ESSAYS ON PRICE TRANSMISSION AND DEMAND ANALYSES OF AGRICULTURAL MARKETS

A Dissertation

by

CHIA-HSIEN SU

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Chair of Committee,	David Leatham
Co-Chair of Committee,	Ariun Ishdorj
Committee Members,	Dmitry Vedenov
	Senarath Dharmasena
Head of Department,	David Leatham

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ABSTRACT

This dissertation consists of three studies that focus on price transmission analyses. The first study investigates the vertical transmission processes among the prices of Taiwanese pork, chicken, hen eggs, international crop prices, and ocean freight rates with monthly data from 2001-2017. Using the Engle-Granger two-step and Johansen methodologies, the study confirmed that the farm-gate prices of livestock products were cointegrated with the export prices of the U.S. and Brazilian corn and soybeans and the Baltic Dry Index (BDI). Consequently, the Enders-Siklos threshold cointegration and nonlinear autoregressive distributed lag approaches were used to test for asymmetric effects on the speeds of price adjustment and the magnitude of price transmission, respectively. The empirical results indicate that the U.S. soybean and corn prices have a nonlinear long-run effect on Taiwanese pork and hen egg prices respectively when the U.S. corn prices and BDI have a nonlinear long-run effect on Taiwanese chicken prices.

The second study investigated dynamic relationships among Taiwanese live eel, vegetable soybean (edamame), and feather and down prices and their major competitors' prices in the Japanese market. For this purpose, vector error correction models were estimated. Directed acyclic graphs based on the PC algorithm characterized the contemporaneous causal relationships among major competitor's prices from different countries. The empirical results reveal that Chinese prepared eel prices dominate the other competitors' prices except for the prepared eel prices from Shizuoka Prefecture.

For the Japanese edamame market, domestic edamame prices are almost independent of import prices, and Chinese and Thai prices have a significant effect on Taiwanese prices. For the Japanese feather and down market, Chinese and French feather and down prices have a stronger influence on Taiwanese feather and down prices.

The third study estimated the U.S. banana import demand disaggregated by exporting countries and offered a comparison of short-term forecasting ability of the inverse national bureau of research (INBR), dynamic inverse almost ideal demand system (DIAIDS) models, and their directed graphical models (DGMs). According to four measures of forecast accuracy, the DGM-DIAIDS model performs the best, whereas the DGM-INBR model performs the worst. In the short run, all Marshallian own-quantity frequencies estimates were less than one in absolute value, indicating that the fresh bananas of six exporting countries are price inflexible. In addition, all statistically significant Marshallian cross-quantity frequencies were found to be negative. This means that bananas from two different exporting countries are gross quantity-substitutes. Finally, the scale frequencies show that the Banana prices from six exporting countries are significantly affected by the quantity of total import bananas.

DEDICATION

I dedicate my dissertation to my beloved grandfather, parents and younger sisters.

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Contributors

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CHAPTER I

INTRODUCTION

Everyone is concerned with fluctuations in market prices because increases and decreases in prices of goods and services affect everyone in everyday life, and volatility in prices of goods and services affects economic agents' decision-making. For example, consumers are concerned with changes in the prices of necessities because they are associated with the cost of maintaining a desired standard of living. In addition, producers are concerned with prices of outputs and inputs of production, since they affect the revenues and profits of their enterprises. The theory of price postulates that the forces of consumption (demand) and production (supply) in a free market economy determine market prices. In a market economy, prices of goods and services provide the information necessary for producers and consumers to make a profit and to make decisions that maximize utility, respectively. Fluctuations in market prices are an indicator of generation of economic activities, and part of endogenous and exogenous variables might affect their fluctuations. Economists use various models to study the welfare effects of a price change, measure the sensitivity of quantity change caused by a price change, investigate whether there a relationship between the prices of related products, etc. Price transmission (PT) analysis measures the effect of changes of prices of one commodity to another commodity in a supply chain. There are three types of price transmission, spatial, vertical, and cross transmission. Spatial price transmission (SPT) occurs when price linkages occur across spatially distributed markets. In SPT, goods are homogeneous, such as world prices and local prices for a given commodity, and local prices for the same commodity in different regions or countries. Vertical price transmission (VPT) happens when price linkages occur in a marketing chain, and it usually explores the extent to which downstream markets are impacted by changes in the upstream prices. Upstream prices are the prices of inputs in the production processes of downstream firms or prices quoted on higher market levels (e.g. wholesale markets). Accordingly, downstream prices are the prices of downstream outputs which are processed or manufactured by the outputs of upstream firms or prices quoted on lower market levels (e.g. retail markets). Cross price transmission (CPT) occurs when two goods are substitutes in consumption and/or production (e.g. maize and rice).

In general, the results of PT analyses can provide solutions to the following areas (Rapsomanikis et al., 2003; Molnár et al., 2013): (1) long-term relationship among prices, (2) magnitude of change in the price of one commodity due to a change in the price of another commodity (3) the speed of the pass-through of the length in time until the reaction of one commodity to a price change in another commodity, and (4) symmetric or asymmetric PT. Symmetric PT means that the price of one commodity would respond in the same manner for both increases and decreases in the price of another commodity. Otherwise, PT is asymmetric. Studies with regard to PT are numerous. Some are interested in financial sectors, such as American depository receipts and their underlying foreign securities (Kim et al., 2000), stock markets (Masih and Masih, 2002), futures markets (Shyy and Lee, 1995). Some studies focus on energy sectors such as crude oil and gasoline (Balke et al., 1998; Chen et al., 2005), crude oil and plastic products (Weinhagen, 2006; Jiang et al., 2015), biofuels and their crops (Serra and Zilberman, 2013). Also, a large part of the literature is concentrated in agro-food sectors such as the relationship between the upstream and downstream prices of agricultural products: the retail and landing prices of fresh cod and the retail and import prices of fresh salmon in France (Simioni et al., 2013), the wholesale and retail prices of aquaculture and capture fisheries in Bangladesh (Sapkota et al., 2015), the fish prices of Canadian fist-hand and processing markets (Gordon, 2017), etc. and the price relationship of a certain agricultural product in different markets: the maize wholesale prices of Accra and Bolgatanga markets in Ghana (Abdulai, 2000), the pork producer prices in Germany, Spain, France, and Denmark (Serra and Gil, 2006), the real wheat prices in 28 Turkish provinces (Brosig et al., 2011), etc.

In general, microeconomics is divided into two categories of private economic units: consumers (or households) and producers (or firms). These two categories result in two research branches: the theory of the consumer and theory of the firm. The theory of the consumer is concerned with the demand for goods and services by rational consumers pursuing maximum utility on a given budget decided upon by themselves. Prices are also an important factor that affects the demand quantity of goods and services. When the price of one good changes, what happens to the demand of the other good? According to the reaction type of its demand, the relationship between two goods can be divided into substitute, complementary, and independent of each other. Market demand analysis can help producers understand how much consumer demand exists for a good or service and how changes in the price of other related goods and services affect the demand of their goods and services. Moreover, market demand forecasting uses scientific theories and methods to analyze and study the market demand and impact demand factors within a certain period in the future analyses. In general, the analytical method can be classified into four groups: a survey of buyers' intentions, sales-force composite, expert opinions, and time series analyses. There is a large amount of literature exploring the demand of goods and services. The related literature can be roughly classified into three groups: (1) The primary sector of the economy such as food demand (Seale et al., 2003), fish demand (Dey et al., 2008), and meat demand (Mutondo and Henneberry, 2007); (2) the secondary sector of the economy such as electricity demand (Erdogdu, 2007) and crude oil or gasoline demand (Cheung and Thomson, 2010; Ziramba, 2010); (3) the tertiary sector of the economy such as travel or tourism demand (Cooper, 2000; Starbuck et al., 2004, Wu et al., 2012).

The relevant literature regarding PT and demand analyses for our study will be reviewed in the following three essays. The essays in this thesis are motivated in part by the broad goal of better understanding price adjustment processes. The first two essays empirically investigate PT and both use time series methods and graphical models. The last essay discusses the demand issues related to the imports of fresh bananas in the U.S. market and applies consumer demand and graphical models.

CHAPTER II

VERTICAL PRICE TRANSMISSION AMONG INTERNATIONAL CROPS, OCEAN FREIGHT, AND TAIWAN MAJOR ANIMAL HUSBANDRY

2.1 Introduction

According to the statistics from Taiwan Council of Agriculture (COA), the top 5 most valuable sectors of agricultural production in Taiwan are hogs, rice, white broilers and colorful chickens, tuna, and hen eggs. Pork and poultry meat are major sources of meat consumption in Taiwan, averaging 89.80 and 77.03 pounds per person in 2017, and the consumption was about 6.79 and 5.83 times the amount of beef consumption, respectively. More than 84% of the poultry meat consumed is chicken. Moreover, egg consumption was estimated at about 337 eggs per person. More than 94% of eggs consumed are hen eggs. Although the demand for pork, chicken, and hen eggs mainly depends on domestic production, their import percentages gradually increased after joining the World Trade Organization (WTO) in 2002, except the import of hen eggs is still minimal. Since 1986, the gross output value of the hog industry exceeded that of rice and became number one among all agricultural products. Its export volume also sharply increased from about 50 thousand metric tons (tmt) in 1984 to a peak of 276.90 tmt in 1996. Taiwan was a net exporting country of pork from 1969 until the outbreak of foot-and-mouth disease in 1997. The Taiwan chicken-meat industry has two types of broilers: white and colored broilers. The typical breeds of colorful chickens in Taiwan are red- and black-feathered chickens. For domestic chicken production, the ratio of white broilers to colorful chickens was three to two in 2017. However, the production value of colorful chickens is higher than that of white broilers because a colorful chicken is more expensive than a white broiler in Taiwan. For the reason that colorful chicken are fed longer than white broilers to reach market weight, the muscles and gonads are more mature, and the meat quality is better than that of white broilers. Taiwan also fully opened chicken imports in 2005, and the import volume hit a record high in 2015. Because most of the imports of poultry meat are white broilers, even in 2015 the imported volume of white broilers accounted for up to 37.64% of the total supply of white broilers. Except for the egg industry, it is obvious that the hog and chicken industries have suffered from market competition since Taiwan has opened their markets to the world market.

According to Taiwan Agriculture Statistics Yearbook 2017, feed costs accounted for approximately 62.33%, 59.61%, and 76.73% of the production costs for hogs, white broilers, and laying hens, respectively. In general, hog and chicken feed is more than 50% of field corn and about 20% of soybeans. Thus, it is reasonable to believe that corn and soybean prices have a major influence on pork and chicken prices. Because both the degrees of self-sufficiency in field corn and soybeans are below 1%, their demand almost exclusively depends on imports. The main import sources for field corn and soybeans are the USA and Brazil. Thus, the fluctuations in the international prices of field corn and soybeans not only directly affect the import prices of feed but also indirectly affect the prices of pork, chicken, and hen eggs.

Figure 2.1 shows that there was a sharp increase in the prices of corn and soybeans during 2007-2008 because of the worldwide food price crisis. Although after the crisis the prices reduced to a lower level, the average prices in recent years were still higher than those before the crisis. High grain prices lead to increased production cost of feeding farm animals, which leads to a decreased profit margin because farmers can not easily transfer the increased costs to consumers. This forced the farmers to decrease outputs or quit farming. Between 2006 and 2008, average worldwide prices for corn and soybeans went up by 125% and 107% respectively, and the average prices of pork, chicken, and hen eggs increased 34%, 29%, and 47%, respectively (Figure 2.2).

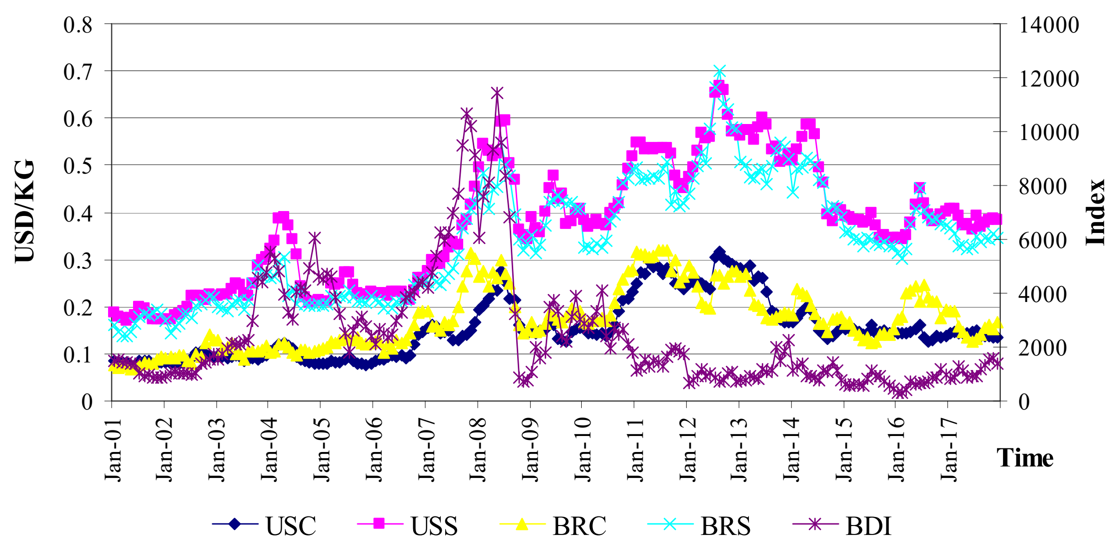


Figure 2.1. Monthly average prices of corn and soybean in the U.S. and Brazil and the average value of the Baltic Dry Index, 2001-2017

Notes: U.S. corn (USC), U.S. soybean (USS), Brazil corn (BRC), Brazil soybean (BRS), and Baltic Dry index (BDI).

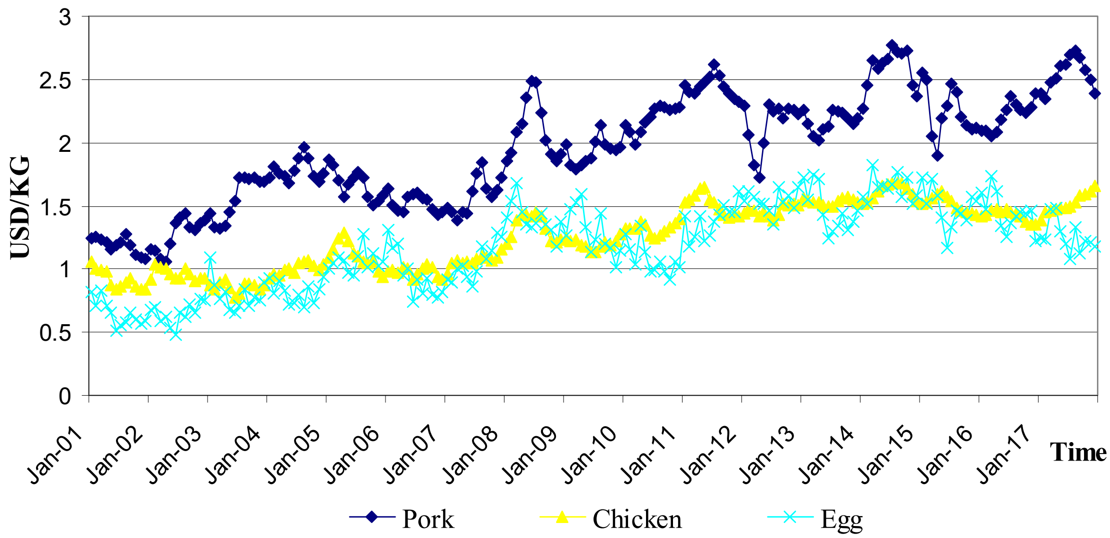


Figure 2.2. Monthly average prices of the selected livestock in Taiwan, 2001-2017
Notes: Farm prices for livestock except eggs by a retail price.

In addition, the global production of corn ethanol gradually increased as oil prices increased. It is expected that the strong increases in ethanol production would result in higher corn prices and an indirect increase in the production costs of stock farming. There has been considerable concern about how much the international prices of grains need to increase to shock Taiwanese animal husbandry. In the feeding process of farm animals, higher input prices could not only reduce the competitiveness of agricultural producers but also increase pricing on outputs. Moreover, the increases in prices of necessities of life would reduce consumer welfare. With this background, the objective of this essay is to use an appropriate time series model to examine the vertical transmission processes among the prices of Taiwanese pork, chicken, and hen eggs, international crop prices, and ocean freight rates, according to the properties of data. The paper is organized as follows. The related literature on the economic topics of VPT is presented in the next section of the paper. Then, the theoretical frameworks for linear and nonlinear cointegration tests and data sources are described. Following that, results and relevant discussions are presented. The summary of main findings is presented in the last section of the paper.

2.2 Literature Review

Analyses of vertical price transmission are extensively applied to agricultural commodities. For example, Kinnucan and Forker (1987) found that the price transmission process among American farm milk and four retail products which are fluid milk, butter, cheese, and ice cream is asymmetric by an econometric model using a pricing relationship between farm and retail prices. Cramon-Taubadel (1998) demonstrated that asymmetric price adjustment exists between the producer and wholesale pork prices in northern Germany. Goodwin and Holt (1999) and Goodwin and Harper (2000) used threshold cointegration models to investigate linkages among farm, wholesale, and retail markets in the U.S. beef and pork sectors, respectively. Both confirmed previous researchers' findings that the transmission of shocks is largely unidirectional and that information tends to flow from farm to wholesale and finally to retail markets. Jaffry (2004) applied the Engle and Granger two-step method, and the Enders and Granger threshold autoregression (TAR) and momentum autoregression (MTAR) approaches to analyze the relationship between auction and retail prices of whole hake in France. Zheng et al. (2010) used asymmetric error correction models (ECM), almost ideal demand systems (AIDS), and the Rotterdam demand models to estimate the welfare impact of asymmetric price transmission among producer, wholesale, and retail pork and beef prices for American consumers. Nakajima (2011) used TAR and repeated TAR models to investigate asymmetric relationship between U.S. domestic and export soybean prices. Asche et al. (2014) employed the Johansen test to investigate the relationship among French retail prices for fresh salmon fillets and smoked salmon and Norwegian export prices of salmon. Ahn and Lee (2015) applied a nonlinear autoregressive distributed lag (NLARDL) model to investigate the asymmetry of the price transmission in the marketing chain of shipping points and terminal markets for apples, table grapes, and peaches in the western U.S.

It is interesting how farm sector shocks, which work through crop prices, influence related food prices in the noncrop sectors of a certain economy. For example, Babula and Bessler (1990) found that the U.S. egg prices at the farm and retail levels rose after a positive shock of the U.S. corn prices happened and the response period persisted for 17 months. Babula et al. (1991) reported similar relationships among the U.S. corn, farm broiler, and retail broiler markets. Anderson and Trapp (2000) constructed a feeder-calf price model that contains elements of a break-even budget analysis to explore the relationship between the U.S. corn and feeder-calf prices. The results showed that feeder-calf prices are less sensitive to the fluctuation of corn prices than popular rules of thumb imply. Xu et al. (2011) found the degree of price transmission between corn and egg markets or feed and egg markets is larger than that between egg-laying chicken and egg markets in China.

For the literature of price transmission on the main animal husbandry in Taiwan, Huang and Wu (2008) showed that regional hog prices converge in the long run, and regional effects significantly affect the cross-city price volatility and price correlations. Lee (2010) reported that the speed of the price transmission to the retail price of pork while the producer price of pork was declining was faster than that, while the producer price of pork was increasing and that the bi-direction feedback relationship existed between farm and retail pork markets in Taiwan. Li et al. (2012) developed an industry-related price model to investigate the impacts of the price volatility of oil on production costs of industries and price levels in Taiwan and discovered that a 1% rise in international prices of crude oil causes an increase in production costs of hogs of 1.65%. Hwang and Yeh (2012) found that there is an asymmetric cointegration relationship between farm prices of chicken and feed prices. Hsu (2015) simulated the influence of increases in both gasoline and electricity prices on the agricultural sector and suggested that positive impacts on the pork, chicken, and hen egg industries are greater than their negative impacts, and rises in consumer prices of pork, chicken, and hen eggs are much greater than those in their farm prices.

2.3 Methodology

2.3.1 Linear Cointegration Tests

The relationship between the cointegration and error correction models was first introduced by Granger (1981) and then developed by Engle and Granger (1987). According to their definition, an *n*-dimensional vector of time series x_t is a cointegrated process of order *d* and *b* (*CI(d, b)*) if it satisfies two conditions: (a) Each series of x_t without deterministic components which has a stationary and invertible autoregressive moving average (ARMA) representation after differenced *d* times is said to be integrated of order *d*, denoted $x_t \sim I(d)$, and (b) there is existence of a linear combination of them so that $z_t = \alpha' x_t \sim I(d-b)$, $b > 0$. The vector α is called the cointegrating vector. In case of *d* = 1, *b* = 1, all components x_t are cointegrated and move together over time, and the distance among them is stable, i.e., the existence of a long-run equilibrium relationship among them. This implies that these time series could deviate from the equilibrium in the short run, but the equilibrating force would push them back towards the long-run relationship. Thus, in order to investigate the existence of a long-run equilibrium relationship among nonstationary time series, Engle and Granger (1987) proposed a two-step estimation procedure that allows explicit tests of the underlying assumption of cointegration. Let $x_t = [x_{1t}, \cdots, x_{Nt}]'$ denote the t^{th} observation on *N* time series. Each component of x_t is known to be *I(1)*. Suppose that there exists a vector α such that $z_t = [1,\ x_t]'\alpha$ is *I(0)*. In the first step, the parameters of the cointegrating vector are estimated generally by using the ordinary least squares (OLS) method in the following cointegrating regression:

$$(2.1)\quad x_{1t} = \alpha_1 + \sum_{i=2}^{N} \alpha_i x_{it} + \varepsilon_t, \quad t = 1, \cdots, T,$$

where ε_t are known as innovations. By the estimate of the true cointegrating vector, $\hat{\alpha} = [1, -\hat{\alpha}_1, \cdots, -\hat{\alpha}_N]'$, one could calculate

$$(2.2)\quad \hat{z}_t = [1,\ x_t]'\hat{\alpha} = x_{1t} - \hat{\alpha}_1 - \hat{\alpha}_2 x_{2t} - \cdots - \hat{\alpha}_N x_{Nt}.$$

In the second step, an augmented Dickey-Fuller (ADF) test is used to check whether a unit root is present in $\hat{z}_t$ and the test regression is

$$(2.3)\quad \Delta\hat{z}_t = \beta_0\hat{z}_{t-1} + \sum_{j=1}^{p}\beta_j\Delta\hat{z}_{t-j} + e_t\ ,$$

where P is the number of lags, β_0 and β_j are the coefficients, and e_t is a white-noise disturbance term. The lag P can be selected using the Akaike information criterion (AIC), Bayesian information criterion (BIC), Liung-Box tests, or other information criteria. One can run equation (2.3) and calculate the t statistic of β_0. If the null hypothesis that $\beta_0 = 0$ is rejected, it implies that there also is enough evidence to reject the null hypothesis of no cointegration in Engle-Granger (EG) tests. Note that it is very important to search appropriate lag length such that the residual process e_t is white noise.

Johansen (1988, 1991) derived the maximum likelihood estimator of the space of cointegration vectors and the likelihood ratio test of the hypothesis that it has a given number of dimensions. Consider a vector autoregression (VAR) model of order P as follows:

$$(2.4)\quad x_t = \Pi_1 x_{t-1} + \cdots + \Pi_p x_{t-p} + \mu + \Phi D_t + \varepsilon_t\ ,\quad t = 1,2,\cdots,T\ ,$$

where x_t is a $(N \times 1)$ vector of series at period t and is allowed to be non-stationary (*I(1)*), $\Pi_i (i = 1,\cdots,p)$ are $(N \times N)$ coefficient matrices of the lagged endogenous variables, μ is a $(N \times 1)$ vector of constants, D_t is a vector of non-stochastic variables such as seasonal or intervention dummies, and ε_t is an independent N-dimensional Gaussian variable with mean zero and variance matrix Λ.

It is convenient to rewrite equation (2.4) in an error correction form

(2.5) $\Delta x_t = \sum_{i=1}^{p-1} \Gamma_i \Delta x_{t-i} + \Pi x_{t-p} + \mu + \Phi D_t + \varepsilon_t$, $\quad t = 1,2,\cdots,T$,

where $\Gamma_i = -(I - \Pi_1 - \cdots - \Pi_i)$ for $i = 1,\cdots,p-1$. $\Pi = -(I - \Pi_1 - \cdots - \Pi_p)$. $\Delta = 1 - L$ with the lag operator L and I is a $(N \times N)$ identity matrix.

Because each component of x_t is at most *I(1)* series, the left-hand side (LHS) of equation (2.5) is stationary. In order to maintain the balance of equation (2.5), Πx_{t-p} must also be stationary. There are three possible cases:

(i) $rk(\Pi) = N,$

(ii) $rk(\Pi) = 0,$

(iii) $0 < rk(\Pi) = r < N,$

where $rk(\cdot)$ is the rank of a matrix. In the first case the matrix Π has full rank; this implies that there exist N linear combinations $\sum_{i=1}^{N} \alpha_i x_{it} = z_t$ such that $\{z_t\}$ is stationary. Only if all variables in the vector process x_t are stationary, the first case could exist. In the second case, the matrix Π has zero rank; it indicates that there is not any linear combination of x_t such that $\{z_t\}$ is stationary except for the trivial solution. All $x's$ are non-stationary. Thus, in this case equation (2.5) corresponds to a VAR model in first differences. The third case is the focus of this cointegration test. It implies the existence of two $(N \times r)$ matrices α and β such that $\Pi = \alpha\beta'$ where α represents the average speed of convergence towards long-run equilibrium, and β denotes the cointegrating vectors. Then, $\alpha\beta' x_{t-p}$ is stationary. By the property of β,

$\beta' x_{t-p}$ also is stationary even if x_t itself is non-stationary. In this case, equation (2.5) is a vector error correction model (VECM).

Johansen (1988, 1991) showed that the likelihood-ratio test statistic for $H_0 : rk(\Pi) \le r$ or $\Pi = \alpha\beta'$ is

(2.6) $-2\ln(Q) = -T\sum_{i=r+1}^{N} \ln(1-\hat{\lambda}_i)$,

where Q denotes the likelihood ratio of the null model to alternative model, and $\hat{\lambda}_{r+1},\cdots,\hat{\lambda}_N$ are the $N-r$ smallest eigenvalues of the equation $\left|\lambda\hat{S}_{pp} - \hat{S}_{p0}\hat{S}_{00}^{-1}\hat{S}_{0p}\right| = 0$ with the product moment matrices

(2.7) $\hat{S}_{ij} = T^{-1}\sum_{t=1}^{T} R_{it}R'_{jt}, \quad i, j = 0,\ p,$

where the residuals R_{0t} and R_{pt} are obtained by regressing Δx_t and x_{t-p} on $\Delta x_{t-1},\cdots,\Delta x_{t-p+1}, D_t,$ and 1, respectively.

Moreover, Johansen and Juselius (1990) proposed the following likelihood ratio test statistic for testing $H_0 : rk(\Pi) = r$ against $H_A : rk(\Pi) = r+1$.

(2.8) $-2\ln(Q; r \mid r+1) = -T\ln(1-\hat{\lambda}_{r+1})$.

2.3.2 Nonlinear Cointegration Test

The above-mentioned cointegration tests assume that the presence of cointegration among non-stationary variables represents such a tendency to move toward a long-run equilibrium is present every period. However, it is possible for changes of the cointegration parameters or of the existence of cointegration relationships at unknown periods. Balke and Fomby (1997) introduced the concept of discrete adjustment into long-run equilibrium relationships among the variables in hand and proposed a two-step approach for checking whether so-called “threshold” effects on the cointegrating relationships exist. The first step utilizes a linear cointegration test such as Engel-Granger approach to examine whether a long-run relationship is present. If there is enough evidence to reject $H_0:$ no cointegration, he developed a sup-Wald test to check whether threshold effects are present in the time series in the second step.

For the above-mentioned Engle-Granger test assuming symmetric adjustment ant its extensions, the statistical inference would be misspecified if the adjustment is asymmetric. Thus, Enders and Siklos (2001) introduced the concept of asymmetric adjustment into the long-run cointegration relationship of the Engle-Granger test. The alternative model modifies equation (2.3) such that:

(2.9) $\Delta\hat{z}_t = I_t\rho_1\hat{z}_{t-1} + I_t\rho_2\hat{z}_{t-1} + \sum_{j=1}^{p}\beta_j\Delta\hat{z}_{t-j} + e_t$,

(2.10a) $I_t = \begin{cases} 1 & \text{if } \hat{z}_{t-1} \geq \tau , \\ 0 & \text{if } \hat{z}_{t-1} < \tau \text{ ; or} \end{cases}$

(2.10b) $I_t = \begin{cases} 1 & \text{if } \Delta\hat{z}_{t-1} \geq \tau , \\ 0 & \text{if } \Delta\hat{z}_{t-1} < \tau , \end{cases}$

where I_t is the Heaviside indicator, P is the number of lags, ρ_1, ρ_2 and β_j are the coefficients, and τ is the threshold value.

Models made up of equation (2.9) and (2.10a) are called the TAR models, while those formed using equation (2.9) and (2.10b) are named as the MTAR models. The appropriate lag length in equation (2.9) could be selected using the AIC or the BIC. According to Petruccelli and Woolford's (1984) proof, the process $\{z_t; t \geq 0\}$ is stationary when ρ_1 and ρ_2 satisfy the following necessary and sufficient conditions: $\rho_1 < 0$, $\rho_2 < 0$, and $(1+\rho_1)(1+\rho_2) < 1$ for any value of τ. If the above-mentioned conditions are fulfilled, $\hat{z}_t = 0$ can be regarded as the long-run equilibrium value of the system and then $x_{1t} = \hat{\alpha}_1 - \hat{\alpha}_2 x_{2t} - \cdots - \hat{\alpha}_N x_{Nt}$. Generally, the threshold value, τ, is unknown and needs to be estimated along with the values of ρ_1 and ρ_2 if the various $\{x_{it}\}$ are cointegrated, whereas there is no threshold and the value of ρ_1 and/or ρ_2 is equal to zero if the various $\{x_{it}\}$ are not cointegrated. Thus, when the threshold value τ exists, TAR (MTAR) threshold adjustment is $\rho_1 \hat{z}_{t-1}$ ($\rho_1 \Delta\hat{z}_{t-1}$) if $\hat{z}_{t-1}$ ($\Delta\hat{z}_{t-1}$) is over its long-run equilibrium value and $\rho_2 \hat{z}_{t-1}$ ($\rho_2 \Delta\hat{z}_{t-1}$) if $\hat{z}_{t-1}$ ($\Delta\hat{z}_{t-1}$) is under the long-run equilibrium value. Two tests are employed to understanding the asymmetric adjustments in the content of a long-run cointegration relationship. First, an *F*-test is applied to examine the null hypothesis of no cointegration $(H_0 : \rho_1 = \rho_2 = 0)$ against the alternative of cointegration with either TAR or M-TAR threshold adjustment. The test statistic is called Φ, does not follow a standard distribution, and its critical values in Enders and Siklos (2001) could be used. Second, a standard *F*-test is employed to test the null hypothesis of symmetric adjustment in the long-run equilibrium $(H_0 : \rho_1 = \rho_2)$ against the alternative of the existence of an asymmetric adjustment process.

2.3.3 Autoregressive Distributed Lag Model

To investigate the long-run relationship of the pork, chicken, and egg VPT and see how much international crop prices (corn and soybeans) and ocean freight rates can explain the changes of Taiwanese pork, chicken, and egg prices, we begin with the following multivariate regression model:

(2.11)

$$y_{it} = \beta_0 + \beta_1 * USC_t + \beta_2 * USS_t + \beta_3 * BRC_t + \beta_4 * BRS_t + \beta_5 * BDI_t + \varepsilon_t, \qquad t = 1, \cdots, T,$$

where $i = 1,2,3$ denote Taiwanese pork, chicken, and egg prices, respectively, USC_t and USS_t are U.S. corn and soybean prices, respectively, BRC_t and BRS_t are Brazilian corn and soybean prices, respectively, BDI_t is a shipping and trade index that measures shipping costs for dry bulk commodities such as grain and metals, and ε_t are known as innovations. The OLS estimators of Equation (2.11) are said to be super-consistent if cointegration among the nonstationary variables is established. In order to assess the short-run effects, we follow Pesaran et al. (2001) and transform equation (2.11) to the error correction form of a linear ARDL (LARDL) model as in equation (2.12):

(2.12)

$$\Delta y_{it} = a + \sum_{i=1}^{n1} b_{1i} \Delta y_{it-i} + \sum_{i=0}^{n2} b_{2i} \Delta USC_{t-i} + \sum_{i=0}^{n3} b_{3i} \Delta USS_{t-i} + \sum_{i=0}^{n4} b_{4i} \Delta BRC_{t-i} + \sum_{i=0}^{n5} b_{5i} \Delta BRS_{t-i} +$$
$$\sum_{i=0}^{n6} b_{6i} \Delta BDI_{t-i} + c_1 y_{it-1} + c_2 USC_{t-1} + c_3 USS_{t-1} + c_4 BRC_{t-1} + c_5 BRS_{t-1} + c_6 BDI_{t-1} + e_t,$$

where coefficients of the first differenced variables, b_{2i}-b_{6i}, represent the short-run effects of international crop prices and shipping cost on Taiwanese pork, chicken and egg prices, respectively and long-run effects can be obtained by estimating coefficients of the lagged level of international crop prices and shipping cost, c_2-c_6, normalized on c_1.

AIC, BIC, or other information criteria can be used to determine the optimum lag length in equation (2.12). However, in order to avoid spurious estimates, cointegration must be established. Pesaran et al. (2001) developed a bounds testing procedure to check the existence of a relationship among variables in levels which is applicable irrespective of whether the underlying repressors are purely $I(0)$, purely $I(1)$ or mutually cointegrated. They suggest using the F-statistic for testing joint significance of lagged level variables, c_2-c_6, in equation (2.12). Since the distribution and critical values of the F-statistic is different from conventional F-statistic, they provide lower and upper bounds for the asymptotic critical values of the F-bounds test. The lower bound values assume that all variables in a model are purely $I(0)$, and the upper bound values assume that those are purely $I(1)$. If the computed F-statistic is more than the upper bound critical value, the null hypothesis of no cointegration can be rejected. Similarly, the null hypothesis cannot be rejected if the computed F-statistic is less than the lower bound value. However, if the computed F-statistic falls between the lower and upper bound values, statistical inference would be inconclusive.

To assess the asymmetric effects of international crop prices and ocean freight rates on Taiwanese pork, chicken, and egg prices, we follow Shin et al. (2014) to build an ARDL model with an asymmetric cointegration. First, international crop prices and ocean freight rates are divided into the partial sum processes of positive and negative changes as outlined by specification equation (2.13):

$$(2.13)\quad x_t^+ = \sum_{j=1}^{t} \max(\Delta x_j, 0), \qquad x_t^- = \sum_{j=1}^{t} \min(\Delta x_j, 0),$$

where x denotes USC, USS, BRC, BRS, or BDI. Then, the error-correction form in equation (2.12) can be rewritten by replacing USC, USS, BRC, BRS, and BDI with the two partial sum variables as follows:

(2.14)

$$
\begin{aligned}
&\Delta y_{it} = a + \sum_{i=1}^{n1} \gamma_{1i} \Delta y_{it-i} + \sum_{i=0}^{n2} \gamma_{2i} \Delta USC_{t-i}^{+} + \sum_{i=0}^{n3} \gamma_{3i} \Delta USC_{t-i}^{-} + \sum_{i=0}^{n4} \gamma_{4i} \Delta USS_{t-i}^{+} + \sum_{i=0}^{n5} \gamma_{5i} \Delta USS_{t-i}^{-} + \\
&\sum_{i=0}^{n6} \gamma_{6i} \Delta BRC_{t-i}^{+} + \sum_{i=0}^{n7} \gamma_{7i} \Delta BRC_{t-i}^{-} + \sum_{i=0}^{n8} \gamma_{8i} \Delta BRS_{t-1}^{+} + \sum_{i=0}^{n9} \gamma_{9i} \Delta BRS_{t-i}^{-} + \sum_{i=0}^{n10} \gamma_{10i} \Delta BDI_{t-i}^{+} + \\
&\sum_{i=0}^{n11} \gamma_{11i} \Delta BDI_{t-i}^{-} + \theta_1 y_{it-1} + \theta_2 USC_{t-1}^{+} + \theta_3 USC_{t-1}^{-} + \theta_4 USS_{t-1}^{+} + \theta_5 USS_{t-1}^{-} + \theta_6 BRC_{t-1}^{+} + \\
&\theta_7 BRC_{t-1}^{-} + \theta_8 BRS_{t-1}^{+} + \theta_9 BRS_{t-1}^{-} + \theta_{10} BDI_{t-1}^{+} + \theta_{11} BDI_{t-1}^{-} + u_t .
\end{aligned}
$$

The error correlation form of the NLARDL model in equation (2.14) can simultaneously analyze the asymmetric effects on both the underlying long-run relationship and the patterns of dynamic adjustment. Shin et al. (2014) followed Pesaran et al. (2001) and developed a NLARDL bound test to check the null hypothesis that an asymmetric long-run level relationship exists in equation (2.14). Similarly, this approach is applicable irrespective of whether the underlying repressors are purely $I(0)$, purely $I(1)$ or mutually cointegrated. Moreover, the null hypothesis of symmetric long-run or short-run coefficients can be tested using the Wald statistic following an asymptotic Chi-square distribution.

2.4 Data

A price transmission analysis, just as its name implies, is conducted to discover the connections among prices of theoretically-related commodities by time series data. This study considers monthly international prices for corn and soybeans and farm prices for Taiwanese hogs, white broilers, and hen eggs because of the difficulties of obtaining daily prices of Taiwanese agricultural products. In addition, we also want to know whether ocean freight rates affect these farm prices because Taiwanese corn and soybean imports depend on ocean shipping. The time span of observation is from January 2001 to December 2017 for the analyzed price series. The starting period reflects data availability. During the period, the Taiwanese hog industry has been a fully open market since 2005 (Taiwan joined the WTO in 2002). The information regarding monthly farm prices for Taiwanese hogs, white broilers, and hen eggs comes from the Taiwan COA. Monthly futures prices of the U.S. corn and soybeans are obtained from the Chicago Board of Trade (CBOT). Because we are unable to collect enough monthly futures prices of Brazilian corn and soybeans, we use Brazilian wholesale prices to replace them. The Baltic freight index (BFI) was first published on January 4, 1985 to get a sense of global shipping freight rates and was replaced by the BDI on November 1, 1999. The monthly BDI is obtained from the Consumer News and Business Channel (CNBC).

2.5 Empirical Results

The descriptive statistics for farm prices of pigs, white broilers, and hen eggs; international prices of corn and soybeans; and the BDI are presented in Table 2.1. Although the standard deviation (SD) value for the BDI cannot be compared with those of price series due to different units of measurement, the coefficient of variation (CV) suggests that the BDI has a high degree of fluctuation. Both the SD and CV of chicken prices are the lowest of selected livestock in Taiwan. For international prices of the selected crops, except for the CV, the values of all statistics can be grouped into two types: corn and soybeans, i.e., they have similar values within each group, respectively. Moreover, the CV reveals that all domestic prices of the selected livestock in Taiwan are less dispersed than the international prices of corn and soybeans, but the SD obtains opposite results, i.e., it suggests that all domestic prices of the selected livestock are more variable than the international prices of corn and soybeans.

Table 2.1. Descriptive Statistics for Monthly Prices (USD/KG) of the Selected Agricultural Products and the Baltic Dry Index, 2001-2017

Variable	Mean	Maximum	Minimum	SD	CV
Taiwan					
Pork	1.95	2.77	1.06	0.44	0.22
Chicken	1.25	1.68	0.78	0.26	0.20
Egg	1.17	1.82	0.48	0.34	0.29
Foreign crops					
U.S. corn	0.15	0.32	0.08	0.06	0.42
U.S. soybean	0.37	0.67	0.17	0.13	0.35
Brazil corn	0.17	0.32	0.07	0.07	0.38
Brazil soybean	0.34	0.70	0.14	0.12	0.36
Baltic Dry Index	2470.60	11440.00	317.00	2201.85	0.89

Notes: SD and CV represent the standard deviation and the coefficient of variation, respectively.

As a rule, nonstationary data cannot be modeled or forecasted because the results obtained by using nonstationary time series might be spurious. Thus, in order to obtain consistent and reliable results for analyzed time series, unit root tests on levels and the first differences of the data were conducted. Results of both the ADF and PP tests are presented in Table 2.2. The null hypothesis of both tests is that each evaluated series is nonstationary. The number of augmenting lags for the ADF test is determined by minimizing the BIC. The statistics of both the ADF and PP tests reveal that unit roots cannot be rejected at the 5% significance level for all time-series in levels but can be rejected for the first differences. Thus, it is concluded that in levels, all time-series are nonstationary, however in their first differences they are stationary. That is to say, they are integrated of order one.

Table 2.2. Unit Root Tests in the Level and First Difference of Monthly Price Series and the Baltic Dry Index, 2001-2017

Variable	ADF		PP	
	Level	1st diff.	Level	1st diff.
Pork	-1.980 (2)	-11.207 (1)**	-1.944 (4)	-9.903 (4)**
Chicken	-1.068 (2)	-10.246 (1)**	-1.081 (4)	-9.399 (4)**
Egg	-2.352 (1)	-19.304 (0)**	-2.428 (4)	-20.857 (4)**
U.S. corn	-1.961 (1)	-10.993 (0)**	-1.909 (4)	-11.088 (4)**
U.S. soybean	-2.271 (1)	-9.994 (0)**	-2.030 (4)	-9.901 (4)**
Brazil corn	-2.817 (2)	-7.941 (1)**	-2.467 (4)	-13.315 (4)**
Brazil soybean	-1.923 (0)	-8.657 (2)**	-2.060 (4)	-13.112 (4)**
Baltic Dry Index	-2.873 (1)	-8.980 (3)**	-2.509 (4)	-10.480 (4)**

Notes: The data are transformed by taking natural logarithms. The numbers in parentheses indicate the lag order in the ADF test and the bandwidth using the Newey-West bandwidth selection method and the Bartlett kernel in the PP test, respectively. The default bandwidth is the integer part of $4 \times (T/100)^{2/9}$ where T is the sample size. ** denotes significance at the 5% level.

2.5.1 Johansen Cointegration Test

Using the Johansen and Engle-Granger approaches, a linear cointegration analysis is conducted. First, the Johansen approach requires the determination of a lag length for the VAR representation of a VECM. The VECM will include one fewer lag of the first differences. Based on the lowest AIC, the optimal lag lengths for the VECM of the pork, chicken, and egg VPT should be 2, 1, and 2, respectively. Without prior information, five model specifications with different deterministic trend assumptions in level data and cointegrating equations are estimated (Table 2.3). For the pork VPT, except for the second and fifth models, the Johansen trace and maximum eigenvalue statistics have the same results for all of the models. However, only one model has the same result for the chicken and egg VPT. Johansen and Juselius (1990) recommend the use of the trace statistic when these two statistics provide conflicting results. Moreover, the trace statistic considers all of the smallest eigenvalues and holds more power than the maximum eigenvalue statistic (Kasa, 1992; Serletis and king, 1997). Thus, when the results of two statistics produce a contradiction in a certain model, the number of cointegrating vectors is determined by the trace statistic.

Table 2.3. Johansen Tests for the Order of Cointegration in 5 Trend Assumptions

Data trend	None	None	Linear	Linear	Quadratic
ECT	None	Intercept	Intercept	Intercept Trend	Intercept Trend
Panel A: Pork vertical price transmission					
Trace	1	1	2	1	2
Max. eigenvalue	1	2	2	1	1
Panel B: Chicken vertical price transmission					
Trace	1	1	2	1	2
Max. eigenvalue	0	1	1	0	0
Panel C: Egg vertical price transmission					
Trace	2	2	2	1	2
Max. eigenvalue	1	1	1	1	1

Notes: Selected number of cointegrating relations at the 5% significance level. ECT denotes the error correction terms in a vector error correction model.

The values of the BIC for each model with different cointegrating ranks (r) are shown in Table 2.4. Based on the lowest BIC values for five models with selected r

values from Johansen's trace statistic, model 2 (r=1), model 2 (r=1), and model 4 (r=1) are the best models for the pork, chicken, and egg VPT, respectively. Their best models imply that the number of cointegration vectors is one.

Table 2.4. Schwarz Criteria by Ranks (Row) and Models (Column)

Data trend	None	None	Linear	Linear	Quadratic
ECT	None	Intercept	Intercept	Intercept Trend	Intercept Trend
Panel A: Pork vertical price transmission					
r=1	-12.976	**-12.993**	-12.868	-12.845	-12.719
r=2	-12.778	-12.824	-12.725	-12.678	-12.579
Panel B: Chicken vertical price transmission					
r=0	-14.268	-14.268	-14.116	-14.116	-13.966
r=1	-14.131	**-14.134**	-14.009	-13.987	-13.863
r=2	-13.913	-13.931	-13.832	-13.805	-13.707
Panel C: Egg vertical price transmission					
r=1	-11.266	-11.242	-11.115	**-11.098**	-10.973
r=2	-11.075	-11.061	-10.960	-10.916	-10.818

Notes: ECT denotes the error correction terms in a vector error correction model.

2.5.2 Engle-Granger and Enders-Siklos Cointegration Tests

Similarly, the Engle-Granger cointegration test is executed to check the null hypothesis that cointegration does not exist among time-series of interest through a two-step procedure. The Ljung-Box test is conducted to see if the residuals e_t are serially correlated in five cointegration models. In the first step, the long-run relationships among variables of the pork, chicken, or egg VPT are estimated, as specified in equation (2.2). In the second step, the residual is used to conduct a unit root test, as specified in equation (2.3). As reported in Table 2.5-2.7, based on the lowest AIC and BIC values, one, two, and zero lag order(s) of the linear AR(p) are selected for the pork, chicken, and egg VPT, respectively. The values of the unit root test statistic are -0.167, -0.127, and -0.298 respectively and are significant at the 1% level. Thus, the Enger-Granger approach also confirms that variables for each VPT are cointegrated, i.e., there is a correlation among these time series of each VPT in the long term.

Table 2.5. Engle-Granger and Enders-Siklos Cointegration Tests for the Pork Vertical Price Transmission

Item	Engle-Granger	TAR	Consistent TAR	MTAR	Consistent MTAR
Lags	1	1	1	1	1
Threshold		0	-0.141	0	-0.014
ρ_1	-0.167***	-0.195***	-0.257***	-0.198***	-0.217***
	(-4.84)	(-3.86)	(-4.10)	(-4.32)	(-4.44)
ρ_2		-0.144***	-0.131***	-0.129**	-0.121**
		(-3.15)	(-3.28)	(-2.58)	(-2.60)
Diagnostics					
AIC	-582.500	-581.084	-583.462	-581.572	-582.624
BIC	-575.883	-571.159	-573.538	-571.647	-572.699
$Q_{LB}(4)$	0.205	0.2118	0.226	0.173	0.196
$Q_{LB}(8)$	0.132	0.1401	0.192	0.106	0.106
$Q_{LB}(12)$	0.113	0.1230	0.167	0.084	0.079
Hypothesis					
$\Phi(H_0: \rho_1=\rho_2=0)$		11.99***	13.31***	12.26***	12.84***
		[0.000]	[0.000]	[0.000]	[0.000]
$F(H_0: \rho_1=\rho_2)$		0.58	2.94*	1.06	2.10
		[0.449]	[0.088]	[0.305]	[0.149]

Notes: TAR and MTAR denote the threshold autoregression and momentum threshold autoregression models, respectively. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The *t*-statistics and *p* values are states in parenthesis and bracket, respectively. $Q_{LB}(k)$ denotes the *p*-value of Ljung-Box Q statistics with *k* lags.

The nonlinear cointegration analysis is conducted using the TAR models. Four models (TAR, MTAR and their consistent counterparts) were examined, and the results are reported in Table 2.5-2.7. The length of lags for the lagged first differences of $\hat{z}_t$

can be determined by an analysis of the regression residuals and/or using information criteria. It is selected by the lowest AIC and BIC values in this study, and one-lagged and two-lagged changes are used in all four TAR models of the pork and chicken VPT, respectively. However, for the egg VPT, zero-lagged change used in the first three TAR models is different from one-lagged change used in the consistent MTAR model.

Table 2.6. Engle-Granger and Enders-Siklos Cointegration Tests for the Chicken Vertical Price Transmission

Item	Engle-Granger	TAR	Consistent TAR	MTAR	Consistent MTAR
Lags	2	2	2	2	2
Threshold		0	0.114	0	0.045
ρ_1	-0.127***	-0.152***	-0.154***	-0.145***	-0.157***
	(-3.66)	(-3.24)	(-3.52)	(-2.87)	(-4.24)
ρ_2		-0.102**	-0.089*	-0.114**	0.019
		(-2.18)	(-1.72)	(-2.56)	(0.25)
Diagnostics					
AIC	-669.470	-668.106	-668.489	-667.701	-672.301
BIC	-659.560	-654.892	-655.275	-654.488	-659.087
$Q_{LB}(4)$	0.999	0.999	0.998	0.998	0.980
$Q_{LB}(8)$	0.239	0.240	0.251	0.214	0.360
$Q_{LB}(12)$	0.096	0.091	0.102	0.086	0.130
Hypothesis					
$\Phi(H_0: \rho_1=\rho_2=0)$		7.00***	7.20***	6.78***	9.22***
		[0.001]	[0.001]	[0.001]	[0.000]
$F(H_0: \rho_1=\rho_2)$		0.62	1.00	0.23	4.79**
		[0.430]	[0.318]	[0.6345]	[0.030]

Notes: TAR and MTAR denote the threshold autoregression and momentum threshold autoregression models, respectively. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The *t*-statistics and *p* values are states in parenthesis and bracket, respectively. $Q_{LB}(k)$ denotes the *p*-value of Ljung-Box Q statistics with *k* lags.

Moreover, except for the threshold value which is set equal to zero, the threshold values with the lowest sum of squared errors are estimated to be -0.141, 0.114, and -

0.146 for the consistent TAR model of the pork, chicken, and egg VPT respectively. The threshold values with the lowest sum of squared errors are estimated to be -0.014, 0.045, and -0.145 for the consistent MTAR model of the pork, chicken, and egg VPT, respectively.

Table 2.7. Engle-Granger and Enders-Siklos Cointegration Tests for the Egg Vertical Price Transmission

Item	Engle-Granger	TAR	Consistent TAR	MTAR	Consistent MTAR
Lags	0	0	0	0	1
Threshold		0	-0.146	0	-0.145
ρ_1	-0.298***	-0.273***	-0.186**	-0.256***	0.072
	(-5.98)	(-3.92)	(-2.54)	(-3.52)	(0.49)
ρ_2		-0.325***	-0.392***	-0.335***	-0.295***
		(-4.54)	(-5.86)	(-4.90)	(-5.34)
Diagnostics					
AIC	-285.490	-283.772	-287.820	-284.1096	-288.267
BIC	-282.177	-277.146	-281.194	-277.4832	-278.342
$Q_{LB}(4)$	0.211	0.227	0.277	0.2510	0.487
$Q_{LB}(8)$	0.146	0.155	0.173	0.1535	0.112
$Q_{LB}(12)$	0.001	0.001	0.001	0.0009	0.000
Hypothesis					
$\Phi(H_0: \rho_1=\rho_2=0)$		17.97***	20.36***	18.17***	14.84***
		[0.000]	[0.000]	[0.000]	[0.000]
$F(H_0: \rho_1=\rho_2)$		0.28	4.33**	0.61	5.85**
		[0.5977]	[0.0386]	[0.4340]	[0.017]

Notes: TAR and MTAR denote the threshold autoregression and momentum threshold autoregression models, respectively. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The *t*-statistics and *p* values are states in parenthesis and bracket, respectively. $Q_{LB}(k)$ denotes the *p*-value of Ljung-Box Q statistics with *k* lags.

As shown in the fourth and fifth columns of Table 2.5, the point estimates for ρ_1 and ρ_2 of the four TAR models of the pork VPT are significantly different from zero at the 5% level. The sample values of Φ are more than the 5% critical value. Therefore, we can reject the null hypothesis that there is no cointegration. Moreover, the consistent TAR model has the lowest AIC statistic of -583.462 and BIC statistic of -573.538 among the four TAR models of the pork VPT. However, all *p* values of the *F* statistic are more than 5% in Table 2.5, and we cannot reject the null hypothesis of symmetric adjustment. Thus, the adjustment process is symmetric when the price series of the pork VPT adjust to achieve the long-run equilibrium.

The results of the four TAR models for the chicken VPT are reported in Table 2.6. The sample values of Φ are more than the 5% critical value, so we can reject the null hypothesis of no cointegration. The consistent TAR model has the lowest AIC statistic of -668.489, while the consistent MTAR model has the lowest BIC statistic of -659.087. Because the point estimates for ρ_2 of the consistent TAR and MTAR models are not significantly different from zero at the 5% level, the asymmetric speed of adjustment does not exist. For the TAR and MTAR models, the point estimates for ρ1 and ρ2 are significantly different from zero at the 5% level. However, because *p* values of the *F* statistic are more than 5%, we cannot reject the null hypothesis of symmetric adjustment. Thus, the speed of adjustment is symmetric when the price series of the chicken VPT adjust to achieve the long-run equilibrium.

The results of the four TAR models for the egg VPT are reported in Table 2.7. The sample values of Φ are more than the 5% critical value, and we can reject the null hypothesis of no cointegration. The consistent MTAR model has the lowest AIC statistic of -288.267, while the consistent TAR model has the lowest BIC statistic of -281.194. Because the point estimate for ρ_1 of the consistent MTAR model is not significantly different from zero at the 5% level, the asymmetric speed of adjustment does not exist. For the TAR and MTAR models, the point estimates for ρ1 and ρ2 are significantly different from zero at the 5% level. However, because *p* values of the *F* statistic are more than 5%, we cannot reject the null hypothesis of symmetric adjustment. Thus, the asymmetric speed of adjustment only exists in the consistent TAR model. To conserve space, only coefficients of the error correction terms in the consistent TAR model are represented in Table 2.8. We imposed a maximum of twelve lags and used a general-to-specific approach to identify the right number of lags, i.e. trim down lags if higher lags are found to be statistically insignificant at the 5% level. The Ljung-Box test shows that the null hypothesis that residuals are not serially correlated cannot be rejected, implying the residuals follow a whiter noise process. The *F* statistic has a *p*-value of 0.035 below a significance level of 5%, and the null hypothesis of symmetric speed of adjustment can be rejected. However, the point estimate of the coefficient for a negative error correction term is insignificantly different from zero at the 5% level. Thus, the model suggests that positive discrepancies from long-run equilibrium are eliminated rather quickly but that others are allowed to persist.

Table 2.8. Estimates of the Asymmetric Error Correction Model for the Egg Vertical Price Transmission

ECT_{t-1}^{+}	ECT_{t-1}^{-}	H_0: $\delta^{+}=\delta^{-}=0$	H_0: $\delta^{+}=\delta^{-}$	$Q_{LB}(12)$
-0.320***	-0.099	17.31***	4.43**	0.585
(-4.00)	(-1.36)	[0.000]	[0.035]	

Notes: ECT denotes the error correction terms in a vector error correction model. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The *t*-statistics and *p* values are states in parenthesis and bracket, respectively. $Q_{LB}(k)$ denotes the *p*-value of Ljung-Box Q statistics with *k* lags.

2.5.3 LARDL and NLARDL Models

We first estimate LARDL models for the pork, chicken, egg VPT outlined by equation (2.12) and then estimate their NLARDL models to find out whether asymmetric effects of international crop prices and ocean shipping rates exist in long-run equilibrium relationships. We use the AIC to select an optimal lag specification for LARDL and NLARDL models and then use the approach of general-to-specific modeling to drop insignificantly lagged-level variables. In other words, *p*-values for the variables are less than a pre-specified significance level. For each VPT, the results are reported in Table 2.9. Panel A and Panel B show the long-run normalized estimated coefficients and some related diagnostic statistics of LARDL and NLARDL models, respectively. Because the values of the *F*-bounds statistic for all models exceed the upper bound at the 1% significance level, we can conclude that there is enough evidence to reject the null hypothesis of no cointegrating relationships among variables for each model.

The Breusch-Godfrey Lagrange multiplier test statistic is reported as BG, and its values reveal statistical insignificance for all models, i.e., their residual series can be regarded as free of autocorrelation at the 0.05% significance level. In addition, the null hypothesis of the Breusch-Pagan-Godfrey (BPG) test that residuals are homoscedastic is rejected for the models of the chicken VPT. Thus, robust standard errors are applied to them. The Ramsey's regression equation specification error test (RESET) is also reported to check on model misspecification. The test results are statistically insignificant in all models, i.e., the functional form for each model is correctly specified.

Table 2.9. Estimates of the Linear (LARDL) and Nonlinear (NLARDL) Autoregressive Distributed Lag Models

	Pork		Chicken		Egg	
	LARDL	NLARDL	LARDL	NLARDL	LARDL	NLARDL
Panel A: Long-run estimates						
USC	-0.818***	-0.324***			-0.466**	
	(-3.644)	(-2.668)			(-2.559)	
USC^+						-0.325**
						(-1.985)
USC^-						-0.383**
						(-2.408)
USS	1.439***		0.253***			
	(5.475)		(3.615)			
USS^+		1.344***		0.300***		
		(4.413)		(6.567)		
USS^-		1.275***		0.629***		
		(4.104)		(4.751)		
BRC					0.552***	0.494***
					(3.687)	(3.874)
BRS		-0.638**			0.663***	0.405***
		(-2.456)			(4.216)	(2.640)
BDI	0.078**		0.030***			
	(2.599)		(2.602)			
BDI^+				0.177***		
				(2.630)		
BDI^-				0.068**		
				(1.991)		
Constant		-1.634***			0.984***	1.521***
		(-2.972)			(6.721)	(3.658)
Trend			0.002***			
			(9.539)			

Notes: *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The *t*-statistics are states in parenthesis. U.S. corn (USC), U.S. soybean (USS), Brazil corn (BRC), Brazil soybean (BRS), and Baltic Dry index (BDI).

The stability of long-run coefficient estimates is measured by cumulative sum (CS) and cumulative sum-of-squares (CS^2) tests of recursive residuals for each model. "S" and "US" indicate that estimated coefficients of a model are stable and unstable, respectively. Clearly all long-run estimated coefficients for each model are stable except for the models of the chicken VPT. In other words, their values of the CS^2 statistic are outside the 5% significance lines, and the null hypothesis is rejected.

Table 2.9. Continued

	Pork		Chicken		Egg	
	LARDL	NLARDL	LARDL	NLARDL	LARDL	NLARDL
Panel B: Diagnostic test statistics						
F	6.675***	7.240***	8.327***	8.135***	6.487***	5.974***
ECT_{t-1}	-0.085***	-0.187***	-0.128***	-0.119***	-0.211***	-0.260***
	(-5.207)	(-6.683)	(-5.024)	(-6.450)	(-5.753)	(-6.064)
RSEST	1.434	0.052	1.807	0.254	0.384	0.264
$CS(CS^2)$	S(S)	S(S)	S(US)	S(US)	S(S)	S(S)
BG	1.301	0.649	0.607	0.710	0.931	0.730
BPG	0.439	0.908	8.766***	2.977***	1.543	1.272
$WALD_1$		9.661***		5.560**		4.998**
$WALD_2$				8.365***		

Notes: *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The *t*-statistics are states in parenthesis. The error correction term (ECT), Ramsey's regression equation specification error test (RESET), the cumulative sum (CS) and the cumulative sum of squares (CS^2) tests, the Breusch-Godfrey Lagrange multiplier (BG) test, and Breusch-Pagan-Godfrey (BPG) test.

Furthermore, the Wald tests $WALD_1$ and $WALD_2$ are applied to check the null hypothesis of long-run symmetry for the first and second variables of interest, which are separated into the partial sums of positive and negative shocks. The null hypothesis is rejected in all NLARDL models implying that the estimated coefficient of the positive component is different from that of the negative component. Moreover, the coefficient estimates for the speed of adjustment (ECT_{t-1}) in all models are significantly different from zero at the 1% level. The larger absolute value for a speed of adjustment parameter suggests a faster convergence toward long-run equilibrium in cases of short-run deviations from this equilibrium. For six analyzed models, the fastest speed of adjustment exists in the NLARDL model of the egg VPT, whereas the slowest that exists is in the LARDL model of the pork VPT. For the pork VPT, the results show that Taiwanese pork prices have a long-run relationship with U.S. corn and soybean prices and the BDI in the LARDL model and that there is an asymmetric effect of U.S. soybean prices on Taiwanese pork prices in the NLARDL model besides symmetric effects of U.S. corn and Brazilian soybean prices. For the chicken VPT, there is a long-run relationship among the U.S. soybean prices, the BDI, and Taiwanese chicken prices in the LARDL model, while two kinds of asymmetric effects, U.S. soybean prices and the BDI, exist in the NLARDL model. For the egg VPT, a long-run equilibrium relationship exists among U.S. corn prices, Brazilian corn and soybean prices, and Taiwanese egg prices in the LARDL model. However, there is an asymmetric effect of U.S. corn prices on Taiwanese egg prices in the NLARDL model besides symmetric effects of the Brazilian corn and soybean prices.

2.6 Conclusions

Pork, chicken, and hen eggs are the main sources of animal protein consumed in Taiwan, and most of the pork, chicken, and hen eggs are supplied by domestic production, with over 93%, 87%, and 99% self-sufficiency rates in 2017, respectively. Moreover, corn and soybeans, in the form of soybean meal, are the main ingredients in hog and poultry feed whose expenses dominate their production costs. Since Taiwan is an island, and both the self-sufficiency rates of corn and soybeans are less than 2%, the prices of international corn and soybeans and dry bulk freight rates will affect feed prices and then indirectly cause the fluctuation of Taiwanese pork, chicken, or egg prices. In this study, the integration and price dynamics in the pork, chicken, and egg VPT are examined by linear and nonlinear cointegration tests and related error correlation models.

Based on the results of Engle-Granger and Johansen cointegration tests, there is a long-run equilibrium relationship among variables for the pork, chicken, or egg VPT. In addition, the results of TAR and M-TAR models show that asymmetric speed of adjustment does not exist for the pork and chicken VPT at the 5% significance level except for the egg VPT, i.e., the first two VPT have a symmetric speed of price adjustment. For the egg VPT, the VECM model with consistent TAR adjustment shows that the speed of adjustment in returning to the long-run equilibrium after positive shocks is more rapid than that after negative shocks. Moreover, we also applied the NLARDL model to investigate the long-run asymmetric magnitude of lagged-level variables. The results show that there is the asymmetric effect of Brazilian soybean prices on Taiwanese pork prices, that two kinds of asymmetric effects, U.S. soybean prices and the BDI, exist in the chicken VPT, and that there is the asymmetric effect of U.S. soybean prices on Taiwanese egg prices.

The role of international crop prices and ocean freight rates as primary determinants of Taiwanese pork, chicken, and hen egg price variations is almost uncontested. Because main ingredients of feed depend on imports, imported meat, poultry, and egg products from corn and soybean producing countries will be more price competitive than the related products in Taiwan. This is the main reason for the gradual increase in chicken and pork imports after jointing the WTO. Thus, how to reduce production costs, improve meat quality, and face the competition in various regional free trade agreements in the world will be important issues for policy makers in Taiwanese animal husbandry.

CHAPTER III

PRICE DYNAMICS IN THE IMPORT MARKETS OF EELS, EDAMAME, AND FEATHERS AND DOWN IN JAPAN

3.1 Introduction

The largest export market for Taiwanese agricultural products is China, followed by Japan and the U.S. The main agricultural products exported to Japan are tuna, feathers and down, edamame, and eels. Except for tuna, the sources of feathers and down, edamame, and eels are mostly farm-sourced. According to the statistics of the Taiwan COA, their shares (rankings) of the total export value for Taiwanese agricultural products were 2.13% (8), 0.98% (18), and 0.98% (19) in 2017, respectively.

An eel is any fish belonging to the order *Anguilliformes*. According to the statistics of the Food and Agriculture Organization (FAO) of the United Nations, global capture production of eels hit an all-time high in 1996 and then showed a decreasing trend. In addition, global capture production of eels only accounted for 5.41% of the global total production of eels in 2015, and global aquaculture production of eels has exceeded the global capture production since 1974. The most important factor affecting eel farming is the capture of wild eel fry and glass eels. Since eels have very special life history that is difficult to simulate in artificial environments, many drawbacks of the artificial breeding technology of eel fry still need to be overcome. The most commonly farmed species of eels in the world are Japanese and European eels, but in 2015, only about 97% of farmed eels were Japanese. The countries that farm Japanese eels all are located in Asia. China dominates in Japanese eel farming. Japan once accounted for more than 50% of the global total consumption of eels. However, because of the reduction of Japanese domestic demand and the rapid increase of the eel farming in China, the share of Japanese eel consumption to the global total consumption of eels gradually decreased and maintained at about 12%-18 % in recent years. Nevertheless, Japan still is the largest import country of eels in the world. The domestic eel production in Japan was within the range of 38 to 41 thousand tons from 1984 to 1991 and then showed a downward trend (Figure 3.1).

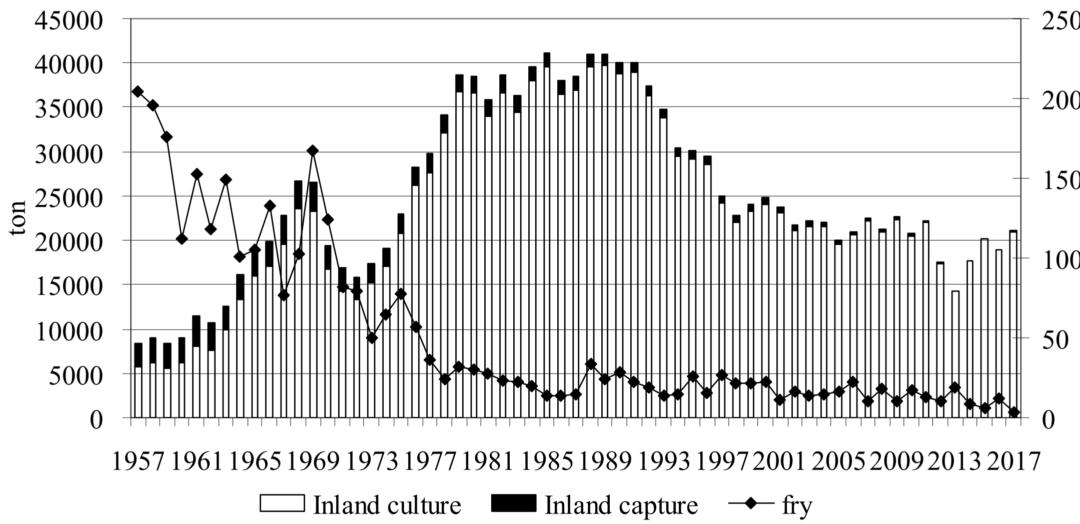


Figure 3.1. The volume of eel fry and the production of eels in Japan, 1957-2017
Notes: Before 1988 the volume of eel fry does not include import sources.

In 2013, this figure even fell to around 14 thousand tons. Conversely, the eel domestic demand in Japan gradually increased from about 20 thousand tons in the 1970s to reach the peak of about 160 thousand tons in 2000 (Figure 3.2). However, a rise in eel prices leads to a decline in the eel consumption and purchase frequency according to the consumer price index and the family income and expenditure survey from the Japanese Statistics Bureau. Japanese eel suppliers cannot satisfy domestic demand, and the gap between eel consumption and production in Japan must be filled with imported eels. Although weak demand and residues of malachite green, a veterinary drug illegally used for the treatment of farm-raised fish, heavily affect the import volume of eels in Japan, imported eels still make up over 50% of the market share of eels.

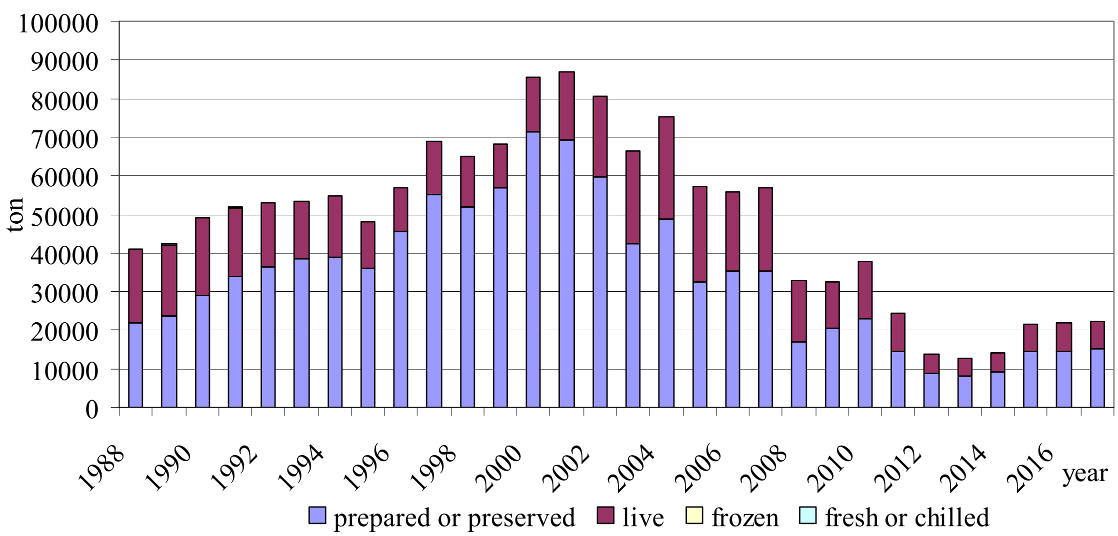


Figure 3.2. Import types of eels in Japan, 1988-2017

Once Taiwan was the largest supplier of the Japanese eel market but was replaced by China since 1994. There are four different types of eel products in international markets, but the import volumes of two of them in the Japanese market that are fresh or chilled and frozen eels are negligible. Due to the lower production costs of the eel farming and processing in China, China has quickly had a dominant presence in the eel market in Japan. The import of prepared eel products in Japan, especially, is mostly from China, and the market share of prepared or preserved eel products from China exceeded that from Taiwan since 1994. Thus, this study will only focus on the Japanese import market of live eels. According to the statistics of the Japan Customs, the main importing sources of live eels are China and Taiwan, and their shares of the total import volume of live eels in the Japanese market were 69.87% and 29.54% in 2017, respectively. Obviously Taiwanese eel farmers face strong competition from China (Figure 3.3).

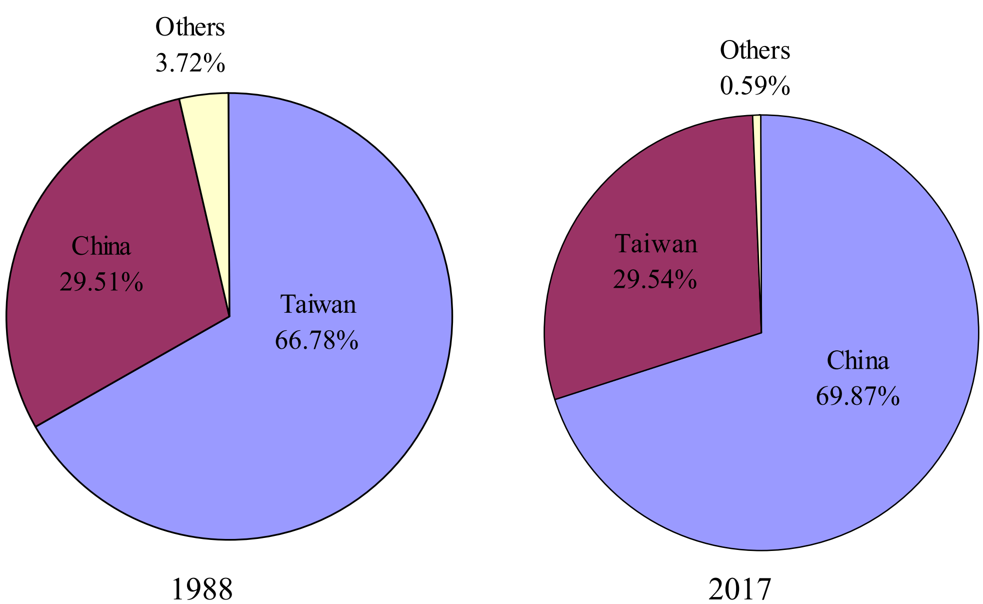


Figure 3.3. Top import partners of live eels in Japan (% of total import volume of the item)

Edamame, or vegetable soybeans, are the immature and green form of edible soybeans in the pod. It is classified as a vegetable and is not a grain crop as in the case of mature soybean seeds. In recent years, edamame has been gradually recognized in the world, but except for China, Japan, and Taiwan, there still are not many edamame customers in the rest of world. In general, it may appear in Japanese and Chinese restaurants throughout the world as a meal starter. Therefore, Japan is the main export market for edamame growers. The Japanese domestic production and planted area hit an all-time high in 1982 (Figure 3.4).

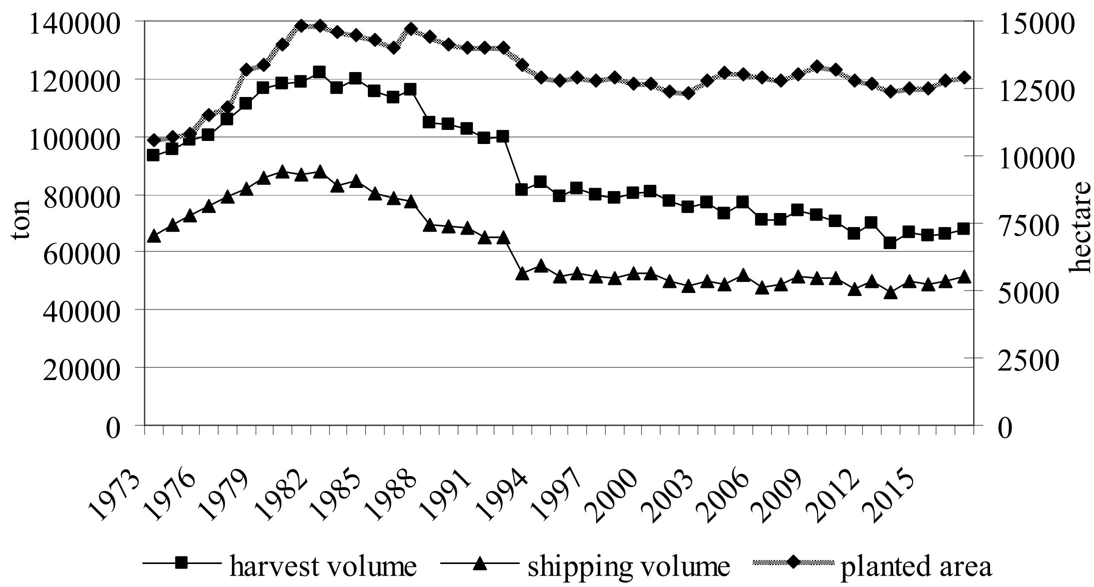


Figure 3.4. Planted area, harvest volume, and shipping volume of edamame in Japan, 1973-2017

Comparing 1982 with 2017, we can find that the planted area only decreases about 12.84%, whereas the harvest and shipping volumes decrease about 44.46% and 41.07%, respectively. The widening gap between the domestic edamame supply and demand in Japan is favorable for exporting countries of edamame. According to the statistics of the Japan Customs and the Ministry of Agriculture, Forestry and Fisheries of

Japan, about 59.56% of edamame consumption depended on imports in 2017 (Figure 3.5). The Japanese edamame market can be divided into two separate markets: fresh and frozen edamame. The import volume of fresh edamame is less than 2% of the total import volume of edamame and is mostly from Taiwan.

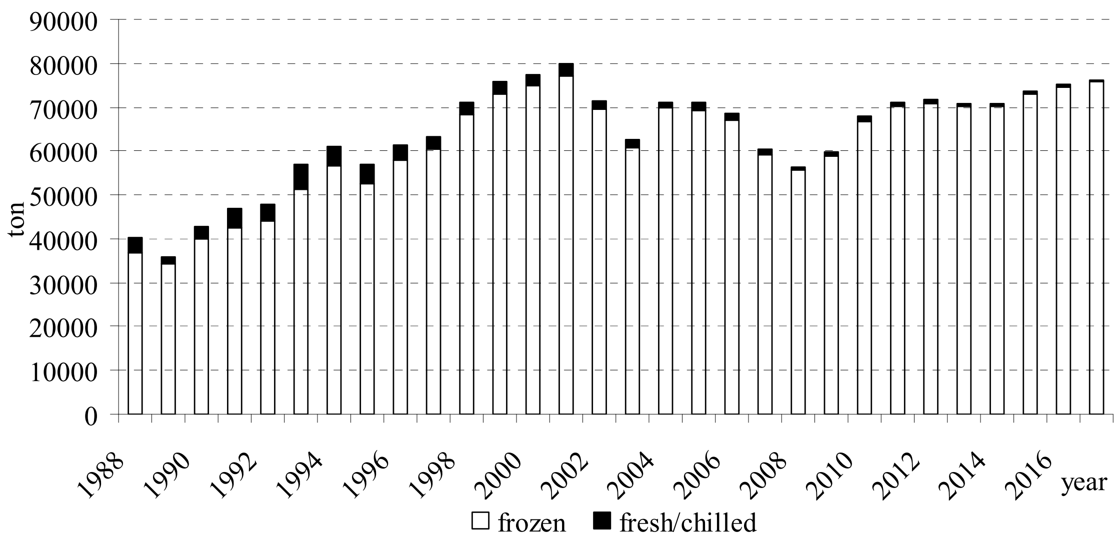


Figure 3.5. Import volume of frozen and fresh/chilled edamame, 1988-2017

According to the 2017 yearbooks of the Taiwan COA, Japan and the U.S. accounted for 85.34% and 9.30% of the total value of Taiwanese edamame exports, respectively. Although Taiwan remained top of the import market of frozen edamame in Japan in 2017, its share shrank largely because Taiwan has faced heavy competition from other exporting countries of frozen edamame since 1993. The major importing sources of frozen edamame in Japan are Taiwan, Thailand, China, and Indonesia, and their shares of the total import volume of frozen edamame were 41.40%, 26.96%, 26.10%, and 5.39% in 2017, respectively (Figure 3.6).

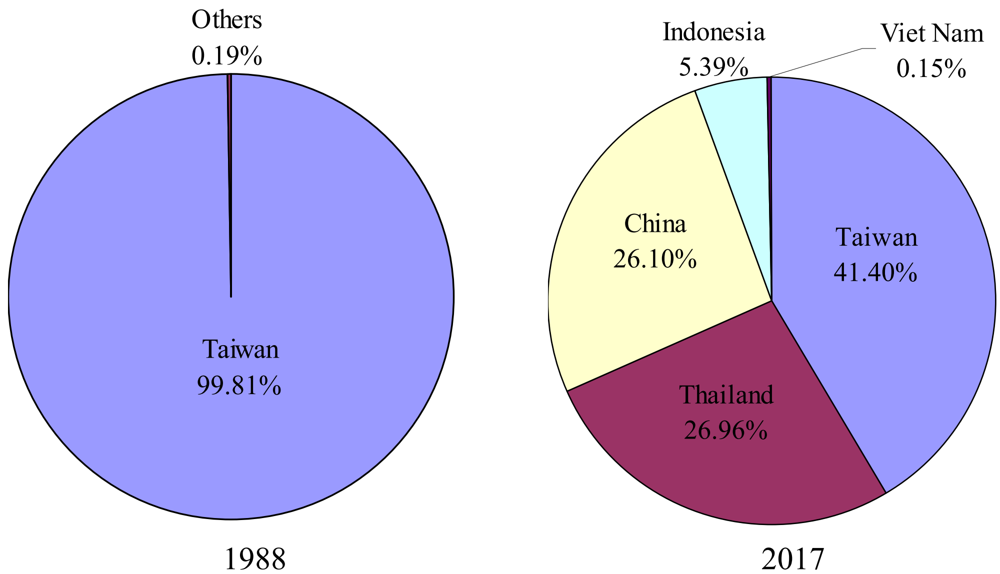


Figure 3.6. Top import partners of frozen edamame in Japan (% of total import volume of the item)

Feathers and down are used for insulation and padding of products like coats, bedclothes, and sleeping bags. The vast majority of them are a by-product of the poultry industry. They may come from the same animal source but are gathered from different parts of the body. Only ducks, geese, penguins, and other water birds have down. According to the statement of the Taiwan COA, the export volume of the Taiwanese down processing ranks the third in the world, behind China and the European Union (EU). In 2017, the share (ranking) of feathers and down in the total export value of agricultural products in Taiwan was about 3.86% (3), behind frozen tuna and bovine leather, and Japan, China, and Vietnam accounted for 29.86%, 27.97%, and 10.79% of the total export value of Taiwanese feathers and down, respectively. Because wearing apparel manufacturing remains a labor-intensive process, the cost of labor is an important consideration. Most of down jacket manufacturers in Taiwan moved production to China and other lower-cost countries in Southeast Asia. Main products of the Taiwanese feather and down processing are presently prepared feathers and down of a kind used for stuffing and their bedding products. According to the statistics of the Japan Customs, import volume and value hit an all-time high in 1989 and then showed a decreasing trend (Figure 3.7).

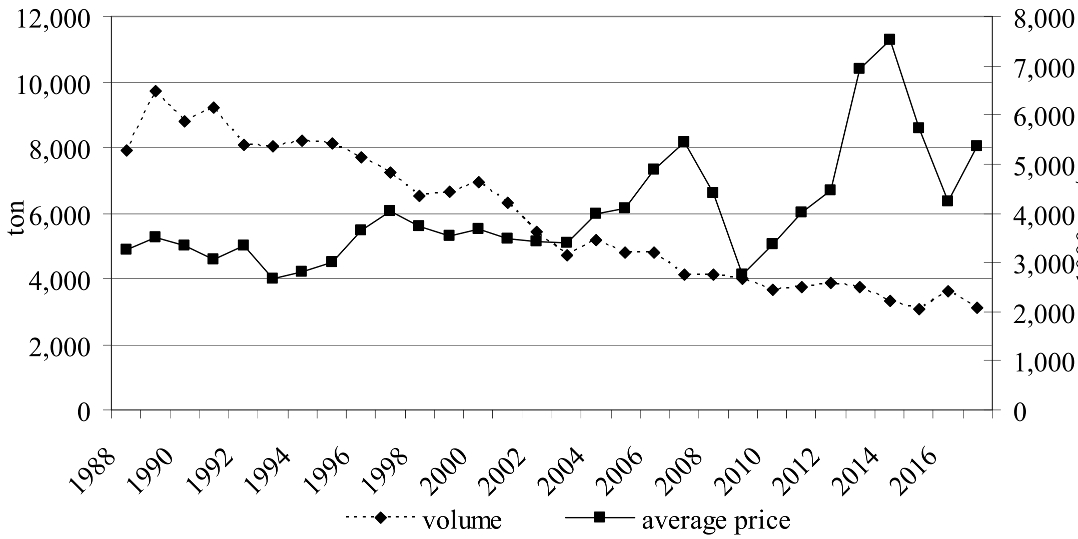


Figure 3.7. The volume and average price of imported feathers and down in Japan, 1988-2017

Both the changes of average global temperatures and the prices of duck and goose meat may affect the demand and prices of feathers and down. For instance, because of the outbreak of bird flu in many provinces of China in 2013, large-scale culling of poultry species on farms resulted in a sharp drop in the supply of feathers and down. This also caused rapid increases in the average import price of feathers and down in Japan, and it jumped to an all-time high of $7,518 thousand yen per ton in 2014. The major importing sources of prepared feathers and down are China, Taiwan, Poland, Hungary, and France, and their shares of the total import value of feathers and down in Japan were 29.19%, 25.39%, 14.12%, 10.36%, and 7.37% in 2017, respectively (Figure 3.8).

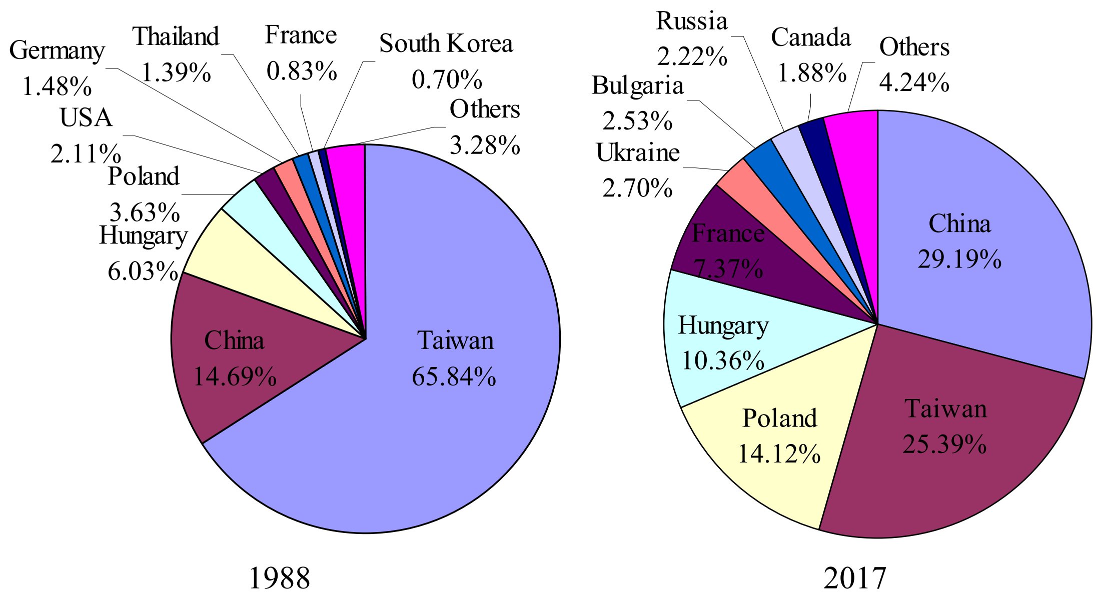


Figure 3.8. Top import partners of feathers and down in Japan (% of total import value of the item)

Comparing 1982 with 2017, we can find that except for Taiwan, all market shares of other main exporting countries in regards to feather and down imports in Japan increase remarkably. Although there is no obvious relationship between the quality and countries of origin of feathers and down, European feathers and down are more preferred by consumers and can be sold at higher prices. Besides the EU, Taiwan still faces the low-price competition from China. Thus, the Taiwanese market share of the Japanese feather and down imports decreased by 40.45% between 1988 and 2017.

This study will employ a time-series model to examine the relationship among Taiwanese main export products and other substitutes from other exporting countries in the Japanese market. The paper is organized as follows. The related literature on the economic topics of spatial price transmission is presented in the next section of the paper. Then, the theoretical framework for a causal search algorithm and data sources are described. Following that, results and relevant discussions are presented. The summary of main findings is presented in the last section of the paper.

3.2 Literature Review

Because the European eel was included in Appendix II of the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) in March 2009, social science researchers mainly focused on discussing the influence of the CITES on eel-farming countries in the past years, such as Crook and Nakamura (2013) and Nijman (2015 and 2017). However, few articles analyze the relationship among local prices of eels in different cities or imported and domestic prices of eels. Lee et al. (2003) employed net private profitability and domestic resources cost approaches to evaluate the competitiveness of the eel aquaculture in China, Japan, and Taiwan. Most papers on edamame focus on agricultural sciences, and a few studies focus on social sciences. Kelley and Sánchez (2005) discussed the consumer preference and potential demand for edamame by the sensory evaluation that contained 113 participants who tasted and ranked three kinds of edamame at the main campus of the Pennsylvania State University system and the telephone survey that produced a total of 401 completed responses in the Metro-Philadelphia area. Wszelaki et al. (2005) applied consumer testing and a descriptive analysis to compare six edamame cultivars which are organically grown in order to understand consumer preference and which is the most popular with Ohio consumers. Sundari et al. (2015) employed a snowball sampling method to get the sample group which consisted of 372 edamame farmers in order to conduct a questionnaire. Then, software Structure Equation Modeling was used to analyze the questionnaire data in order to decide what factors affect the successful implementation of quality culture farmers.

In the literature of price transmission analyses, there are some articles investigating the relationship among prices of the same or homogeneous commodities which are produced in different regions or countries. For example, Gallagher (1983) applied linear regression equations to examine whether international price margins in the U.S. Pacific Northwest-Japan softwood trade are influenced by nontariff trade barriers and inelastic supplies of international transportation services. Ghoshray (2007) used linear and nonlinear cointegration tests and an asymmetric ECM to explore the relationship of monthly average prices of durum wheat exported by Canada and the U.S. Asche et al. (2007) investigated smoked salmon exported by Norway and United Kingdom in the French retail market and found that there is a very high degree of price transmission in both supply chains. Balcombe et al. (2007) applied a generalized threshold ECM to investigate relationships of pairs of monthly wheat, maize, and soybean prices for Brazil, the U.S., and Argentina. Sun (2011) employed linear and nonlinear cointegration tests and an asymmetric ECM to evaluate the dynamic relationship of monthly import prices of wooden beds from China and Vietnam in the

U.S. market. Myers and Jayne (2012) developed a threshold ECM which allows multiple long-run equilibria and multiple speeds of adjustment to examine the linkage of monthly maize prices for South Africa and Zambia. Jezghani et al. (2013) used a standard VECM to examine the relationship of monthly wholesale prices of rice for Thailand and Iran. Sun and Ning (2014) applied a threshold ECM and a generalized impulse response function on monthly prices from 1978 to 2011 to investigate the spatial price linkage among three mainly suppliers of the softwood lumber market in North America: the Southern U.S., the Western U.S., and Canada. Santeramo (2015) applied a threshold autoregressive model to explore the dynamics of tomato and cauliflower prices among EU spatially separated regions.

3.3 Methodology

Probabilistic graphical models contain graph theory, probability theory, and computer science to represent and visualize the associations among stochastic variables. One of the two most common types of graphical models is a Bayesian network presented by Pearl (1986) (also called a belief network or a causal network). Bayesian networks use directed graphs to represent causal relationships among random variables. A directed graph is the generalization of a tree data structure in which a nonempty set of vertices V (or nodes) is connected by a set of edges (or links) that has an orientation (directed path) and is represented by arrows. An arrow from vertex A to vertex B indicates that there is a direct causal effect of A on B. The directed graph that does not contain directed cyclic paths (e.g. $A \rightarrow B$, $B \rightarrow A$) is called a directed acyclic graph (DAG) corresponding to a Bayesian network. A DAG is used not only to represent causal relations between vertices corresponding to variables but also to represent a set of probability measures over a set of vertices. According to the definition of Lauritzen et al. (1990), for a DAG *G* with a set of vertices *V*, a probability measure *P* over *V* obeys the local directed Markov property if and only if each variable X_V in *V* is independent of its nondescendants, conditional on its parents. Lauritzen et al. (1990) also proved that for *G*, the local directed Markov condition is equivalent to the other two conditions: (a) *P* over *V* obeys the global directed Markov property if and only if for any triple (*J*, *K*, *L*) of disjoint subsets of *V*, *J* is d-separated from *K* given *L* in *G*, that is, *J* is conditionally independent of *K* given *L* in *G*. (b) *P* admits a recursive factorization according to *G*. That is, a joint density function $f(X)$ for *P* over *V* factorizes according to *G* if and only if for each subset $X \subseteq V$,

$$(3.1)\quad f(x) = \prod_{v \in V} k_v(x_v, Pa(x_v, G)),$$

where $f(x)$ and x_v is the abbreviations of $f(X = x)$ and $X_V = x_v$, respectively. k_v is a non-negative kernel function. $Pa(x_v, G)$ is the set of parents of the variable X_v in G. Since *P* admits a recursive factorization, the term $k_v(x_v, Pa(x_v, G))$ is the conditional density of x_v given $Pa(x_v, G)$. Thus,

$$(3.2)\quad f(x) = \prod_{v \in V} f_v(x_v | Pa(x_v, G)).$$

In a DAG, all of the conditionally independent relationships can be generated using the concept of d-separation ("d" implies "directional"). If A is d-separated from B by C, this means that all the paths (information) between subsets A and B are blocked given the vertices in a set C. There are three situations under which a path is blocked given a set of vertices C: (a) In a causal chain such as $A \rightarrow C \rightarrow B,$ A and B are conditionally independent given the middle node C. The encoded joint distribution is $P(A,B,C) = P(A)P(C|A)P(B|C)$, that is to say, it assumes the probability Markov condition (the joint probability distribution among set of causal variable is determined by the product of all unconditional marginal probabilities and conditional probabilities where one condition only on the parent causal variable). (b) In a collider structure such as $A \rightarrow C \leftarrow B,$ A and B are unconditionally independent. However, A and B are conditionally dependence (d-connected) given their common effect C. The encoded joint distribution is $P(A,B,C) = P(A)P(B)P(C|A,B)$. (c) In a causal fork such as $A \leftarrow C \rightarrow B,$ A and B are conditionally independent given their common parent C. The encoded joint distribution is $P(A,B,C) = P(C)P(A|C)P(B|C)$. These configurations of triples are viewed as base cases of Bayesian networks and used to analyze more complex causal structures.

It is not enough for policy makers and social scientists to only obtain optimal estimation of a covariance matrix or have best parameter estimates by least square methods. To establish causal relationships among variables generated via observational data, many algorithms have been developed. Wermuth and Lauritzen (1983) specified a subclass of the recursive models for contingency tables proposed by Goodman (1973). Each of these matches a special kind of a directed graph instead and can be represented by a nontrivial decomposition of the joint probability distribution in terms of the response variables. The term ‘recursive’ means that endogenous (response) factors are permitted to explain themselves regardless of direct or indirect effects. The vertices in any possible DAG are labeled by numbering them so that edges $X(i) \rightarrow X(j)$ happen only if $i < j$ in the complete ordering of variables. However, this algorithm requires that an ordering of the variables is known in advance. Thus, in order to remove this requirement, improve its computational efficient, and decrease the difficulty of statistical decisions, several algorithms for finding causal relations among variables have been developed such as the Spirtes-Glymour-Scheines (SGS) algorithm (Spirtes et al., 1990 and 2000) and the PC algorithm (Spirtes and Glymour, 1991) with the assumptions of causal sufficiency, causal faithfulness and causal Markov conditions. The SGS and the PC algorithms have similar procedures for discovering causal structure and the main difference between them is the step of edge elimination. Because the revised edge-removal step omits needless tests of the null hypothesis of conditional independence, the PC algorithm has more computationally efficient than the SGS algorithm. The main steps of the PC algorithm is as follows: (a) Build the complete undirected graph *G* on a set *V* of variables, that is, every unordered pair of vertices (also called nodes or points) is connected by an edge (also called an arc or line) without a direction. (b) For each pair of variables (a,b) in *V*, try to find a conditioning set S_{ab} where all variables are adjacent to either *a* or *b* except for *a* and *b* themselves such that the null hypothesis of $(a \perp\!\!\!\perp b | S_{ab})$ is not rejected. In other words, S_{ab} should disconnect *a* and *b*. In this step the cardinality of the set S_{ab} starts at 0, then 1, and so on. Edges are recursively removed from *G* as soon as a conditional independence relation is found between *a* and *b*. A predetermined cut-off probability (p-value) is used to reject the null hypothesis of no correlation (most studies use p-value 0.05 for 95% statistical significance in the removal of edges). The ultimately resulting undirected graph is named as G'. (c) For each pair of nonadjacent variables a and b that are linked through a variable c in G', examine whether $c \in S_{ab}$. The edges of $a-c-b$ are oriented as $a \rightarrow c \leftarrow b$ (called an unshielded collider or v-structure) if and only if $c \notin S_{ab}$. (d) In the partially directed graph G'' produced by step (c), the rest of the undirected edges will be oriented by repeated application of the following two conditions: (i) The orientation should avoid producing a new v-structure. (ii) The orientation should avoid producing a directed cycle (search through causal chains and causal forks).

3.4 Data

The period of data covered concerning the imported edamame is from January 1992 through December 2017. China and Thailand have been exporting edamame to Japan since 1988 and 1990, respectively. However, trade volumes for China and Thailand were insubstantial, and their monthly import prices were volatile before 1992. Thus, the starting period is set at January 1992. Furthermore, the period of data covered concerning imported eels and down/feathers is from January 1988 to December 2017. The starting period reflects data availability. Their monthly import volumes and values are obtained from the Japan Customs and applied to calculate unit prices (JPY1000/kg) for each main exporting country. In addition, monthly wholesale prices of domestic eels and edamame are obtained from the Tokyo Metropolitan Central Wholesale Market.

3.5 Empirical Results

3.5.1 Eel Imports in Japan

The descriptive statistics for import prices from China and Taiwan and wholesale prices in the Tsukiji fish market are presented in Table 3.1. Aichi and Shizuoka prefectures are the main areas of eel production in Japan. The highest price of live eels is reported from Shizuoka prefecture, while Taiwanese live eels have the lowest price among four analyzed price series. For prepared eels, the price from Shizuoka prefecture is higher than that from China. Thus, comparing contemporaneous prices, we can find that prices of Japanese domestic eels are higher than those of imported eels. The CV suggests that there is a similar degree of variability within two groups of live eel prices, imports and domestics. Similarly, the SD also shows the same result. However, for between-group variations, the CV suggests that prices of domestic live eels in Japan are less dispersed than those of imported live eels, while the SD suggests that the prices of imported live eels are less changeable than the domestic prices. For prepared eels, both the SD and CV show that the domestic price fluctuation is bigger than the fluctuation of import prices.

As a rule, nonstationary data cannot be modeled or forecasted because the results obtained by nonstationary time series might be spurious. Thus, in order to obtain consistent and reliable results for analyzed time series, unit root tests on levels and the first differences of data were conducted. The results of both ADF and PP tests are presented in Table 3.2. The null hypothesis of both tests is that each evaluated time-series is nonstationary. The number of augmenting lags for the ADF test is determined by minimizing the BIC. The statistics of both ADF and PP tests reveal that the presence of a unit root cannot be rejected at the 5% significance level for all eel price series in levels but can be rejected for the first differences. Thus, it is concluded that all eel price series are integrated of order one.

Table 3.1. Descriptive Statistics for Monthly Eel Prices (JPY/KG), 2002-2017

Variable	Mean	SD	Minimum	Maximum	CV
Import (live)					
China	2083.825	991.837	766.264	4671.317	0.476
Taiwan	2022.474	944.041	747.652	4455.652	0.467
Domestics (live)					
Shizuoka	2923.943	1244.000	1093.000	5629.000	0.425
Aichi	2948.266	1245.250	1135.000	5486.000	0.422
Import (prepared)					
China	1867.098	691.012	901.898	3600.394	0.370
Domestics (prepared)					
Shizuoka	3359.531	1952.342	1054.000	7419.000	0.581

Notes: SD and CV represent the standard deviation and the coefficient of variation, respectively.

Table 3.2. Unit Root Tests in the Level and First Difference of Monthly Eel Prices, 2002-2017

Series	ADF		PP	
	Level	1st diff.	Level	1st diff.
Aichi	-1.919 (1)	-8.220 (0)**	-1.916 (4)	-8.041 (4)**
China 1	-1.570 (2)	-8.994 (1)**	-1.622 (4)	-9.600 (4)**
China 2	-1.852 (0)	-13.042 (0)**	-1.844 (4)	-13.016 (4)**
Shizuoka 1	-1.822 (2)	-9.172 (1)**	-1.916 (4)	-8.844 (4)**
Shizuoka 2	-1.232 (1)	-11.340 (2)**	-1.006 (4)	-20.018 (4)**
Taiwan	-1.867 (2)	-9.392 (1)**	-1.888 (4)	-8.271 (4)**

Notes: The data are transformed by taking natural logarithms. The numbers in parentheses indicate the lag order in the ADF test and the bandwidth using the Newey-West bandwidth selection method and the Bartlett kernel in the PP test, respectively. The default bandwidth is the integer part of $4 \times (T/100)^{2/9}$ where T is the sample size. ** denotes significance at the 5% level. 1 and 2 denote live and prepared eel prices, respectively.

A linear cointegration analysis is conducted using the Johansen approach. First, the Johansen approach requires the determination of a lag length for the VAR representation of a VECM. The order of the VECM fitted is always one less than the order of the corresponding VAR model. Based on the lowest Hannan-Quinn information criterion (HQ), one lag is used in the VECM. Without prior information, five model specifications with different deterministic trend assumptions in level data and cointegrating equations are estimated (Table 3.3). Except for the second and fourth models at the 5% level of significance, the results show that the Johansen trace and maximum eigenvalue tests determine different numbers of cointegrating vectors, called cointegrating ranks (*r*). Johansen and Juselius (1990) recommended the use of the trace statistic when these two statistics provide conflicting results. Moreover, the trace test statistic considers all of the smallest eigenvalues and holds more power than the maximum eigenvalue statistic (Kasa, 1992; Serletis and king, 1997). Thus, when the results of two statistics produce a contradiction in a certain model, *r* is determined by the trace statistic.

Table 3.3. Johansen Tests for the Order of Cointegration of Monthly Eel Prices in 5 Trend Assumptions

Data trend	None	None	Linear	Linear	Quadratic
ECT	None	Intercept	Intercept	Intercept Trend	Intercept Trend
Trace	4	3	4	4	6
Max. eigenvalue	2	3	3	4	4

Notes: Selected number of cointegrating relations at the 5% significance level. ECT denotes the error correction terms in a vector error correction model.

The values of the BIC for each model with different *r* values are shown in Table 3.4. The lowest BIC value is -16.550 in the model that has no deterministic trends in level data and whose cointegrating equations have intercepts. Thus, the innovations generated from this model are used to identify causal structure among the eel price series.

Table 3.4. Schwarz Criteria by Ranks (Row) and Models (Column) Using Monthly Eel Prices

Data trend	None	None	Linear	Linear	Quadratic
ECT	None	Intercept	Intercept	Intercept Trend	Intercept Trend
Rank (*r*)					
2	-16.709	-16.702	-16.600	-16.631	-16.527
3	-16.480	**-16.550**	-16.475	-16.483	-16.406
4	-16.237	-16.293	-16.242	-16.281	-16.230
6	-15.620	-15.653	-15.653	-15.666	-15.666

Notes: ECT denotes the error correction terms in a vector error correction model.

As discussed earlier in this report, the innovations generated from the VECM are used to study the contemporaneous causal relations among the six eel prices. The analysis of directed graphs is carried out using the PC algorithm and its more refined extensions, which are implemented in the software package TETRAD VI. At the 5% significance level, the end result after removing the insignificant edges and directing the remaining edges is given in Figure 3.9. It shows us that a change in Taiwanese (live) eel prices leads to a change in the (live) eel prices from Aichi prefecture, Shizuoka prefecture, and China in contemporaneous time. Both the prices of prepared eels from China and Shizuoka prefecture (China 2 and Shizuoka 2) have a causal effect on those of their live eels (China 1 and Shizuoka 1), respectively. In addition, the fact that no directed edges (or arrows) leave the vertex (or node) for the price of Chinese (live) eels implies that the price of Chinese (live) eels does not cause the other price variables and is completely an information receiver.

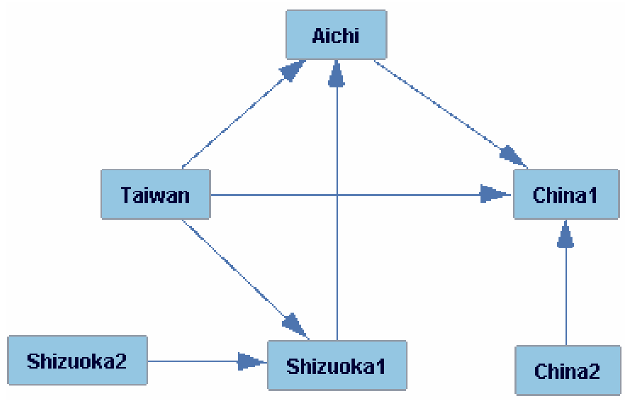


Figure 3.9. Directed acyclic graph on innovations from the VECM with eel prices
Notes: 1 and 2 denote live and prepared eel prices, respectively.

The impulse response functions (response of a given variable for one-time only shock of another variable) of our estimated model for selected eel price series are depicted in Figure 3.10-3.15. The x-axis of graphs covers 24 months. Figure 3.10 shows that a shock in the price of Taiwanese live eels has a positive impact on all eel prices throughout all 24 months. Overall, the graphs show that the responses of all eel prices to the shock immediately increase to reach their peaks in the first month, decrease thereafter, and gradually tend towards stability except for the prepared eel price from Shizuoka Prefecture.

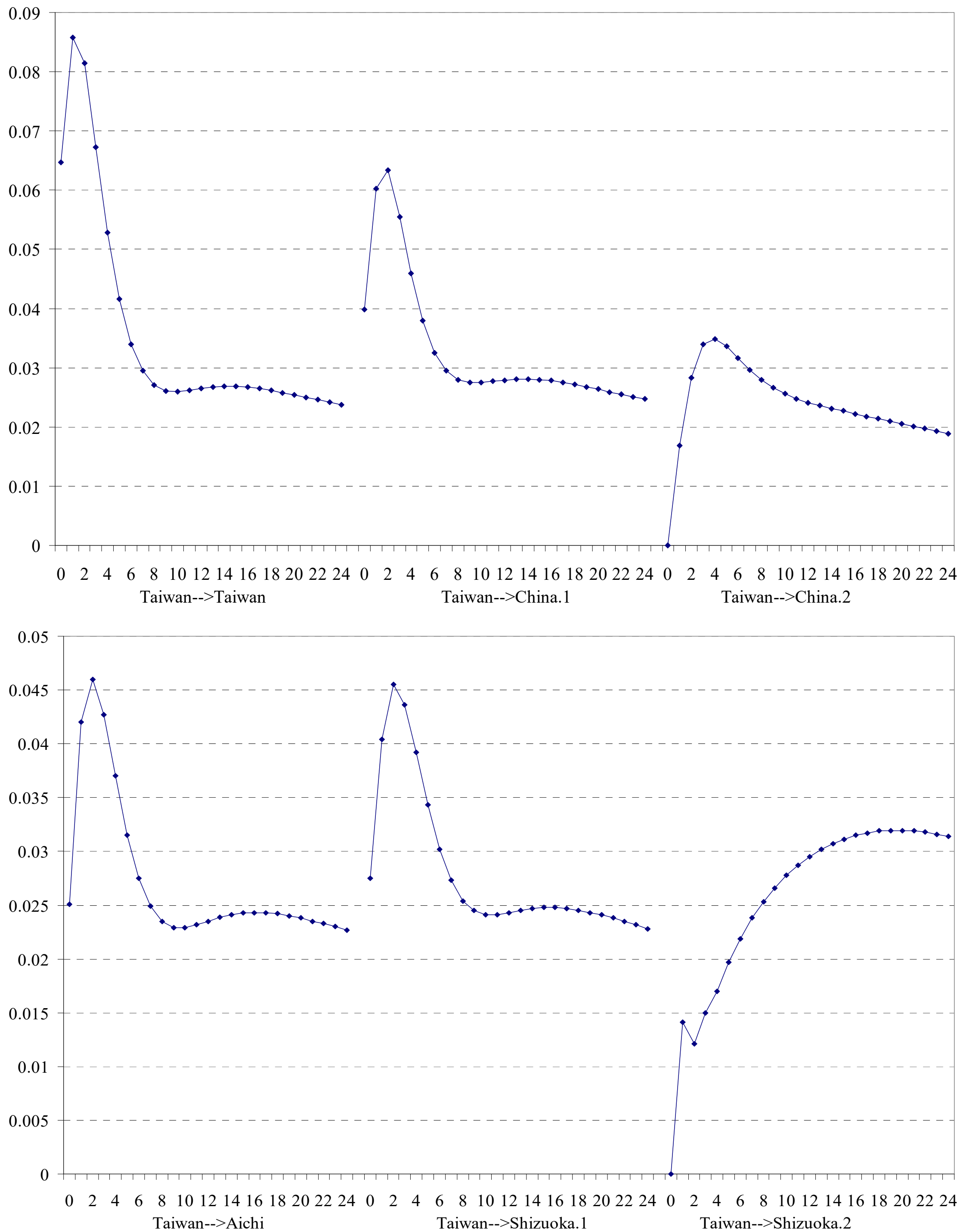


Figure 3.10. Impulse response function to a shock in Taiwanese live eel prices
Notes: 1 and 2 denote live and prepared eel prices, respectively.

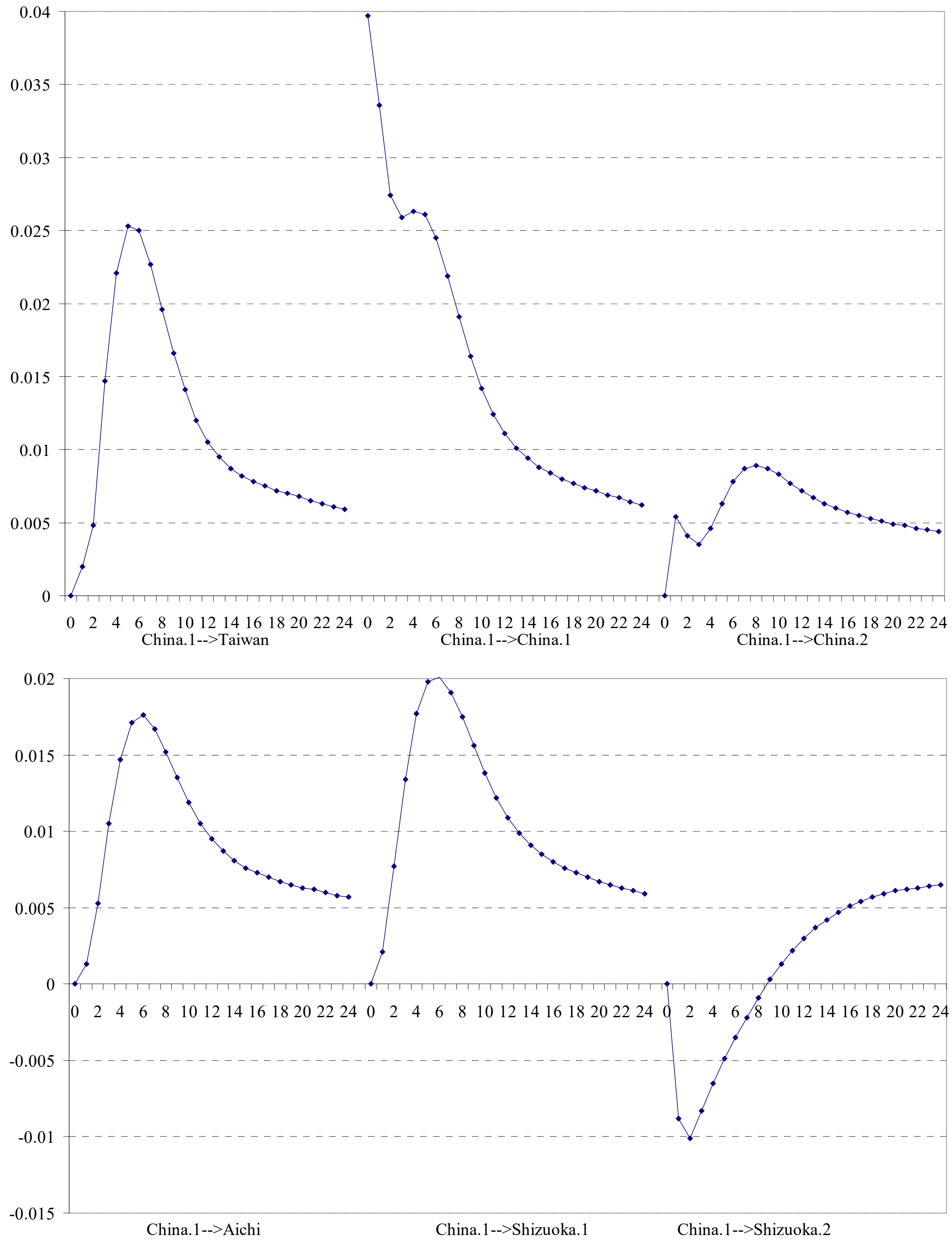


Figure 3.11. Impulse response function to a shock in Chinese live eel prices

Notes: 1 and 2 denote live and prepared eel prices, respectively.

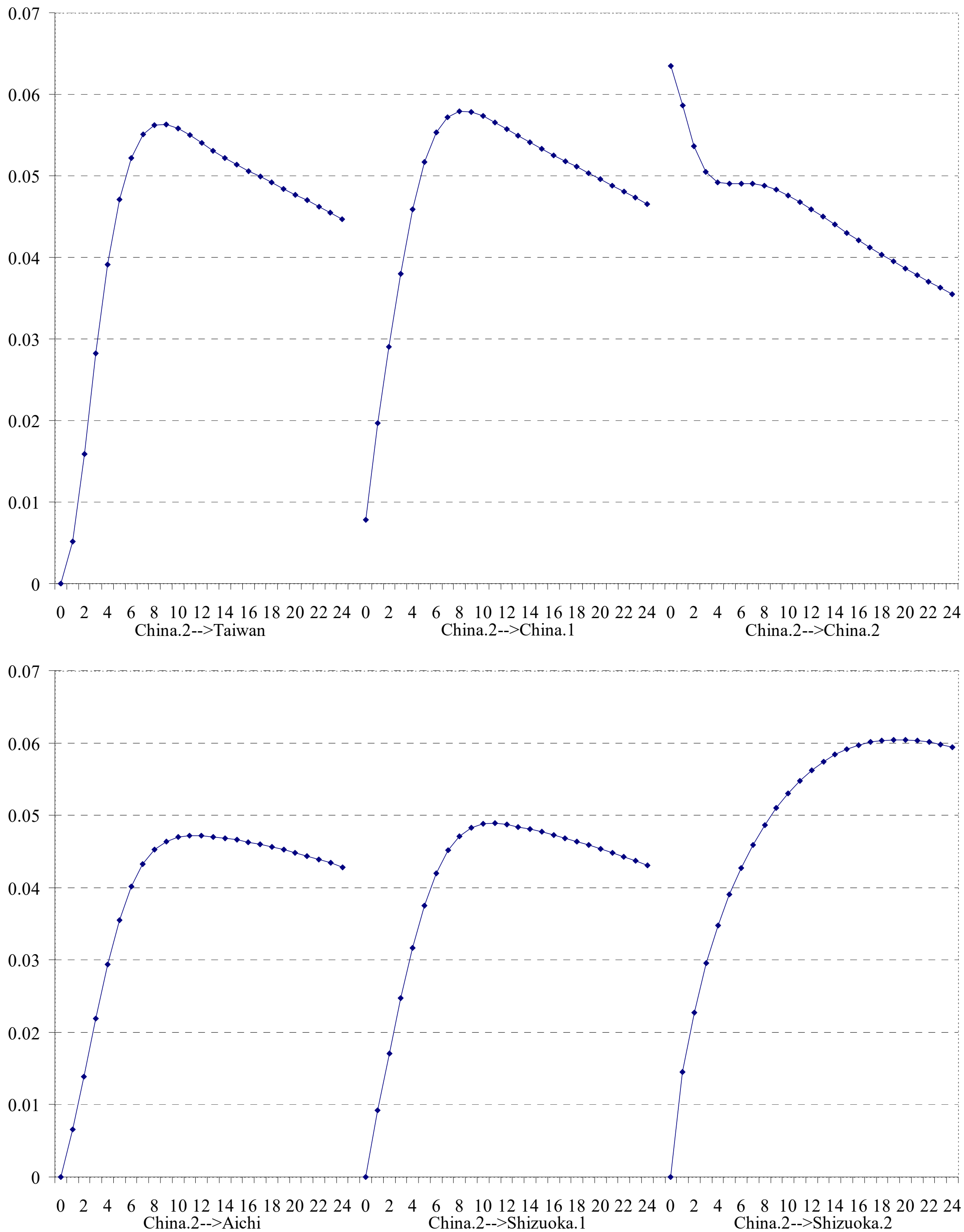
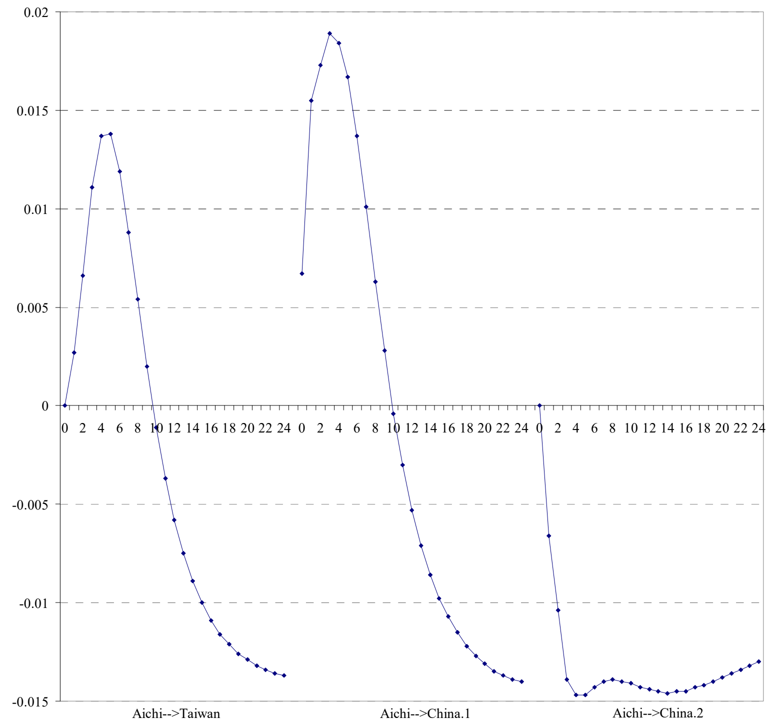


Figure 3.12. Impulse response function to a shock in Chinese prepared eel prices
Notes: 1 and 2 denote live and prepared eel prices, respectively.



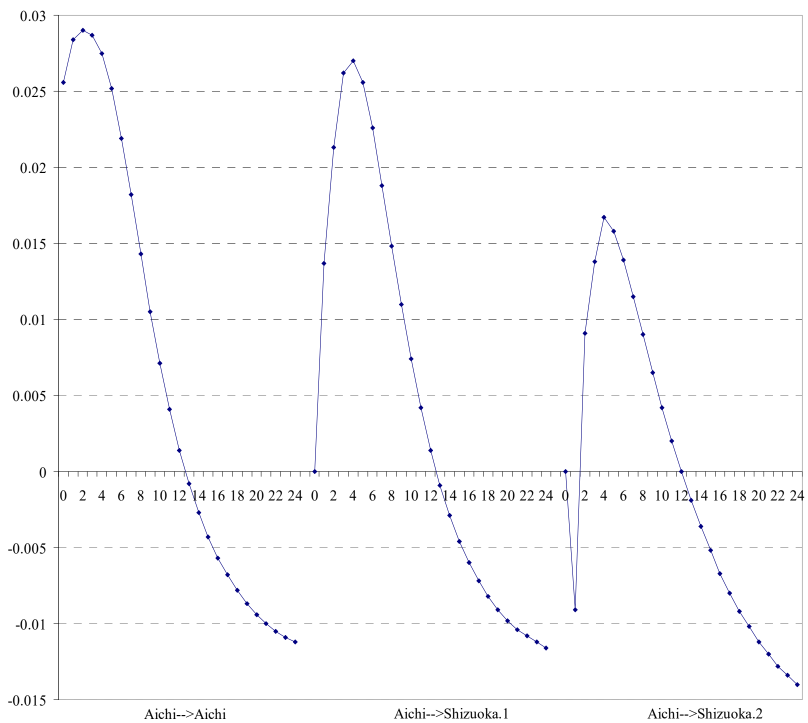


Figure 3.13. Impulse response function to a shock in the live eel prices from Aichi Prefecture, Japan

Notes: 1 and 2 denote live and prepared eel prices, respectively.

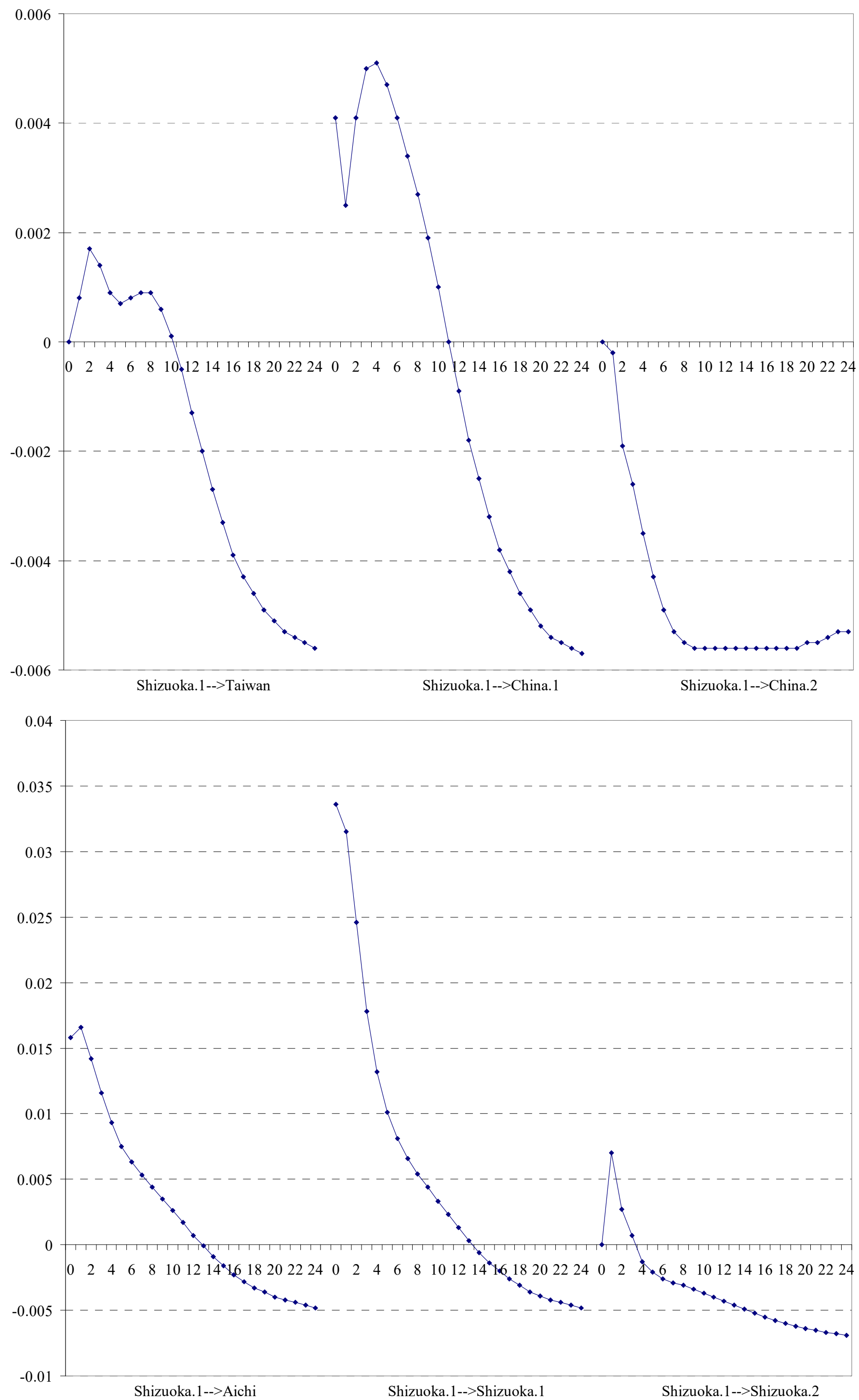


Figure 3.14. Impulse response function to a shock in the live eel prices from Shizuoka Prefecture, Japan
Notes: 1 and 2 denote live and prepared eel prices, respectively.

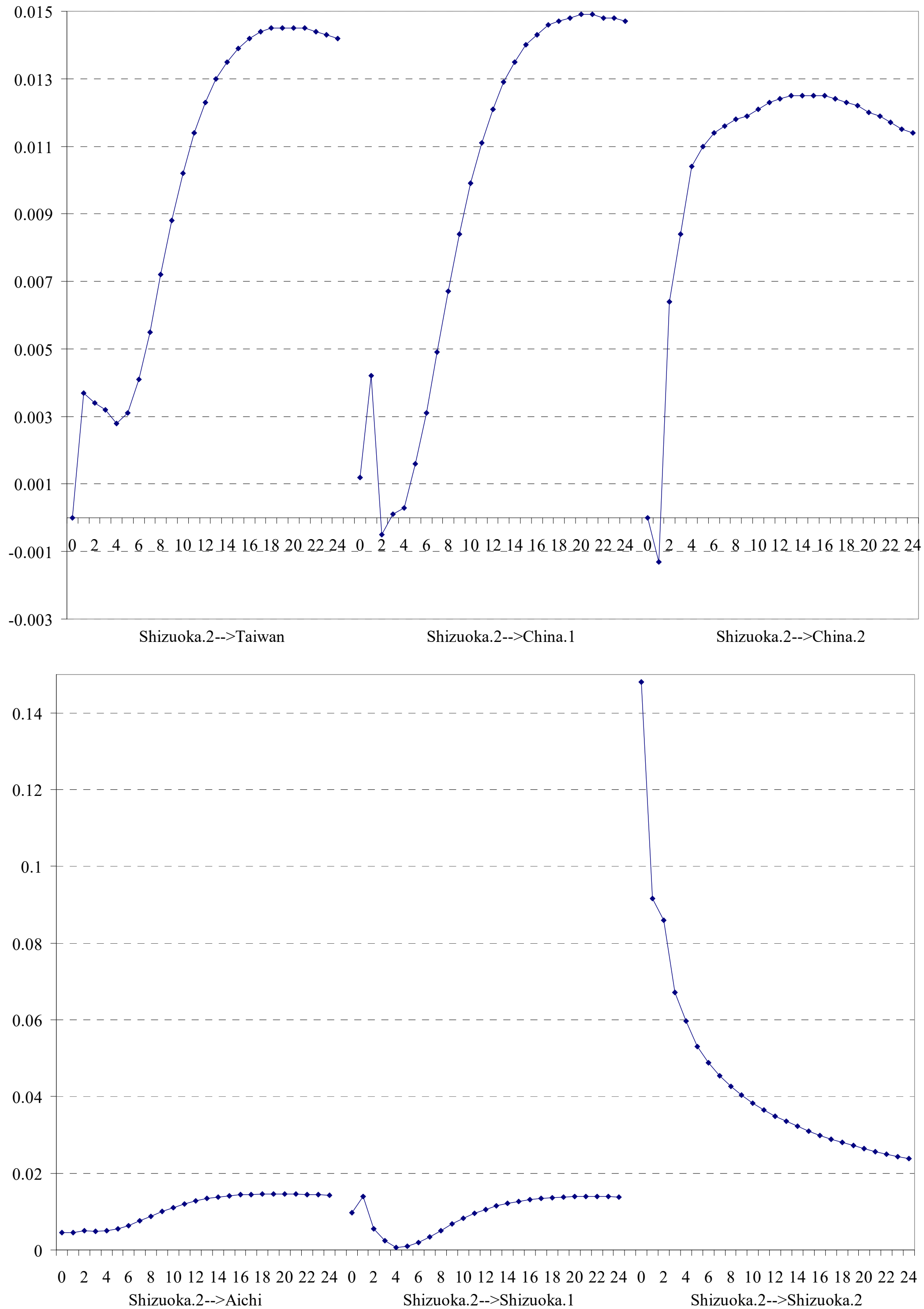


Figure 3.15. Impulse response function to a shock in the prepared eel prices from Shizuoka Prefecture, Japan

Notes: 1 and 2 denote live and prepared eel prices, respectively.

Before the response of the prepared eel price from Shizuoka Prefecture reaches a peak after 18 months, it continuously rises except for the second month. Then, after being unchanged over a four-month period, it slowly declines.

Figure 3.11 shows that a shock in the price of Chinese live eels has a positive impact on all eel prices except for the prepared eel price from Shizuoka Prefecture. The response of Chinese live eel prices to its own shock has roughly downward trend. The line graph of the response of the prepared eel price from Shizuoka Prefecture looks like a check mark, i.e., its response keeps an upward tendency after reaching rock bottom in the second month. Overall, the responses of the remaining price series have an inverted V-curve.

Figure 3.12 shows that a shock in Chinese prepared eel prices has a positive impact on all eel prices. The responses of all eel prices initially exhibit an upward trend until reaching their peaks and then decrease gradually except that there is a downward trend in the response of Chinese prepared eel prices to its own shock throughout all 24 months. In Figure 3.13 the effect of a shock in the live eel price from Aichi Prefecture on Taiwanese and Chinese live eel prices and on the live eel prices from Aichi and Shizuoka Prefectures and the prepared eel price from Shizuoka Prefecture (except for the 1st month) changes from positive to negative in the 10th month and 13th month, respectively. Although the shock has a negative impact on Chinese prepared eel prices, the fluctuation in response of Chinese prepared eel prices slows down after the 3rd month. To compare Figure 3.13 to Figure 3.14, roughly speaking, shocks in the live eel prices from Aichi and Shizuoka Prefectures have similar effects on all eel prices.

Overall, Figure 3.15 shows that a shock in the prepared eel price from Aichi Prefecture has a positive impact on all eel prices. It is also worth mentioning that the shapes of line graphs describing the effects of the shock on the import eel prices are similar.

Based on the result given in Figure 3.9, the forecast error variance decomposition for each eel price at alternative time horizons is given in Table 3.5. The percentage share of a forecast error variance is attributable to earlier shocks from each other series (including itself) at a specific time horizon. In this study, we list horizons of 1, 6, 12, 18, and 24 months ahead. Since the eel farmers in China produce eels considerably more cheaply than those in other producing countries, Taiwanese farmers have completely lost the prepared eel market and still face strong competition from China in the live eel market in Japan. China is the only competitor for Taiwanese eel farmers in the Japanese import market. This also reflects that at the longer horizon of two years besides its own innovations, the Taiwanese price variation is mainly explained by innovations in prices of eels imported from China (China 1 and China 2, about 55.57% in total). Before the 12-month horizon, the influence of its own prices on the uncertainty of Taiwanese live eel prices sharply decreases, while the influence of Chinese prepared eel prices (China 2) dramatically increases. It is not unexpected that the price variation of Chinese live eels is initially determined mostly by the shocks in Taiwanese live eel prices (48.22%) and its own prices (48.00%). However, the explanatory power of its own innovations sharply decreases to 18.00% at the 6-month horizon. In contrast, the influence of Chinese prepared eel prices on Chinese live eel prices dramatically increases before the 12-month horizon and then gradually increases.

Table 3.5. Variance Decomposition on Monthly Eel Prices

Step	SE	Taiwan	China1	China2	Aichi	Shizuoka1	Shizuoka2
Taiwan							
1	0.065	100.000	0.000	0.000	0.000	0.000	0.000
6	0.184	80.020	4.020	14.162	1.622	0.020	0.155
12	0.245	53.493	5.864	38.491	1.367	0.016	0.770
18	0.287	44.020	4.817	47.557	1.626	0.081	1.898
24	0.320	39.162	4.140	51.428	2.297	0.221	2.753
China1							
1	0.057	48.216	47.996	1.848	1.374	0.523	0.043
6	0.175	51.904	18.000	24.557	5.094	0.373	0.071
12	0.241	36.030	13.071	46.667	3.288	0.267	0.677
18	0.286	31.105	9.862	54.024	2.922	0.253	1.834
24	0.322	28.622	8.108	56.859	3.326	0.358	2.727
China2							
1	0.063	0.000	0.000	100.000	0.000	0.000	0.000
6	0.154	19.461	0.510	75.095	3.303	0.174	1.457
12	0.212	20.582	1.204	70.670	4.408	0.487	2.649
18	0.249	19.973	1.252	69.482	5.215	0.656	3.421
24	0.275	19.669	1.215	68.628	5.774	0.776	3.937
Aichi							
1	0.039	40.453	0.000	0.000	42.160	16.059	1.328
6	0.134	48.708	3.635	15.892	25.339	5.614	0.812
12	0.191	33.379	5.188	40.884	15.629	3.033	1.887
18	0.234	28.630	4.173	51.145	10.634	2.057	3.361
24	0.269	26.362	3.494	55.307	8.831	1.697	4.308
Shizuoka1							
1	0.044	38.119	0.000	0.000	0.000	57.155	4.726
6	0.141	45.867	4.788	17.167	13.732	16.804	1.642
12	0.201	32.595	6.468	40.949	9.898	8.674	1.416
18	0.243	28.332	5.237	51.062	6.944	5.931	2.493
24	0.277	26.262	4.377	55.140	6.121	4.691	3.410
Shizuoka2							
1	0.148	0.000	0.000	0.000	0.000	0.000	100.000
6	0.235	2.251	0.566	7.842	1.598	0.114	87.629
12	0.292	6.136	0.396	22.323	1.589	0.151	69.404
18	0.344	9.255	0.386	33.520	1.278	0.241	55.320
24	0.389	11.243	0.450	40.538	1.528	0.353	45.888

Notes: SE is the standard error. 1 and 2 denote live and prepared eel prices, respectively.

The influence of Taiwanese live eel prices on Chinese live eel prices shows a decreasing trend after reaching its peak at the 6-month horizon. Furthermore, after the 1-month horizon, the influence of the six eel prices on Chinese prepared eel prices becomes more stable, and the main sources of influence are from its own prices (68% to 75%) and Taiwanese live eel prices (19% to 20%) at each horizon. At the 1-month horizon, the price variation of Aichi's live eels is determined mainly by its own innovations (42.16%) and the innovations of Taiwanese live eel prices (40.45%). As time goes on, the influence of Aichi's own prices on its live eel prices sharply declines to 8.83%, and the influence of Taiwanese live eel prices shows a decreasing trend after the 6-month horizon. In contrast, the explanatory power of shocks in Chinese prepared eel prices displays an increasing trend, and there is a surge in the influence of Chinese prepared eel prices on Aichi's live eel prices before the 12-month horizon. The relationships among the price variation of Shizuoka's live eels and the main sources of influence (Shizuoka1, China 2, Taiwan) are similar to those among the price variation of Aichi's live eels and the main sources of influence (Aichi, China 2, Taiwan). Finally, the price volatility of Shizuoka's prepared eels (Shizuoka 2) is mostly determined by its own innovations at the initial stage of time horizons. As time passes, its own influence has a decreasing trend. A considerable proportion of the reduction is reflected in the increase of the explanatory power of shocks in Chinese prepared eel prices (China 2) for the price variation of Shizuoka's prepared eels.

3.5.2 Vegetable Soybean (Edamame) Imports in Japan

The descriptive statistics for import prices of vegetable-type soybeans from China, Indonesia, Taiwan, and Thailand and wholesale prices of domestic edamame in the Tokyo Metropolitan Central Wholesale Market are presented in Table 3.6. The highest price is reported from domestic edamame, while Indonesian edamame has the lowest price among five analyzed prices. Because of higher production costs, the preference for domestic goods, and product types, domestic prices of fresh edamame in Japan are much higher than those of imported frozen edamame. The CV suggests that prices of imported edamame are less dispersed than those of domestic edamame. Similarly, the SD also shows the same result. In the same way as the statistical mean, the SD is easily influenced by extreme values, i.e., the SD increases as the average increases. In this case, the CV is the best way to summarize the variation.

Table 3.6. Descriptive Statistics for Monthly Edamame Prices (JPY/KG), 1999-2017

Variable	Mean	SD	Minimum	Maximum	CV
Import					
China	167.122	22.692	129.740	223.603	0.136
Indonesia	180.681	31.867	106.299	263.751	0.176
Taiwan	208.463	27.341	162.513	277.501	0.131
Thailand	198.923	27.525	155.514	270.600	0.138
Domestics					
Japan	1181.741	494.698	387.000	2299.700	0.419

Notes: SD and CV are the standard deviation and coefficient of variation, respectively.

Table 3.7 presents both ADF and PP unit root tests. The null hypothesis for both test procedures is that a unit root exists in an evaluated series. The number of augmenting lags for the ADF test is determined by minimizing the BIC. Except for Indonesia, both ADF and PP tests have the same results for all analyzed price series. The results consistently suggest that the level of Japanese domestic prices is stationary, while levels of import prices from China, Taiwan, and Thailand are nonstationary at the 5% significance level. Both tests reveal that the null hypothesis is rejected for the first differences of all price series. Thus, it is concluded that all nonstationary price series in levels are integrated of order one.

Table 3.7. Unit Root Tests on the Level and First Difference of Monthly Edamame Prices, 1999-2017

Series	ADF		PP	
	Level	1st diff.	Level	1st diff.
China	-2.411 (0)	-16.211 (0)**	-2.172 (4)	-16.440 (4)**
Indonesia	-2.150 (1)	-25.028 (0)**	-3.078 (4)**	-27.438 (4)**
Japan	-3.169 (12)**	-7.783 (11)**	-7.010 (4)**	-14.346 (4)**
Taiwan	-1.691 (0)	-15.563 (0)**	-1.724 (4)	-15.558 (4)**
Thailand	-1.750 (2)	-9.100 (1)**	-1.549 (4)	-17.392 (4)**

Notes: The data are transformed by taking natural logarithms. The numbers in parentheses indicate the lag order in the ADF test and the bandwidth using the Newey-West bandwidth selection method and the Bartlett kernel in the PP test, respectively. The default bandwidth is the integer part of $4 \times (T/100)^{2/9}$ where T is the sample size. ** denotes significance at the 5% level.

Based on the lowest HQ, one lag is used in the VECM. Except for the second and fourth models, the Johansen trace and maximum eigenvalue statistics have different results for the five VECMs (Table 3.8). As mentioned above, when results of two statistics produce a contradiction in a certain model, the number of cointegrating vectors is determined by the trace statistic. The values of the BIC for each model with different r values are shown in Table 3.9. The lowest BIC value is -13.884 in the model that has linear trends in level data and its cointegrating equations. Thus, the innovations from this model are used to identify causal structure among the edamame price series.

Table 3.8. Johansen Tests on the Order of Cointegration of Monthly Edamame Prices in 5 Trend Assumptions

Data trend	None	None	Linear	Linear	Quadratic
ECT	None	Intercept	Intercept	Intercept Trend	Intercept Trend
Trace	3	2	3	2	3
Max. eigenvalue	2	2	2	2	2

Notes: Selected number of cointegrating relations at the 5% significance level. ECT denotes the error correction terms in a vector error correction model.

Table 3.9. Schwarz Criteria by Ranks (Row) and Models (Column) Using Monthly Edamame Prices

Data trend	None	None	Linear	Linear	Quadratic
ECT	None	Intercept	Intercept	Intercept Trend	Intercept Trend
Rank (*r*)					
2	-13.831	-13.827	-13.757	**-13.884**	-13.815
3	-13.660	-13.648	-13.602	-13.722	-13.676

Notes: ECT denotes the error correction terms in a vector error correction model.

At the 5% significance level, the result after removing the insignificant edges and directing the remaining edges is given in Figure 3.16. It clearly shows that changes in Chinese and Indonesian edamame prices lead to a change in Taiwanese edamame prices in contemporaneous time, while changes in Chinese and Taiwanese edamame prices affect a change in Thai edamame prices in contemporaneous time. In addition, the Thai edamame price is completely an information receiver.

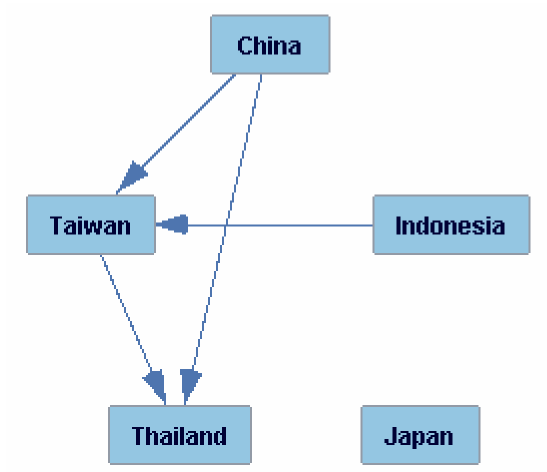


Figure 3.16. Directed acyclic graph on innovations from the VECM with edamame prices

The impulse response functions of our estimated model for selected edamame price series are depicted in Figure 3.17-3.21. In Figure 3.17 it is observed that a shock of Taiwanese edamame prices has an immediate positive effect on all edamame pries. All the effects peak in the 1st month expert for its own price in the origin and remain positive throughout all 24 months except that the shock has a negative impact on the price of Japanese domestic edamame after the 6th month. Comparing Figure 3.17 to Figure 3.18, shocks in the Taiwanese and Chinese edamame prices have similar effects on all edamame prices. The main differences are that the initial value from the response of Taiwanese prices to a Chinese price shock is nonzero and that the shock has a negative impact on the price of Japanese domestic edamame after the 3rd month. Figure 3.19 shows that a shock in Indonesian edamame prices has a positive impact on all edamame prices except for the price of Japanese domestic edamame.

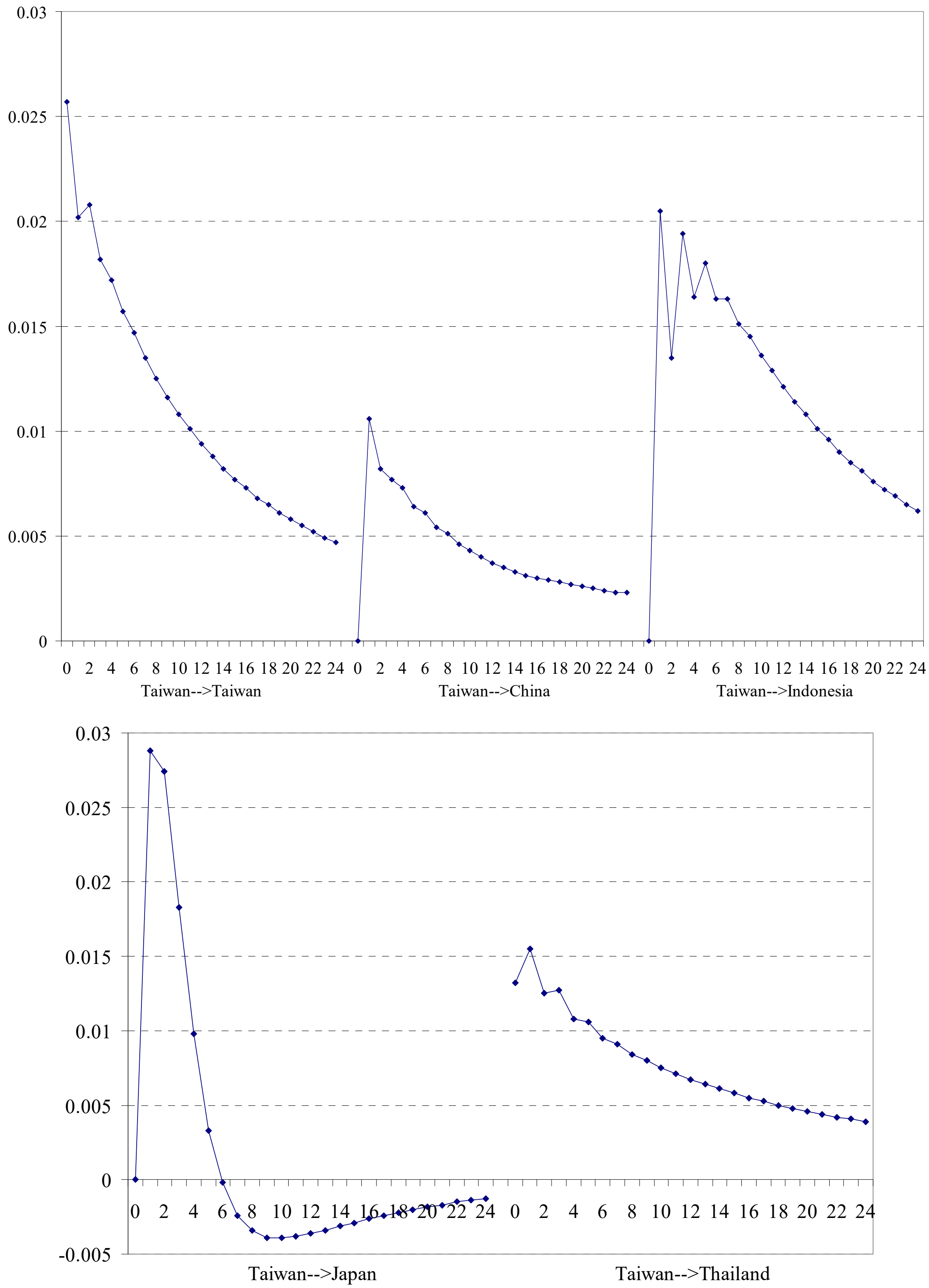


Figure 3.17. Impulse response function to a shock in Taiwanese edamame prices

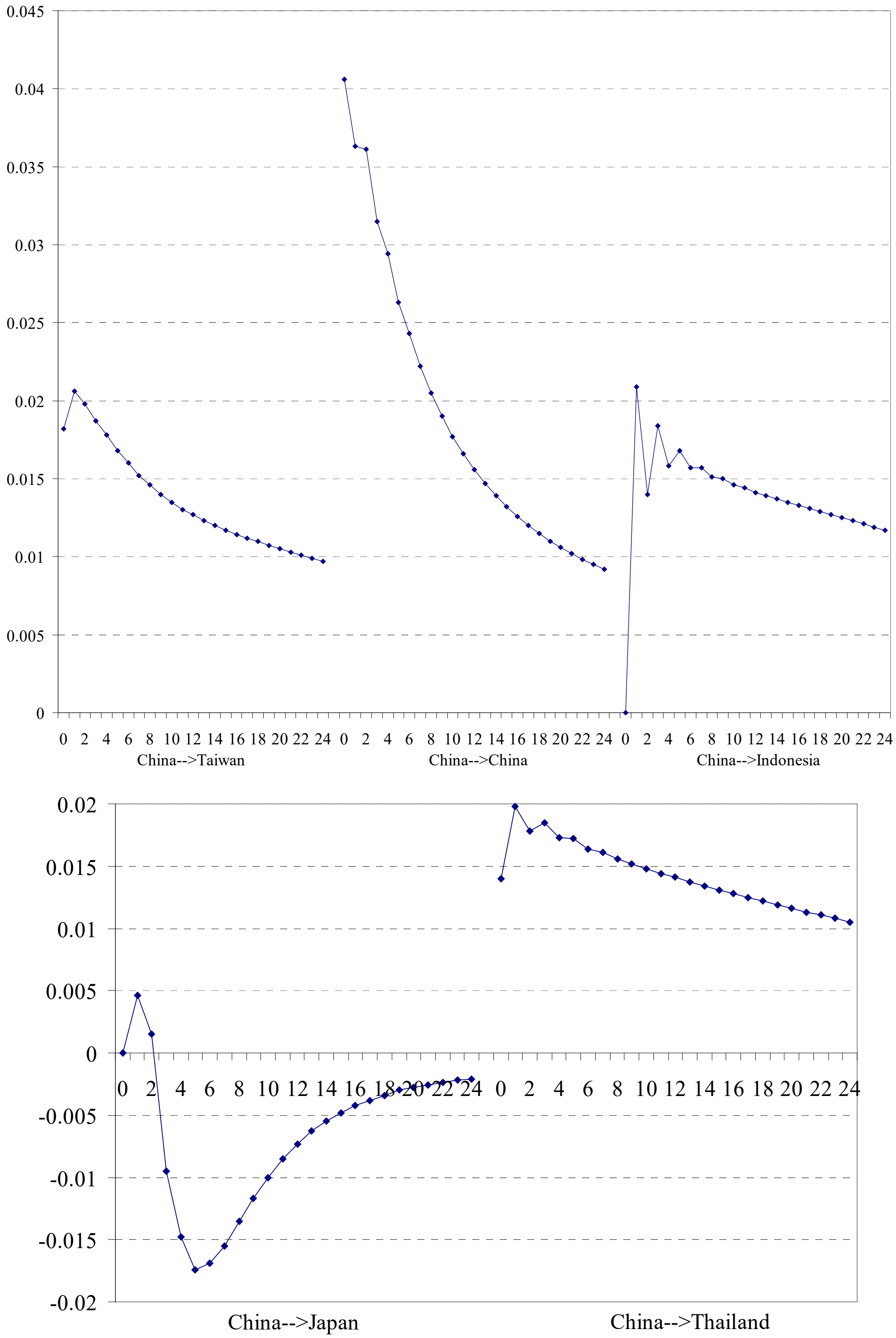
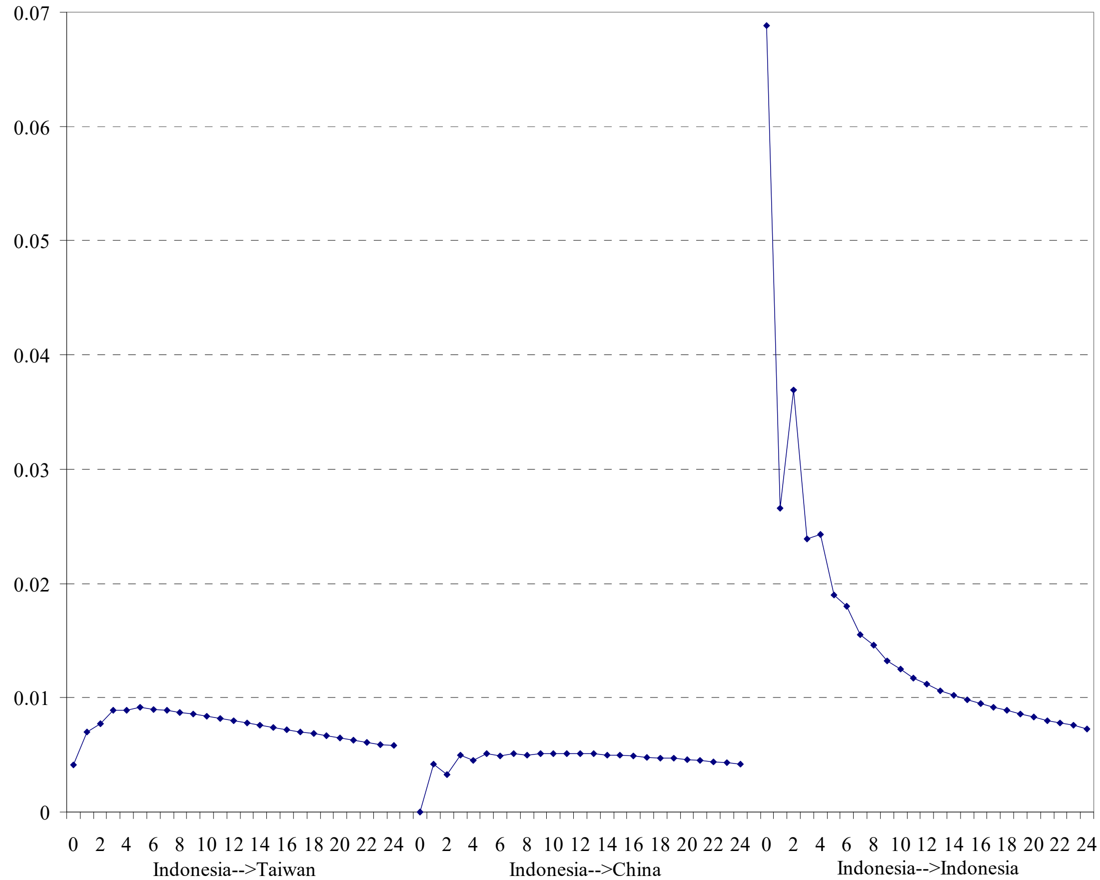


Figure 3.18. Impulse response function to a shock in Chinese edamame prices



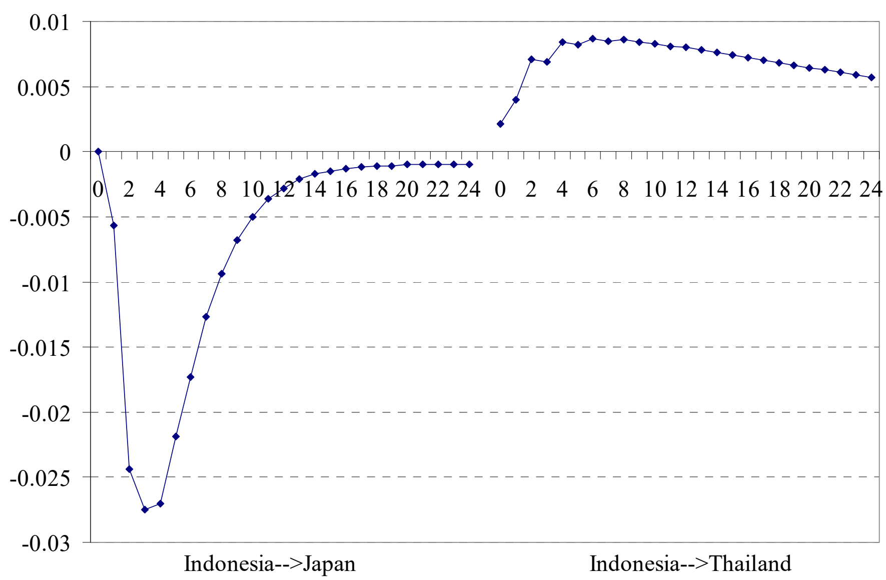
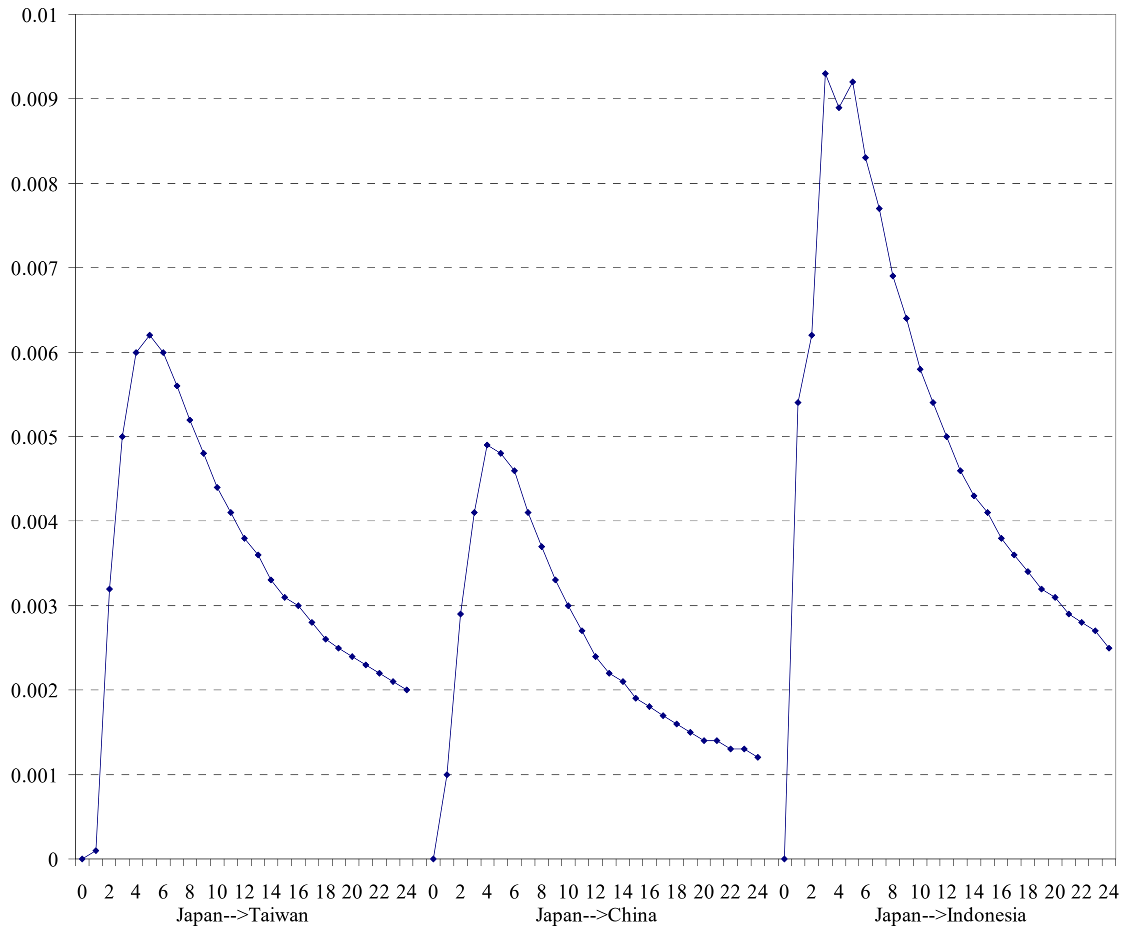


Figure 3.19. Impulse response function to a shock in Indonesian edamame prices



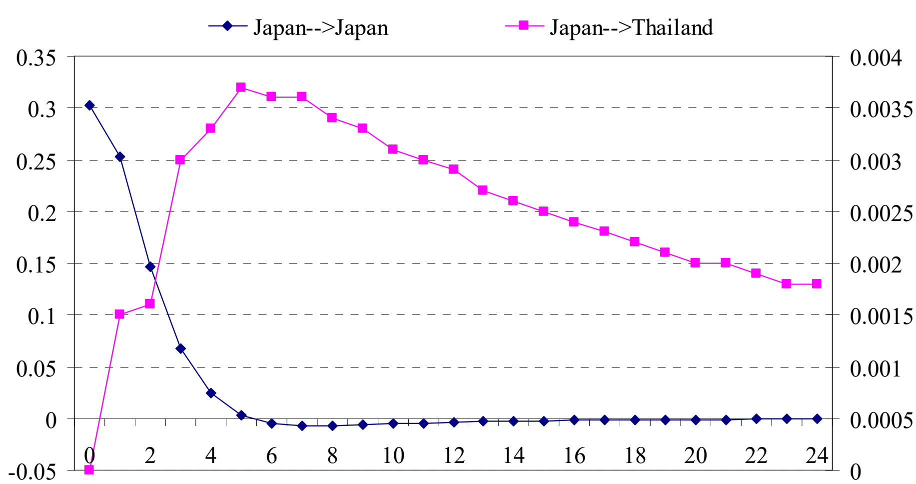


Figure 3.20. Impulse response function to a shock in Japanese edamame prices

Notes: The responses of Thai edamamea use a y-axis on the right side.

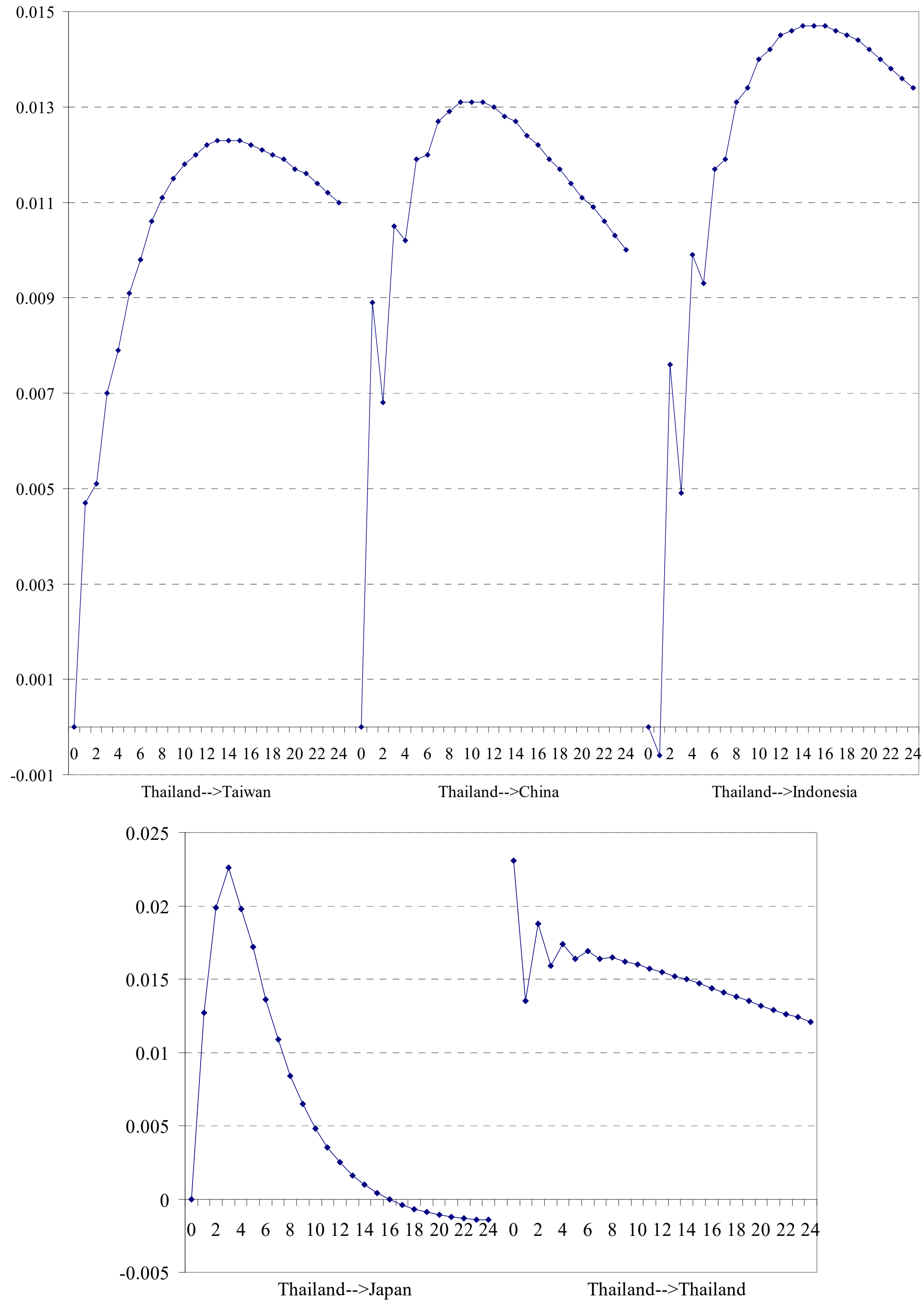


Figure 3.21. Impulse response function to a shock in Thai edamame prices

Additionally, the responses of Taiwanese, Chinese, and Thai edamame prices exhibit a slowly decreasing trend after reaching the peaks. The response of its own price takes a jump in the 1st month and continuously declines after the 6th month.

Figure 3.20 shows that a shock in the price of Japanese domestic edamame has a positive impact on all edamame prices except that the shock has a negative impact on its own prices after the 6th month. It is also worth mentioning that the shapes of line graphs describing the effects of the shock on the import edamame prices are similar. Figure 3.21 reveals that a shock of Thai edamame prices has positive effects on all edamame prices throughout all 24 months except for the response of Indonesian edamame prices in the 1st month and the response of the price of Japanese domestic edamame after the 16th month. The responses of all edamame prices appear as a downward trend after reaching a peak except the response of its own prices.

Based on the result of the directed graph given in Figure 3.16, the forecast error variance decomposition for each edamame price at alternative time horizons is given in Table 3.10. These values indicate how much of the volatility of the variable of interest can be explained by different variables in the model. For example, besides for its own innovations, price variations of edamame imported from Taiwan are explained mainly by innovations in prices of edamame imported from China (32 to 40 percent), Thailand (0 to 20 percent), and Indonesia (1 to 10 percent) and somewhat by innovations in prices of domestic edamame (0 to 3 percent). After the 6-month horizon, the influences of its own prices and Chinese edamame prices on the uncertainty of Taiwanese edamame prices have a decreasing trend, while the influences of Thai and Indonesian edamame prices are gradually increased.

Table 3.10. Variance Decomposition of Monthly Edamame Prices

Step	SE	Taiwan	China	Indonesia	Japan	Thailand
Taiwan						
1	0.032	65.438	32.885	1.677	0.000	0.000
6	0.072	45.740	40.348	7.107	2.112	4.693
12	0.093	37.730	38.418	9.400	3.033	11.419
18	0.106	32.679	37.287	10.307	2.924	16.803
24	0.115	29.346	36.753	10.661	2.746	20.496
China						
1	0.041	0.000	100.000	0.000	0.000	0.000
6	0.088	4.235	87.381	1.283	0.951	6.150
12	0.108	4.109	79.767	2.184	1.318	12.622
18	0.118	3.891	74.666	2.886	1.278	17.279
24	0.124	3.749	71.409	3.388	1.228	20.226
Indonesia						
1	0.069	0.000	0.000	100.000	0.000	0.000
6	0.109	13.110	12.558	69.456	2.656	2.219
12	0.131	16.803	16.671	55.544	3.474	7.508
18	0.145	16.962	18.952	48.459	3.366	12.261
24	0.155	16.310	20.499	44.247	3.187	15.757
Japan						
1	0.302	0.000	0.000	0.000	100.000	0.000
6	0.435	1.068	0.337	1.371	96.294	0.930
12	0.437	1.088	0.864	1.684	95.209	1.155
18	0.438	1.115	0.956	1.692	95.079	1.158
24	0.438	1.125	0.979	1.695	95.040	1.161
Thailand						
1	0.030	19.195	21.654	0.492	0.000	58.658
6	0.071	19.261	36.893	5.154	0.761	37.931
12	0.094	15.434	36.671	7.680	1.180	39.036
18	0.109	13.385	36.396	8.595	1.219	40.404
24	0.119	12.163	36.298	8.970	1.202	41.367

Notes: SE is the standard error.

Moreover, the variation of Chinese edamame prices is influenced primarily by its own shocks (71 to 100 percent) and secondarily by shocks in Thai edamame prices (0 to 20 percent). The explanatory power of shocks in its own prices gradually declines, while the explanatory power of shocks in Thai edamame prices has an increasing trend. The price volatility of Indonesian edamame is completely determined by its own innovations at the initial stage of time horizons. As time passes, its own influence has a decreasing trend. The reduction is mainly reflected in the increase of the explanatory power of shocks in Chinese (0 to 20 percent), Taiwanese (0 to 16 percent), and Thai (0 to 15 percent) edamame prices for the price variation of Indonesian edamame. In contrast, Japanese domestic price variations are determined almost solely by its own innovations at all steps (95 to 100 percent). In addition, Thai price variations are determined mainly by innovations of its own (41 to 58 percent), Chinese (21 to 36 percent), and Taiwanese (12 to 19 percent) edamame prices and somewhat by those of Indonesian (0 to 8 percent) edamame prices at all steps. The explanatory power of shocks in its own prices gradually declines, and the influences of Chinese and Taiwanese edamame prices have a decreasing trend after the six-month horizon. Conversely, the influence of Indonesian edamame price has an increasing trend.

3.5.3 Feather and Down Imports in Japan

The descriptive statistics for prices of feathers and down imported from China, France, Hungary, Poland, and Taiwan and of eiderdowns imported from China are presented in Table 3.11. According to the statistics of the Japan Customs, Japanese eiderdown imports are mostly from China, accounting for about 92 percent of total imports of eiderdowns in 2017. Extreme values have large impact on the arithmetic mean of data and cause bigger SDs in Hungarian and Polish price series than those in the rest of price series. The highest price of feathers and down is found from Poland, while French feathers and down have the lowest price among five analyzed price series of feathers and down. The CV suggests that the Polish and French price series are more dispersed than the rest of price series. The results are partly different from those of the SD. Moreover, both the SD and CV suggest that prices of eiderdown imported from China have the least dispersed among six analyzed prices.

Table 3.11. Descriptive Statistics for Monthly Feather and Down Prices (JPY/KG), 2004-2017

Variable	Mean	SD	Min.	Max.	CV
Feather and down					
China	4571.636	1643.750	1979.090	10287.220	0.360
France	3849.774	1801.656	723.667	8761.789	0.468
Hungary	7781.382	3098.671	3162.718	24143.520	0.398
Poland	9419.518	4638.041	1958.763	31450.000	0.492
Taiwan	4082.398	1566.003	1220.233	8834.913	0.384
Eiderdown					
China	1343.311	380.882	808.349	2544.947	0.284

Notes: SD and CV represent the standard deviation and the coefficient of variation, respectively.

Table 3.12 presents both ADF and PP unit root tests. Except for Hungary, results of the ADF test are different from those of the PP test. At a significance level of 0.05, the ADF test suggests that all price series are nonstationary in levels except for Hungary, whereas the PP test suggests that all price series are stationary in levels. Moreover, the ADF test reveals that the null hypothesis is rejected for the first differences of all price series. Thus, according to the results of the ADF test, it can be concluded that all nonstationary price series in levels are integrated of order one.

Table 3.12. Unit Root Tests on the Level and First Difference of Monthly Feather and Down Prices, 2004-2017

Series	ADF		PP	
	Level	1st diff.	Level	1st diff.
Feather and down				
China	-2.503 (2)	-14.535 (1)**	-4.311 (4)**	-19.142 (4)**
France	-2.191 (2)	-16.510 (1)**	-5.697 (4)**	-30.320 (4)**
Hungary	-3.167 (2)**	-14.480 (1)**	-6.767 (4)**	-27.462 (4)**
Poland	-1.914 (3)	-12.343 (2)**	-5.259 (4)**	-31.616 (4)**
Taiwan	-2.862 (1)	-20.308 (0)**	-4.093 (4)**	-22.088 (4)**
Eiderdown				
China	0.032 (12)	-5.670 (11)**	-3.215 (4)**	-16.813 (4)**

Notes: The data are transformed by taking natural logarithms. The numbers in parentheses indicate the lag order in the ADF test and the bandwidth using the Newey-West bandwidth selection method and the Bartlett kernel in the PP test, respectively. The default bandwidth is the integer part of $4 \times (T/100)^{2/9}$ where T is the sample size. ** denotes significance at the 5% level.

Based on the lowest HQ, one lag is used in the VECM. Both the Johansen trace and maximum eigenvalue statistics have the same results for the five VECMs (Table 3.13). The results suggest that rank r in the first model is equal to three and is the least than those in the rest of models, while the fifth model has full rank, i.e., rank r is equal to the number of equations in the VECM system. The values of the BIC for each model with different r values are shown in Table 3.14. The lowest BIC value is 0.554 in the model that has no deterministic trends in level data and whose cointegrating equations do not have intercepts. Thus, the innovations of this model are used to identify causal structure among the six analyzed price series.

Table 3.13. Johansen Tests on the Order of Cointegration of Monthly Feather and Down Prices in 5 Trend Assumptions

Date trend	None	None	Linear	Linear	Quadratic
ECT	None	Intercept	Intercept	Intercept Trend	Intercept Trend
Trace	3	4	5	5	6
Max. eigenvalue	3	4	5	5	6

Notes: Selected number of cointegrating relations at the 5% significance level. ECT denotes the error correction terms in a vector error correction model.

Table 3.14. Schwarz Criteria by Ranks (rows) and Models (columns) Using Monthly feather and down prices

Data trend	None	None	Linear	Linear	Quadratic
ECT	None	Intercept	Intercept	Intercept Trend	Intercept Trend
Rank (*r*)					
3	**0.554**	0.616	0.704	0.781	0.873
4	0.831	0.871	0.929	0.970	1.031
5	1.150	1.183	1.210	1.231	1.262
6	1.519	1.562	1.562	1.597	1.597

Notes: ECT denotes the error correction terms in a vector error correction model.

At the 5% significance level, the result after removing the insignificant edges and directing the remaining edges is given in Figure 3.22. It clearly shows that changes in Chinese eiderdown (China 2) and Taiwanese feather and down prices lead to a change in Chinese feather and down prices (China 1) in contemporaneous time, while changes in Chinese (China 1), Taiwanese, and Polish feather and down prices affect a change in Hungarian feather and down prices in contemporaneous time. In addition, the Hungarian feather and down price is completely an information receiver.

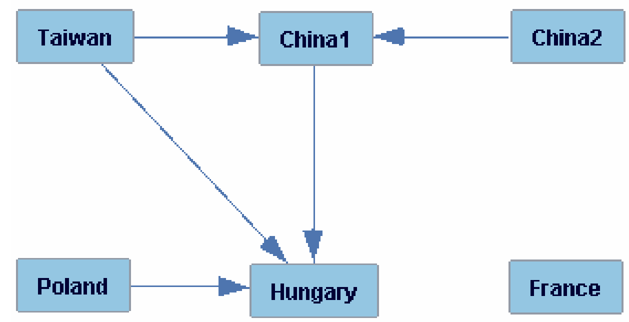


Figure 3.22. Directed acyclic graph on innovations from the VECM with feather-down and eiderdown prices

Notes: 1 and 2 denote feather-down and eiderdown prices, respectively.

The impulse response functions of our estimated model for selected feather-down and eiderdown price series are depicted in Figure 3.23-3.28. Figure 3.23 shows that a shock of Taiwanese feather-down prices has positive effects on all selected prices throughout all 24 months except for the response of Chinese eiderdown prices during the first two months. The effects of the shock on all the selected price series fluctuate wildly during the early stage of the time horizon and then go down gradually except that the response of Chinese eiderdown prices has a declining trend after reaching a peak. Figure 3.24 reveals that the effects of a stock of Chinese feather-down prices on all selected price series are positive except for the responses of French and polish feather-down prices in the 2nd month. The effects have a downward trend after the peaks of the responses of Taiwanese feather-down, Chinese eiderdown, and Polish feather-down prices, the initial value of the response of its own prices, and the 8th and 9th month of the responses of Hungarian and French prices, respectively.

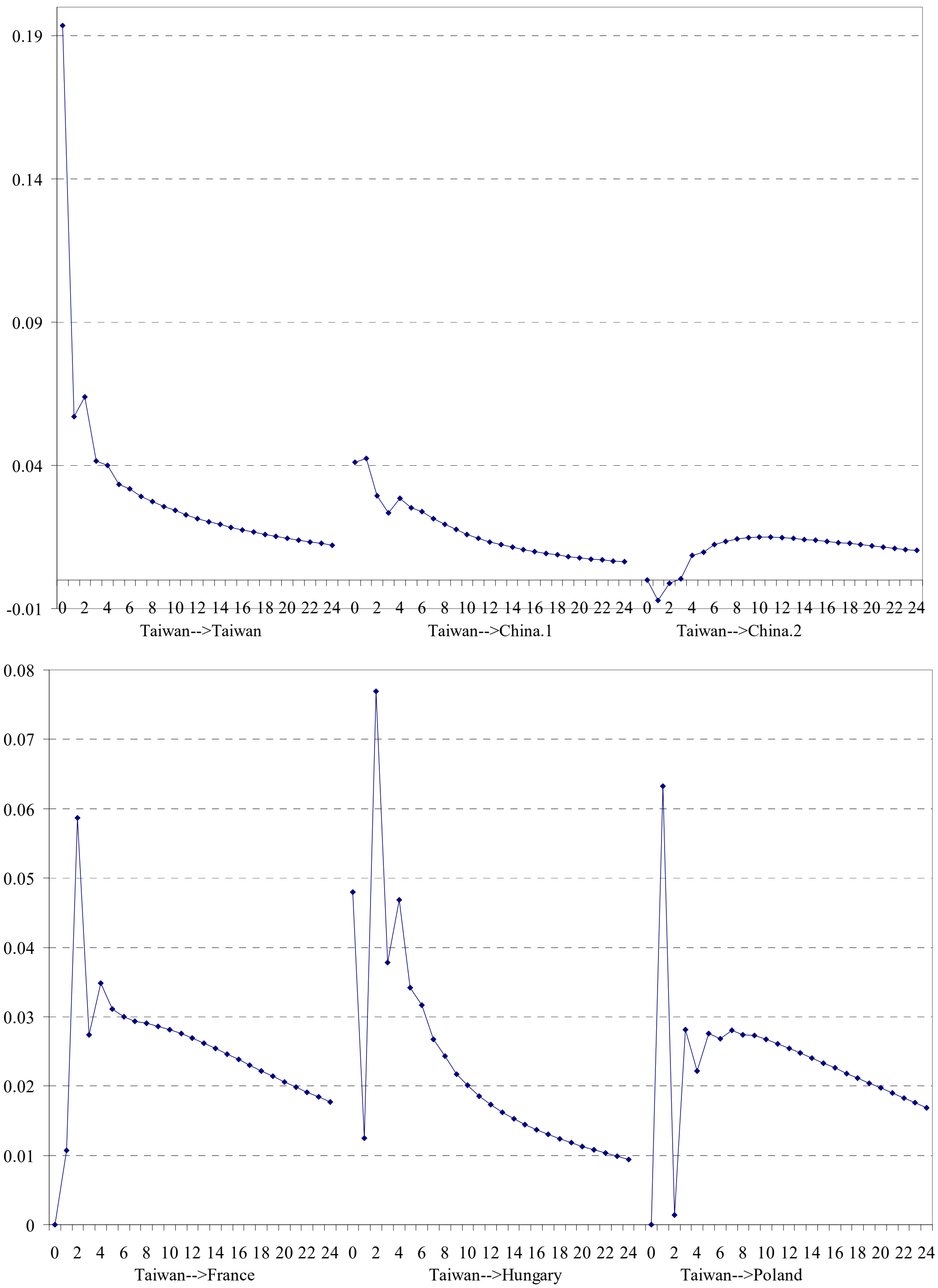


Figure 3.23. Impulse response function to a shock in Taiwanese feather and down prices

Notes: 1 and 2 denote feather-down and eiderdown prices, respectively.

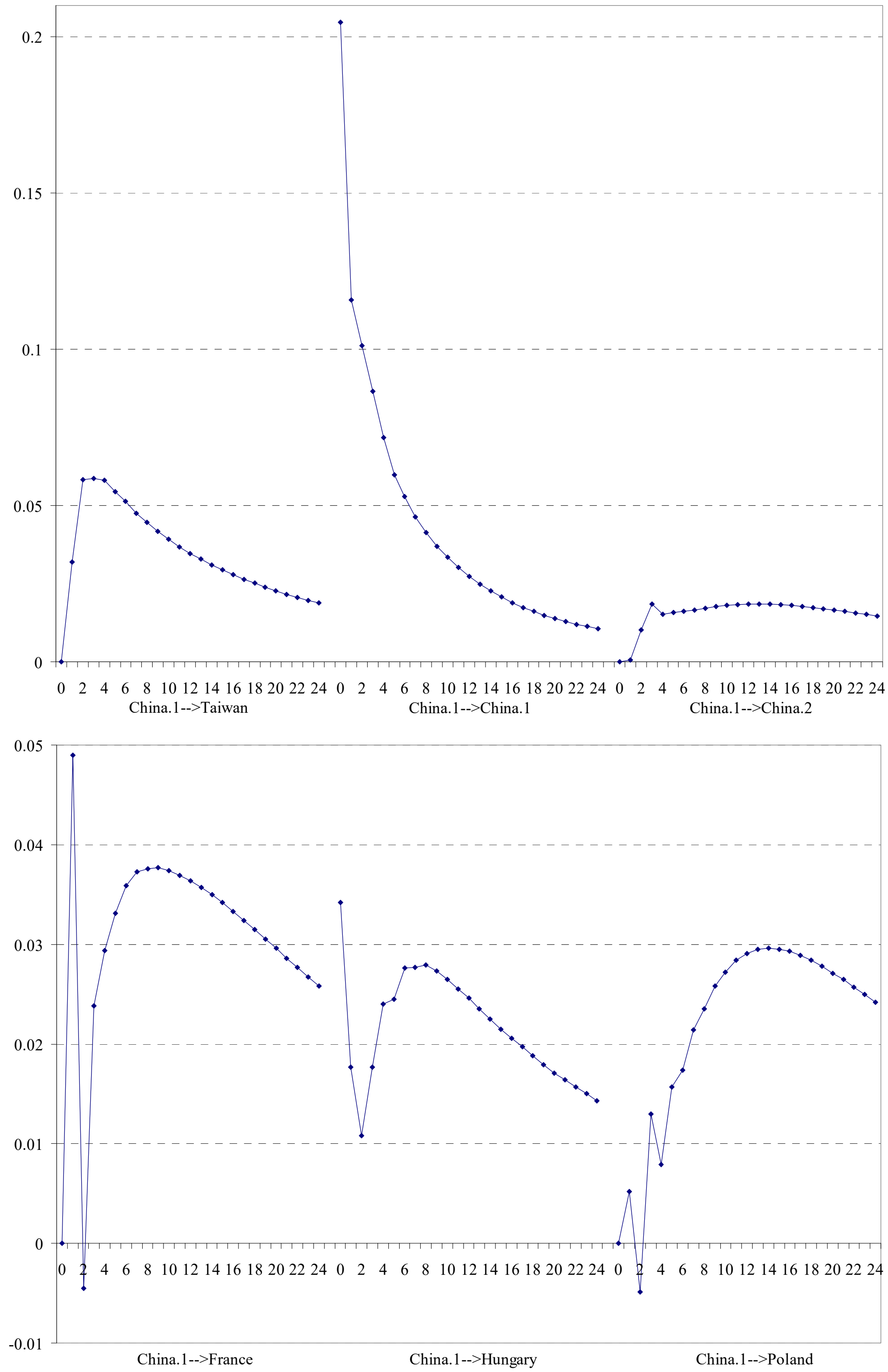


Figure 3.24. Impulse response function to a shock in Chinese feather and down prices

Notes: 1 and 2 denote feather-down and eiderdown prices, respectively.

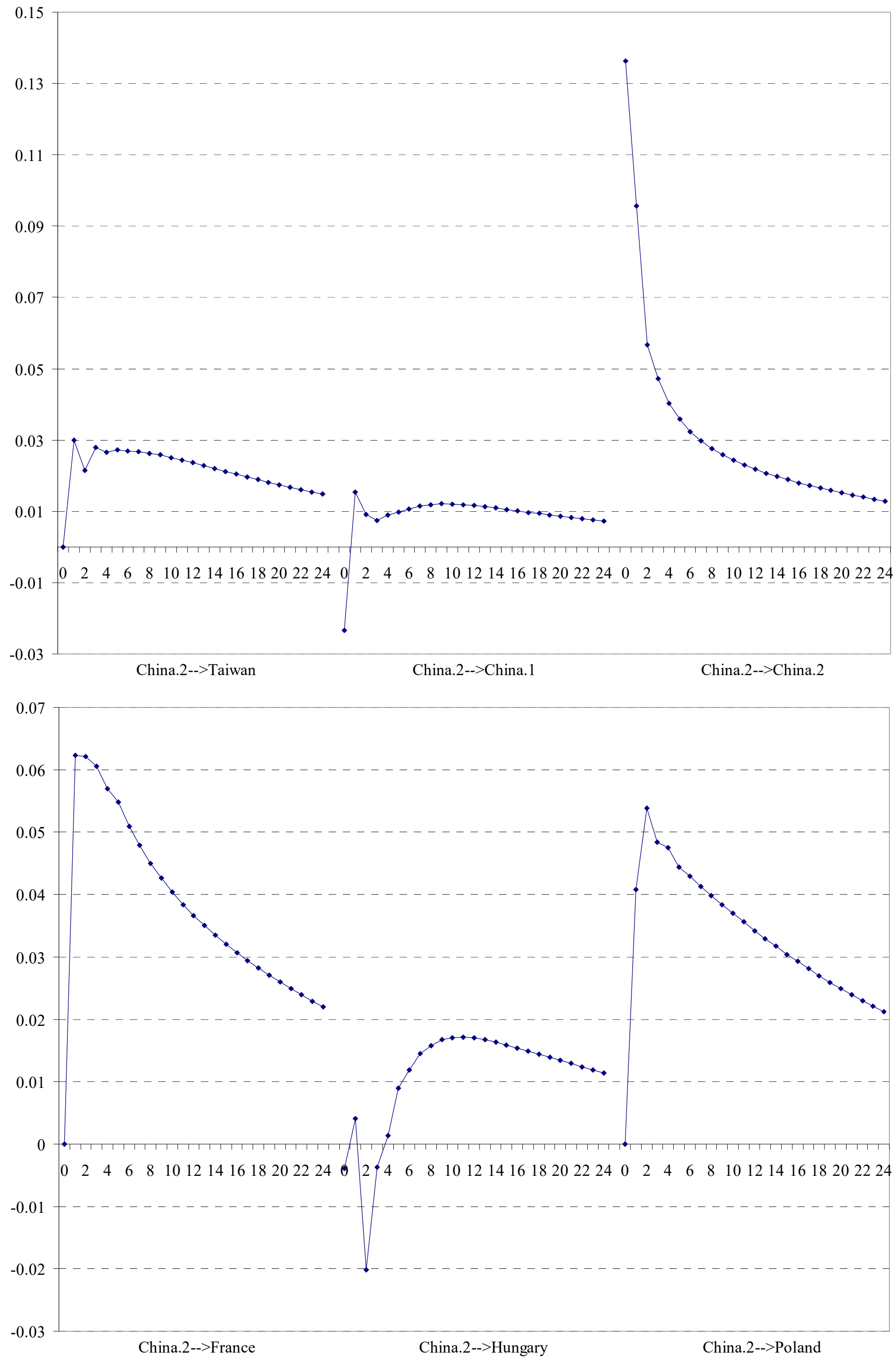


Figure 3.25. Impulse response function to a shock in Chinese eiderdown prices

Notes: 1 and 2 denote feather-down and eiderdown prices, respectively.

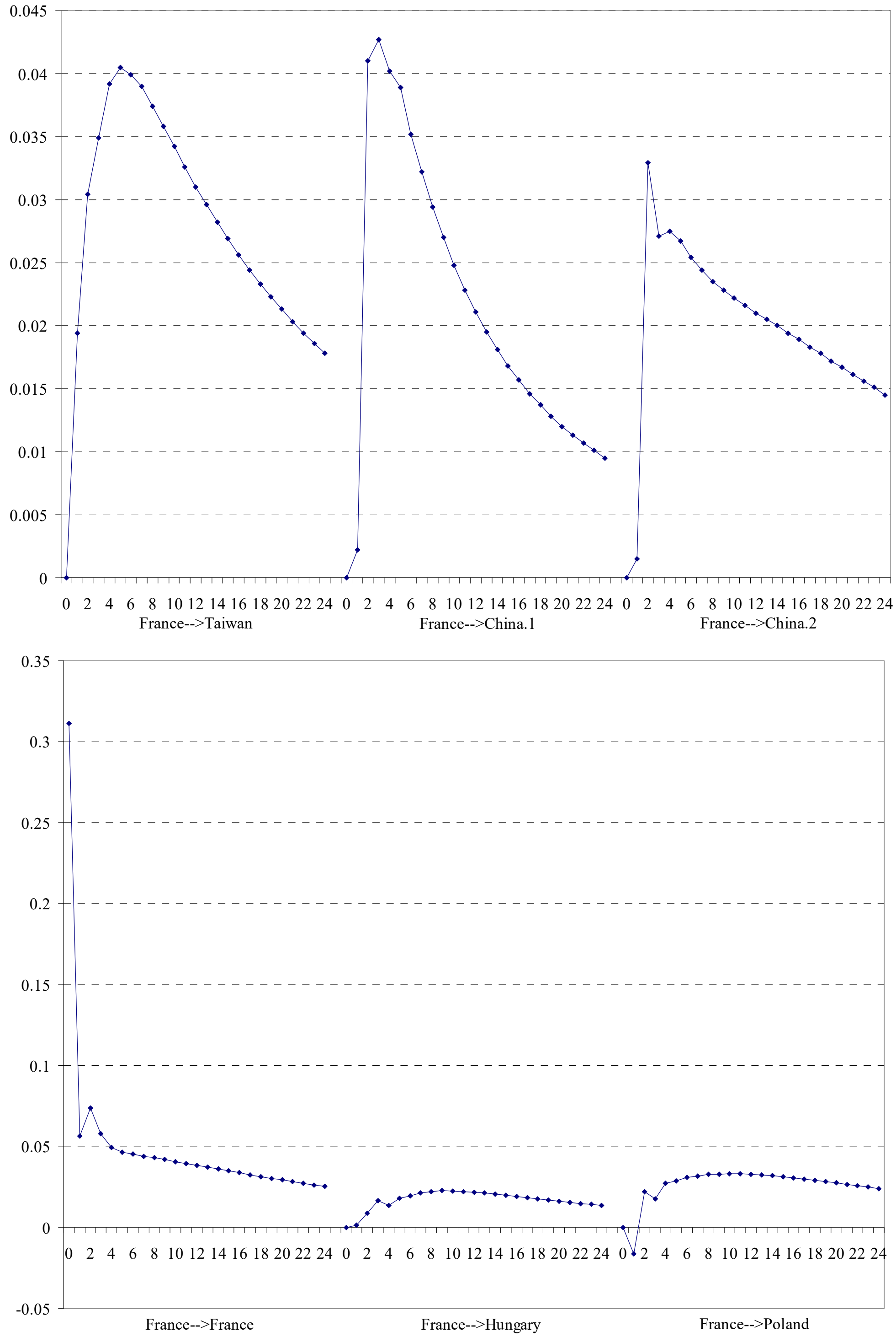


Figure 3.26. Impulse response function to a shock in French feather and down prices

Notes: 1 and 2 denote feather-down and eiderdown prices, respectively.

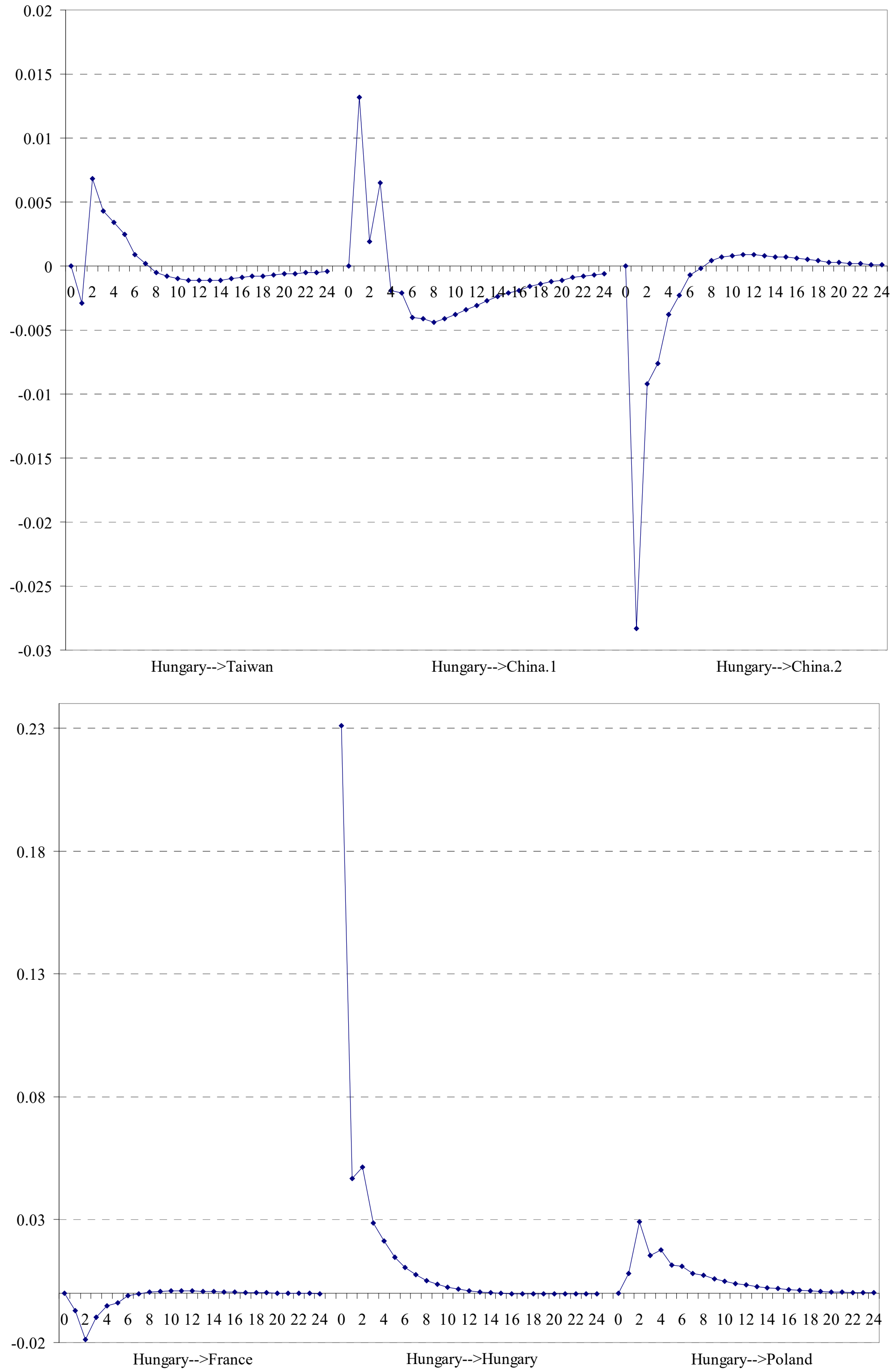


Figure 3.27. Impulse response function to a shock in Hungarian feather and down prices

Notes: 1 and 2 denote feather-down and eiderdown prices, respectively.

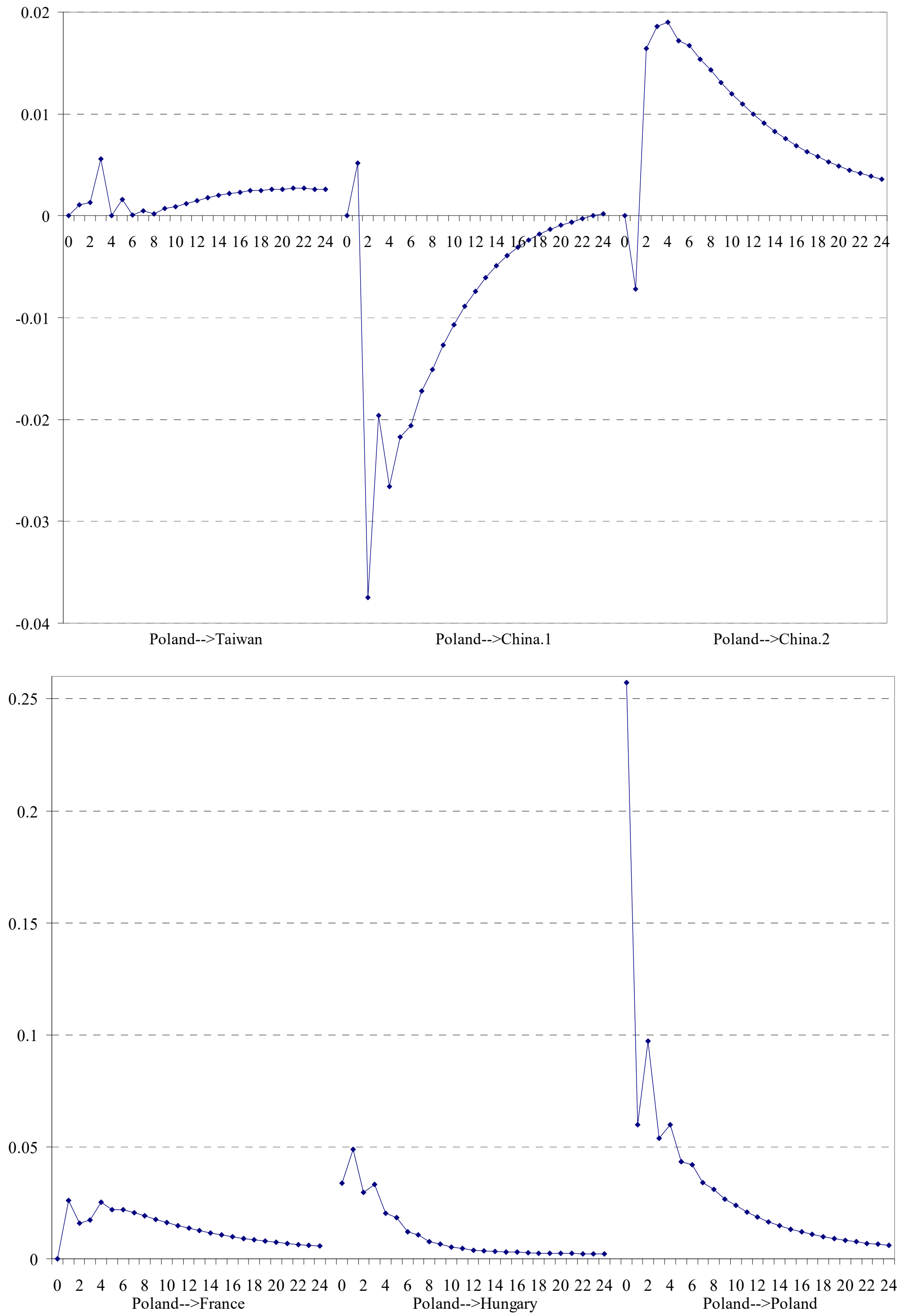


Figure 3.28. Impulse response function to a shock in Polish feather and down prices

Notes: 1 and 2 denote feather-down and eiderdown prices, respectively.

Figure 3.25 shows that a shock of Chinese eiderdown prices has positive effects on all selected prices throughout all 24 months except for the response of Hungarian feather-down price during the 2nd and 3rd months. In addition, the responses of all the selected prices appear a downward trend after reaching peaks except for the response of its own prices. Figure 3.26 reveals that a shock of French feather-down prices has positive effects on all selected prices throughout all 24 months except for the response of Polish feather-down price in the 1st month. Additionally, the responses of all the selected prices go down gradually after reaching peaks except for the response of its own prices.

Figure 3.27 shows that a shock of Hungarian feather-down prices has positive and negative effects on the responses of all the selected prices except for the response of Polish feather-down prices. In complete contradiction of the response of French feather-down and Chinese eiderdown prices, most positive effects are greater than negative effects on the responses of Taiwanese, Chinese, and Hungarian feather-down prices. Figure 3.28 shows a shock of Polish feather-down prices has positive effects on French, Hungarian, and Polish feather-down prices throughout all 24 months, whereas there is zero or negative effects on the response of the remaining selected prices. In complete contradiction of the response of Chinese feather-down prices, most of the effects on the response of Chinese eiderdown prices at each time point are positive.

Based on the result of the directed graph given in Figure 3.22, the forecast error variance decomposition is given in Table 3.15. Now China is the largest exporter of down raw materials and its products in the world.

Table 3.15. Variance Decomposition of Monthly Feather and Down Prices

Step	SE	Taiwan	China1	China2	France	Hungary	Poland
Taiwan							
1	0.194	100.000	0.000	0.000	0.000	0.000	0.000
6	0.270	67.579	19.496	4.933	7.815	0.126	0.051
12	0.318	53.205	25.501	7.558	13.602	0.095	0.039
18	0.341	48.107	26.963	8.999	15.786	0.088	0.056
24	0.353	45.757	27.489	9.789	16.796	0.084	0.086
China1							
1	0.210	3.851	94.912	1.237	0.000	0.000	0.000
6	0.315	6.416	82.524	1.107	6.697	0.231	3.025
12	0.344	7.206	77.455	1.619	9.818	0.274	3.629
18	0.353	7.433	75.813	2.085	10.824	0.287	3.558
24	0.357	7.547	75.053	2.379	11.249	0.286	3.486
China2							
1	0.136	0.000	0.000	100.000	0.000	0.000	0.000
6	0.207	0.512	2.150	84.303	7.687	2.252	3.096
12	0.234	2.598	4.971	74.124	12.002	1.766	4.540
18	0.251	4.132	7.488	68.103	14.155	1.541	4.582
24	0.261	4.996	9.217	64.567	15.385	1.417	4.417
France							
1	0.311	0.000	0.000	0.000	100.000	0.000	0.000
6	0.381	4.463	3.402	12.149	77.998	0.369	1.620
12	0.428	6.253	7.212	16.081	67.743	0.295	2.416
18	0.457	7.280	9.741	17.221	63.011	0.260	2.487
24	0.475	7.833	11.274	17.677	60.535	0.240	2.441
Hungary							
1	0.241	3.979	2.025	0.026	0.000	92.015	1.955
6	0.289	15.765	3.702	0.641	1.031	71.368	7.493
12	0.310	17.315	7.787	2.074	3.837	62.067	6.920
18	0.324	17.237	9.972	3.386	5.845	57.130	6.429
24	0.331	17.120	11.070	4.176	6.955	54.511	6.168
Poland							
1	0.257	0.000	0.000	0.000	0.000	0.000	100.000
6	0.331	5.518	0.482	10.171	2.382	1.450	79.996
12	0.373	7.515	2.922	14.677	6.415	1.371	67.100
18	0.400	8.603	5.741	16.334	9.262	1.206	58.854
24	0.419	9.153	7.705	17.004	10.960	1.105	54.072

Notes: SE is the standard error. 1 and 2 denote feather-down and eiderdown prices, respectively.

The clothing industry is a labor-intensive industry, i.e., its production process relies on a large amount of manpower, and the proportion of labor costs to manufacturing costs is high. Thus, most processing factories of down jackets and coats in Taiwan move to countries where wages are relatively cheaper. At present the Taiwanese feather and down industry mainly produces feathers of a kind used for stuffing, down, and eiderdowns filled with them. Because China has lower production costs and prices of raw materials, Taiwanese manufacturers have lost the Japanese eiderdown market and still face strong competition from China in the Japanese feather and down market.

This also reflects that besides its own innovations, the price variation of Taiwanese feathers and down is explained chiefly by innovations in the prices of feathers, down, and eiderdowns filled with them and imported from China (China 1 and China 2, 0 to 37 percent in total) and by those of feathers and down imported from France (0 to 16 percent). As time goes by, the influence of its own prices declines to 45.76%. In contrast, the explanatory powers of Chinese feather and down prices (China 1), Chinese eiderdown prices (China 2), and French feather and down prices have an increasing trend.

The price variation of Chinese feathers and down (China 1) is determined primarily by its own innovations at all steps (75 to 94 percent) and partly by innovations of French (0 to 11 percent) and Taiwanese (3 to 7 percent) feather and down prices. Similarly, the influence of its own prices gradually decreases, while the influences of French and Taiwanese feather and down prices on Chinese feather and down prices

(China 1) have an increasing trend. The uncertainty in Chinese eiderdown prices (China 2) is influenced mainly by its own innovations (64 to 100 percent). As time goes by, its own influence has a decreasing trend. The reduction is reflected largely in the increase of the explanatory power of shocks in French (0 to 15 percent) and Chinese (0 to 9 percent) feather and down prices and somewhat in that in Taiwanese (0 to 4 percent) and Polish (0 to 4 percent) feather and down prices. For the French price series besides itself, its price variation is explained mostly by Chinese (China 1 and China 2, 0 to 28 percent in total) innovations and rather by Taiwanese (0 to 8 percent) innovations. At the longer horizon of two years, the explanatory power of shocks in its own prices for the variation of Hungarian prices declines to 54.51%. The reduction is reflected mainly in the increase of the explanatory power of shocks in Taiwanese and Chinese (China 1 and China 2) prices and somewhat in that in French and Polish prices. Moreover, for the Polish price series besides itself, its price variation is explained largely by Chinese (China 1 and China 2, 0 to 24 percent in total) innovations and partly by Taiwanese (0 to 9 percent) and French (0 to 10 percent) innovations.

3.6 Conclusions

This paper examines dynamic price relationships in the Japanese eel, edamame, and feather and down import markets. We study observational data in an error correction framework using causal DAGs. For the Japanese eel import market, the DAG shows that a change in Taiwanese (live) eel prices leads to changes in (live) eel prices from Aichi prefecture, Shizuoka prefecture, and China in contemporaneous time. At the longer horizon of two years besides its own innovations, the Taiwanese price variation is mainly explained by innovations in prices of eels exported from China (China 1 and China 2, about 55.57% in total). The results of the impulse response functions reveal that the effect of a change in Taiwanese live eel prices on live eel prices from other markets is stronger than on prepared eel prices from other markets in initial phase. The volatility in Taiwanese live eel prices is significantly influenced by shocks in Chinese eel prices, whereas the effect of a change in eel prices from other markets is weak.

For the Japanese edamame import market, the DAG shows that changes in Chinese and Indonesian edamame prices lead to a change in Taiwanese edamame prices in contemporaneous time. In addition, a change in Taiwanese edamame prices leads to a change in Thai edamame prices in contemporaneous time. Besides its own innovations, price variations of Taiwanese edamame are explained primarily by innovations of Chinese (32 to 40 percent) and Thai (0 to 20 percent) edamame prices and somewhat by innovations of Indonesian edamame prices (1 to 10 percent). According the results of impulse response functions, the effect of a shock of Taiwanese edamame prices on Japanese edamame prices is stronger and positive in the first months but rapidly decline to negative. The effect of a change in edamame prices from other markets on Taiwanese edamame prices is insignificant.

For the Japanese feather and down import market, the DAG shows changes in Taiwanese feather and down prices lead to changes in Chinese (China 1) and Hungarian feather and down prices in contemporaneous time. Besides its own innovations, price variations of Taiwanese feathers and down are explained largely by innovations in prices of feathers, down, and eiderdowns exported from China (China 1 and China 2, 0 to 37 percent in total) and partly by those of feathers and down exported from France (0 to 16 percent). The results of the impulse response functions show that the volatility in feather-down prices from other markets is significantly influenced by a shock in Taiwanese feather-down prices. Additionally, the response of Taiwanese feather-down prices to Chinese and French feather-down prices is significant, whereas the response to Hungarian and Polish feather-down prices is insignificant.

CHAPTER IV

AN ANALYSIS OF THE BANANA IMPORT MARKET IN THE U.S.

4.1 Introduction

According to the statistics of the U.S. Department of Agriculture (USDA) and the U.S. International Trade Commission (USITC), banana is the number one fresh fruit consumed in the U.S. Its share is over 22% of the yearly quantity of fresh fruit consumption per capita and even exceeds the sum of the annual consumption of all citrus fruit since 1989. The annual volume of banana imports increased steadily until it peaked in 1999. After fluctuating between 3,500 and 4,100 thousand tons in the first decade and a half of the 21st century, the import volume of bananas reached a new historic high 4.38 million tons in 2017. The annual value of banana imports has fluctuated; however, the value increased between 2004 and 2012 and hit a historic high \$1.93 billion. Because of the geographic location of the United States, the production of bananas is limited to the state of Hawaii, which is less than 1,000 acres of land. The ratio of this production to domestic consumption is much smaller than the imports. In other words, the American consumption of bananas mostly depends on imports. Moreover, in terms of the import quantity of fresh fruits, bananas are the largest staple fruit consumed in the United States. This makes U.S. the biggest importer of bananas in the world with an approximate 4,379.34 thousand tons in 2017 and whose average share in global banana net import during 2008 to 2017 is about 24.66%. The share of banana imports in the EU taken as a whole is more than that of the U.S. and accounts for about 30.81% share in the period; however, it is made up of 28 countries and has about 1.56 times the population of the U.S.

Global banana exports are highly concentrated in five countries: Ecuador, Costa Rica, Guatemala, Colombia, and the Philippines. Along with wheat, rice, and corn, bananas are a significant staple commodity for these developing countries. Nevertheless, banana trade has a number of inherent complications. They include the consideration of transportation costs, time, delicate and perishable properties in banana distribution, and diverging import policies in the consuming countries. For this reason, U.S. banana imports originate almost entirely from Latin American countries near the equator, with imports from other parts of the world considered negligible. Colombia, Costa Rica, Ecuador, Guatemala, Honduras, and Mexico are the largest providers of fresh bananas to the United States. These equatorial countries together supply over 99% of total U.S. fresh banana imports, which make up about 35.71% of the fresh or chilled fruit quantity shipped by them to the United States in 2017. Furthermore, according to statistics from the WTO and the FAO, the percentage of banana export value to total export value (the volume share of bananas exported to the U.S. to total banana exports) in Colombia, Costa Rica, Ecuador, Guatemala, Honduras, and Mexico in 2017 are 2.26% (14.96%), 11.63% (32.55%), 15.48% (12.71%), 7.21% (87.32%), 2.88% (92.95%), 0.06% (68.79%), respectively. These show that the U.S. banana demand market plays a decisive role in the economic development and acquisition of foreign exchange of these countries.

Thus, structural and competitive changes in the demand for fresh bananas in the U.S. may have the possibility to cause severe economic shock in Latin American countries, which largely depend on the banana trade. Analyzing demand conditions of the import banana market in the U.S. could provide information for policy makers in banana export countries. In addition, bananas from these countries are called "dollar bananas" because they are mainly exported to North America by US-based transnational corporations (TNCs). The three largest producers and marketers of bananas in the world are all US-based TNCs. They are Chiquita Brands International (formerly known as the United Fruit Company, then United Brands), Fresh Del Monte Produce, and Dole Food Company (formerly Standard Fruit). Each accounts for about 11-13% of all bananas traded in the world. In addition to these US-based TNCs, the fourth largest is Fyffes plc, which controls about 6% of the world banana trade and whose headquarters is in Dublin, Ireland. Then the fifth largest banana export company in the world is Exportadora Bananera Noboa, which is one of the largest exporters of Ecuadorian bananas and which controls about 2% of total world trade. The U.S. banana market is free of tariffs or quantitative import restrictions and is basically controlled by these five companies, along with some relatively small ones. Thus, the banana import market has an oligopolistic market structure. In addition, due to producing and marketing large quantities of bananas, these TNCs can generate economies of scale at all levels of the supply chain to make profit.

The U.S. banana market in the past two decades has become saturated such that the volume and price (share, wholesale, and retail prices) generally remain fixed even during peak periods. Moreover, the U.S. is the largest banana importer in the world. Therefore, the primary goal of this article is to investigate the U.S. import demand for fresh bananas differentiated by country of origin to evaluate implication for the six main exporting countries. An ancillary goal is to compare forecasting performances among four inverse demand systems applied to evaluate the intensity of interaction of the six largest exporters of fresh bananas in the U.S. The paper is organized as follows. The related literature on the economic topics of bananas is presented in the next section of the paper. Then, the theoretical framework for inverse demand systems and data sources are described. Following that, results and relevant discussions are presented. The summary of main findings is presented in the last section of the paper.

4.2 Literature Review

Banana is the most important fresh fruit product traded internationally. According to the statistics of the FAO, in 2018, its global exports reached about 19.21 million tons, and it stood second in the global fruit production after watermelon. Thus, banana related issues are of interest to researchers such as determining consumer behavior, investigating market structures and supply chain, analyses of production efficiency, plant disease and pest control, etc. Some studies have investigated banana consumption and are described as follows. For the related literature in banana markets outside the U.S., Stuckey and Anderson (1974) used time series data at wholesale and cross-section data at retail to estimate the demand functions for bananas at wholesale and retail levels in Sydney, Australia. Lee et al. (1992) applied three demand systems: a general demand model, Rotterdam, and Central Bureau of Statistics (CBS) to estimate

Canadian demand for fresh fruits and juice. Behr and Ellinger (1995) used linear regression equations to estimate German banana demand of three household types. Deodhar and Sheldon (1995, 1996) estimated the degree of market imperfection in the German market for banana imports using the new empirical industrial organization (NEIO) approach and its dynamic version and concluded that the market is imperfectly competitive, respectively. James and Anderson (1998) used a standard comparative-static partial equilibrium approach to estimate the economic welfare consequences of lifting the import ban on fresh bananas in Australia.

Burrell and Henningsen (2001) investigated the consumer demand for bananas and for other fruits in Germany. They found that the demand for bananas is significantly responsive to their own price, and suggested that policy-induced price increases generate the usual dead-weight losses. Florido et al. (2002) applied structural econometric models of market equilibrium where both the market demand and the firm's strategies are specified to determine the type of strategic behavior adopted by firms in the German banana market. Moreover, a linear approximated almost ideal demand system (LA/AIDS) is applied to test the separability and homotheticity of the demand model of the German banana imports. Schmitz and Seale (2002) used likelihood ratio tests to compare a general demand model with other four demand models (AIDS, Rotterdam, CBS, and National Bureau of Research) in order to determine which models are applied to estimate Japanese import demand for fresh fruits. Hatirli et al. (2003) measured the market power of the banana import market in Turkey and concluded that the market is not perfectly competitive and the behavior of firms is much closer to price-taking than to collusion. Abdullah et al. (2011) applied a differentiated double logarithmic demand system to analyze Japanese demand for fruits such as bananas. Kikulwe et al. (2011) used a latent class model to analyze the choice experiment data which are collected by a household interview survey to evaluate consumer acceptance and valuation of genetically modified bananas in Uganda. Mortazavi et al. (2013) used an inverse AIDS (IAIDS) and residual demand model to analyze Iranian import demand for bananas exported from four major exporters. Weerahewa et al. (2013) used a liner regression approach to analyze the demand for bananas, mangos, papaws, and all fruits in Sri Lanka.

For the related literature in the U.S. banana market, Houck (1964) used an inverse log linear demand function to estimate the U.S. retail demand for bananas. The results suggested that the retail demand for bananas is price elastic, and seasonal relationships with other fruits are strong, while the competitive relationship with other fruits is not as strong as one might think. Durham and Eales (2010) applied an double-log demand system, AIDS, and its linear and quadratic (QUAIDS) versions to evaluate the demand for the U.S. fresh fruits (apples, pears, bananas, oranges, grapes, and others), and compare forecasting performances among four demand systems. The results showed that the QUAIDS has the lowest root mean square among them. Nzaku et al. (2010) applied a dynamic AIDS to estimate U.S. demand for fresh fruits (imported avocados, bananas, grapes, mangos, papayas, pineapples, and domestic graphs) and vegetables. The results suggested that the expenditure elasticity of bananas is about 0.25, that is, bananas are a normal and necessity good. When the import price of banana increases

1%, its import quantity will decrease about 0.10%. Moreover, imported bananas are a statistically significant substitute for imported avocados and mangos and domestic grapes. Muhammad et al. (2015) used a generalized dynamic Rotterdam model to analyze monthly import data from January 2000 to March 2010 in order to estimate the U.S. import demand for fresh bananas exported from five major exporters.

4.3 Inverse Demand Systems

In contrast with a regular system of demand equations, an inverse system of demand equations means that price changes are explained by quantity changes. In general, the regular demand system is suitable to describe the commodity whose consumers are price takers, that is, they have no ability to influence market prices. However, for perishable commodities such as fresh seafood and fresh fruit and vegetables, their producers behave like price takers and the supply is extremely inelastic in the short run. In such situations the causality goes from quantity to price, i.e. prices become endogenous and quantities demanded are exogenous. Thus, the inverse demand system is more appropriate to estimate the consumer demand of perishable commodities.

4.3.1 Inverse Almost Ideal Demand System

The traditional AIDS model can be used to model a complete demand system when the assumption of predetermined prices at the market level is tenable (Deaton and Muellbauer, 1980). However, for the demand of perishable commodities, which are produced in response to biological lags rather than price, the AIDS model would become inappropriate because of the preceding assumption is not met (Eales and Unnevehr, 1994). For this situation, inverse demand functions, where prices are functions of quantities, may be suitable to modeling agricultural demand using monthly or quarterly time series data. In the IAIDS model, the consumer preference is derived from the distance function (transformation function), which is dual to the cost function (expenditure function) of the AIDS. As the properties of cost function, the distance function is continuous in utility and quantity, decreasing in utility, and non-decreasing, concave, and homogeneous of degree one in quality (Moschini and Vissa, 1992). It measures the proportional amount by which all quantities consumed need to be inflated in order to reach a particular indifference curve. Let $U(q)$ represent the direct utility function, where q denotes the vector of quantities. Then, the distance function $F(u,q)$ is implicitly defined by $U\left[q / F(u,q) \right] = u$, where u denotes the reference utility level. The distance function has a derivative property similar to the cost function (Deaton, 1979). That is, differentiation of the distance function with respect to the optimal quantity of a particular good yields the compensated demand for that good in the same way that differentiation of the cost function with respect to a particular price yields a compensated demand function. Thus, following Deaton and Muellbauer's derivation of the AIDS model (1980), a logarithmic distance function is defined by Eales and Unnevehr (1994):

$$(4.1) \quad \ln F(u,q) = (1-u)\ln a(q) + u \ln b(q).$$

Because the distance function possesses the same properties as the cost function, except for substituting quantities for prices, $\ln a(q)$ and $\ln b(q)$ are basically defined analogous to those in the development of the AIDS model.

(4.2) $\ln a(q) = \alpha_0 + \sum_j \alpha_j \ln q_j + \frac{1}{2}\sum_i \sum_j \gamma_{ij}^* \ln q_i \ln q_j$,

(4.3) $\ln b(q) = \ln a(q) + \beta_0 \prod_j q_j^{-\beta}$.

Thus, the IAIDS distance function is written

(4.4) $\ln F(u,q) = \alpha_0 + \sum_j \alpha_j \ln q_j + \frac{1}{2}\sum_i \sum_j \gamma_{ij}^* \ln q_i \ln q_j + u\beta_0 \prod_j q_j^{-\beta_j}$.

The compensated inverse demand function can be derived directly from equation (4.4). The quantity derivatives of the distance function are the normalized prices demanded, i.e., by Shepherd's Lemma $\frac{\partial F(u,q)}{\partial q_i} = \frac{p_i}{m}$, where p_i and *m* denote the price of good *i* and total expenditure, respectively. In addition, if *q* is the bundle for which $u(q) = U$, then $F(U,q) = 1$. Thus, multiplying both sides by $\frac{q_i}{F(u,q)}$ to yield

(4.5) $\frac{\partial \ln F(u,q)}{\partial \ln q_i} = \frac{p_i q_i}{m} = w_i$,

where w_i is the budget share of good i. Hence, logarithmic differentiation of (4.4) gives the budget shares as a function of quantities and utility:

(4.6) $w_i = \alpha_i + \sum_j \gamma_{ij} \ln q_j - \beta_i u \beta_0 \prod_j q_j^{-\beta_j}$,

where $r_{ij} = \frac{1}{2}(\gamma_{ij}^* + \gamma_{ji}^*)$.

Inverting the distance function at the optimal quantity yields the direct utility function that may be substituted into equation (4.6).

(4.7) $U(q) = -\ln a(q)/[\ln b(q) - \ln a(q)]$.

This yields a system of inverse demand functions that Eales and Unnevehr (1994) call IAIDS.

(4.8) $w_i = \alpha_i + \sum_j \gamma_{ij} \ln q_j + \beta_i \ln Q$,

where the natural logarithm of the quantity index, $\ln Q$, is expressed as follows:

(4.9) $\ln Q = \alpha_0 + \sum_k \alpha_k \ln q_k + \frac{1}{2} \sum_j \sum_k \gamma_{kj} \ln q_j \ln q_k$.

Finally, as with the AIDS model, the theoretical restrictions of the fixed and unknown coefficients are imposed as:

(4.10a) Adding up: $\sum_i \alpha_i = 1$, $\sum_i \beta_i = 0$, $\sum_i \gamma_{ij} = 0$,

(4.10b) Homogeneity: $\sum_j \gamma_{ij} = 0$,

(4.10c) Symmetry: $\gamma_{ij} = \gamma_{ji}$.

Eales and Unnevehr (1994) also provide the relevant formulas for the flexibilities, when estimating the static IAIDS model as follows,

(4.11) $f_i = -1 + \beta_i / w_i$,

(4.12) $f_{ij} = -\delta_{ij} + \{\gamma_{ij} + \beta_i (w_j - \beta_j \ln Q)\} / w_i$,

(4.13) $f_{ij}^c = f_{ij} - w_j f_i$,

where f_i, f_{ij}, and f_{ij}^c denote scale, Marshallian (uncompensated) quantity, and Hicksian (compensated) quantity flexibilities, respectively. δ_{ij} denotes the Kronecker delta that equals one if $i = j$ and zero otherwise.

Because both static AIDS and IAIDS ignore the problem of estimation and inference with nonstationary variables, Balcombe and Davis (1996) employed the canonical cointegrating regression procedure to estimate the AIDS, and Karagiannis and Velentzas (1997) developed a dynamic formulation of the AIDS based on the ECM. Following the previous work, Klonaris (2014) derived an inverse version of dynamic AIDS based on the ECM. To understand the statistical properties of the data, first unit root tests are used to examine whether the variables used in the static IAIDS are stationary. If the variables are nonstationary, the next step is to test for cointegration in equation (4.8). When it is ensured that all variables are cointegrated, a dynamic IAIDS (DIAIDS) based on an error correction can be expressed as

(4.14) $$\Delta w_{i,t} = \lambda_i \hat{v}_{i,t-1} + \sum_j \varphi_{ij} \Delta \ln q_{j,t} + \phi_i \Delta \ln Q_t + \varepsilon_t,$$

where Δ is the first difference operator, $\hat{v}_{t-1}$ is the estimated lagged residuals with a lag of one period from the static IAIDS model and can be obtained by:

(4.15) $$\hat{v}_t = w_{it} - \hat{\alpha}_i + \sum_j \hat{\gamma}_{ij} \ln q_{jt} + \hat{\beta}_i \ln Q_t.$$

Similar to the static IAIDS model, the DIAIDS is required to satisfy the properties of adding-up, homogeneity, and symmetry, as expressed in equation (4.10) with the corresponding parameters being substituted. Similarly, for the calculation of the scale and quantity flexibilities of the DIAIDS, the parameter estimates β_i and γ_{ij} in equation (4.11) and (4.12) are replaced by short-run those ϕ_i and φ_{ij}, respectively.

4.3.2 Inverse National Bureau of Research Demand System

Barten and Bettendorf (1989) derived a Rotterdam inverse demand system and used it to estimate fish demand in Belgian fishery ports. Ordinary demand functions can be derived from the analysis of (direct) utility maximization subject to a budget constraint. From the duality between direct and indirect utility functions, an inverse demand function can be derived by minimizing the indirect utility function subject to the budget constraint (Weymark, 1980). Formally, this problem can be expressed as:

(4.16) Min. $v(\pi)$ subject to $\pi' q = 1$

where v is the indirect utility function, $\pi = \left(\frac{1}{m}\right)p$ is the normalized price vector, $m = p'q$ is total expenditure on all commodities in the demand system, p is a $n \times 1$ price vector for the commodities purchased in the demand system, and q is the corresponding quantity vector. The method of Lagrange multipliers is used to solve the constrained minimum problem. As quantities are varied, the normalized prices produce the inverse demand functions: $\pi = g(q)$. The total derivative of π_i with respect to q_j can be written as:

(4.17) $d\pi_i = \sum_j \left(\frac{\partial \pi_i}{\partial q_j}\right) dq_j$,

According to Anderson's paper in 1980, the total effect $\frac{\partial \pi_i}{\partial q_i}$ can be divided into the Antonelli substitution effect, analogous to the Slutsky equation for direct demands, and a scale effect. Thus, equation (4.17) can be rewritten as:

(4.18) $d\pi_i = \sum_j \left(\xi_{ij} + h\pi_j \left(\frac{\partial \pi_i}{\partial h} \right) \right) dq_j$,

where ξ_{ij} refers to the degree of responsiveness of π_i given a marginal change of q_j when consumers maintain the same indifference level. *h* is a scalar variable. We can multiply both sides of equation (4.18) by q_i and rearrange terms to obtain

(4.19)

$$q_i\pi_i \frac{d\pi_i}{\pi_i} = \sum_j q_i q_j \left(\xi_{ij} + h\pi_j \left(\frac{\partial \pi_i}{\partial h} \right) \right) \frac{dq_j}{q_j} = \sum_j \beta_{ij} \frac{dq_j}{q_j} + q_i\pi_i \frac{\partial \pi_i}{\partial h} \frac{h}{\pi_i} \sum_j q_j \pi_j \frac{dq_j}{q_j} ,$$

where $\beta_{ij} = q_i q_j \xi_{ij}$. Because $w_i = \frac{q_i p_i}{m} = q_i \pi_i$ is the share of expenditure on commodity *i* in total expenditure, equation (4.19) can be written as:

(4.20) $w_i \frac{d\pi_i}{\pi_i} = \sum_j \beta_{ij} \frac{dq_j}{q_j} + w_i \xi_{i,h} \sum_j w_j \frac{dq_j}{q_j}$,

where $\xi_{i,h}$ is the scale flexibility of commodity *i*. Because $\frac{dx_i}{x_i} = d\ln x_i$ (*ln*: the natural logarithm), equation (4.20) can be rewritten as:

(4.21) $w_i d\ln \pi_i = \sum_j \beta_{ij} d\ln q_j + \theta_i d\ln Q$,

where $\theta_i = w_i \xi_{i,h}$ and $d\ln Q = \sum_j w_j d\ln q_j$. In general, $\overline{w}_{it} = \frac{1}{2}(w_{i,t} + w_{i,t-1})$, is used to replaces $w_{i,t}$ (*t* is the current time period). According to Barten and Bettendorf (1989), β_{ij} and θ_i have the following properties:

(4.22a) Adding up: $\sum_i \theta_i = -1$ and $\sum_i \beta_{ij} = 0$, (4.22b) Homogeneity: $\sum_j \beta_{ij} = 0$,

(4.22c) Antonelli symmetry: $\beta_{ij} = \beta_{ji}$.

To add $w_i d\ln Q$ to both sides of equation (4.21) and treat the $c_i = \theta_i + w_i$ as constants, the variable on the left-hand side is then

(4.23)

$$w_i(d\ln\pi_i + d\ln Q) = w_i(d\ln p_i - d\ln m + d\ln Q) = w_i(d\ln p_i - d\ln P) = w_i d\ln(p_i / P),$$

where $\ln P$ is the Divisia price index. The inverse CBS (ICBS) model can be written as follows:

(4.24) $$w_i d\ln(p_i / P) = \sum_j \beta_{ij} d\ln q_j + c_i d\ln Q.$$

To add $w_i(d\ln q_i - d\ln Q)$ to both sides of equation (4.24) and treat the $c_{ij} = \beta_{ij} + w_i\delta_{ij} - w_i w_j$ (δ_{ij} is Kronecker delta) as constants, the variable on the left-hand side is then

(4.25) $$w_i(d\ln p_i + d\ln q_i - d\ln P - d\ln Q) = w_i d\ln w_i = dw_i.$$

The differential IAIDS model can be obtained as follows:

(4.26) $$dw_i = \sum_j c_{ij} d\ln q_j + c_i d\ln Q.$$

To subtract $w_i d\ln Q$ from both sides of equation (4.26) and $c_i - w_i = \theta_i$ as constants, the inverse National Bureau of Research (INBR) model can be obtained as follows:

(4.27) $$dw_i - w_i d\ln Q = \sum_j c_{ij} d\ln q_j + \theta_i d\ln Q.$$

Scale flexibilities refer to the degree of responsiveness of π_i given a change of the aggregated quantity and are calculated as:

(4.28) $\xi_{h,i} = \frac{\theta_i}{w_i}$.

The Hicksian (compensated) quantity flexibilities can be expressed as follows:

(4.29) $\xi_{ij}^c = -\delta_{ij} + \frac{c_{ij}}{w_i} + w_j$.

The Marshallian (uncompensated) quantity flexibilities are given by

(4.30) $\xi_{ij} = \xi_{ij}^c + w_j \xi_{h,i}$.

4.4 Data

Quarterly data on imported fresh bananas to the U.S. are used to estimate inverse demand systems. The data were obtained from the USITC and included 116 pieces of import quantities in kilograms and import values in dollars from the first quarter of 1989 to the fourth quarter of 2017. The data for all imported fresh bananas are disaggregated by countries of origin, Colombia, Costa Rica, Ecuador, Guatemala, Honduras, Mexico, and the rest of the world.

4.5 Empirical Results

The descriptive statistics for market shares and prices of fresh bananas exported to the U.S. from main departure countries are presented in Table 4.1. In terms of import values of fresh bananas in the U.S. market from 1989 to 2017, average shares from Costa Rica, Guatemala, and Ecuador were compositely greater than 20%, and those from Colombia, Honduras, and Mexico were about 12%, 12%, and 4%, respectively. Because the market share from Guatemala sharply grew from under 10% in 1989 to over 40% in 2017, bigger SD and CV values reflect the rapid change of its market share. The CV suggests that the Mexican share series is the most dispersed of share series. With respect to import prices, both the SD and CV suggest import prices of fresh bananas exported from Honduras have the least dispersal among six analyzed import prices, while those exported from Costa Rica have the biggest dispersal.

Table 4.1. Descriptive Statistics for Imported Fresh Bananas, 1989/Q1-2017/Q4

Variable	Mean	Maximum	Minimum	SD	CV
Share					
Colombia	12.14%	21.42%	4.56%	3.51%	0.29
Costa Rica	23.89%	36.30%	12.22%	4.70%	0.20
Ecuador	22.68%	37.27%	7.79%	5.72%	0.25
Guatemala	23.31%	47.10%	7.67%	10.71%	0.46
Honduras	11.56%	22.72%	0.95%	3.55%	0.31
Mexico	4.02%	10.84%	1.02%	2.36%	0.59
Price (USD/kg)					
Colombia	0.349	0.557	0.257	0.082	0.24
Costa Rica	0.338	0.614	0.195	0.087	0.26
Ecuador	0.322	0.589	0.230	0.082	0.25
Guatemala	0.332	0.603	0.245	0.076	0.23
Honduras	0.308	0.635	0.221	0.065	0.21
Mexico	0.342	0.546	0.163	0.084	0.24

Notes: SD and CV represent the standard deviation and the coefficient of variation, respectively.

Table 4.2 presents both ADF and PP unit root tests. The null hypothesis for both test procedures is that a unit root exists in an evaluated series. The number of augmenting lags for the ADF test is determined by minimizing the BIC. Except for Costa Rica and Ecuador, both ADF and PP tests have the same results for all series of market shares. They consistently suggest that the level of the Honduran market share series is stationary, while levels in the market share series of the rest of the exporting countries are nonstationary. With regard to import quantities, both ADF and PP tests have the same results. They clearly imply that levels of import quantities from Costa Rica, Honduras, and the others are stationary, while those of the rest of the exporting countries are nonstationary. Both unit root tests reveal that the null hypothesis is rejected for the first differences of all market share and import quantity series. Thus, it is concluded that all nonstationary price series in levels are integrated processes of order one.

Table 4.2. Unit Root Tests in the Level and First Difference of the Data for Imported Fresh Bananas, 1989/Q1-2017/Q4

	ADF		PP	
Variable	Level	1st diff.	Level	1st diff.
Share				
Colombia	-2.830 (0)	-12.163 (0)**	-2.600 (4)	-12.776 (4)**
Costa Rica	-2.701 (1)	-15.333 (0)**	-3.603 (4)**	-16.423 (4)**
Ecuador	-1.136 (4)	-6.184 (3)**	-3.292 (4)**	-17.975 (4)**
Guatemala	1.285 (6)	-9.513 (2)**	-0.220 (4)	-14.433 (4)**
Honduras	-3.867 (1)**	-15.616 (0)**	-4.309 (4)**	-15.527 (4)**
Mexico	-1.824 (0)	-11.622 (0)**	-1.967 (4)	-11.591 (4)**
Quantity				
Colombia	-2.408 (0)	-13.256 (0)**	-2.014 (4)	-14.118 (4)**
Costa Rica	-4.281 (0)**	-14.719 (0)**	-4.129 (4)**	-15.749 (4)**
Ecuador	1.822 (11)	-5.335 (10)**	-2.694 (4)	-16.436 (4)**
Guatemala	-1.172 (7)	-8.056 (6)**	-1.749 (4)	-16.130 (4)**
Honduras	-3.727 (0)**	-12.669 (0)**	-3.854 (4)**	-12.684 (4)**
Mexico	-1.262 (0)	-12.357 (0)**	-1.247 (4)	-12.259 (4)**
Others	-3.847 (0)**	-12.451 (0)**	-3.739 (4)**	-13.287 (4)**

Notes: The data are transformed by taking natural logarithms. The numbers in parentheses indicate the lag order in the ADF test and the bandwidth using the Newey-West bandwidth selection method and the Bartlett kernel in the PP test, respectively. The default bandwidth is the integer part of $4 \times (T/100)^{2/9}$ where T is the sample size. ** denotes significance at the 5% level.

We applied the directed graph method (DGM) to identify the causal relationship among the variables in DIAIDS and INBR models. For example, consider the equation associated with differentially Colombian market shares (dw_1) in the DIAIDS. We formed the starting undirected graph by connecting all pairs of vertices formed by differentially Colombian market shares, differentially logarithmic banana quantities exported from Colombia, Costa Rica, Ecuador, Guatemala, Hondurans, Mexico, and the other countries ($dlnq_i$), the differentially logarithmic Divisia volume index (dlnQ), and lagged innovations from the Colombia equation in the static IAIDS model ($lresid_1$). We chose a 0.2 significance level in removing edges from the graph consistent with the sample size (Scheines, Spirtes, Glymour, and Meek, 1994, P. 81). Similarly, the same steps and causal discovery algorithm are applied to the INBR model. Figure 4.1 and 4.2 are final graphs of DIAIDS and INBR models, respectively. According to the final DGM model of the DIAIDS, dw_1 will be estimated and forecasted by $dlnq_1$, $dlnq_4$, $dlnq_5$, and $lresid_1$. Furthermore, we could find that changes in its own quantity cause changes in the dependent variable for each equation regardless of DIAIDS or INBR models.

Based upon the four models identified earlier, we generated forecasts for a post-sample period (2013Q1-2017Q4) and assess the forecast performance for each equation. The root mean squared error (RMSE), mean absolute error (MAE), mean absolute scaled error (MASE), and Theil inequality coefficient (Theil) are selected as measures of evaluation because they are widely used in combining and selecting forecasts for measuring the bias and accuracy of models as empirical methods.

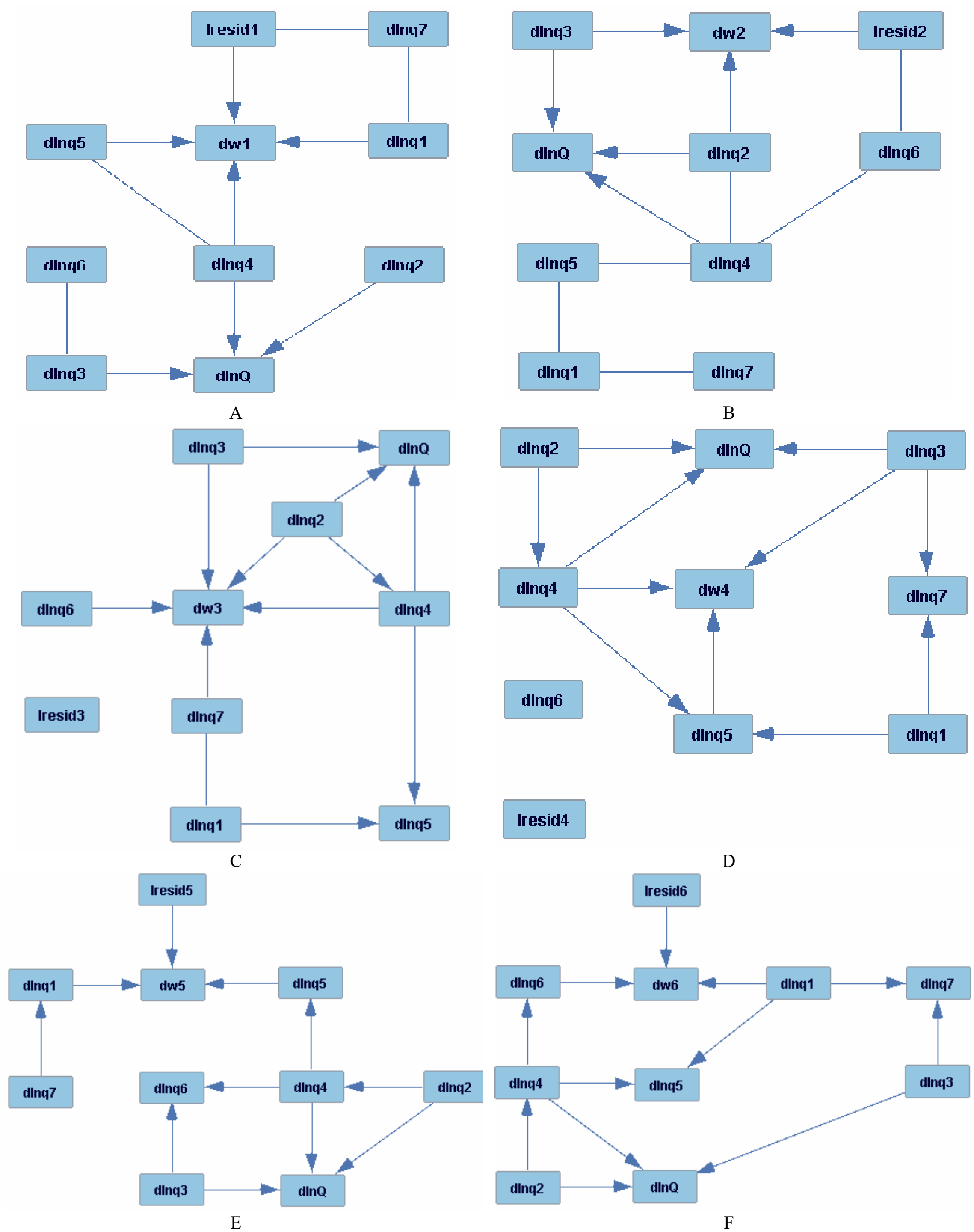


Figure 4.1. Directed acyclic graphs based on the PC algorithm for each equation of the dynamic inverse almost ideal demand system model

Notes: 1-7 denote Colombia, Costa Rica, Ecuador, Guatemala, Honduras, Mexico, and the rest of the world. dw 1-6 are the dependent variable of each equation. dlnq 1-7 and dlnQ are the first difference of log-transformed import volumes of fresh bananas from the foregoing countries and the quantity index, respectively. lresid 1-6 are the estimated lagged residuals from the static IAIDS.

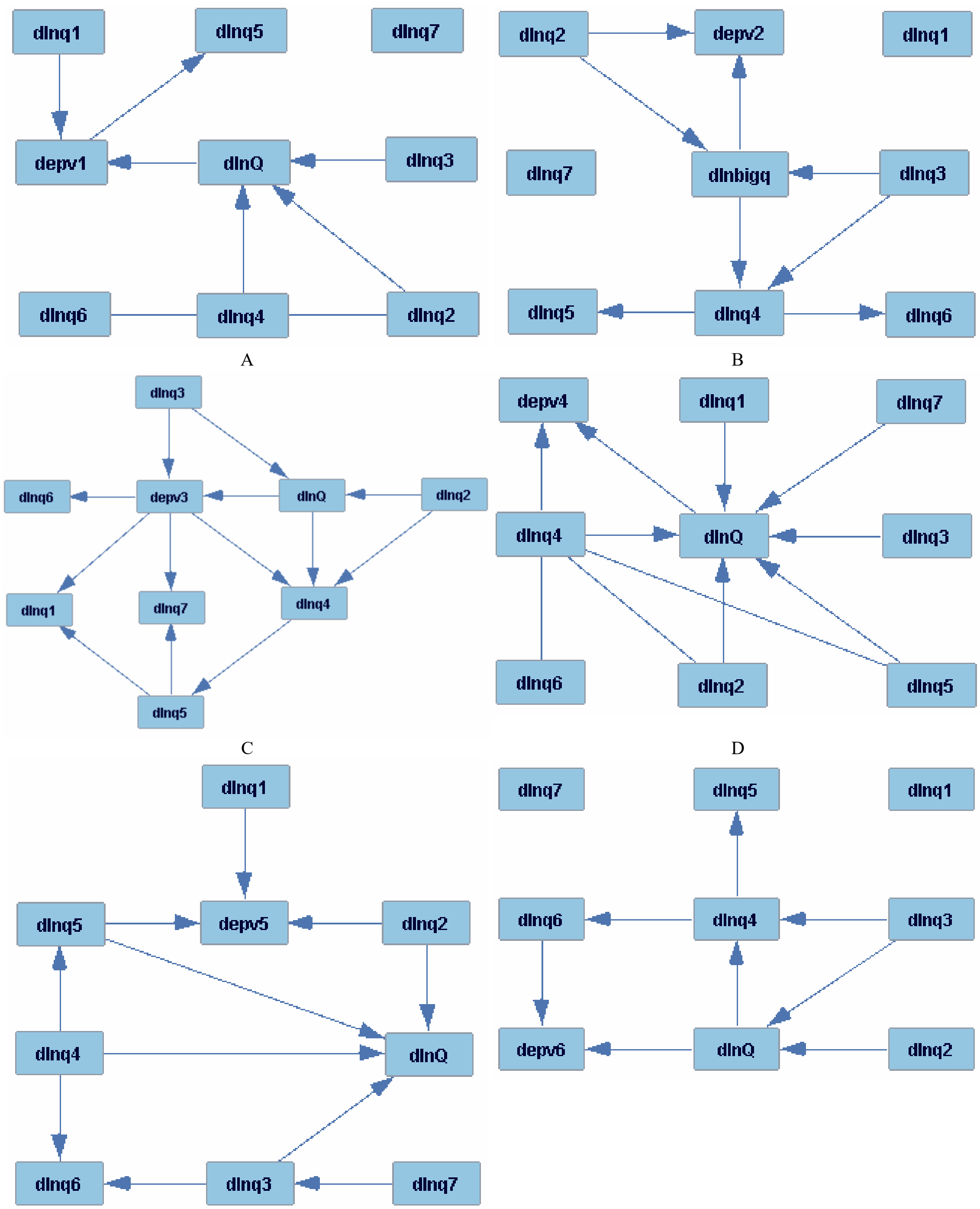


Figure 4.2. Directed acyclic graphs based on the PC algorithm for each equation of the inverse national bureau of research demand system model

Notes: 1-7 denote Colombia, Costa Rica, Ecuador, Guatemala, Honduras, Mexico, and the rest of the world. depv 1-6 are the dependent variable of each equation. dlnq1-7 and dlnQ are the first difference of log-transformed import volumes of fresh bananas from the foregoing countries and the quantity index, respectively.

Table 4.3 shows the prediction performances of the four models. The RMSE and MAE depend on the scale of dependent variables and could only be used to compare forecasts for the same dependent variables across an ordinary inverse demand system and its DGM (or DAG-) model. The MAPE is scale independent of dependent variables and its value is lower if the forecasting performance of a model is better than another model. The Theil coefficient is scale invariant for dependent variables and lies between zero and one. If the Theil coefficient equals one, the forecasting performance of a model is very poor. Conversely, a model completely predicts future values if the Theil coefficient equals zero.

For the comparison of the ordinary and its DGM (or DAG-) models, the forecasting performance of the DAG-DIAIDS is better than the DIAIDS in Ecuador, Guatemala, and Mexico equations, although the MASE results are inconsistent with the rest of the measurement statistics in Guatemala and Mexico equations. The forecasting performance of the DAG-INBR is better than the INBR in the Colombia and Costa Rica equations, but the RMSE results are inconsistent with the rest of the measurement statistics in the Colombia equation. For the comparison of four models identified earlier, the MASE and the Theil coefficient have the same results except for the Ecuador and Mexico equations. They suggest that the DIAIDS, DAG-INBR, INBR, and DIAIDS models have the best forecast accuracy compared to the rest of the evaluating models in the Colombia, Costa Rica, Guatemala, and Honduras equations, respectively. For the Ecuador and Mexico equations, the MASE suggests that the DAG-DIAIDS and INBR models are respectively the best compared to the rest of the evaluating models, while the

Theil coefficient suggests that the INBR and DAG-DIAIDS models are respectively the best compared to the rest of the evaluating models.

Table 4.3. Comparison of the Forecasting Performance of the Four Demand Models, Forecasting Periods: 2013-2017

Equation	Model	RMSE	MAE	MASE	Theil
Colombia	DIAIDS	**0.0093**	**0.0077**	**0.5618**	**0.2868**
	DAG-DIAIDS	0.0128	0.0098	0.5997	0.3532
	INBR	0.0107	0.0084	0.7047	0.4102
	DAG-INBR	0.0109	0.0080	0.6712	0.3907
Costa Rica	DIAIDS	0.0121	0.0099	0.4252	0.2677
	DAG-DIAIDS	0.0205	0.0167	0.7542	0.3588
	INBR	0.0131	0.0104	0.2991	0.2136
	DAG-INBR	**0.0120**	**0.0096**	**0.2766**	**0.1987**
Ecuador	DIAIDS	0.0168	0.0134	0.2660	0.2035
	DAG-DIAIDS	**0.0163**	**0.0127**	**0.2182**	0.2000
	INBR	0.0194	0.0147	0.2412	**0.1804**
	DAG-INBR	0.0251	0.0205	0.3375	0.2228
Guatemala	DIAIDS	0.0199	0.0156	0.3693	0.4130
	DAG-DIAIDS	**0.0141**	**0.0109**	0.4303	0.3253
	INBR	0.0208	0.0162	**0.2632**	**0.2281**
	DAG-INBR	0.0251	0.0193	0.3120	0.2905
Honduras	DIAIDS	**0.0077**	**0.0063**	**0.1429**	**0.1575**
	DAG-DIAIDS	0.0135	0.0105	0.2723	0.3413
	INBR	0.0098	0.0077	0.1881	0.2322
	DAG-INBR	0.0188	0.0154	0.3775	0.4935
Mexico	DIAIDS	0.0050	0.0039	0.3922	0.3632
	DAG-DIAIDS	**0.0045**	**0.0035**	0.4045	**0.3232**
	INBR	0.0078	0.0049	**0.3332**	0.3603
	DAG-INBR	0.0087	0.0051	0.3492	0.4173

Notes: The dynamic inverse almost ideal demand system (DIAIDS), inverse national bureau of research (INBR) demand system, directed acyclic graphs (DAG) from Figure 4.1 and 4.2, root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

After the demand models are estimated, several diagnostic tests are conducted, and results are reported in Table 4.4. For example, for the six equations in the DIAIDS model at a 10% significance level, three pass the Jarque-Bera (JB) Lagrange multiplier test of the null hypothesis that residuals are normally distributed, five pass the Harvey (Harvey) Lagrange multiplier test of the null hypothesis that there is no autocorrelation, five pass the Ramey regression equation specification error test (RESET) of the null hypothesis that the model has no omitted variables, and four pass the Hall-Pagan (HP) Lagrange multiplier test of the null hypothesis that the variance of the residuals is homogenous, or the residual variance is said to be homoscedastic. For the JB test, the DAG-DIAIDS model has a best fit, and there are no equations to violate the assumption of the normal distribution for disturbances. For the Harvey test, the DIAIDS model has one equation that violates the assumption that there is no serial correlation in disturbances, and the rest of the demand system models have two equations. For the RESET test, both versions of the DIAIDS models have better performance than those of the INBR models. For the HP test, the DAG-INBR model has a best fit, and there are no equations to violate the assumption that the covariance matrix of disturbances is homoscedastic.

The long-run and short-run scale flexibilities are reported in Table 4.5 and 4.6. All scale flexibilities are significant at a 1% significance level and negative. The scale flexibilities measure the percentage change in the normalized import price of fresh bananas from a certain exporting country due to one percentage change in the import supply of US fresh bananas. When the quantities increase, all the scale flexibilities show that the normalized price also decreases as expected.

Table 4.4. Results from the Diagnostic Tests on Inverse Demand System Models

	Jarque-Bera		Harvey		RESET		Hall-Pagan	
Equation	statistic	*p*-value	statistic	*p*-value	statistic	*p*-value	statistic	*p*-value
DIAIDS								
Colombia	0.434	0.805	0.130	0.718	0.48	0.694	1.349	0.245
Costa Rica	33.493	**0.000**	2.104	0.147	1.85	0.145	0.497	0.481
Ecuador	0.153	0.926	0.156	0.693	1.54	0.210	0.001	0.976
Guatemala	0.703	0.704	0.041	0.840	0.85	0.469	0.825	0.364
Honduras	120.433	**0.000**	0.170	0.680	9.10	**0.000**	18.509	**0.000**
Mexico	8.528	**0.014**	3.132	**0.077**	1.25	0.298	4.797	**0.029**
DAG-DIAIDS								
Colombia	1.218	0.544	0.173	0.678	1.72	0.170	0.457	0.499
Costa Rica	1.721	0.423	8.549	**0.004**	2.03	0.116	1.493	0.222
Ecuador	1.129	0.569	0.011	0.915	2.06	0.112	3.472	**0.062**
Guatemala	0.264	0.876	0.707	0.401	1.15	0.335	2.299	0.130
Honduras	2.531	0.282	8.558	**0.003**	9.07	**0.000**	17.294	**0.000**
Mexico	4.358	0.113	0.022	0.883	0.94	0.425	6.808	**0.009**
INBR								
Colombia	2.957	0.228	3.542	**0.060**	0.60	0.619	2.041	0.153
Costa Rica	43.043	**0.000**	3.036	**0.081**	3.76	**0.014**	2.937	**0.087**
Ecuador	0.354	0.838	1.974	0.160	0.47	0.705	0.002	0.967
Guatemala	0.752	0.687	1.999	0.157	8.93	**0.000**	0.451	0.502
Honduras	221.632	**0.000**	0.062	0.804	15.65	**0.000**	24.102	**0.000**
Mexico	18.962	**0.000**	1.137	0.286	0.31	0.820	3.852	**0.050**
DAG-INBR								
Colombia	2.161	0.340	3.978	**0.046**	0.51	0.674	2.042	0.153
Costa Rica	0.342	0.843	0.386	0.534	5.03	**0.003**	1.432	0.232
Ecuador	29.313	**0.000**	7.094	**0.008**	2.26	**0.087**	1.073	0.300
Guatemala	9.778	**0.008**	0.000	0.993	5.12	**0.003**	1.571	0.210
Honduras	0.279	0.870	0.776	0.378	6.74	**0.000**	2.382	0.123
Mexico	25.818	**0.000**	1.768	0.184	0.28	0.838	2.220	0.136

Notes: The dynamic inverse almost ideal demand system (DIAIDS), inverse national bureau of research (INBR) demand system, directed acyclic graph (DAG), and Ramey regression equation specification error test (RESET).

Table 4.5. Long-run Marshallian Quantity and Scale Flexibilities of the Static Inverse Almost Ideal Demand System, 1989Q1-2017Q4

	Own and cross quantity ε_{ii}						Scale η_i
	Colombia	Costa Rica	Ecuador	Guatemala	Honduras	Mexico	
Colombia	-0.064	-0.202***	-0.195***	-0.120***	-0.028	-0.015	-0.652***
	(0.045)	(0.032)	(0.042)	(0.016)	(0.024)	(0.010)	(0.097)
Costa Rica	-0.192***	-0.382***	-0.331***	-0.231***	-0.084***	-0.042***	-1.278***
	(0.024)	(0.024)	(0.034)	(0.013)	(0.015)	(0.008)	(0.077)
Ecuador	-0.107***	-0.181***	-0.192***	-0.116***	-0.027	-0.015**	-0.657***
	(0.018)	(0.024)	(0.029)	(0.012)	(0.018)	(0.007)	(0.057)
Guatemala	-0.146***	-0.257***	-0.264***	-0.311***	-0.109***	-0.012	-1.147***
	(0.018)	(0.026)	(0.025)	(0.017)	(0.018)	(0.009)	(0.077)
Honduras	-0.119***	-0.185***	-0.215***	-0.217***	-0.516***	-0.058***	-1.303***
	(0.022)	(0.040)	(0.031)	(0.026)	(0.039)	(0.015)	(0.105)
Mexico	-0.123**	-0.259***	-0.230***	-0.072	-0.168***	-0.283***	-1.178***
	(0.055)	(0.080)	(0.084)	(0.059)	(0.063)	(0.041)	(0.283)

Notes: Figures in parentheses are standard errors. ***, **, and * indicate significant at 1%, 5%, and 10% levels, respectively.

Table 4.6. Short-run Marshallian Quantity and Scale Flexibilities of the Dynamic Inverse Almost Ideal Demand System, 1989Q1-2017Q4

	Own and cross quantity ε_{ii}						Scale η_i
	Colombia	Costa Rica	Ecuador	Guatemala	Honduras	Mexico	
Colombia	-0.290***	0.015	-0.265***	-0.036	-0.146***	-0.065***	-0.785***
	(0.070)	(0.130)	(0.048)	(0.069)	(0.053)	(0.025)	(0.082)
Costa Rica	-0.054	-0.658***	-0.204***	-0.285***	-0.011	-0.006	-1.253***
	(0.056)	(0.162)	(0.059)	(0.058)	(0.072)	(0.027)	(0.065)
Ecuador	-0.160***	-0.121	-0.288***	-0.185***	-0.098***	-0.034**	-0.909***
	(0.027)	(0.079)	(0.037)	(0.038)	(0.029)	(0.015)	(0.049)
Guatemala	-0.061*	-0.309***	-0.267***	-0.337***	-0.046	-0.018	-1.064***
	(0.033)	(0.085)	(0.029)	(0.053)	(0.031)	(0.014)	(0.064)
Honduras	-0.172***	0.086	-0.182***	-0.029	-0.485***	-0.024	-0.810***
	(0.054)	(0.191)	(0.052)	(0.077)	0.090	(0.026)	(0.115)
Mexico	-0.254***	0.044	-0.233***	-0.068	-0.090	-0.313***	-0.924***
	(0.074)	(0.226)	(0.066)	(0.096)	(0.065)	(0.053)	(0.167)

Notes: Figures in parentheses are standard errors. ***, **, and * indicate significant at 1%, 5%, and 10% levels, respectively.

In both long-run and short-run scale flexibilities, the price of fresh bananas from Colombia is least affected by the quantity of total imported fresh bananas. However, the most influential price in the long-run results is different from that in the short-run results.

The former is the price of fresh bananas from Honduras, while the latter is that from Costa Rica. All Marshallian own-quantity flexibilities, as reported in Table 4.5 and 4.6, are negative and significant at the 1% significance level in both the long run and short run except for the long-run flexibility in Colombia. All Marshallian own-quantity flexibilities are less than one in absolute values, indicating that fresh bananas of six main exporting countries are price inflexible. In terms of the long-run Marshallian own-quantity flexibilities at the price-imported level, the U.S. own price for fresh bananas from Honduras with respect to the import quantity from Honduras appears to be the largest variation in absolute value (0.516). That is, a one percent increase (decrease) in the import quantity of fresh bananas from Honduras was found to decrease (increase) the import price of fresh bananas from Hondurans in the U.S. market by approximately 0.516%. However, for the short- run Marshallian own-quantity flexibilities, Costa Rica has the largest variation in absolute value (0.658).

The cross-quantity flexibilities measure the percentage change in the price of fresh bananas from a certain exporting country when the quantity demanded of fresh bananas from another exporting country increases by one percent. From Table 4.5 and 4.6, all long-run and short-run Marshallian cross-quantity flexibilities significant at the 10% significance level were found to be negative and indicate that fresh bananas from any two exporting countries are gross quantity substitutes for each other. To better understand the competition relationship among exporting countries, the long-run and short-run Hicksian cross-quantity flexibilities are calculated and reported in Table 4.7 and 4.8.

Table 4.7. Long-run Hicksian Quantity Flexibilities of the Static Inverse Almost Ideal Demand System, 1989Q1-2017Q4

	Own and cross quantity					
	Colombia	Costa Rica	Ecuador	Guatemala	Honduras	Mexico
Colombia	0.022	-0.041	-0.036	0.009	0.047***	0.009
	(0.038)	(0.033)	(0.030)	(0.020)	(0.017)	(0.010)
Costa	-0.022	-0.067***	-0.019	0.021	0.064***	0.005
Rica	(0.018)	(0.025)	(0.020)	(0.014)	(0.012)	(0.007)
Ecuador	-0.020	-0.019	-0.031	0.013	0.049***	0.009
	(0.016)	(0.021)	(0.024)	(0.011)	(0.014)	(0.006)
Guatemala	0.006	0.026	0.017	-0.085***	0.023*	0.030***
	(0.013)	(0.017)	(0.014)	(0.018)	(0.013)	(0.009)
Honduras	0.054***	0.136***	0.103***	0.040*	-0.365***	-0.010
	(0.019)	(0.025)	(0.029)	(0.022)	(0.031)	(0.014)
Mexico	0.033	0.031	0.058	0.161***	-0.032	-0.240***
	(0.036)	(0.047)	(0.043)	(0.046)	(0.046)	(0.039)

Notes: Figures in parentheses are standard errors. ***, **, and * significant at the 1%, 5%, and 10% levels, respectively.

Table 4.8. Short-run Hicksian Quantity Flexibilities of the Dynamic Inverse Almost Ideal Demand System, 1989Q1-2017Q4

	Own and cross quantity					
	Colombia	Costa Rica	Ecuador	Guatemala	Honduras	Mexico
Colombia	-0.185**	0.209*	-0.073	0.119**	-0.056	-0.036
	(0.080)	(0.112)	(0.056)	(0.059)	(0.056)	(0.025)
Costa	0.112*	-0.349**	0.102	-0.038	0.134*	0.040
Rica	(0.060)	(0.146)	(0.068)	(0.056)	(0.077)	(0.028)
Ecuador	-0.040	0.103	-0.066	-0.006	0.007	-0.001
	(0.031)	(0.068)	(0.047)	(0.032)	(0.031)	(0.014)
Guatemala	0.080**	-0.047	-0.007	-0.127***	0.077**	0.021
	(0.039)	(0.070)	(0.040)	(0.044)	(0.037)	(0.014)
Honduras	-0.064	0.286*	0.015	0.131**	-0.392***	0.005
	(0.064)	(0.165)	(0.066)	(0.062)	(0.102)	(0.025)
Mexico	-0.131	0.272	-0.007	0.115	0.017	-0.279***
	(0.090)	(0.186)	(0.096)	(0.077)	(0.080)	(0.053)

Notes: Figures in parentheses are standard errors. ***, **, and * significant at the 1%, 5%, and 10% levels, respectively.

A positive quantity flexibility between import bananas from two countries denotes net substitutes and a negative value denotes net complements. All long-run and short-run Hicksian cross-quantity flexibilities significant at the 10% significance level were found to be positive and indicate that fresh bananas from any two exporting countries are net quantity complements for each other.

The Marshallian and Hicksian flexibilities of the INBR model are reported in Table 4.9 and 4.10. All scale flexibilities are significant at the 1% significance level and negative. However, the least and most influential prices in the INBR model are the fresh bananas from Honduras and Guatemala, while those in the DIAIDS model are Colombia and Costa Rica, respectively. All Marshallian own-quantity flexibilities are negative and significant at the 1% significance level and less than one in absolute values, indicating that fresh bananas of the six main exporting countries are price inflexible. The results are consistent with those of the DIAIDS model but the estimated flexibilities of the former are less than those of the latter in absolute values except Ecuador and Guatemala. For Marshallian and Hicksian cross-quantity flexibilities, the results are consistent with those of the DIAIDS model. All Marshallian cross-quantity flexibilities significant at the 10% significance level were negative and indicate that fresh bananas from any two exporting countries are gross quantity substitutes for each other. Contrarily, all Hicksian cross-quantity flexibilities significant at the 10% significance level are positive and indicate that fresh bananas from any two exporting countries are net quantity complements for each other.

Table 4.9. Marshallian Quantity and Scale Flexibilities of the Inverse National Bureau of Research Demand System, 1989Q1-2017Q4

	Own and cross quantity ε_{ii}						Scale η_i
	Colombia	Costa Rica	Ecuador	Guatemala	Honduras	Mexico	
Colombia	-0.174***	-0.238***	-0.180***	-0.129***	-0.040	-0.047***	-0.803***
	(0.046)	(0.037)	(0.034)	(0.039)	(0.026)	(0.018)	(0.089)
Costa Rica	-0.157***	-0.326***	-0.257***	-0.170***	-0.083***	-0.009	-1.021***
	(0.023)	(0.036)	(0.027)	(0.031)	(0.020)	(0.011)	(0.073)
Ecuador	-0.122***	-0.252***	-0.294***	-0.208***	-0.054***	-0.034***	-0.989***
	(0.018)	(0.022)	(0.026)	(0.022)	(0.015)	(0.009)	(0.055)
Guatemala	-0.162***	-0.298***	-0.350***	-0.343***	-0.146***	-0.035**	-1.368***
	(0.030)	(0.037)	(0.033)	(0.047)	(0.025)	(0.015)	(0.082)
Honduras	-0.035	-0.103**	-0.050	-0.122***	-0.386***	-0.018	-0.725***
	(0.035)	(0.050)	(0.045)	(0.047)	(0.043)	(0.016)	(0.133)
Mexico	-0.175**	-0.014	-0.189***	-0.083	-0.069	-0.292***	-0.842***
	(0.074)	(0.072)	(0.067)	(0.082)	(0.050)	(0.059)	(0.160)

Notes: Figures in parentheses are standard errors. ***, **, and * indicate significant at 1%, 5%, and 10% levels, respectively.

Table 4.10. Hicksian Quantity Flexibilities of the Inverse National Bureau of Research Demand System, 1989Q1-2017Q4

	Own and cross quantity					
	Colombia	Costa Rica	Ecuador	Guatemala	Honduras	Mexico
Colombia	-0.067*	-0.040	0.016	0.029	0.053**	-0.017
	(0.040)	(0.035)	(0.028)	(0.037)	(0.024)	(0.018)
Costa Rica	-0.021	-0.074**	-0.008	0.031	0.035*	0.029***
	(0.019)	(0.035)	(0.020)	(0.027)	(0.019)	(0.011)
Ecuador	0.009	-0.008	-0.053**	-0.013	0.060***	0.002
	(0.015)	(0.020)	(0.022)	(0.020)	(0.014)	(0.008)
Guatemala	0.020	0.039	-0.016	-0.073	0.012	0.015
	(0.025)	(0.034)	(0.025)	(0.046)	(0.023)	(0.015)
Honduras	0.061**	0.075*	0.127***	0.020	-0.302***	0.009
	(0.028)	(0.040)	(0.030)	(0.040)	(0.041)	(0.015)
Mexico	-0.063	0.194***	0.016	0.083	0.029	-0.261***
	(0.064)	(0.072)	(0.056)	(0.079)	(0.047)	(0.057)

Notes: Figures in parentheses are standard errors. ***, **, and * significant at the 1%, 5%, and 10% levels, respectively.

4.6 Conclusions

Banana consumption in the U.S. is highly dependent on imports, and these imports come from a concentrated market that is controlled by a few TNCs. First, we used inverse demand systems including DIAIDS and INBR models and their DGM (or DAG-) models to understand consumer behavior for U.S. fresh bananas from six major exporting countries and evaluate their forecasting accuracy. Overall, the forecasting performances of the DIAIDS and its DGM models are equally good, that is, the forecasting accuracy of a half of the equations in one model is better than that in the other. However, the forecasting performance of the INBR model is better than that of its DGM model, i.e., forecasting accuracy of four of six equations in the INBR model is clearly better than that in its DGM model. When comparing the four models together, we can find that forecasting performances of the DIAIDS and INBR models are equally good and better than those of their DGM models. Furthermore, according to the results of several diagnostic tests, both versions of the DIAIDS model have better performance than those of the INBR model. Next, we estimated the long-run scale and quantity flexibilities of the static IAIDS and INBR models and the short-run those of the DIAIDS model. As expected, all Marshallian own-quantity flexibilities for each inverse demand system significant at the 1% significance level are negative and relatively inelastic. Moreover, all Marshallian cross-quantity flexibilities significant at the 10% significance level show that fresh bananas from any two exporting countries are gross quantity substitutes for each other, while all Hicksian cross-quantity flexibilities significant at the

10% significance level show that fresh bananas from any two exporting countries are net quantity complements for each other.

CHAPTER V

SUMMARY

This dissertation presented results from three different empirical studies of price transmission analyses and consumer demand systems. The first study (Chapter II), titled "Vertical price transmission among international crops, ocean freight, and Taiwan major animal husbandry," examined the relationship among pork, chicken, and hen egg prices, the prices of the main ingredients in their feed, and the BDI. Because asymmetric price transmission may exist in the magnitude of price transmission and/or speeds of adjustment, we employed the NARDL model and Enders-Siklos threshold cointegration approach to check whether there is an asymmetric effect in the VPT between output prices (Taiwanese pork, chicken, and hen eggs) and input prices (ocean freight rates, the U.S. and Brazilian corn, and soybeans). The empirical results indicate that except for the VPT between hen egg prices and the input prices, the other VPT have no obvious asymmetrical effects in speed of price adjustment. However, the results of the NARDL models show that asymmetric effects on the magnitude of long-run price transmission significantly exist in all VPT.

Japan is the second largest export market for Taiwanese agricultural products. Because Taiwanese agricultural technology, cultivars, and talents continuously flow to China over two decades plus its lower production costs, the market shares of Taiwanese agricultural products in major export markets have dropped significantly. In this context the second study (Chapter III), titled "Price dynamics in the import markets of eels, edamame, and feathers and down in Japan," explored the relationship among the prices of Taiwanese eel, edamame, and feathers and down and their major competitor's prices in the Japanese market. We first used the partial correlations of the VECM residuals as input to graphical causal models from the PC algorithm. The empirical results suggest that a change in Taiwanese (live) eel prices leads to a change in the (live) eel prices from Aichi prefecture, Shizuoka prefecture, and China in contemporaneous time. Chinese prepared eel price is the most influential among the six evaluated eel prices in the long run except the uncertainty associated with the prepared eel price from Shizuoka Prefecture. Also, the effect of a change in Chinese prepared eel price on other evaluated eel prices is significant.

For the Japanese edamame market, price changes in China and Indonesia lead to a price change in Taiwan in contemporaneous time. The influence of other imported edamame prices on Japanese edamame price is very small. Taiwanese edamame price is mainly affected by Chinese and Thai edamame prices in the long run besides its own price. For the Japanese feather and down market, a price change in Taiwan leads to price changes in China and Hungary in contemporaneous time. The uncertainty in each evaluated price is primarily explained by its own price. In addition, Taiwanese feather and down price is mainly affected by Chinese and French feather and down prices in the long run besides its own price.

Measured by value of volume, banana is still the major fresh fruit imported to the U.S. Because of the consideration of transportation costs, time, the delicate and perishable properties in banana distribution, and diverging import policies in the consuming countries, the U.S. banana market reveals an absolutely dominance by neighboring Latin America. In this context, the third study (Chapter IV), titled "An analysis of the banana import market in the U.S.," investigated the factors that determine the country composition of the U.S. fresh banana imports and estimated the level of price competition among the Latin American countries. Two static and one dynamic inverse demand system were used in estimating the demand for disaggregated fresh bananas in the U.S. The empirical results suggest the fresh bananas of six exporting countries are price inflexible, and any two exporting countries are gross quantity substitutes for each other in the short run and long run. In addition, the Banana prices from six exporting countries are significantly affected by the quantity of total import bananas.

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