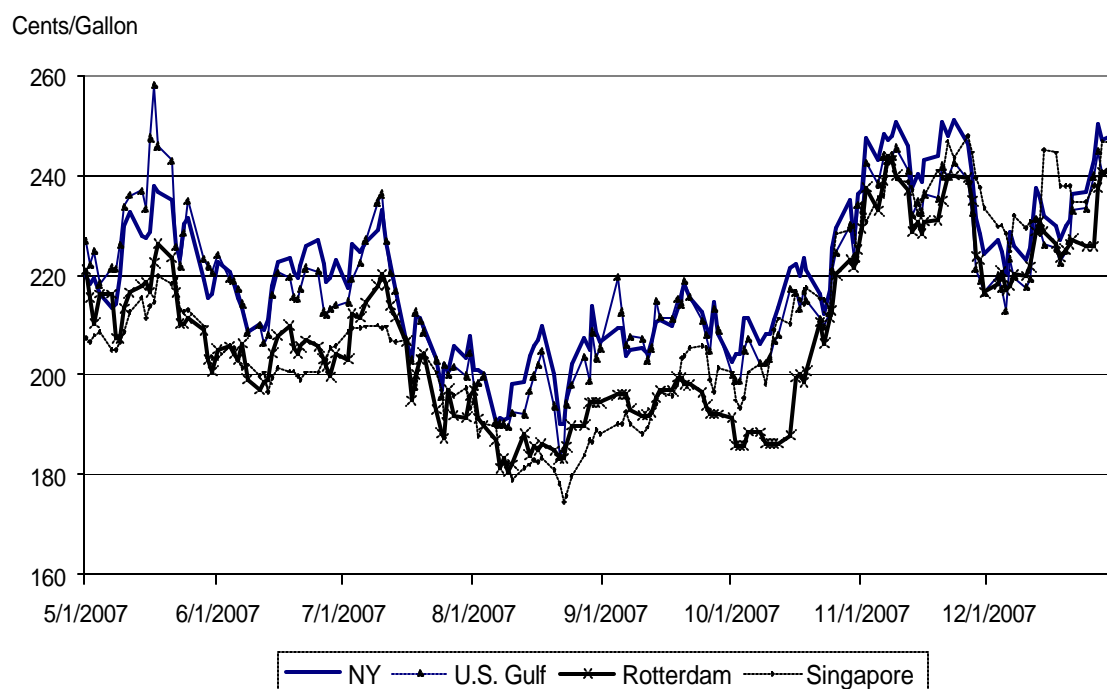


Figure 4-1. Plots of daily gasoline spot prices (FOB)

We constrain our analysis to the period from May 1, 2007 through December 31, 2007. The data included are daily data of five days a week. Total number of business days included in this study is 170. That is at least one market was open during 170 business days. Among the 170 business days, we have five days on which one or two markets were not open. Closing of markets occurs because of the different holiday

systems across the four areas. For the missing observations we insert the previous business day's price. Figure 4-1 presents the prices of gasoline for four regions.

Table 4-1. Unit Root Test Results with Daily Gasoline Data

	Price in NY	Price in U.S. Gulf	Price in Rotterdam	Price in Singapore
Augmented Dickey-Fuller	-2.2462 (0.4606)	-2.3693 (0.3943)	-1.5965 (0.7906)	-1.4299 (0.8489)
Phillips-Perron	-2.2993 (0.4317)	-2.3618 (0.3982)	-1.7099 (0.7429)	-1.3754 (0.8648)

(Note) H_0 : the variable has a unit root. Values are adjusted t-statistics and (p-values).

To find the stationarity of each series we establish the order of integration of the individual price series. The test methods for variable stationarity are the augmented Dickey-Fuller (1979) unit root test and the Phillips-Perron (1988) unit root test, based on critical values provided by MacKinnon (1996). We test for a unit root assuming a series is subject to both deterministic trend and intercept. As shown in Table 4-1, all the gasoline price series have unit roots at 5% significance level.

Vector Error Correction Model (VECM)

The vector autoregression (VAR) model and vector error correction model (VECM) are widely used for the analysis of multivariate time series. The two models are especially useful for describing the dynamic behavior of economic time series and for forecasting. But, in some cases some variables are $I(1)$ and they may be cointegrated. In this case

the VAR model is not the most appropriate tool for analysis, and thus we need another model, such as VECM, in which the cointegrating relations are explicitly contained.

Let's consider $(k \times 1)$ random vectors $Y_t = (y_{1t}, \dots, y_{kt})$ and $X_t = (x_{1t}, \dots, x_{kt})$ where y_{it} and x_{it} are $(T \times 1)$ vectors for all $i = 1, \dots, k$. We assume that a data generating process (DGP) of the form $Y_t = \mathbf{m}_t + X_t$, and X_t has a VECM representation of the form $\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{l-1} \Gamma_i \Delta X_{t-i} + e_t$ where Π is a $(k \times k)$ coefficient matrix. We further assume that the deterministic component (\mathbf{m}_t) is defined as $\mathbf{m}_t = \mathbf{m}_0 + \mathbf{m}_1 t$ where \mathbf{m}_0 and \mathbf{m}_1 are arbitrary $(k \times 1)$ vectors and k is the number of variables included in the vector error correction model (VECM). Different forms of \mathbf{m}_t give different functional forms of VECM. We briefly discuss the various functional forms of VECMs with different types of \mathbf{m}_t . Lütkepohl (2005) provides three different forms of deterministic terms in VECM.

The first case is that the deterministic component is a constant (i.e. $\mathbf{m}_t = \mathbf{m}_0$) and the constant term is included in the cointegration space. Then data generation process of Y_t has the following VECM representation

$$(4-1) \quad \Delta Y_t = (\Pi, \nu) \begin{pmatrix} Y_{t-1} \\ 1 \end{pmatrix} + \sum_{i=1}^{l-1} \Gamma_i \Delta Y_{t-i} + e_t$$

where Π is a $(k \times k)$ matrix, ν is a $(k \times 1)$ vector, and l is the number of lags in level vector autoregression (VAR).

The second case is a process with a linear trend (t), that is, $\mathbf{m}_t = \mathbf{m}_0 + \mathbf{m}_1 t$. Then the data generation process of Y_t has the VECM representation

$$(4-2) \quad \Delta Y_t = \mathbf{n}_1 + (\Pi, v_2) \begin{pmatrix} Y_{t-1} \\ t-1 \end{pmatrix} + \sum_{i=1}^{l-1} \Gamma_i \Delta Y_{t-i} + e_t$$

where v_1 and v_2 are $(k \times 1)$ vectors.

The third case to be considered is that the variables have a linear trend but there is no such term in the cointegrating relations. Lütkepohl (2005, p.331) describes this case as “Formally this case occurs if $\mathbf{m}_1 \neq 0$ and $\Pi \mathbf{m}_1 = \mathbf{a} \mathbf{b}' \mathbf{m}_1 = 0$, or, equivalently, if $\mathbf{b}' \mathbf{m}_1 = 0$ ”. Here \mathbf{a} and \mathbf{b} are $(k \times r)$ matrices. Then the Eq. (4-2) reduces to

$$(4-3) \quad \Delta Y_t = \mathbf{n}_1 + \Pi Y_{t-1} + \sum_{i=1}^{l-1} \Gamma_i \Delta Y_{t-i} + e_t$$

For the empirical analysis we follow these steps: (i) we first determine the number of lags of the endogenous variables for a VAR representation, (ii) we then determine the cointegrating rank for VECMs with various kinds of deterministic terms, and (iii) we determine the form of deterministic terms by likelihood ratio (LR) test.

Finally we estimate the VECM and check the validity of the vector error correction model. The specification of a vector error correction model starts by determining a suitable lag length (Lütkepohl, 2005). To determine lag length we apply the Schwarz information criterion (SIC) to our four international gasoline market price data set and a constant in the model. At two lags the levels VAR gives the lowest SIC statistics. Thus we conclude that the data support vector autoregression (VAR) with two lags, which corresponds to one lagged difference in VECM.

With the various functional forms of VECM in Eq. (4-1), (4-2) and (4-3), we determine the number of cointegration rank. Remember that at present we do not know

the correct form of the deterministic component of the VECM. For the determination of the cointegrating rank we apply the trace test suggested by Johansen (1991, 1992).

Table 4-2 gives trace test statistics and corresponding p-values from Eq. (4-1) to (4-3). The p-values are approximated using the Γ -distribution, see Doornik (1998). For all the cases in Table 4-2, we find that, at $r=0$, all the p-values are less than 0.05 thus we reject $r=0$ at 5% significance level. At $r=1$ the p-values are larger than 0.05, we fail to reject $r=1$ at 5% significance level. Hence we conclude that the trace tests give one cointegrating equation for all VECM considered.

Table 4-2. Trace Test for Determination of Deterministic Terms

Cointegration rank	$m_t = m_0$		$m_t = m_0 + m_1 t$		$m_t \neq 0, b' m_t = 0$	
	Trace statistic	p-value	Trace statistic	p-value	Trace statistic	p-value
$r=0$	54.749	0.042	67.063	0.024	53.639	0.012
$r=1$	27.679	0.259	37.944	0.145	26.569	0.115
$r=2$	12.723	0.395	17.931	0.356	11.615	0.179
$r=3$	1.124	0.920	4.092	0.729	0.061	0.805
Log- Likelihood	-742.741		-741.162		-742.186	

Based on one cointegration equation (i.e. $r=1$) we determine the type of deterministic component of VECMs. Johansen (1991, 1992) and Lütkepohl (2005) proposed the likelihood ratio (LR) tests for hypotheses regarding the deterministic terms. We employ the likelihood ratio (LR) test in two stages.

First, under the situation that there is a deterministic linear trend in the variables, we test whether the trend is orthogonal to the cointegration relations. A pair of

hypotheses is $H_0 : \mathbf{b}'\mathbf{m}_1 = 0$ versus $H_1 : \mathbf{b}'\mathbf{m}_1 \neq 0$. In other words the test checks the model in Eq. (4-2) against the model in Eq. (4-3): that is, Eq. (4-2) is the unrestricted model and Eq. (4-3) is the restricted model. The corresponding LR test follows a χ^2 distribution with r degrees of freedom because r zero restrictions are specified in H_0 . With one degree of freedom we get χ^2 statistic of 2.05 which is less than the critical value 3.84 at 5% significance level. Thus we fail to reject $H_0 : \mathbf{b}'\mathbf{m}_1 = 0$.

Next we test a model with an unrestricted intercept, Eq. (4-3), against the model where no linear trend is present, and, thus the constant can be absorbed into the cointegration relations as in Eq. (4-1): here Eq. (4-3) is unrestricted model and Eq. (4-1) is the restricted model. The hypothesis is $H_0 : \mathbf{m}_1 = 0$ versus $H_1 : \mathbf{m}_1 \neq 0, \mathbf{b}'\mathbf{m}_1 = 0$. The corresponding LR test follows a $\chi^2(k-r)$. With $r=1$ and $k=4$ we got χ^2 statistic = 1.11 which is less than the critical value 7.82 at 5% significance level. Thus we fail to reject $H_0 : \mathbf{m}_1 = 0$. From the above two tests we conclude the suitable deterministic component for data generating process (DGP) Y_t is $\mathbf{m}_1 = \mathbf{m}_0$. Thus we select the Eq. (4-1) as our final VECM.

Estimation Results of the VECM with Gasoline Prices

Based on one cointegrating rank ($r=1$) and two lags of level VAR ($l=2$) the VECM in Eq. (4-1) is regressed by maximum likelihood estimation (MLE) method suggested by Johansen (1991). The values in parentheses are t-statistics. In Eq. (4-4) $p_{NY_t}, p_{ROT_t}, p_{SP_t}$

are the prices in NY, Rotterdam and Singapore respectively, e_{jt} is the error term for j -th regression equation.

$$(4-4) \quad \begin{pmatrix} \Delta p_{NY_t} \\ \Delta p_{USgulf_t} \\ \Delta p_{ROT_t} \\ \Delta p_{SP_t} \end{pmatrix} = \begin{pmatrix} -0.362 \\ (-3.775) \\ -0.320 \\ (-2.806) \\ 0.066 \\ (0.908) \\ 0.109 \\ (1.985) \end{pmatrix} \begin{pmatrix} 1.000 & -0.195 & -0.458 & -0.183 & -43.709 \\ & (-1.703) & (-3.124) & (-1.999) & (-4.263) \end{pmatrix} \begin{pmatrix} p_{NY_{t-1}} \\ p_{USgulf_{t-1}} \\ p_{ROT_{t-1}} \\ p_{SP_{t-1}} \\ 1 \end{pmatrix} + \begin{pmatrix} 0.220 & 0.102 & -0.220 & 0.300 \\ (1.345) & (0.799) & (-2.020) & (2.795) \\ 0.280 & -0.047 & -0.138 & 0.198 \\ (1.441) & (-0.310) & (-1.068) & (1.555) \\ 0.169 & 0.261 & -0.228 & 0.216 \\ (1.355) & (2.683) & (-2.745) & (2.632) \\ 0.377 & 0.064 & 0.056 & -0.124 \\ (4.015) & (0.882) & (0.902) & (-2.008) \end{pmatrix} \begin{pmatrix} \Delta p_{NY_{t-1}} \\ \Delta p_{USgulf_{t-1}} \\ \Delta p_{ROT_{t-1}} \\ \Delta p_{SP_{t-1}} \end{pmatrix} + \begin{pmatrix} e_{NY_t} \\ e_{USgulf_t} \\ e_{ROT_t} \\ e_{SP_t} \end{pmatrix}$$

From now on, for national convenience, we represent Eq. (4-4) as

$$(4-5) \quad \Delta Y_t = ab'Y_{t-1} + \Gamma_i \Delta Y_{t-i} + e_t$$

Table 4-3 presents Lagrangian Multiplier (LM) statistics for the test of autocorrelation on the innovations (or residuals) from the VECM. The tests are not on individual series but for the multivariate residuals as a whole. Since the p-values are larger than 0.05, we fail to reject H_0 : no serial correlation at lag order 1 (and 2) at 5% significance level.

Table 4-3. Test of Autocorrelation on Residuals from the VECM with Gasoline Prices

	Test statistics	p-value
LM(1)	19.731	0.233
LM(2)	15.891	0.461
LM(3)	14.071	0.593
LM(4)	21.926	0.146

Once the VECM is regressed, restrictions on the cointegration space can be tested using log-likelihood ratio (LR) test. The following hypotheses are of particular interest.

The first is the null of long-run exclusion of a series from the cointegration space. The null of long-run exclusion is given as $H_0 : \mathbf{j}_i' b = 0$, where \mathbf{j}_i is a $(k+1) \times 1$ vector whose i -th element is one and all other elements are zero. For example, if we want to test whether the price of NY variable belongs to the cointegration space, the null will be $H_0 : \mathbf{j}_i' b = (1,0,0,0,0)b = 0$ and the test is asymptotically distributed as $\mathbf{c}^2(r)$. That is, the null is H_0 : the i -th series is excluded from cointegration space. As shown in Table 4-4, at one cointegrating rank ($r=1$), the p-values for the variables U.S. Gulf Coast and Singapore are larger than 0.05. Thus we conclude that the two variables can be excluded from cointegration space at 5% significance level.

Weak exogeneity test examines a hypothesis about the rows of a , and tests if any of the variables can be regarded as weakly exogenous when the parameter of interest is b (Dennis et al., 2006). The null is given as $H_0 : R_i' a = 0$, where R_i' is a $(k \times 1)$ vector

whose i -th element is one and all other elements are zero. A weakly exogenous variable does not respond to the perturbations in the cointegration space, that is, a weakly exogenous variable does not respond to restore equilibrium. Table 4-4 suggests that prices in Rotterdam and Singapore do not respond to perturbations in the single long-run relation at 5% significance level.

Table 4-4. Test of Long-Run Exclusion, and Weak Exogeneity at $r = 1$

Test	Critical value(5%)	P_{NY}	P_{USgulf}	P_{ROT}	P_{SP}	Constant
Long-run exclusion	3.841	8.764* (0.003)	0.628 (0.428)	4.228** (0.040)	1.502 (0.220)	10.177* (0.001)
Weak exogeneity	3.841	9.258* (0.002)	4.404** (0.036)	0.510 (0.475)	3.216 (0.073)	-

(note) p-values are in parentheses. * Significance at 1% level, ** Significance at 5% level.

(note) P_{NY} is the conventional gasoline regular spot price (FOB) in the New York Harbor.

Identification of VECM

For a VECM with k variables of the form in eq. (4-5), the identification problem is to find a $(k \times k)$ matrix G such that

$$(4-6) \quad e_t = G\mathbf{e}_t \quad \text{with } \mathbf{e}_t \sim (0, I_k)$$

where e_t is a vector of regression innovations, \mathbf{e}_t is a vector of pure innovations of Y_t , and I_k is a $(k \times k)$ identity matrix.

It is known that if there are more than $k(k-1)/2$ free parameters in G , the model is definitely not identified and sometimes the model can not be identified even with less free parameters in G . Thus it is necessary to impose $k(k-1)/2$ additional

restrictions on G to completely identify the VECM system. In this section, we briefly discuss the identification problem of a structural VECM and the role of directed acyclic graph (DAG) in setting up a structural VECM.

Let \mathbf{e}_{jt} 's be the pure innovations in y_j 's and assume that \mathbf{e}_{jt} 's are serially uncorrelated and orthogonal to each other (Enders, 2003). If the regression innovations are linear combinations of the pure innovations, then the regression innovations e_{jt} 's can be expressed as a linear combination of \mathbf{e}_{jt} 's.

$$(4-7) \quad \begin{pmatrix} e_{1t} \\ \mathbf{M} \\ e_{kt} \end{pmatrix} = \begin{pmatrix} g_{11} & \mathbf{K} & g_{1k} \\ \mathbf{M} & \mathbf{O} & \mathbf{M} \\ g_{k1} & \mathbf{K} & g_{kk} \end{pmatrix} \begin{pmatrix} \mathbf{e}_{1t} \\ \mathbf{M} \\ \mathbf{e}_{kt} \end{pmatrix} \quad \text{or} \quad e_t = \mathbf{G}\mathbf{e}_t$$

Eq. (4-7) shows that the pure innovation in Y_{it} will have a contemporaneous effect on Y_{jt} if $g_{ji} \neq 0$. Since \mathbf{e}_{jt} 's are serially uncorrelated and orthogonal to each other, we obtain the following diagonal matrix,

$$(4-8) \quad E(\mathbf{e}_{it}\mathbf{e}_{jt}) = \Sigma_e = \begin{pmatrix} \mathbf{s}_{e,1}^2 & 0 & \mathbf{K} & 0 \\ 0 & & & \\ \mathbf{M} & \mathbf{O} & \mathbf{M} & \\ 0 & \mathbf{K} & \mathbf{s}_{e,k}^2 & \end{pmatrix}$$

where $\mathbf{s}_{e,j}^2$ is the variance of \mathbf{e}_{jt} for $j=1, \dots, k$.

Let's recall that we do not know the unobserved \mathbf{e}_{jt} 's. Thus we have to identify the \mathbf{e}_{jt} 's from the observed regression innovations e_{jt} 's. If we know all g_{ij} ($i, j=1, \dots, k$) we can figure out all of the structural shocks for the regression residuals.

The variance/covariance matrix of the regressed residuals gives some information for finding the values of each g_{ij} . Let

$$(4-9) \quad Ee_t e_t' = \Sigma_e$$

If we denote the elements of Σ_e as \mathbf{s}_{ij} we get

$$(4-10) \quad \Sigma_e = \begin{pmatrix} \mathbf{s}_{11} & \mathbf{K} & \mathbf{s}_{1k} \\ \mathbf{M} & \mathbf{O} & \mathbf{M} \\ \mathbf{s}_{k1} & \mathbf{K} & \mathbf{s}_{kk} \end{pmatrix}$$

Since $e_t = G\mathbf{e}_t$ the Eq. (4-9) is written as

$$(4-11) \quad E(e_t e_t') = E(G\mathbf{e}_t \mathbf{e}_t' G')$$

Since $E(e_t e_t') = \Sigma_e$, and if we set $E(\mathbf{e}_t \mathbf{e}_t') = \Sigma_e$, the following holds

$$(4-12) \quad \Sigma_e = G\Sigma_e G'$$

Since all the \mathbf{s}_{ij} can be obtained from the regression residuals e_{jt} 's, and our model has four price series, we have $k^2 (=16)$ equations to get all the g_{ij} . But here's a problem. Since there are symmetric elements in $Ee_t e_t' = \Sigma_e$ (i.e. $\mathbf{s}_{ij} = \mathbf{s}_{ji}$) we have only $k^2 - k(k-1)/2 (=10)$ independent equations to determine the 16 elements of G matrix. Thus we have to apply $k(k-1)/2 (=6)$ additional restrictions to completely identify the nine g_{ij} ($i, j = 1, 2, 3, 4$). This gives rise to the identification problem in a VECM. In the following we briefly discuss how to give the additional restrictions and identify the vector error correction system.

The Choleski factorization is a common method used to solve an identification problem (Enders, 2003). Choleski factorization method gives the upper diagonal

elements of G to be zero, thus yields a just-identified system. But the results of the identification scheme using the Choleski factorization method are dependent on the ordering of the variables: that is, during the decomposition of Σ_e different choices of an ordering of the rows and columns of Σ_e may give different factorized matrices. Of course this may give us different results for impulse response functions and forecast error variance decompositions.

As an alternative to the Choleski factorization, several researchers such as Bernanke (1986), Sims (1986) have proposed, so called, the contemporaneous structural VECM. The structural VECM approach is, in essence, a transformation of the Eq. (4-1) into a model with orthogonal innovations by imposing zero restrictions such as those suggested by economic theory.

The structural VECM make it possible to impose over-identifying restrictions on the VECM model. But the structural VECM model still contains some problems to solve. First, there are neither uniquely accepted nor clear counting rules for identifying the factorized matrix G . Second, theory-based restrictions may give some help in imposing some restrictions, but such restrictions may not reflect the intrinsic properties contained in the data. Even in many cases there may be no (or almost no) established theory to guide restriction imposition. Thus we have to find another alternative. In this paper we apply data-based restrictions in imposing over-identifying restrictions on the structural VECM. The identification is achieved from directed acyclic graphs (DAGs) derived from contemporaneous VECM innovations.

We use DAG to find the $k(k-1)/2$ additional restrictions. If we give more restrictions by giving more g_{ij} 's to be zero, then the system is over-identified, and then we have to test the over-identification problem using LR test. Actually, this method is a modification of the Bernanke factorization in which the contemporaneous causal path of the model innovations is determined by directed acyclic graphs results.

Identification of the Contemporaneous Structure

In this section we briefly discuss the directed acyclic graphs (DAGs) and GES algorithm. And then using the DAGs we investigate the identifying restrictions for the structural VECM and test the over-identification using the likelihood-ratio (LR) test. Chickering (2002a) and Chickering (2002b) discuss DAG and GES algorithm in detail. The discussion on DAG and GES algorithm in this section depends on the prior two materials.

A directed acyclic graph is a directed graph which contains no cyclic paths. Only directed acyclic graphs are used in this analysis. For example we do not allow graphs of the form such as $X \rightarrow Y \rightarrow Z \rightarrow X$.

More formally, a Bayesian-network model Φ for a set of variables $U = (x_1, x_2, \dots, x_n)$ is a pair (Ψ, Θ) . $\Psi = (V, E)$ is a directed acyclic graph consisting of (i) nodes V in one-to-one correspondence with the variables U and (ii) directed edges E that connect the nodes. Θ is a set of conditional probability distributions such that $\Theta_i \in \Theta$ defines the conditional probability of node x_i given its parents in Ψ . A

Bayesian network represents a joint distribution over U which factors according to the structure Ψ as follows:

$$(4-13) \quad P_{\Phi}(x_1, x_2, x_3, \dots, x_n) = \prod_{i=1}^n P(x_i | \mathbf{p}_{x_i}, \Theta_i)$$

where \mathbf{p}_{x_i} is the set of parents of node x_i in Ψ (Chickering, 2002a).

As mentioned in Chickering (2002b) the structure Ψ of a Bayesian network is itself a model that represents the independence constraints that must hold in any distribution that can be represented by a Bayesian network with that structure. Further the set of all independence constraints imposed by the structure Ψ via Eq. (4-13) can be characterized by the Markov conditions, which are the constraints that each variable is independent of its non-descendants given its parents (Chickering, 2002b).

Two DAGs Ψ and Ψ' are 'distributionally equivalent' if for every Bayesian network $B = (\Psi, \Theta)$, there exists a Bayesian network $B' = (\Psi', \Theta')$ such that B and B' define the same probability distribution, and vice versa (Chickering, 2002b). Two DAGs Ψ and Ψ' are 'independence equivalent' if the independence constraints in the two DAGs are identical (Chickering, 2002b). Two DAGs Ψ and Ψ' are equivalent if they are both distributionally and independence equivalent.

In this study Greedy Equivalence Search (GES) is used to find causal flows from correlation relationships among the variables. GES, which is introduced by Meek (1997), is a greedy algorithm that searches over equivalence classes of DAGs. Following Chickering (2002b) let \mathcal{E} represent an equivalence class of DAG models. Further let the neighbors of state \mathcal{E} be represented as $\mathcal{E}^+(\mathcal{E})$ which contains equivalence classes that are

obtained by adding a single edge from DAGs in \mathcal{G} . Similarly let the neighbors of state \mathcal{G} be represented as $\mathcal{G}^-(\mathcal{G})$ which contains equivalence classes that are obtained by deleting a single edge from DAGs in \mathcal{G} . Figure 4-6 of Chickering (2002b) illustrates a good graphical example for \mathcal{G} , $\mathcal{G}^+(\mathcal{G})$ and $\mathcal{G}^-(\mathcal{G})$.

In Chickering (2002b, p. 522) GES is described as “We first initialize the state of the search to be the equivalence class \mathcal{G} corresponding to the (unique) DAG with no edges. That is, the first state of the search corresponds to all possible marginal and conditional independence constraints. In the first phase of algorithm, we repeatedly replace \mathcal{G} with the member of $\mathcal{G}^+(\mathcal{G})$ that has the highest score, until no such replacement increases the score. Once a local maximum is reached, we move to the second phase of the algorithm and repeatedly replace \mathcal{G} with the member of $\mathcal{G}^-(\mathcal{G})$ that has the highest score. Once the algorithm reaches a local maximum in the second phase, it terminates with the solution equal to the current state \mathcal{G} ”. We employ the software Tetrad IV to derive DAGs using GES algorithm.

Innovations from the estimated VECM give the contemporaneous innovation correlation matrix, Σ_e . The lower triangular elements of the correlation matrix on innovations (errors) from the VECM are given as Table 4-5. The positive correlation coefficient in Table 4-5 shows the changes in international gasoline prices are positively related. Correlation of NY–U.S. Gulf Coast is highest among other correlations. Also we can see that the correlations of Rotterdam-NY and Rotterdam-U.S. Gulf Coast are larger than those of Singapore-NY, Singapore-U.S. Gulf Coast and Rotterdam-Singapore, which mean that the gasoline prices between U.S. markets and European market are

more closely related than the prices between Asia-Northwest European market and Asia-U.S. markets.

Table 4-5. Correlation Matrix of Innovations from VECM with Gasoline Prices

	Δp_{NY}	Δp_{USgulf}	Δp_{ROT}	Δp_{SP}
Δp_{NY}	1.000			
Δp_{USgulf}	0.867	1.000		
Δp_{ROT}	0.523	0.478	1.000	
Δp_{SP}	0.025	0.030	0.132	1.000

(note) ΔP_{NY} is the first differenced value of P_{NY} , and P_{NY} is the conventional gasoline regular spot price (FOB) in the New York Harbor.

The innovation correlation matrix given by Table 4-5 is used as the starting point for our analysis of the innovations. GES algorithm is applied to this correlation matrix to get the patterns of directed acyclic graphs. Tetrad IV gives DAGs in Figure 4-2. Following the convention the analysis in this study is conducted mainly based on the same calendar day. But this kind of analysis causes the problem of non-synchronism because the four gasoline markets operate in different time zones. So we impose a time-gap restriction that innovations in market A cannot influence market B in contemporaneous time, if the latter (B) is closed before the former (A) opens on the same calendar day.

This restriction considers Singapore, Rotterdam and U.S. markets have about six hours of time gap each and the time periods on which the markets are open together is almost slim or none. Thus we two time tier restrictions: that is, Singapore market can not

cases (3) and (4) give DAG-2. For any time-tier restriction, Singapore does not influence any other markets in contemporaneous time.

Let's note that the two DAGs show that there is no connection between the price series in Singapore and any other price series, which means that Singapore market does not influence any other markets in contemporaneous time. DAG-1 informs us the existence of some relationships between gasoline prices in the four markets, but does not give us the definite causality directions. DAG-2 shows that Europe (Rotterdam) market directly affects NY market and NY market directly affects U.S. Gulf Coast market, but Europe (Rotterdam) market indirectly affects U.S. Gulf Coast market via NY market. It is worth noticing that the U.S. Gulf Coast market is an information sink which is affected by other markets but does not affect any other markets in contemporaneous time.

Now we use DAG-2 to give the identifying restrictions for the structural VECM and test the over-identification using the likelihood-ratio (LR) test. More specifically, we have DAG-2 place zeros on the matrix G which solves $\Sigma_e = G\Sigma_e G'$. Given a four variable system we only need 6 ($k(k-1)/2 = 4(4-1)/2$) restrictions to get a just-identified model. But DAG-2 imposes 10 restrictions, and thus these over-identifying restrictions can be tested via an LR test.

According to the LR test the directed graph restriction results in a χ^2 statistic of 3.7062 with 4 degree of freedom. The corresponding p-value is 0.4472 and it is larger than 0.05. Thus the over-identifying restriction can not be rejected at a 5% significance level, which suggests that the restrictions are consistent with the data.

Dynamic Behavior of the Variables in the VECM System

In this section the dynamic price relationships are summarized through analysis of both impulse response functions and forecast error variance decomposition. An impulse response function traces out the response of a variable of interest to an exogenous shock.

The impulse response analysis is a device to display the dynamics of the variables tracing out the reaction of each variable to a particular shock at time (t). Figure 4-3 presents the impulse response functions (IRF) for the VECM model identified through DAG-2 results.

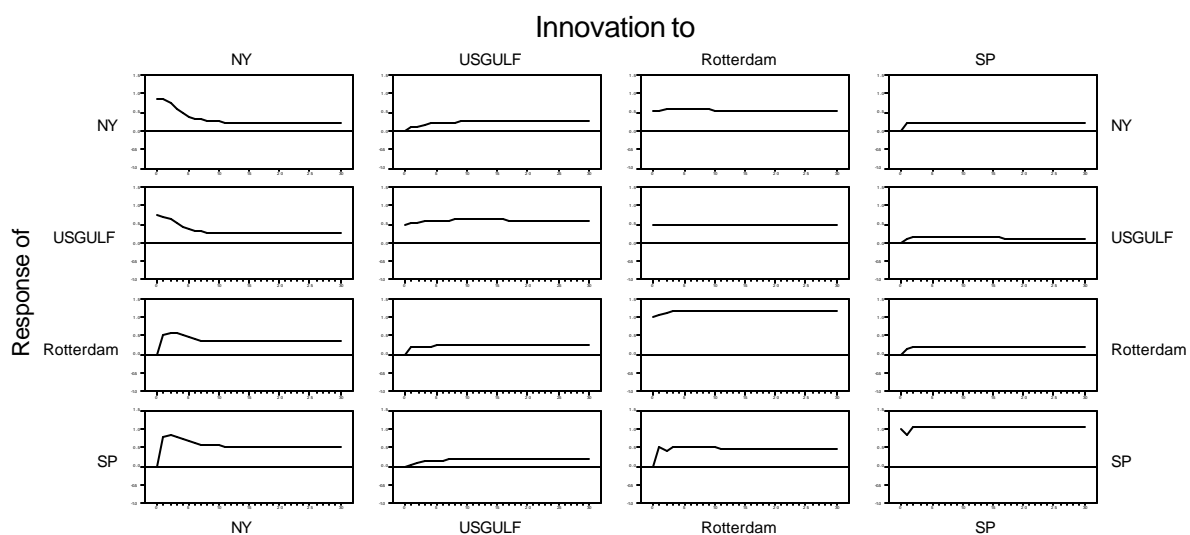


Figure 4-3. Impulse response functions for the VECM model identified through DAG-2

The impulse response functions in Figure 4-3 show that the time period in which a shock in a market affects the other market is very short and most fluctuations become almost constant within a week at most. We can observe that the effect on the two U.S. markets from the shock in Rotterdam market is bigger than that from Singapore. Also the effect on the Rotterdam market from the shock in NY market is bigger than that from Singapore. Actually the effects to other markets from the shocks in Singapore market are almost negligible. Among the two U.S. markets NY market dominates U.S. Gulf Coast market, which means that gasoline trading area dominate the shocks from gasoline producing area.

Another tool for interpreting a VECM is the forecast error variance decomposition (FEVD) which provides complementary information on the dynamic behavior of the variables in the system. Since variance decomposition separates the variation in an endogenous variable into the component shocks to the VECM, the variance decomposition provides information about the relative importance of each random innovation in affecting the variables in the VECM.

The forecasted error variance decompositions (FEVDs) based on the DAG-2 are presented in Table 4-6. Entries in Table 4-6 give the percentage of forecast error variance at horizon h , which are attributable to shocks from each other series including itself. We list steps or horizons of 0 (contemporaneous time) to 5 period differences and 10, 20 and 30 days ahead (longer horizon). In each row they add up to 100%.

Let's note that the zero values on horizon of 0 (contemporaneous time) in FEVDs are due to the zero restrictions placed on the matrix G by DAG-2. Among them the zero

Table 4-6. FEVD for the VECM Identified through DAG-2

Horizon	Decomposition of Variance for P_{NY}				Decomposition of Variance for $P_{U.S.Gulf}$			
	P_{NY}	$P_{Gulf}^{U.S.}$	P_{ROT}	P_{SP}	P_{NY}	$P_{Gulf}^{U.S.}$	P_{ROT}	P_{SP}
0	71.59	0.00	28.41	0.00	53.81	24.83	21.36	0.00
1	71.23	0.50	26.16	2.11	52.76	25.31	21.17	0.77
2	67.34	0.91	28.94	2.81	49.20	27.00	22.72	1.09
3	63.23	1.57	31.58	3.64	45.21	29.43	23.98	1.38
4	59.17	2.24	34.36	4.23	41.46	31.82	25.15	1.56
5	55.47	2.94	36.86	4.74	38.16	34.05	26.09	1.70
10	42.30	5.74	45.67	6.29	27.57	41.59	28.83	2.01
20	30.43	8.43	53.58	7.57	19.56	47.64	30.63	2.17
30	25.13	9.63	57.12	8.12	16.40	50.20	31.21	2.20
Horizon	Decomposition of Variance for P_{ARA}				Decomposition of Variance for P_{SP}			
	P_{NY}	$P_{Gulf}^{U.S.}$	P_{ROT}	P_{SP}	P_{NY}	$P_{Gulf}^{U.S.}$	P_{ROT}	P_{SP}
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	100.00
1	11.68	1.46	85.94	0.93	23.61	0.08	9.68	66.64
2	15.05	1.59	81.92	1.45	28.42	0.29	9.46	61.83
3	15.84	1.82	80.52	1.83	29.81	0.38	10.45	59.36
4	15.58	2.03	80.32	2.07	29.45	0.53	10.91	59.12
5	14.97	2.24	80.55	2.25	25.21	1.06	12.44	61.30
10	12.14	2.91	82.33	2.63	21.41	1.49	13.40	63.69
20	9.89	3.38	83.90	2.83	20.07	1.66	13.75	64.52
30	9.07	3.54	84.50	2.90	19.98	1.68	13.77	64.58

(note) ΔP_{NY} is the first differenced value of P_{NY} , and P_{NY} is the conventional gasoline regular spot price (FOB) in the New York Harbor.

values in decomposition of variance for p_{SP} come from the zero restrictions on G due to the disconnection from Singapore to other markets in DAG-2. On the contrary, the zero values of the first two columns in decomposition of variance for p_{ARA} come from the zero restrictions on G because of the unilateral influence from Rotterdam market to the U.S. markets in DAG-2.

From Table 4-6 we can observe that the volatility in all of the markets is explained predominantly by the innovations in their own market in the short-run: in case of 1 day time horizon, for the NY market, about 71% of volatility is explained by its own innovations, and about 26% of the volatility is explained by the innovation in Rotterdam market but less than 3% of the volatility in NY market is explained by the innovation in Singapore market and U.S. Gulf Coast market.

In case of the U.S. Gulf Coast market, in the very short-run time period, about 50% of the volatility is explained by the innovations in NY market, but less than 30% of the volatility is explained by the innovation in its own market. From this result we conclude that the U.S. Gulf Coast market is much dependent on the NY market in the short-run.

For long-run time horizon the volatilities in Rotterdam, Singapore and U.S. Gulf Coast markets are still heavily dependent on the innovations of their own market. But the NY market shows different pattern from the other three markets in the long-run. As shown in Table 4-6 the volatilities in NY market is heavily explained by the innovations in Rotterdam market. With 30 days time difference about 57% of the volatility in NY is

explained by the innovations in Rotterdam market, but only 25% of volatility is explained by its own innovations.

In summary, FEVD shows that in all markets, except the U.S. Gulf Coast market, current and past shocks in their own market explain the most of the volatility in their own market in the Short-run. But the U.S. Gulf Coast market is much dependent on the NY market in short-run. FEVD shows that the two U.S. markets are affected much by the shock from Rotterdam markets. But FEVD also reveals the influence of the shocks from NY, U.S. Gulf Coast and Singapore markets do not play an important role in explaining the volatility in Rotterdam market.

Conclusion

This paper combined structural VECM model and directed acyclic graphs (DAGs) to facilitate a more in-depth exploration of the structure of interdependence in international gasoline markets using spot FOB gasoline prices. We explored the direction of causality between innovations across gasoline markets through a VECM and applied directed acyclic graphs as an aid to identifying the structural VECM.

The DAG with two time-tier restrictions showed the ARA and NY market played important roles in the information flow. With the same time tier environment the DAG clearly showed that Rotterdam market led the NY in contemporaneous time. DAG showed that the Singapore and U.S. Gulf Coast markets did not show any influences on the other markets in contemporaneous time. Further, in contemporaneous time, the DAG

showed that Singapore market did not have any connection to other markets in information flow.

Our empirical evidence as derived through the VECM models suggest that there is a substantial amount of interdependence among the international gasoline spot markets. The impulse response functions (IRF) showed that the impacts from one market were rapidly transmitted to other markets and the impacts were very shortly lived. Further, the empirical results from forecast error variance decomposition (FEVD) indicated that current and past shocks in their own market explain the most of the volatility in their own markets in the short-run.

CHAPTER V

OVERALL CONCLUSION

The main objectives through the dissertation were twofold: One is to measure the consumer welfare in U.S. meat consumption, and the other is the empirical exploitation of the time series methodology.

In chapter II the welfare effects of a set of price changes on the U.S. meat consumption was investigated in a multivariate framework. The price and quantity data used are quarterly time series data of beef, pork and chicken in U.S. We first investigated the consumer behavior depending on a linear expenditure system (LES) which is consistent with the theory of utility maximization and has been extensively applied for the past several decades as a basis of deriving empirically estimable demand equations. Compensating variation (CV) measure associated with the LES was derived and evaluated based on the set of parameters estimated from the LES.

One of the interesting findings is that the combined CV with the same rate of price changes in the three meats is larger than the sum of CVs with price changes in individual meats separately. This result suggests that the more the number of commodities in price changes the more the consumer utility decrease under the situation that consumer budgets are fixed. Also the result indicates that it is more preferable to estimate welfare change from a demand system as a whole instead of estimating welfare change through a single demand function separately. Secondly, the simulation results

showed that the amount of consumer welfare change for each meat is not same across the meats under the same percentage change of price. Thirdly, the simulation results also showed that when all the prices are doubled the total amount of CV reaches almost the same amount of total current quarterly expenditures for the three meats. That is to say, so long as meats are concerned, the minimum amount of money to be compensated to make the consumers stay at the prior utility level is approximately equal to the additional expenditure that is caused by the price changes setting the quantity consumed at current level.

In chapter III, we applied the compensating variation (CV) approach for the measurement of consumer welfare losses associated with beef price changes. We applied the long-run cointegrating relationship in vector error correction model (VECM) to estimate the Marshallian demand function. Apparently, the use of long-run cointegration relationship in VECM in deriving the direct Marshallian demand function to measure the consumer welfare change is the first attempt in the literature. This is one of the contributions of the study. Basically our methodology is similar with the one suggested by Hausman (1981).

Data used in this study consist of quarterly per capita consumption, quarterly per capita disposable income and price series for beef. Compensating variation (CV) measure was derived and evaluated based on the set of parameters estimated from the long-run cointegrating equation of the vector error correction model (VECM). We simulated the compensating variation (CV) with various levels of beef price changes. The simulation results with various levels of price changes revealed that the CV

measures derived using the Marshallian demand function were compatible with the CV measures derived using linear expenditure system (LES).

In chapter IV, an empirical framework to summarize the interdependence of four international gasoline markets (New York, U.S. Gulf Coast, Rotterdam and Singapore) was presented. For that purpose, the dynamic structure of gasoline prices from four international markets was investigated by a structural vector error correction model (VECM) and directed acyclic graphs (DAGs). The DAG representation provided a structure of causality among these markets in contemporaneous time.

NY, Rotterdam (the Antwerp, Rotterdam, and Amsterdam area in the Netherlands) and Singapore markets are the main hubs of petroleum products markets in each area. The data series used in this analysis are daily conventional gasoline regular spot price (FOB) in the New York Harbor, U.S. Gulf Coast and Rotterdam (ARA). For the Singapore market leaded regular gasoline spot price (FOB) data were used.

The unit root tests suggested by Dickey-Fuller (1979) and Phillips-Perron (1988) showed that all the gasoline price series had unit roots. Even though unit root test showed that the individual price series might be non-stationary, the trace test suggested by Johansen (1991, 1992) showed that there existed a linear combination of the individual series which was stationary, thus we concluded that the gasoline price series had a co-movement over time.

Based on the unit root and trace test results we applied vector error correction model (VECM) to the four international gasoline price series. The likelihood ratio (LR) tests for the determination of the deterministic terms of VECM proposed by Johansen

(1991, 1992) and Lütkepohl (2005) suggested that the VECM should have a constant term and the constant term should be included in the cointegration space.

To solve the identification problem inherently contained in structural VECM, we applied data-based restrictions in imposing over-identifying restrictions on the structural VECM. That is, the identification was achieved from directed acyclic graphs (DAGs) derived from contemporaneous VECM innovations.

DAG showed that there was no connection between the price series in Singapore and any other price series, which meant that Singapore market did not influence any other markets in contemporaneous time. DAG also showed that Europe (Rotterdam) market directly affected NY market, and NY market directly affected U.S. Gulf Coast market, but Europe (Rotterdam) market indirectly affected U.S. Gulf Coast market via NY market. It is worth noticing that the U.S. Gulf Coast market was an information sink which is affected by other markets but did not affect any other markets in contemporaneous time. The LR test for the over-identifying restriction showed that the restrictions derived from DAG are consistent with the data.

Based on the contemporaneous structure and lagged relationships captured by the VECM model, the dynamics of the model were studied through impulse response functions and forecast error variance decompositions.

The impulse response functions showed that the time period in which a shock in a market affects the other market was very short and most fluctuations became almost constant within a week at most. We observed that the effect on the two U.S. markets from the shock in Rotterdam market is bigger than that from Singapore. Also the effect

on the Rotterdam market from the shock in NY market was bigger than that from Singapore. Actually the effects to other markets from the shocks in Singapore market were almost negligible. Among the two U.S. markets NY market dominated U.S. Gulf Coast market, which meant that gasoline trading area dominate the shocks from gasoline producing area.

Forecast error variance decompositions (FEVD) showed that in all markets, except the U.S. Gulf Coast market, current and past shocks in their own market explained the most of the volatility in their own market in the Short-run. But the U.S. Gulf Coast market was much dependent on the NY market in short-run. FEVD showed that the two U.S. markets were affected much by the shock from Rotterdam markets. But FEVD also revealed the influence of the shocks from NY, U.S. Gulf Coast and Singapore markets did not play an important role in explaining the volatility in Rotterdam market.

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