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ASSESSING THE IMPORT DEMAND OF WOODEN FURNITURE IN THE UNITED STATES AND ITS IMPACT ON THE FURNITURE INDUSTRY

By

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The U.S. furniture industry has faced the challenge from increasing imports of furniture over the last decades. In the first part of this thesis, the import pattern of wooden bedroom furniture and the antidumping investigation against China were summarized, and furthermore, intervention analysis was employed to assess its impacts on the import value and unit price. The results revealed that the impact on import values was temporary but there was no significant impact on unit prices. The traditional suppliers have been substituted by the developing countries such as China and Vietnam. In the second part of this thesis, to explain the market structure change, a dynamic AIDS model was used to analyze consumer behavior and evaluate the impacts of antidumping investigation on the major competitors. The results indicated that most imported wooden bedroom furniture can be substituted between suppliers and trade diversion occurred from China to Vietnam, Indonesia, and Brazil.

Key words: Almost Ideal Demand System (AIDS), antidumping investigation, ARIMA, Engle-Granger cointegration, intervention analysis, wooden bedroom furniture

DEDICATION

I dedicate this research to my parents, Ruiguo Wan and Chunju Ma.

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CHAPTER I

INTRODUCTION

The United States is the largest furniture market worldwide and has been experiencing a rapid growth in the consumption of furniture over the past decades. Its furniture industry has made significant contribution to the domestic economy during the same period. However, the gap between domestic consumption and production in the United States has been filled by the increasing furniture imports from foreign countries. In addition, the market structure has changed over time. The traditional suppliers have been substituted by the new suppliers such as China, Vietnam, and Brazil. In particular, China has been the leading supplier with more than a 40% share of the U.S. import market in recent years. This trade phenomenon has raised question about the competitiveness of the U.S. furniture industry, and resulted in the antidumping investigation against China during the period of 2003 – 2005.

To our knowledge, existing studies have mainly compared trade patterns across supplier countries and explained them through qualitative analyses. No studies have examined the impact of the antidumping investigation on wooden bedroom furniture from China and its impact on the U.S. furniture industry. Despite the large scale of the furniture import, few studies have been conducted to examine the price competitiveness of furniture imports from different countries over the past two decades. Therefore, there is a need to analyze consumer behavior, examine the price competition in this furniture import market, and furthermore, evaluate the impacts of the antidumping investigation.

The overall purpose of this thesis was to assess the import demand of wooden furniture in the United States and its impact on furniture industry. Specific objectives were: (1) to evaluate the antidumping investigation on wooden bedroom furniture from China and its impact; and (2) to examine the price competitiveness and substitutability of furniture imports from different countries.

This thesis followed the style of *Canadian Journal of Forest Research*. Two relatively independent papers in journal article style were included. The first one investigated the impacts of the 2003 antidumping investigation on wooden bedroom furniture from China. Over the last decade, the market structure has undergone considerable change as global trade liberalization increases. To explain this change, the second paper analyzed consumer behavior and evaluated the impacts of this antidumping investigation on the major suppliers. Each paper included its own introduction, methodology, data source and variables, empirical results, and conclusions.

The thesis was organized as follows. Chapter II contained the first article, entitled "An appraisal of the antidumping investigation on wooden bedroom furniture imports from China." The impacts on the import value and unit price of this antidumping investigation were appraised using monthly import data from China. Chapter III contained the second article, entitled "Competition of imported wooden bedroom furniture in the United States." The degree of substitution was examined using monthly import data from the top seven supplier countries over the period 2001 – 2008. Finally, Chapter IV summarized the conclusions for this thesis. It also provided the discussion for the future studies.

CHAPTER II

AN APPRAISAL OF THE ANTIDUMPING INVESTIGATION ON WOODEN BEDROOM FURNITURE IMPORTS FROM CHINA

Introduction

The United States is the largest furniture market worldwide and its domestic retail sales have been constantly growing in the last decades (Gazo and Quesada 2005). One noteworthy market phenomenon in recent years is that an increasing share of the domestic demand has been met by imported furniture. In particular, wooden bedroom furniture imports have climbed from US$1.1 billion in 1997 to $5.1 billion in 2007 (U.S. ITC. 2009). China has been the leading supplier with more than a 40% share of the U.S. import market. Consequently, a group of domestic furniture firms filed an antidumping petition against China in October 2003. In December 2004, the U.S. International Trade Commission (ITC) and the Department of Commerce (DOC) decided to impose various antidumping duties (0.83% – 198.08%) on wooden bedroom furniture imports from China.

The use of antidumping laws has grown rapidly and become an important trade protection instrument worldwide during the last three decades (Niels 2000). The United States, Canada, the European Union, and Australia have been traditional users of this instrument while developing countries (e.g., India) also have initiated increasing antidumping investigations in recent years. Furthermore, the probability of affirmative decisions and the amount of duties applied have been high. From 1980 to 2000, the United States has imposed antidumping duties in more than 95% of its investigations (Prusa 2005). Blonigen (2003) documented the rapid rise in U.S. antidumping duties from around 15% in the early 1980s to over 60% by 2000. The widespread use of antidumping protection has motivated numerous studies, as summarized in Niels (2000) and Blonigen and Prusa (2001). A number of research issues related to antidumping have been examined, including political manipulability, contract theory, optimal tariffs, predatory pricing, legislative delegation, and trade diversion.

In particular, a fundamental question related to antidumping has been the impact of antidumping investigations and duties on trade. Staiger and Wolak (1994) investigated the effect of not only antidumping duties but also various investigation events from 1980 to 1985. The effects on import and domestic production were found to be dependent on the outcomes of the investigation events. Krupp and Pollard (1996) provided empirical evidence of the effects of the U.S. antidumping policies on the chemical industry from 1976 to 1988. Antidumping policies affected import volumes in about half of the cases. Lloyd et al. (1998) examined the effects of the antidumping investigation process on the European polypropylene film market in the 1980s. Announcement effects on both import values and unit values were identified. Durling and Prusa (2006) examined the effects of antidumping cases on the hot-rolled steel market from 1996 to 2001 and found strong evidence of trade depression but little evidence of trade diversion. Overall, the impact of antidumping investigations on trade has varied with the industries, commodities, and time periods considered.

The competitiveness of the U.S. furniture industry and rapidly increasing imports from China have been the subject of a number of studies. Robb and Xie (2003) investigated the manufacturing strategy of 72 Chinese furniture companies based on a survey in 2001. Cao et al. (2004) examined the rapid growth of the Chinese furniture industry with regard to timber imports, production, marketing, and furniture exports. Gazo and Quesada (2005) reviewed and compared the comparative advantages of different furniture exporting countries in the U.S. market. Buehlmann et al. (2006) surveyed the attitudes of U.S. retailers toward U.S., Canada, and China as manufacturing sources for furniture. Overall, existing studies have mainly compared trade patterns across supplier countries and explained them through qualitative analyses. No studies have examined the impact of the antidumping investigation on wooden bedroom furniture from China in 2003 and its implications to the U.S. furniture industry. Therefore, there has been a critical need to analyze the furniture antidumping case in terms of motivation, participants, and effectiveness.

The purpose of this study was to investigate the impact of the 2003 antidumping investigation on wooden bedroom furniture from China. Intervention analysis was employed and various techniques related to multiple interventions were used. This methodology can characterize a response variable by combining an autoregressive integrated moving average (ARIMA) model for the response variable and transfer functions for interventions. Data used in this study were import values and unit prices for four individual furniture commodities so the impact of the antidumping policy was examined at a disaggregated level. The time period covered was January 1997 to June 2008. The antidumping policy was implemented in January 2005 so there has been sufficient time for the full impact of the policy to be revealed and observed. Overall, the methodology employed has been well established to examine the impact of interventions on time series; the data and variables defined were at disaggregated levels and had adequate observations before and after the intervention; and the policy impacts were linked to individual investigation periods. With an increasingly competitive and globalized market, this study should be beneficial to both furniture firms and policy makers in understanding the impact and value of the antidumping investigation.

The antidumping investigation

U.S.-China economic relations have strengthened substantially over the past several decades. Total exports from U.S. to China have reached $3.8, 4.8, 16.3, and 65.2 billion in 1980, 1990, 2000, and 2007, respectively, while the corresponding total imports have progressed even faster at $1.1, 15.2, 100.1, and 321.5 billion (Morrison 2008). Similarly, the furniture industry in the United States has experienced increasing import competition from China in the last decade. Particularly, the market of wooden bedroom furniture has undergone rapid import growth from China in recent years and has aroused wide concerns in the United States. In October 2003, the American Furniture Manufacturers Committee for Legal Trade and its individual members filed a petition with the ITC and DOC. The petitioners alleged that wooden bedroom furniture from China has been dumped in the United States at less than fair value. The investigation resulted in extensive debates among various participants, and finally, an affirmative determination of antidumping duties in December 2004.

Import patterns of wooden bedroom furniture

In Table 2.1, U.S. imports of wooden bedroom furniture from the world and China were compared by commodity and year (U.S. ITC. 2009). As defined in the variable and data section, wooden bedroom furniture was comprised of four commodities: *bed*, *other*, *part*, and *mirror*. In aggregate, the total U.S. imports grew dramatically from $1,115.3 million in 1997 to $5,075.4 million in 2007. China has been leading the import growth. Total imports from China were $79.2, 1,215.9, and 2,193.9 million in 1997, 2002, and 2007, respectively; the corresponding share of China was 7%, 39%, and 43%. Among the four commodities, most imports from China have been in *other* and *bed*. The import share of China in recent years has been over 40% for *other* and *bed*, over 35% for *part*, and over 65% for *mirror*. In a word, China has been the major contributor to the increase in wooden bedroom furniture imports in recent years.

Investigation process and participants

According to the antidumping law (U.S. ITC 2007), interested parties may file an antidumping petition with the DOC and ITC. Petitioners should provide evidence to show that the domestic industry is materially injured and the domestic-like products imported from foreign countries are sold at less than fair value. The overall investigation process for antidumping cases can be divided into five stages, each ending with a determination by either the DOC or ITC. These stages are (I) initiation of the investigation by the DOC; (II) preliminary investigation phase by the ITC; (III)

Table 2.1 Annual U.S. imports of wooden bedroom furniture from the world and China over 1997 – 2008 for four HTS commodities

	World	China					Share of China (%)				
Year	*Sum*†	*Sum*	*Other*	*Bed*	*Part*	*Mirror*	*Sum*	*Other*	*Bed*	*Part*	*Mirror*
1997	1,115.3	79.2	30.3	14.0	27.6	7.3	7	5	8	9	16
1998	1,347.5	138.5	59.0	32.9	32.7	13.9	10	8	14	9	29
1999	1,869.9	289.8	124.7	77.6	63.9	23.5	15	13	23	13	34
2000	2,408.0	571.6	265.8	166.9	101.9	37.0	24	22	34	16	39
2001	2,545.9	727.8	368.2	197.4	108.9	53.3	29	28	37	18	46
2002	3,156.6	1,215.9	617.0	341.0	172.8	85.1	39	39	47	25	54
2003	3,676.4	1,713.2	924.6	477.3	197.6	113.7	47	49	53	28	63
2004	4,220.7	1,888.2	1,025.6	480.5	247.1	135.1	45	46	49	30	65
2005	4,998.1	2,202.7	1,169.8	539.5	330.0	163.5	44	46	44	34	64
2006	5,168.9	2,401.3	1,234.7	581.6	396.4	188.8	46	49	47	36	69
2007	5,075.4	2,193.9	1,043.5	547.2	410.0	193.3	43	44	43	35	70
2008	2,219.5	850.7	363.1	218.1	183.9	85.6	38	37	38	34	70

† All values were the import cost-insurance-freight values (US$, millions). Other, bed, part, and mirror represented HTS 9403.50.9080, 9403.50.9040, 9403.90.7000, 7009.92.5000, respectively. Sum was the aggregate value for the four commodities. The share of China was calculated as the U.S. import values from China over the total from the world for each commodity. All the data were nominal data without any adjustment. For 2008, data were only available from January to June at the time of this study. Source: U.S. ITC (2009).

preliminary investigation phase by the DOC; (IV) final investigation phase by the DOC; and (V) final investigation phase by the ITC.

For the antidumping investigation against wooden bedroom furniture imports from China, the petition was filed on October 31, 2003. The petitioners included the American Furniture Manufacturers Committee for Legal Trade, an ad hoc association of U.S. manufacturers of wooden bedroom furniture, and six labor unions. Respondents included the Furniture Retailers of American, an ad hoc association of 35 retailers and importers of wooden bedroom furniture; the Committee for Free Trade in Furniture, an ad hoc association of retailers and manufacturers; Furniture Brands International, the largest U.S. producer of wooden bedroom furniture; the Coalition of Certain China Furniture

Producers; and several big Chinese producers and importers. The petition identified 133 Chinese producers and exporters of wooden bedroom furniture and the ITC received responses from 154 Chinese producers (U.S. ITC. 2004).

The polarized positions of these participants were typical of an antidumping case for imports. U.S. furniture firms and labor unions were on one side of the investigation. A group of U.S. furniture firms alleged that wooden bedroom furniture from China was dumped at unfairly low prices, resulting in the low value of shipments from the domestic industry during the period of investigation (2001 – 2003). Employees and labor unions in the U.S. furniture industry also signed various supporting declarations. On the other side, Chinese furniture firms, import agencies, and U.S. furniture retailers showed strong opposition to the antidumping investigation. U.S. furniture retailers argued that the imposed tariff would undoubtedly cause harm to furniture retail sales and the impact on retail jobs could be far more negative than any positive effect to U.S. manufacturing jobs (Cater 2005).

The position of U.S. furniture manufacturing firms has been unique in this case and is worth more explanation. It has become common in recent years for members of the U.S. furniture industry to import wooden bedroom furniture to supplement their domestic production. U.S. ITC (2004) reported that one-third of wooden bedroom furniture imports from China over 2001 – 2003 were imported by U.S. manufacturing firms. As a result, a substantial proportion of the U.S. furniture industry opposed the antidumping petition. Nine members of the U.S. furniture industry, accounting for 45.6% of the industry's shipments (measured in value) in 2003, opposed the petition. Thirty-eight members of the industry, accounting for 47.6% of the industry's shipments in 2003, supported the petition. This split of the U.S. furniture industry revealed the increasing integration and globalization of the world economy. It has made the debate of the antidumping investigation more intensive and policy design more challenging.

The investigation of antidumping allegation against wooden bedroom furniture followed typical investigation stages (Table 2.2). Various events occurred during the process. The major events were the petition in October 2003, the affirmative decision in the preliminary phase and collection of antidumping duties in July 2004, and the formal implementation in January 2005.

Major findings and duties

During the investigation process, ITS collected detailed firm-specific production, cost, and trade data through questionnaires. Several conclusions were reached through the investigation (U.S. ITC. 2004) . First, the volume of subject imports was large both in absolute terms and relative to the consumption in the United States during the period of investigation (2001 – 2003). Second, there was a moderate to high degree of substitutability between domestic wooden bedroom furniture and the subject imports, and therefore, price has been a critical factor for consumers to determine their purchases. Third, the subject imports had a great adverse impact on the condition of the domestic industry. From 2001 to 2003, the capacity of the U.S. furniture industry fell by 2.9%, its number of production workers declined by 19.9%, and its quantity of shipments declined by 9.8%. Therefore, the DOC and ITC concluded that the U.S. furniture industry was materially injured by wooden bedroom furniture imports from China.

Table 2.2 Timetable of the antidumping petition and investigation against wooden bedroom furniture imports from China from October 2003 to December 2004

Date	Action
10/31/2003	Petition filed with the DOC and ITC by the American Furniture Manufacturers Committee for Legal Trade and six labor unions
	Investigation stage I
10/31/2003	Investigation No. 731-TA-1058 instituted by the ITC
11/10/2003	Notice of institution published by the ITC in the Federal Register
11/21/2003	Public conference held by the ITC
11/24/2003	Notice extending the date of initiation of investigation published by the DOC
12/17/2003	Notice of its initiation published by the DOC
	Investigation stage II
1/9/2004	Unanimous agreement reached by the ITC committee in the preliminary phase to continue its investigation of wood bedroom furniture dumping from China
1/12/2004	Preliminary determination announced by the DOC that producer/exporters have sold wooden bedroom furniture from China in the U.S. market at less than fair value, with margin ranging from 4.9% to 198.08%
	Investigation stage III
6/24/2004	Affirmative preliminary antidumping determination published by the DOC
7/17/2004	Preliminary antidumping duties collected on wooden bedroom furniture imports from China
8/15/2004	Preliminary antidumping determination amended by the DOC
9/9/2004	Preliminary antidumping determination amended by the DOC again
	Investigation stage IV
11/17/2004	Final antidumping determination published by the DOC
	Investigation stage V
12/10/2004	Vote on final determination conducted by the ITC
12/22/2004	Final determination and views transmitted by the ITC to DOC
1/1/2005	Final antidumping duties imposed formally

DOC — U.S. Department of Commerce; ITC — U.S. International Trade Commission.
Source: U.S. ITC (2004).

Based on the damage to the U.S. furniture industry, the final antidumping duties had three categories (U.S. ITC. 2004). The first was company-specific margins. Seven big Chinese firms accounted for about 40% of all the imports from China in 2003 and many of them have been joint ventures between U.S. and China. They received separate duty rates at 0.83%, 2.32%, 2.66%, 4.96%, 7.87%, 15.78%, and 198.08%, respectively. One of the seven firms faced the highest rate because it failed to provide the needed information. The second category was a weighted average margin of 6.65% for 82 Chinese firms, representing another 40% of the import values in 2003. The final category was 198.08% for all other Chinese firms. These firms accounted for approximately 20% of wooden bedroom furniture imports from China in 2003. Overall, the duties for most firms in this case were not high. The low duty rates for big firms protected them and the prohibitive rates for small firms removed them from the U.S. import market of wooden bedroom furniture.

Methodology

In this study, intervention analysis was employed to evaluate the impact of antidumping policy on wooden bedroom furniture imports from China. In their seminal study, Box and Tiao (1975) examined the effect of interventions on a given response variable in the presence of a dependant noise structure. Thereafter, intervention analysis has been applied to numerous issues. Lloyd et al. (1998) used intervention analysis to estimate the effects of antidumping action by the European Commission on film imports from Japan. Other studies, for instance, have been conducted to analyze the effect of a room tax on hotel revenues (Bonham et al. 1992; Bonham and Gangnes 1996), law reforms on consumer bankruptcies (Nelson 2000), and regulatory policies on air pollutants (Lee and List 2004). In forestry, the method has been used to evaluate the impact of hurricanes or regulatory policies on timber prices in several studies (Prestemon 2009; Prestemon and Holmes 2000; Yin 2001; Yin and Newman 1999).

In general, intervention analysis concentrates on the evolution pattern of a single time series, often referred to as a response variable. The basis of intervention analysis is a univariate ARIMA model for the response variable. An intervention disturbs the normal evolution of the response variable. It is usually represented by a dummy variable (often referred to as an input variable) and it has an impact on the response variable through a transfer function. The focus of intervention analysis is to characterize the response variable by combining the ARIMA model and the transfer function. Therefore, intervention analysis can take advantage of the virtues of ARIMA modeling and thoroughly considers the stochastic property of data. The transfer function for the input variable can measure the influence of the intervention on the response variable. Box et al. (2008), Pankratz (1991), and McCleary and Hay (1980) contained excellent practical guides for intervention analysis. Given the study objective, several techniques from the literature were employed.

General form of intervention analysis

Intervention analysis characterizes a response variable by the following deterministic and stochastic components (Pankratz 1991):

$$Y_t = C + \sum_{i=1}^{I} f(X_{i,t}^k) + N_t \tag{2-1}$$

where Y_t is a response variable, *C* is a constant, $X^k_{i,t}$ is the input variables for interventions, $f(X^k_{i,t})$ is the transfer function, and N_t is a stochastic disturbance. The subscript *i* indexes multiple interventions, *I* the total number of interventions, *k* intervention types, and *t* time.

The disturbance N_t can be represented by a ARIMA (*p*, *d*, *q*)(*P*, *D*, *Q*)$_s$ mechanism as:

$$N_t = \frac{\theta_q(B)\theta_Q(B^s)}{\phi_p(B)\phi_P(B^s)\nabla^d\nabla^D_s} a_t \tag{2-2}$$

where *B* is a backshift operator, *s* is a seasonal notation (e.g., *s* = 12 for monthly data), and a_t is a white noise. The regular *p*-order autoregressive (AR) operator is $\phi_p(B)$ = $1-\phi_1(B)-\cdots-\phi_p(B^p)$ and *q*-order moving average (MA) operator is $\theta_q(B)$ = $1+\theta_1(B)+\cdots+\theta_q(B^q)$. The seasonal *P*-order AR operator and *Q*-order MA operator are similarly defined. ∇^d is *d*-order regular differencing operator and ∇^D_s is *D*-order seasonal differencing operator so ∇^d = $(1-B)^d$ and ∇^D_s = $(1-B^s)^D$.

The transfer function $f(X^k_{i,t})$ captures the effects of interventions $X^k_{i,t}$ as deterministic input variables. It can be expressed explicitly in a linear distributed lag form:

$$\begin{aligned} f(X^k_{i,t}) &= \upsilon_i(B)X^k_{i,t} \\ &= \left(\sum_{j=0}^{J_i}\upsilon_{i,j}B^j\right)X^k_{i,t} \\ &= (\upsilon_{i,0}B^0+\upsilon_{i,1}B^1+\cdots+\upsilon_{i,J_i}B^{J_i})X^k_{i,t} \\ &= \upsilon_{i,0}X^k_{i,t}+\upsilon_{i,1}X^k_{i,t-1}+\cdots+\upsilon_{i,J_i}X^k_{i,t-J_i} \end{aligned} \tag{2-3}$$

where $\upsilon_i(B)$ is impulse response weights, B is a backshift operator, j indexes time lag, and J_i is the maximum lag for intervention i. The entire set of υ weights is called the impulse response function and it reveals how Y_t reacts to a change in $X_{i,t}^k$ at specific time lags. The linear distributed lag form is intuitive, but without a theoretical guide, the maximum lag of J_i is often specified arbitrarily (Pankratz 1991). Furthermore, with a large number of lags for multiple interventions, the model is not parsimonious for estimation, result interpretation, and forecasting. As a result, the linear distributed lag form has been mainly used for model identification.

Alternatively, the transfer function can be specified in a rational distributed lag form:

$$f(X_{i,t}^k) = \upsilon_i(B)X_{i,t}^k = \frac{\omega_i(B)B^{b_i}}{\delta_i(B)}X_{i,t}^k \tag{2-4}$$

where $\upsilon_i(B)$ is specified as a ratio of several finite order polynomials. The numerator factor B^{b_i} captures dead time, i.e., the number of time periods that an intervention has no impact on the response variable. The numerator factor $\omega_i(B) = \omega_{i,0} + \omega_{i,1}B + \cdots + \omega_{i,h_i}B^{h_i}$ captures unpatterned spikes and decay start-up values. The denominator factor $\delta_i(B) = 1 - \delta_{i,1}B - \cdots - \delta_{i,r_i}B^{r_i}$ represents the decay patterns. Therefore, for intervention i, the key parameters in a rational distribution lag specification is (b_i, h_i, r_i). In particular, the Koyck model, one of the most frequently used specification, can be represented by $(b_i, h_i, r_i) = (b_i, 0, 1)$ so that $\upsilon_i(B) = \omega_{i,0}B^{b_i} / (1 - \delta_{i,1}B)$.

In this study, Y_t was defined as the import value or unit price for a specific type of wooden bedroom furniture commodity from China. The antidumping investigation started in October 2003 and ended in December 2004 and several distinct events occurred during the process. The challenges were how to define the multiple interventions $X_{i,t}^{k}$, identify the six orders in ARIMA $(p, d, q)(P, D, Q)_s$ for the disturbance N_t, specify the three orders of (b_i, h_i, r_i) in the impulse response function $\upsilon_i(B)$ for each intervention, and finally estimate the combined model.

Intervention definitions and hypotheses

Several decisions were made in defining the input variables for the interventions in this study. First, multiple interventions were employed. The whole antidumping investigation took 15 months and experienced several distinct stages. Preliminary analysis revealed that a single intervention would be too simple to represent the long process. Therefore, several key dates were identified to define three interventions: the investigation announcement in October 2003 (intervention I), the affirmative preliminary decision and duty collection in July 2004 (intervention II), and the final implementation of antidumping duty since January 2005 (intervention III).

Given the chosen dates, the second issue was how to define a dummy variable for an intervention. Intervention dummy variables are usually in the form of either pulse $X_{i,t}^{P}$ or step $X_{i,t}^{S}$. A step intervention can also be defined for certain time periods so it need not be literally permanent (Pankratz 1991). To differentiate, this is called mixed intervention $X_{i,t}^{M}$. Mathematically, these three types of interventions $X_{i,t}^{k}$ ($k = P, S, M$) can be defined as:

$$
X_{i,t}^{P} = \begin{cases} 0, t \neq T \\ 1, t = T \end{cases}
$$
$$
X_{i,t}^{S} = \begin{cases} 0, t < T \\ 1, t \geq T \end{cases} \tag{2-5}
$$
$$
X_{i,t}^{M} = \begin{cases} 0, t < T_1 \text{ or } t > T \\ 1, t = T_1, \cdots, T_2 \end{cases}
$$

where a pulse or step intervention occurs at date *T*, and a mixed intervention occurs over the time period from T_1 to T_2 only. A pulse intervention implies that the impact is temporary while a step or mixed intervention has permanent impacts over the relevant time periods.

The choice among the three types of intervention dummy variables can be determined either theoretically or empirically. For intervention III in this study, theories provided some limited help. The duty rate on these small firms has been 198.08% since January 2005. It was too high for them to survive so there might be a permanent step drop of export from these firms. This effect could be best represented by a step intervention variable. However, the effects on other firms were unknown *a priori*; they could be permanent or temporary, and in addition, could last one or multiple time periods. So intervention III might have different impacts on individual groups of firms. This situation has been called compound intervention (McCleary and Hay 1980). In a word, interventions III could be represented as $X_{3,t}^{P}$ or $X_{3,t}^{S}$, or a combination of them.

For intervention I and II, it was difficult to postulate if they would produce a temporary or permanent effect on firm behavior. Thus, an empirical approach was employed. Both intervention I and II could be represented as $X_{i,t}^{P}$ or $X_{i,t}^{M}$ ($i = 1, 2$). In total, there were eight combinations of the three intervention definitions. McCleary

(1980) and Pankratz (1991) suggested that pulse interventions be examined first, then through a series of selections, other forms of interventions could be identified.

Identification of the disturbance and transfer function

The structure of the disturbance N_t and impulse response function $\upsilon_i(B)$ can be determined in several ways. One way for N_t is to determine the ARIMA structure of Y_t without considering the intervention $X_{i,t}^k$. Either the preintervention sample or the full sample can be used for that purpose. Unfortunately, preliminary data analyses in this study revealed that the intervention events changed the ARIMA patterns for most response variables dramatically so it failed to disclose the nature of data generating mechanism consistently. For $\upsilon_i(B)$, sometimes economic theories may help identify the patterns, but it was not the case for this study. Give these considerations, the linear transfer function (LTF) — a little complicated but more powerful method — was employed in this study.

The spirit of LTF method is that a linear distributed lag form for the transfer function is estimated first to give a set of sample impulse response weights (Pankratz 1991). At the same time, a low-order proxy model for the disturbance is included; this is designed to provide some more efficient estimates of the impulse response weights by accounting for most of the autocorrelation pattern in the disturbance. To begin with, the first step of LTF method for identification is to estimate a preliminary model as follows:

$$Y_t = C + \sum_{i=1}^{I} \left(\sum_{j=0}^{J_i} \upsilon_{i,j} B^j \right) X_{i,t}^k + \frac{1}{(1-\phi_1 B)(1-\phi_s B^s)} a_t \qquad (2\text{-}6)$$

where the maximum lag of J_i is often chosen arbitrarily. In this study, for the three interventions, the corresponding values were J_1 = 8, J_2 = 5, and J_3 = 14. Thus, for intervention I, there were nine impulse weights (j = 0, 1, …, 8). Following Pankratz (1991), the low-order AR model was represented by ARIMA $(p, d, q)(P, D, Q)_s \sim (1, 0, 0)(1, 0, 0)_s$.

The second step is to consider if regular first differencing (i.e., $d = 1$) is needed for N_t. The estimated disturbance series from the above model can be computed as:

$$\hat{N}_t = Y_t - \hat{C} - \sum_{i=1}^{I}\left(\sum_{j=0}^{J_i}\hat{\upsilon}_{i,j}B^j\right)X_{i,t}^k \tag{2-7}$$

where ^ indicates estimated values. The pattern of the sample autocorrelation function (SACF) of $\hat{N}_t$ can reveal the stationarity property of the disturbance. If it goes to zero slowly, the disturbance is nonstationary in the mean. Then the ARIMA specification of the disturbance should be changed to ARIMA $(p, d, q)(P, D, Q)_s \sim (1, 1, 0)(1, 0, 0)_s$. To consider $d = 1$, all the response and input variables need to be differenced accordingly and the equation can be reestimated as:

$$\nabla^d Y_t = C + \sum_{i=1}^{I}\left(\sum_{j=0}^{J_i}\upsilon_{i,j}B^j\right)\nabla^d X_{i,t}^k + \frac{1}{(1-\phi_1 B)(1-\phi_s B^s)}a_t \tag{2-8}$$

where C, ϕ_1 and ϕ_s may differ from those in the previous equations because of the differencing.

The third step is similar to the second step and it determines if seasonal first differencing (i.e., $D = 1$) is needed for the disturbance. The estimated disturbance series for the differenced data can be similarly calculated from the above estimation. If the

SACF for the disturbance decays slowly at the seasonal lags (i.e., *s*, 2*s*, 3*s*, …), then seasonal differencing in addition to regular differencing is needed. This is equivalent to specify the ARIMA $(p, d, q)(P, D, Q)_s \sim (1, 1, 0)(1, 1, 0)_s$ for the disturbance as:

$$\nabla^d \nabla_s^D Y_t = C + \sum_{i=1}^{I} \left(\sum_{j=0}^{J_i} \upsilon_{i,j} B^j \right) \nabla^d \nabla_s^D X_{i,t}^k + \frac{1}{(1-\phi_1 B)(1-\phi_s B^s)} a_t \qquad (2\text{-}9)$$

where C, ϕ_1 and ϕ_s may be different again because of the differencing. This cycle is repeated until a stationary disturbance is achieved by differencing. In practice, the first regular ($d = 1$) and seasonal differencing ($D = 1$) are usually sufficient.

Once a stationary disturbance is achieved, the fourth step is to study the SACF, the sample partial autocorrelation function (SPACF), and the extended sample autocorrelation function (ESACF) of the most recently estimated disturbance to identify a tentative ARMA model for the disturbance. This is similar to the identification procedure for a pure ARIMA model. For example, the SPACF of a moving average process MA(q) generally has spikes through lag q and has a decay pattern. Attentions usually are paid to the patterns revealed on lags 1, 2, 3, 1*s*, 2*s*, and 3*s*.

Finally, the estimated impulse response function for each intervention can be demonstrated graphically. By comparing its patterns to theoretical graphs (Pankratz 1991), a rational distributed lag form of the transfer function can be identified for each intervention. In addition, it should be noted that while multiple interventions can be conveniently examined through the LTF method, compound interventions usually cannot be handled directly because of the apparent multicolinearity problem among intervention dummy variables. In identifying the transfer function of compound interventions, relevant theories need to be employed to make some hypotheses.

Estimation and software

Once the structure of N_t and $\upsilon_i(B)$ are identified, the whole intervention model in equation (2-1) can be estimated by maximum likelihood method. The adequacy of the model can be evaluated by examining the SACF and SPACF of the residuals. In this study, the software R was used to estimate all the models (R Development Core Team 2009). The program for the linear transfer function was developed by following the steps in Pankratz (1991). The Time Series Analysis (TSA) package developed by Cryer and Chan (2008) was used to estimate the intervention model.

Variable definitions and data sources

The response variable was defined with several considerations. First of all, wooden bedroom future was defined by following the classifications in the antidumping investigation (U.S. ITC. 2004). Wooden bedroom furniture includes a variety of related products: wooden beds, headboards, footboards, side rails, night tables, dressers, dressers with framed glass mirrors, and similar furniture used in bedrooms. In the Harmonized Tariff Schedule (HTS) of the United States, wooden bedroom furniture involves four statistical categories (U.S. ITC. 2004). They are *bed* — HTS 9403.50.9040 wooden furniture of a kind used in the bedroom (beds); *other* — HTS 9403.50.9080 wooden furniture of a kind used in the bedroom (others); *part* — HTS 9403.90.7000 parts of furniture made of wood; and *mirror* — HTS 7009.92.5000 framed glass mirrors used in the bedroom.

Disaggregated data for each of the four commodities was used. This was consistent with the treatment in the investigation by the U.S. ITC. In addition, empirical evidence on the impacts of antidumping policies has been relatively scarce in the disaggregated form (Krupp and Pollard 1996). Disaggregated data are helpful for analyzing the impacts of different antidumping investigation stages (Durling and Prusa 2006). Furthermore, the antidumping policy might have different impacts on import values and unit prices so both of them were considered in the analyses. The import values were based on the cost-insurance-freight data. The unit prices were defined as the import values divided by the import quantities for a specific type of furniture. Both import values and quantities were downloaded from the U.S. ITC (2009). Only the quantities for *bed* and *mirror* were available. At the end, six series were constructed: import values of *bed*, *other*, *part*, and *mirror*; and unit prices of *bed* and *mirror*.

The time period covered was January 1997 to June 2008. The start date was set to 1997 for several considerations. The major reason was that imports from China before 1997 were very small. The antidumping investigation by the U.S. ITC focused on the rapid import increase during the period of investigation from 2001 to 2003. In addition, there had been gradual reductions of general tariff rates for wooden bedroom furniture from China before 1997 (U.S. ITC 2008). The rates were less than 2% for *bed*, *other*, and *part* in 1997 and have been zero since 1999. For *mirror*, the rates were 7.9% in 1997, 7.2% in 1998, and have been 6.5% since 1999. In total, there were 138 monthly observations for each series.

Empirical results

Preliminary data analyses

In Figure 2.1, nominal data for the six response variables were presented from January 1997 to June 2008. Several patterns emerged from the graphs. First, the four import value series demonstrated an increasing trend and the two unit price series were more stable. To remove the impact of inflation, the six series were deflated first using the Consumer Price Index (1997 as the base) (U.S. Department of Labor 2008). Second, the four import value series had increasing variance over the study period while the two unit price series had decreasing variance. During the early years around 1997, the import values were small and trading was thin; the series variation was small for import values but big for unit prices. In recent years, import values had grown quickly and reached $100 million per month, which resulted in increasing volatility in the imports values but stable variance of the unit prices. Thus, logarithm was taken on all the series to make the variance constant. In the end, the data used for the following intervention analysis were the logarithm of real import values and unit prices.

In addition, the four import value series showed strong seasonality. Averaging the data by month revealed that peak imports usually occurred in June and December, and bottom imports were in March and September. Thus, there was a cycle of three months for wooden bedroom furniture imports from China. In contrast, the two unit price series did not show much variation by month. The seasonality needs to be considered in identifying the ARIMA mechanism for the disturbance.

Finally, during the antidumping investigation period (October 2003 − December 2004), there had been great fluctuations in the import values of *bed* and *other*. However,

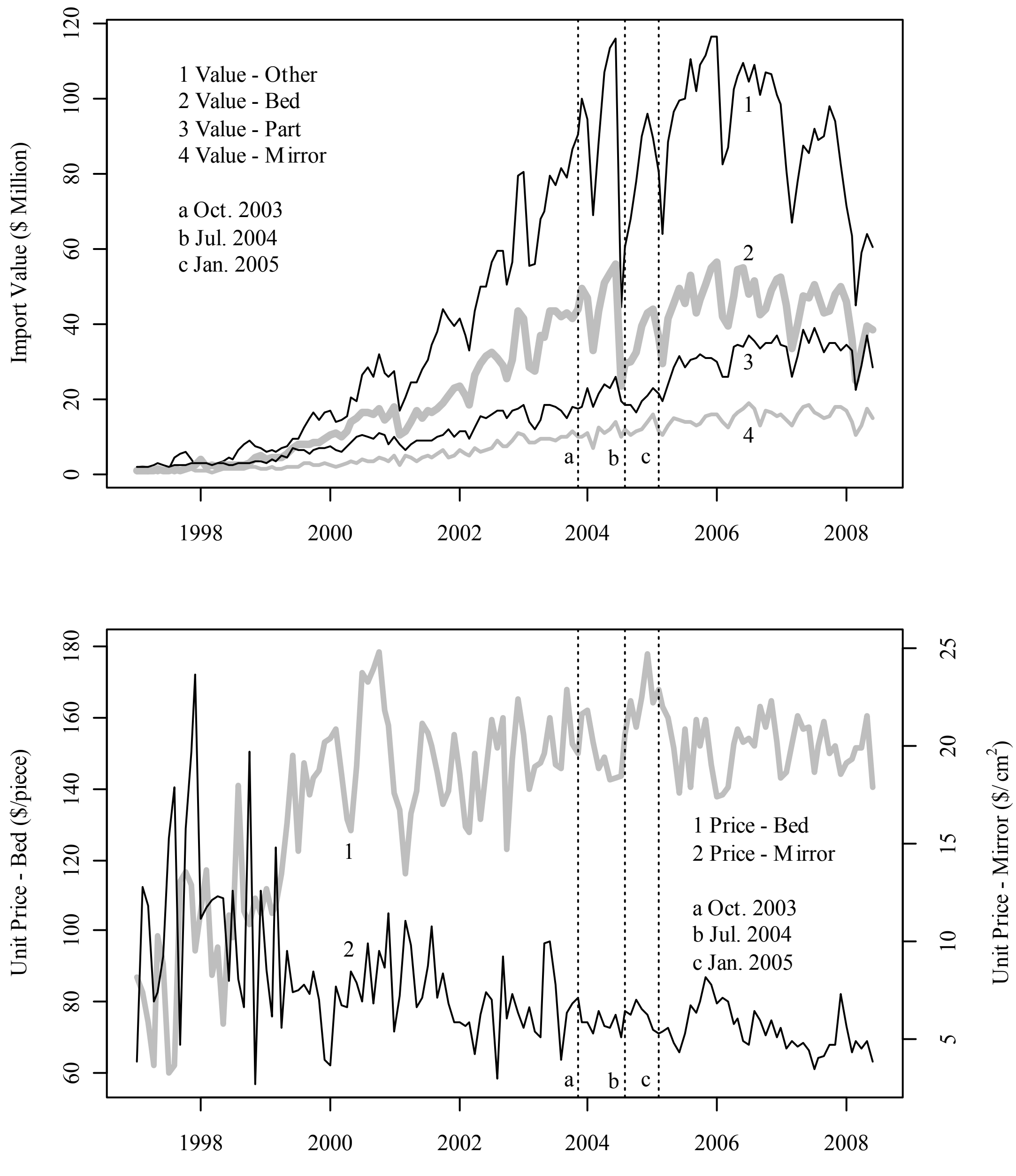

Figure 2.1 Monthly import values and unit prices for wooden bedroom furniture from China from January 1997 to June 2008

changes for the other series were less apparent. This indicated that the impact of interventions on wooden bedroom furniture imports might be different by commodity type. It further confirmed the use of disaggregated data for each furniture commodity for the following intervention analysis.

Results for the import value of other

Intervention analysis was first applied on the import value of *other* (i.e., the real import value of HTS 9403.50.9080 in logarithm) because it was the largest value among the four commodities. Three pulse interventions were defined at October 2003, July 2004, and January 2005. The LTF method was used to identify the model. In Figure 2.2, the SACF and SPACF from three models were presented. When no differencing was applied (i.e., $d = 0$, $D = 0$), the SACF had very slow decay pattern so there was a need for regular differencing ($d = 1$). Similarly, when $d = 1$ was applied, the SACF revealed a slow decay pattern at the seasonal lags so there was a need for seasonal differencing ($D = 1$). When $d = D = 1$ was applied as in equation (2-9), the SACF and SPACF did not show any nonstationarity so the differencing was appropriate. Based on the final model estimates, the SACF revealed that the autocorrelation was significant at the first lag, and the SPACF revealed that the partial autocorrelation was significant at the first and second lag. This indicated a MA(1) specification. Similarly, the SACF had some decay pattern at lag 12 and 24 and the SPACF at lag 12, indicating an $AR(1)_{12}$ specification. Overall, for the import value of *other*, the LTF method resulted in a final specification for the disturbance as ARIMA $(p, d, q)(P, D, Q)_s \sim (0, 1, 1)(1, 1, 0)_{12}$.

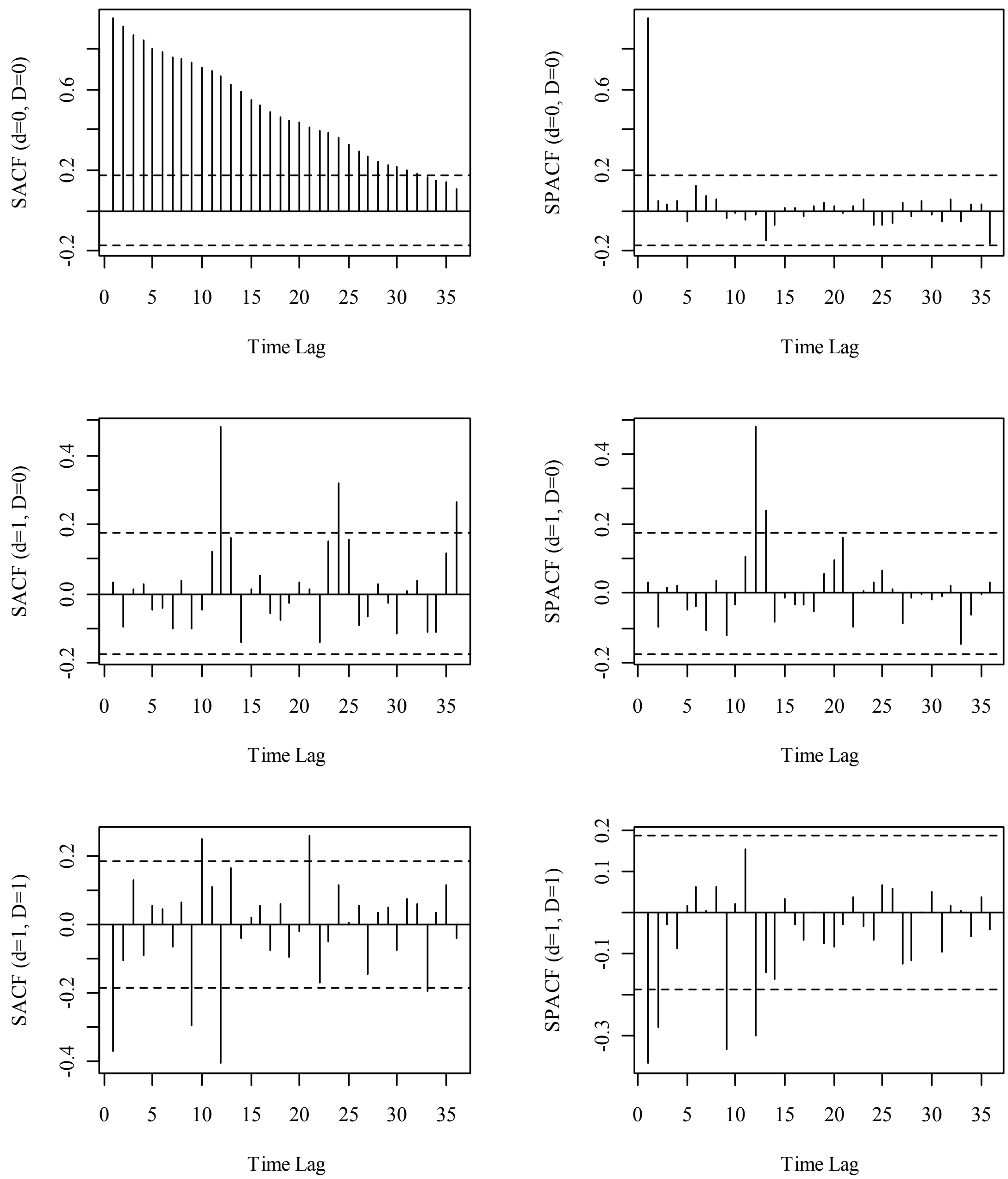

Figure 2.2 The SACF and SPACF for the import value of *other* with different order of regular (*d*) and seasonal (*D*) differencing

In Figure 2.3, the impulse response function for the import value of *other* from equation (2-9) was presented for all the interventions. The magnitudes and significance of these coefficients guided us to identify the transfer function for each intervention. For intervention I, the responses during the first five months were small and insignificant so the dead time was specified as $b_1 = 5$. A large spike of impulse occurred at the sixth month (i.e., March 2004) and the decay pattern was apparent after that. That was a typical Koyck pattern and was represented by $h_1 = 0$ and $r_1 = 1$. In total, the transfer function for intervention I was represented as $(b_1, h_1, r_1) \sim (5, 0, 1)$. For intervention II, there was a large negative spike in July 2004 so $b_2 = 0$. After that, the recovery patterns of the imports were consistent with a Koyck model. Thus, the transfer function for intervention II was represented by $(b_2, h_2, r_2) \sim (0, 0, 1)$. For intervention III, the pattern was similarly identified as $(b_3, h_3, r_3) \sim (0, 0, 1)$.

The above specifications for the disturbance and transfer functions were combined in the final estimation and the results were presented as Model A in Table 2.3. Diagnostics revealed that the disturbance was white noise. To detect other impact patterns, various hypotheses were tested. First, attention was focused on intervention III because it was the beginning of the formal implementation of the antidumping duty. Other four models were tried for the import value of *other*: Model B — one-period temporary effect; Model C — multiple-period permanent impacts; Model D — one-period permanent impact; Model E — a compound intervention impacts assumed with a step dummy and pulse dummy for intervention III. However, none of the four models produced a significant initial response. The model statistics were similar across the five models. Thus, it was concluded that there was no significant impact from intervention III. For intervention I and II, the same process was followed. As a result of various experiments, the best estimates were the multiple-period temporary impacts as presented in Model A.

Several interesting results emerged from Model A about the impacts of the antidumping investigation on the import value of other. The petition announcement (i.e., intervention I) in October 2003 did not generate any significant impact until March 2004.

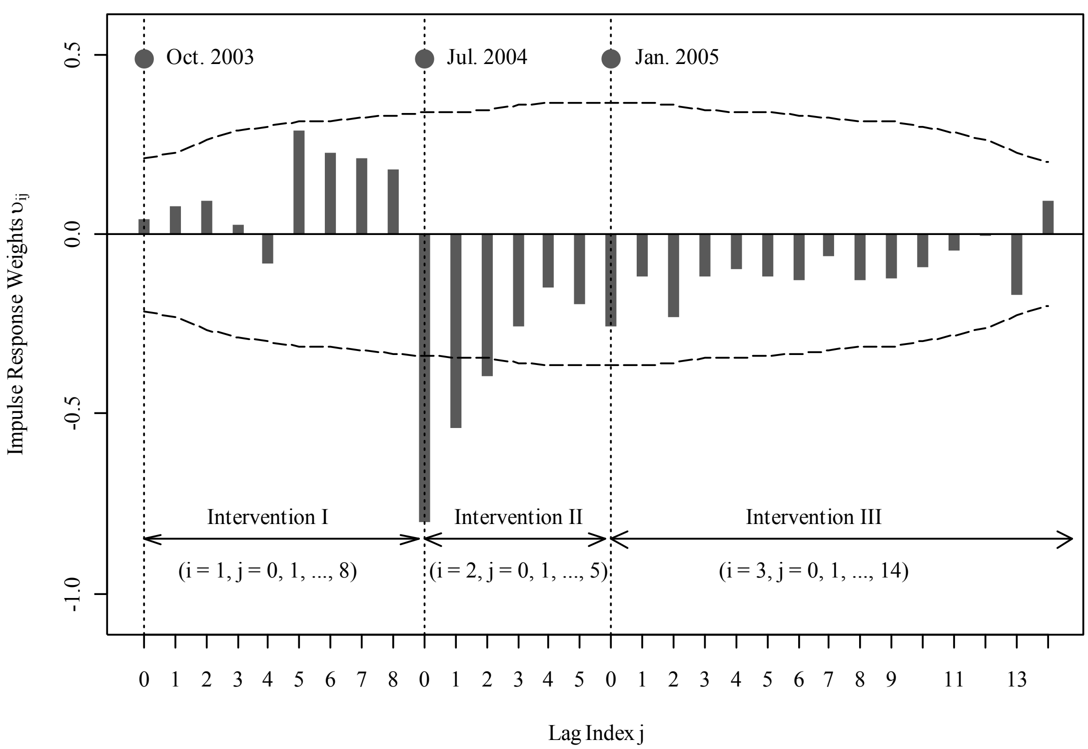

Figure 2.3 Estimated impulse response weights ($\upsilon_{i,j}$) for the import value of *other* from the linear transfer function method with three pulse interventions

Table 2.3 Empirical results for the import value of *other* † from intervention analysis with various combinations of intervention definitions

	Model A		Model B		Model C		Model D		Model E	
Coefficient*	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
MA(1)	-0.42 [a]	-3.78	-0.43 [a]	-3.87	-0.43 [a]	-3.82	-0.44 [a]	-3.95	-0.42 [a]	-3.75
$AR(1)_{12}$	-0.26 [b]	-2.22	-0.27 [b]	-2.31	-0.26 [b]	-2.29	-0.27 [b]	-2.33	-0.26 [b]	-2.22
$\omega_{1,0}^{P}$	0.30 [b]	2.55	0.32 [a]	2.72	0.28 [b]	2.40	0.30 [b]	2.48	0.29 [b]	2.48
$\delta_{1,1}^{P}$	0.85 [a]	5.07	0.84 [a]	5.02	0.86 [a]	3.74	0.84 [a]	4.09	0.85 [a]	4.84
$\omega_{2,0}^{P}$	-0.92 [a]	-7.51	-0.91 [a]	-7.36	-0.93 [a]	-7.31	-0.92 [a]	-7.17	-0.92 [a]	-7.40
$\delta_{2,1}^{P}$	0.71 [a]	6.64	0.71 [a]	6.70	0.73 [a]	7.05	0.73 [a]	6.94	0.71 [a]	6.47
$\omega_{3,0}^{P}$	-0.12	-1.53	-0.12	-1.09	–	–	–	–	-0.12	-1.39
$\delta_{3,1}^{P}$	-0.66 [b]	-2.50	–	–	–	–	–	–	-0.67 [b]	-2.49
$\omega_{3,0}^{S}$	–	–	–	–	-0.17	-1.50	-0.08	-0.64	-0.02	-0.15
$\delta_{3,1}^{S}$	–	–	–	–	-0.77 [a]	-4.06	–	–	–	–
(*d*, *D*)	(1, 1)		(1, 1)		(1, 1)		(1, 1)		(1, 1)	
σ^2	0.03		0.03		0.03		0.03		0.03	
Log-L	48.95		48.03		48.71		47.65		48.96	
AIC	-81.90		-82.06		-81.42		-81.30		-79.92	
BIC	-56.81		-59.76		-56.33		-59.00		-52.05	

a, b, c Significant at the 1%, 5%, and 10%, respectively.

* $\omega_{i,0}^{k}$ was the coefficient associated with intervention i, and k indicated intervention type (i = 1, 2, 3, k = P, S, M). The model statistics from the regressions reported were the disturbance variance (σ^2), the log-likelihood ratio (Log-L), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC).

† The import value of other used in intervention analysis was the logarithm of real import value. See Table 2.1 for the definition of *Other*

Apparently, furniture firms waited for more certain information from the investigation. The positive reaction of the market revealed that these firms increased trading to avoid any possible antidumping duties in the future. In July 2004, the affirmative decision in the preliminary phrase (i.e., intervention II) produced a large negative impact on the market. Both the initial response and the decay rate were large. In contrast, the formal implementation of the antidumping duties in January 2005 (i.e., intervention III) did not generate the expected negative impact. While the decay rate was significant at the 5% level, the initial response (-0.12) was small and insignificant.

Results for the other five response variables

Similar analyses were conducted for the other five response variables. For the import value of *bed*, *part*, and *mirror*, the differencing order was (d, D) ~ (1, 1), and the final LTF estimated was equation (2-9). For the unit price of *bed* and *mirror*, only regular differencing was necessary so the differencing order was (d, D) ~ (1, 0) and the final LTF estimated was eq. 8.

From the final equation estimated by the LTF method, the specification for the disturbance was identified. The ARMA structure was $(1, 0)(0, 1)_{12}$ for the import value of *bed*, $(2, 0)(1, 0)_{12}$ for the import value of *mirror*, $(0, 1)(0, 1)_{12}$ for the import value of *part*, $(1, 1)(0, 0)_{12}$ for the unit price of *bed*, and $(4, 0)(0, 0)_{12}$ for the unit price of *mirror*. The specifications of the transfer functions for the three interventions were the same for all the five response variables. They were identified as (b_1, h_1, r_1) ~ (5, 0, 1), (b_2, h_2, r_2) ~ (0, 0, 1), and (b_3, h_3, r_3) ~ (0, 0, 1).

In Table 2.4, the results from the finally selected models were presented for each response variable. Diagnostic statistics revealed the disturbance was white noise. Only the intercept for import value of *bed* was significant and the size was small at -0.01. All the ARMA parameters were highly significant at the 1% level. For the import value of *bed*, the results for the impulse response weights were very similar to these for the import value of *other*. During the first period, there were positive multiple-period temporary responses from intervention I. Intervention II generated negative multiple-period

Table 2.4 Empirical results for the import values of *bed*, *part*, and *mirror* and unit prices of *bed* and *mirror* from intervention analysis

	Value – *Bed*†		Value – *Part*		Value – *Mirror*		Price – *Bed*		Price – *Mirror*	
Coefficient*	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Intercept	-0.01 [a]	-3.00	–	–	–	–	–	–	–	–
AR(1)	-0.28 [a]	-3.23	–	–	-0.73 [a]	-8.49	0.38 [a]	3.37	-0.93 [a]	-11.10
AR(2)	–	–	–	–	-0.44 [a]	-4.97	–	–	-0.72 [a]	-6.56
AR(3)	–	–	–	–	–	–	–	–	-0.46 [a]	-4.09
AR(4)	–	–	–	–	–	–	–	–	-0.31 [a]	-3.55
MA(1)	–	–	-0.36 [a]	-4.50	–	–	-0.82 [a]	-13.40	–	–
$AR(1)_{12}$	–	–	-0.43 [a]	-4.64	-0.36 [a]	-3.77	–	–	–	–
$MA(1)_{12}$	-0.78 [a]	-6.56	–	–	–	–	–	–	–	–
$\omega^P_{1,0}$	0.36 [a]	3.07	0.28 [a]	2.85	0.34 [b]	2.49	-0.07	-0.73	0.02	0.09
$\delta^P_{1,1}$	0.85 [a]	4.84	0.44	1.36	0.83 [a]	2.61	0.73 [c]	1.90	-0.49	-0.15
$\omega^P_{2,0}$	-0.81 [a]	-6.63	-0.28 [a]	-2.71	-0.15	-0.95	-0.05	-0.51	-0.16	-0.60
$\delta^P_{2,1}$	0.75 [a]	5.59	0.91 [a]	10.90	0.74	1.56	0.06	0.05	-0.05	-0.03
$\omega^P_{3,0}$	-0.05	-1.16	-0.02	-0.88	0.17	1.22	-0.02	-0.28	-0.22	-1.13
$\delta^P_{3,1}$	-0.93 [a]	-7.80	-0.98 [a]	-15.04	0.06	0.10	-0.35	-0.27	0.87 [a]	5.15
(*d*, *D*)	(1, 1)		(1, 1)		(1, 1)		(1, 0)		(1, 0)	
σ^2	0.02		0.02		0.04		0.01		0.09	
Log-L	68.66		75.24		21.31		108.49		-26.42	
AIC	-119.32		-134.47		-24.61		-200.99		72.85	
BIC	-91.44		-109.38		3.26		-175.04		104.56	

[a], [b], [c], * See the footnotes at Table 2.3.
† See Table 2.1 for the definition of *bed*, *part*, and *mirror*. All the data were deflated and then converted to logarithm.

temporary responses. The import value of *part* had similar patterns as the import value of *other* and *bed*; the exception was that the decay rate for intervention I was not significant. For the import value of *mirror*, there was only significant impact from intervention I.

The two unit price series had very different patterns than these for import values. For the unit price of *bed*, only the decay rate in the first period was significant at the 10% level. For the unit price of *mirror*, only the decay rate in the third period was significant. None of the initial response estimates were significant. The magnitudes of these estimates were also very small for all the three interventions; the largest was -0.07 for the unit price of *bed* and -0.22 for the unit price of *mirror*. Therefore, these analyses revealed that the antidumping investigation had no significant impacts on the import unit prices.

Impact summary

All the response variables used in intervention analysis were in logarithms. The estimates in Table 2.3 and 2.4 indicated the impact on the log-level of the variables. To express the impact in the original metric, the estimates need to be transformed back by taking exponentiation (McCleary and Hay 1980). For example, for the import value of *other*, the initial response for intervention I in March 2004 was 0.30 in log metric. This indicated a 35% increase of the postintervention series level to the preintervention series level (i.e., $(e^{0.30} - 1) \times 100\% = 35\%$). In June 2004, the impact was 0.18 in log metric (i.e., $\omega_{1,0}\delta_{1,1}^{3} = 0.30 \times 0.85^{3} = 0.18$) and 20% in original metric (i.e., $(e^{0.18} - 1) \times 100\% = 20\%$).

In Table 2.5, all significant estimates were transformed into the original metric. For the import value of *other*, intervention I increased imports by a total of 107%, and intervention II decreased imports by a total of -208% over the preintervention level. In total, the net effect of the antidumping policy reduced total imports by -101%. The preintervention level was approximately defined as the average monthly import value over the two years before the antidumping investigation (i.e., November 2001 – October 2003). For the import value of *other*, the average import value was $59.64 million per month so the total impact of the antidumping policy was -$60.23 million. Similarly, the total impact of the antidumping policy was -71% and -$22.73 million for the import value

Table 2.5 Summary of the significant impacts on the import values of wooden bedroom furniture from the two interventions in October 2003 and July 2004

Item*	Value – *Other*†		Value – *Bed*		Value – *Part*		Value – *Mirror*	
	Log‡	Original	Log	Original	Log	Original	Log	Original
	Intervention I (*October 2003 – June 2004*)							
Estimate $\omega_{1,0}^{P}$	0.30 [b]	–	0.36 [a]	–	0.28 [a]	–	0.34 [b]	–
Estimate $\delta_{1,1}^{P}$	0.85 [a]	–	0.85 [a]	–	0.44	–	0.83 [a]	–
Impact at Mar. 2004	0.30	35%	0.36	44%	0.28	32%	0.34	41%
Impact at Apr. 2004	0.25	29%	0.31	36%	–	–	0.28	33%
Impact at May 2004	0.21	24%	0.26	30%	–	–	0.24	27%
Impact at Jun. 2004	0.18	20%	0.22	25%	–	–	0.20	22%
Sub-total	–	107%	–	134%	–	32%	–	122%
	Intervention II (*July 2004 – December 2004*)							
Estimate $\omega_{2,0}^{P}$	-0.92 [a]	–	-0.81 [a]	–	-0.28 [a]	–	-0.15	–
Estimate $\delta_{2,1}^{P}$	0.71 [a]	–	0.75 [a]	–	0.91 [a]	–	0.74	–
Impact at July. 2004	-0.92	-60%	-0.81	-56%	-0.28	-25%	–	–
Impact at Aug. 2004	-0.65	-48%	-0.61	-45%	-0.26	-23%	–	–
Impact at Sept. 2004	-0.46	-37%	-0.45	-36%	-0.23	-21%	–	–
Impact at Oct. 2004	-0.32	-28%	-0.34	-29%	-0.21	-19%	–	–
Impact at Nov. 2004	-0.23	-20%	-0.25	-22%	-0.19	-18%	–	–
Impact at Dec. 2004	-0.16	-15%	-0.19	-17%	-0.18	-16%	–	–
Sub-total	–	-208%	–	-205%	–	-121%	–	–
	Combined							
Total	–	-101%	–	-71%	–	-89%	–	122%
Average ($ million)#	–	59.64	–	32.02	–	14.87	–	7.84
Total impact ($ million)	–	-60.23	–	-22.73	–	-13.23	–	9.56

[a], [b], [c], * See the footnotes at Table 2.3.

† See Table 2.1 for the definition of *bed*, *other*, *part*, and *mirror*.

‡ Log indicated the log-level of the response variable and Original indicated the response variable without taking logarithm.

The average import value for each series was calculated as the nominal monthly average over the two years before the antidumping investigation (i.e., November 2001 – October 2003). The total impact equaled to the product of total impact in percentage and average import value.

of *bed*, -89% and -$13.23 million for the import value of *part*, and 122% and $9.56 million for the import value of *mirror*. In aggregate, the total impact for all the four commodities was -$86.63 million and it was close to the total imports for the four commodities in one month.

Conclusions

From 1997 to 2007, U.S. imports of wooden bedroom furniture have grown from $1.1 billion to $5.1 billion. Since 2002, more than 40% of these imports have come from a single supplier — China. With the rapid import growth in such a short time period, the domestic furniture industry has experienced tremendous pressure to compete with foreign firms. As a result, an antidumping petition against wooden bedroom furniture from China was filed in October 2003. Since January 2005, antidumping duties ranging from 0.83% to198.08% have been imposed on individual Chinese firms. To assess the impact of this antidumping case, intervention analysis was employed to examine the evolution of the import values and unit prices of wooden bedroom furniture imports from China. The data used were monthly observations from 1997 to 2008 for four disaggregated furniture commodities.

Several conclusions were reached from the analyses. The petition announcement in October 2003 increased the import values for all the four furniture commodities with the aggregate impact ranging from 32% to 134% on a monthly basis. The affirmative determination in the preliminary stage and the collection of antidumping duties in July 2004 decreased the import values for three of the furniture commodities with the impact ranging from -121% to -208%. In contrast, the final implementation in January 2005 did not produce any significant effect on any of them. In total, the combined effect on import values was small. It was approximately equal to a reduction of imports by $86.63 million, or the import amount for one month. All impacts were temporary and no permanent impacts on import values were found. Finally, the antidumping duties did not generate any significant impact on unit prices.

These empirical results are consistent with several observations of the furniture industry and the antidumping investigation. First of all, there has been increasing integration of the furniture industry between U.S. and China. Chu and Prusa (2004) reported that since China relaxed the regulations for inward foreign direct investment in 1992, foreign firms or joint ventures have accounted for about 50% of exports from China. For the case of wooden bedroom furniture, U.S. ITC (2004) also reported that one-third of wooden bedroom furniture from China over 2001 – 2003 were imported by U.S. manufacturers. Thus, it is not surprising that the final duties implemented have been very low (less than 5%) for several big joint ventures. This explained the impact patterns of the antidumping case: increased trading after the petition because firms felt uncertain and then tried to perform existing contracts as early as possible; decreased trading after the affirmative determination in the preliminary phase because duties have been collected; and no impact after the final implementation because the duty rates were low for most firms and they have digested the information already.

Second, small Chinese furniture firms have become increasingly disadvantaged in the furniture import market in the United States. One particular feature of manufacturing sectors in China has been its low concentration ratios (Chu and Prusa 2004). In the furniture industry, there have been at least 30,000 firms in China (Robb and Xie 2003).

For this antidumping case, it is well known that U.S. furniture firms have imported more than one-third of wooden bedroom furniture from China in recent years as a sourcing strategy, and furthermore, during the investigation almost half of the U.S. firms opposed the petition (U.S. ITC. 2004). Apparently, it was difficult to impose large antidumping duties on these U.S. firms that have investment in China. A reasonable solution for the trade dispute was a large duty on these small furniture firms in China to reduce their import share. In fact, the high duty rate of 198.08% on small firms basically eliminated these small firms from the U.S. import market. In a word, small furniture firms in China have become the final target of the antidumping case.

Several years have passed since antidumping duties on wooden bedroom furniture from China were implemented in January 2005. At present, imports of wooden bedroom furniture by the United States continue to rise. The antidumping case against China had a very limited temporary impact during the investigation period. Furthermore, other developing countries (e.g., Vietnam) with low production costs also have increased their exports rapidly in recent years. There may be a trade diversion effect associated with the antidumping case again China. Future studies need to examine the import competition of different suppliers in the furniture market in the United States and the strategies for the domestic furniture industry to compete in a global market

CHAPTER III

COMPETITION OF IMPORTED WOODEN BEDROOM FURNITURE IN THE UNITED STATES

Introduction

The United States has been experiencing a rapid growth in the consumption of furniture. Domestic furniture retail sales have steadily grown up in recent years, exceeding $100 billion in 2003 (Gazo and Quesada 2005). The domestic furniture industry has made significant contributions to the economy over the last decade. According to U.S. Bureau of Census (2006), the total value of furniture shipments reached $85.6 billion in 2006, which was equal to 5.4 % of the manufacturing industries GDP. The furniture industry also contributed to the U.S. with 518,989 employees in 2006. The revenue for the wood household furniture manufacturing industry in 2006 was approximately $10.7 billion and the gross profit was $3.2 billion.

However, an increasing share of the rising furniture demand has been met by the large imports from foreign countries. The import value of wooden bedroom furniture climbed from $0.6 billion in 1996 to $3.8 billion in 2006 (U.S. ITC. 2009). Traditionally, the United States imported furniture from Canada, Italy, and Taiwan, to name a few. As global trade liberalization and international competition increased, the furniture market changed considerably over the last decade. This change has affected consumer behavior and market structure. Furniture made in newly developing countries such as China, Vietnam, and Malaysia has substituted for the furniture from traditional suppliers and has begun to dominate the U.S. furniture import market in recent years. In particular, China became the largest wooden bedroom furniture supplier in the market and accounted for 44% of import share over 2001 – 2008. This trade phenomenon has led to a serious threat to the domestic furniture manufacturing industry and aroused wide concerns. To protect the domestic furniture industry, an antidumping investigation (U.S. ITC. 2004) on China was conducted during 2003 – 2005. Antidumping duties (0.83% – 198.08%) have been imposed on wooden bedroom furniture from China, but its total import value continues to rise.

In the study of international trade of forest products, various models including Almost Ideal Demand System (AIDS), Armington model, Market-share model, and Translog cost function, have been used for demand analysis. Aguiar-Roman et al. (2006) used a static AIDS model to examine the competition of softwood lumber imported from Mexico, Brazil, New Zealand in the U.S. market. Gan (2006) employed Armington model to analyze the substitutability between U.S. domestic and imported forest products. In addition, a market-share model was adopted to examine the price competitiveness of lumber (Castillo and Laarman 1984; Haji-Othman 1991). Nagubadi et al. (2004) applied a translog cost function to address the softwood lumber trade dispute between U.S. and Canada. This model has also been used to analyze the import competition of coniferous sawnwood (Mutanen 2006) and the substitution in global wood imports (Uusivuori and Kuuluvainen 2001).

In addition, measuring the responsiveness of demand to the changes in income, own-price and price of other goods are of great interest in trade policy analysis.

Numerous studies have estimated income elasticity, own-price elasticity, and cross-price elasticity for the demand of forest products. Turner and Buongiorno (2004) made a comprehensive summary about the elasticity estimation of import demand for forest commodities such as wood, paper products, and furniture. Moreover, substitution between different categories of imported products can be measured by the cross-price elasticities (Nagubadi et al. 2004; Uusivuori and Kuuluvainen 2001). Overall, these elasticities have produced valuable implications for trade policy analysis.

Regarding the furniture market in the United States, research has mainly focused on comparing the import values across supplier countries over different time periods. Gazo and Quesada (2005) compared the value of imports from the top 25 supplier countries and analyzed the advantages and disadvantages of competitors all over the world. Schuler et al. (2001) summarized several strategies for the furniture industry based on the lessons learned from the softwood moulding industry. To the best of our knowledge, very few rigorous analyses have been conducted on the basis of contemporary economics and trade theories. No study has been conducted to analyze the import furniture market. Therefore, there is a need to comprehend trade pattern, consumer behavior, and market competition in the U.S. furniture import market. Although the AIDS model has been widely employed in food and tourism demand analysis, it has not been applied to the forest products market so far.

The objective of this study was threefold. First, the consumer behavior in the import market of wooden bedroom furniture was examined in this changing market setting. Products from traditional and newly developing countries were considered as the choices for U.S. consumers. Since the preferences of U.S. consumers could change over time, the long-run behavior was detected to reflect equilibrium status and the short-run behavior was examined to reveal instantaneous adjustments. Second, how major wooden bedroom furniture supplier countries compete in this market was analyzed. The common approach is to examine the cross-price elasticities suppliers. From these elasticities, the substitute or complement relationship between suppliers can be disclosed. The estimation of various elasticities is valuable to both marketers confronting global competition and policymakers facing the need to protect the domestic industry.

Third, the effectiveness of the antidumping investigation on China during the period of 2003 – 2005 was evaluated. The effectiveness of antidumping policy has been analyzed for a long time in various theoretical and empirical studies (Blonigen and Prusa 2003; Kinnucan and Myrland 2006). In addition, the ineffectiveness is often supported by trade diversion in the case of antidumping policy, especially in the manufacturing section (Brenton 2001; Durling and Prusa 2006; Krupp and Pollard 1996). Thus, there has been a need to integrate this antidumping investigation into the theoretical model. The analysis of its impacts can provide empirical evidence of theoretical expectations and better understanding of our existing policy.

To complete the above objectives and fill in the research gaps in furniture market, the dynamic AIDS model was employed and various tests were used to examine theoretical properties and model robustness. The expenditure, own-price, and cross-price elasticities were calculated based on the estimated parameters from the dynamic AIDS model. The results from this study are helpful in understanding the competition among suppliers, consumer behavior in this market, and the impact of current policies.

The rest of this paper was organized as follows. The market overview of imported wooden bedroom furniture in the United States was presented in the next section. The dynamic AIDS model applied to this import market was introduced and demonstrated based on a serial of assumptions. The data source, time period selection, and country selection were stated, followed by the variable constructions. Next, the empirical results were reported and discussed. Finally, the conclusions and policy implication were offered.

Market overview and antidumping investigation against China

U.S. imports of wooden bedroom furniture (wbf) grew steadily over the period 1996 – 2008, as shown in Figure 3.1. U.S. monthly import value was about $50 million in 1996 and reached its peak value of $353.8 million in August 2005. During the same period, the average annual growth rate of wbf was 30%. Beds are one of the major products included in wooden bedroom furniture as defined by the International Trade Commission (ITC). There was an upward trend over the same period. The rapid growth of imported wbf was largely due to the increasing import of beds from all over the world. In 1996, monthly import value for beds was about $10 million, one fifth of wbf. It rapidly climbed to $100 million per month since 2004, about one third of wbf. The annual growth rate was 57% over the period 1996 – 2008. However, as the import value increased, the market structure experienced a dramatic change due to the competition among traditional and new suppliers.

Historically, the U.S. imported beds mainly from suppliers such as Canada, Indonesia, and Italy. During the 1990s, countries such as Canada and Italy were the major players in the U.S. imported furniture market. From 1996 – 2000, about 20% originated from Canada, 15% from Indonesia, and another 12% from Italy. In 1996, the import value from Canada was $35.0 million, accounting for 24.8% of the import share. In contrast, its corresponding value in 2008 was $22.9 million, only 1.9 % in this market. Italy was the largest furniture exporter to the United States from Europe. Imports from Italy steadily grew from $17.7 million in 1996 to $51.1 million in 2003, with an annual growth rate of 27%. After reaching its peak value, it began to decline and the value was $14.0 million in 2008. Overall, both Canada and Italy dramatically lost their import shares in the U.S. market.

The market structure of beds in the U.S. began to change at the beginning of this

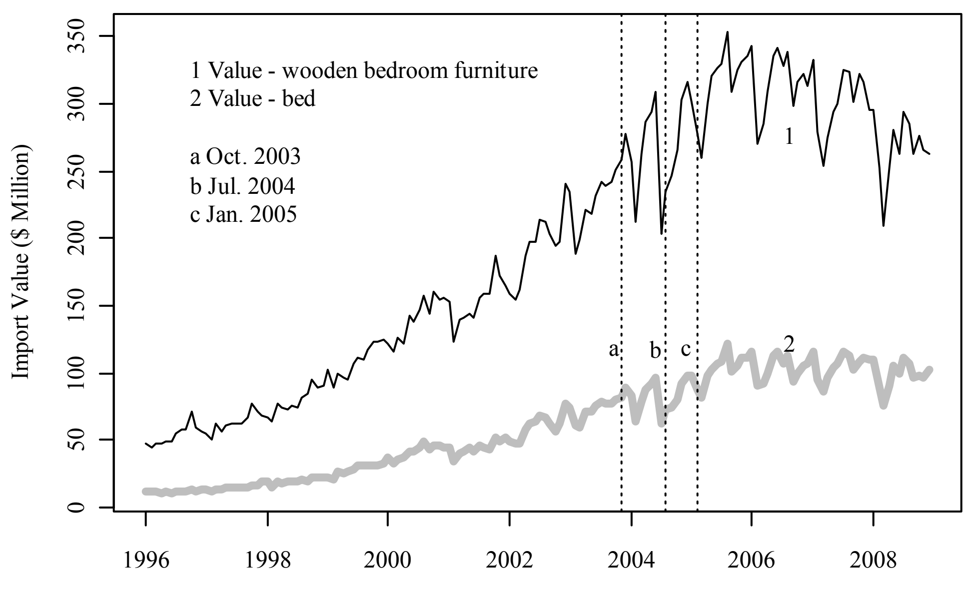

Figure 3.1 Monthly import value of wooden bedroom furniture and beds from January 1996 to December 2008

century. Newly developing Asian countries such as China and Vietnam have demonstrated their potential to dominate the U.S. market. China has been steadily increasing its exports to the U.S and became the leading supplier to the U.S. market in 2001. The import value from China was only \$5.6 million in 1996, but climbed to \$418.1 million in 2008, accounting for a 35.4% import share. After joining the WTO in 2001, the import value from China increased at an annual rate of 16.0% (Table 3.1). Although the annual import value of Vietnam was smaller than that of China, it still was an important supplier in the U.S. import furniture market. Vietnam began to export its beds to U.S. from 2001 and reached \$357.8 million in 2008, closely following China. Imports from Vietnam trended upward quickly and accounted for more than 30% of import share from 2008. It should be noted that the monthly import value from Vietnam has exceeded China in October 2008. Meanwhile, imports from Malaysia grew from \$15.9 million in 2001 to \$106.3 million in 2007. As a result, imports from China, Vietnam, Indonesia, and Malaysia together have been over 70% of the import share during the period of 2001 – 2008.

The above trade pattern, especially the large value of imports from China, has aroused wide concerns about the competitiveness of the U.S. furniture industry over the last decade. The serious threat to the furniture industry has led to the antidumping investigation against China by ITC from October 2003 to January 2005. To protect the U.S. furniture industry, antidumping duties (0.83% – 198.08%) were imposed on China from July 2004 on. As shown in Figure 3.2, China's import share dropped sharply from 55% to 38% after this affirmative determination. In contrast, imports from Vietnam, Indonesia, Malaysia, and Brazil increased dramatically in the same month. Overall,

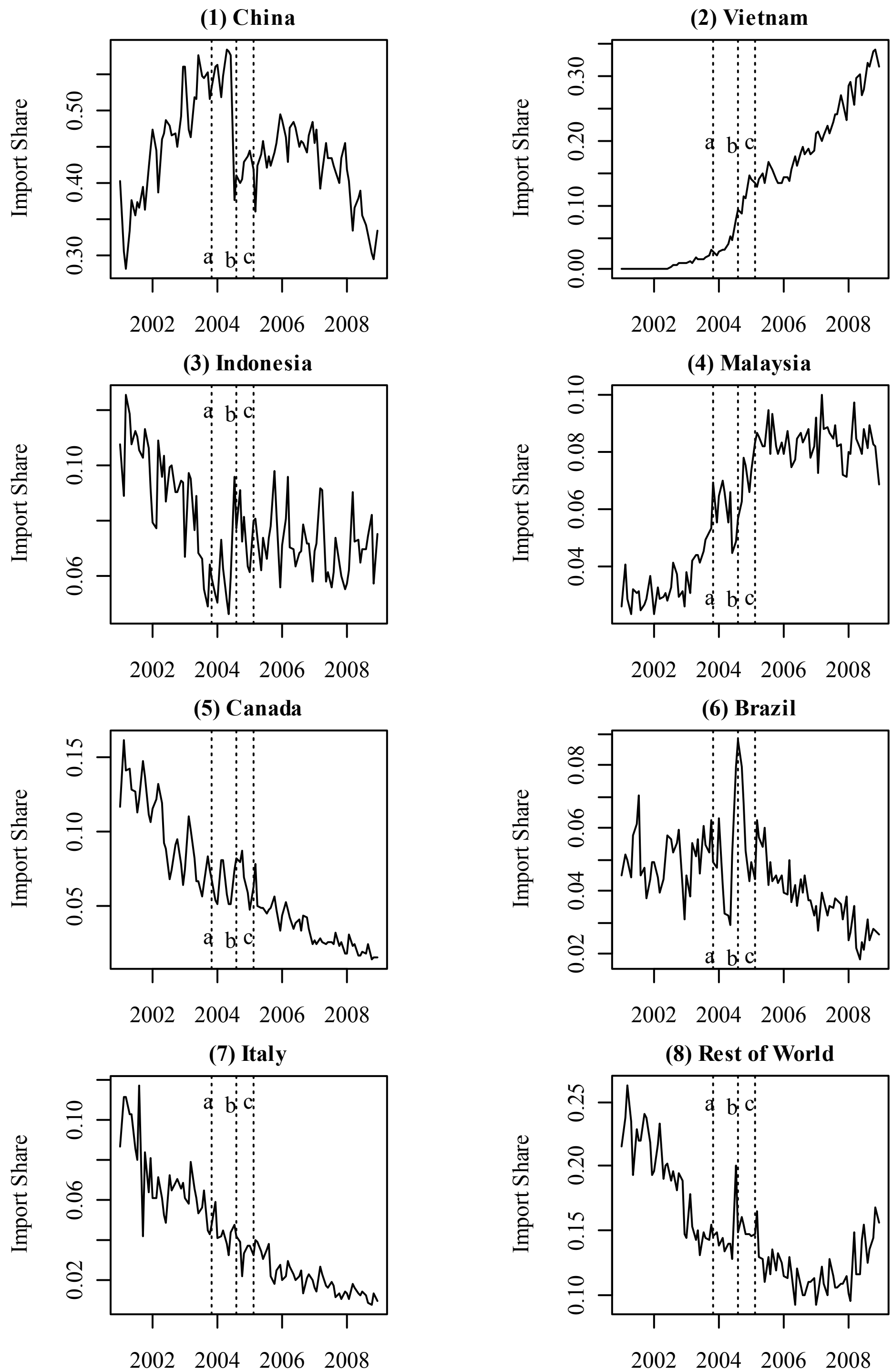

Figure 3.2 Monthly import share of top seven suppliers from January 2001 to December 2008

Note: a. Antidumping petition in October 2003; b. Preliminary determination in July 2004; c. Final determination in January 2005

Table 3.1 Annual U.S. import values (Million $) of beds† from the top seven supplier countries from 2001 to 2008

Country	*Mean*‡	2001	2002	2003	2004	2005	2006	2007	2008
China	447.8	197.4	341.0	477.3	480.5	539.5	581.6	547.2	418.1
Vietnam	141.2	0.5	3.5	16.9	71.1	177.8	211.1	290.6	357.8
Indonesia	75.2	57.1	67.3	61.7	66.3	91.2	90.0	85.0	83.2
Malaysia	69.2	15.9	22.4	43.0	61.7	103.4	102.9	106.3	97.7
Canada	54.1	68.1	66.3	66.1	66.2	62.1	49.6	31.8	22.9
Brazil	43.0	26.5	34.7	46.3	52.7	60.7	49.4	44.3	29.8
Italy	35.2	47.0	45.9	51.1	37.2	38.7	27.3	20.3	14.0
ROW#	141.3	119.1	138.2	132.9	144.1	161.3	138.7	138.2	157.8
Total	1007.0	531.7	719.3	895.2	979.6	1,234.6	1,250.5	1,263.7	1,181.3

† beds are defined under the HTS 9403.50.9040 by ITC. All values were the cost-insurance-freight (*CIF*) values of the imported beds.
‡ *Mean* was based on the average import value over the period 2001 – 2008. All the data were nominal data without any adjustment.
# ROW denotes Rest of World.
Source: U.S. ITC (2009).

Figure 3.1 and 3.2 revealed that total imports are still increasing and the import shares of Vietnam and Malaysia have been rapidly growing over this period.

Methodology

Almost Ideal Demand System

In this study, a dynamic AIDS model was employed to examine the consumer behavior, evaluate the competition among different supplier countries, and assess the effectiveness of antidumping investigation in the import market for wooden bedroom furniture. The AIDS model (Deaton and Muellbauer 1980a) has become one of the major demand models over the past three decades. The frequent application of the AIDS model over other demand models is largely due to its advantages. First, the AIDS model is consistent with consumer theory (Deaton and Muellbauer 1980a). It can satisfy the axioms of choice and is derived from minimizing the expenditure function subject to a utility level. It also gives an arbitrary first-order approximation to demand system.

Second, the system of demand equations can overcome the limitations of single equation approach. This system of demand equations allows us to examine how consumers make decision among bundles of goods to maximize their utility under the budget constraints. Moreover, the change of relative prices among suppliers is taken into consideration in AIDS model to analyze the different decisions made by consumers. Theoretical properties of homogeneity and symmetry can be tested or imposed by linear restrictions on the parameters from a system view. The system is jointly estimated to consider contemporaneously related errors. Hence, the demand curve depicted by AIDS model is a comprehensive picture of demand in this market.

AIDS model is also a desirable and flexible demand system, which can take different functional forms to incorporate dynamic factors. Various function forms have been applied in the empirical demand studies so far. The first-difference AIDS model is employed to avoid serial correlation (Deaton and Muellbauer 1980a; Seale et al. 2003). Anderson and Blundell (1982, 1983) first put forward the dynamic adjustment of consumers' expenditure, leading to important implications for the specification of dynamic AIDS model . With the development of econometric techniques, autoregressive distributed lagged technique allows for several periods of short-run adjustments to long-run equilibrium status in AIDS model. The two-step cointegration and error correction techniques suggested by Engle and Granger (1987) have been introduced into AIDS model, also known as error correction AIDS model. In addition, Pesaran and Shin (2002) developed a general framework for cointegrated systems based on the a cointegration technique introduced by Johansen and Juselius (Johansen 1988; 1992).

Due to the benefits mentioned above, the dynamic AIDS model has been widely used in estimating consumer expenditures on food (Balcombe and Davis 1996; Karagiannis and Mergos 2002; Pesaran and Shin 2002), meat products (Ben Kaabia and Gil 2001; Fanelli and Mazzocchi 2002; Feleke and Kilmer 2007; Karagiannis et al. 2000), and olive oil (Duffy 2003; Gil et al. 2004). It also has been employed frequently in estimating tourism demand (De Mello and Fortuna 2005; Li et al. 2004, 2006).

Model assumption, specification, and estimation

In this study, weak separability[1] in consumers' preferences between domestic and imported furniture was assumed (Deaton and Muellbauer 1980b). Together with the above assumption, the three-stage budgeting was further assumed to allocate consumption on the imported furniture. At the first budget stage, the expenditure was allocated between furniture and other goods. The expenditure on furniture was allocated between imported and domestic furniture at the second stage. At the last stage, the expenditure was allocated among the major supplier countries. This study focused on the import market for beds and the AIDS model was applied to the third stage.

Considering this imported beds market, AIDS model can be derived from minimizing the total expenditure on beds subject to a specific utility level. s_i is the import share of beds from supplier country i (i = China, Vietnam, Indonesia, Malaysia,

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[1] Weak separability implies that the marginal rate of substitution between two goods in one group is independent of quantities of goods consumed in the other group. It is a necessary condition for assuming the multi-stage budgeting.

Canada, Brazil, Italy, and Rest of World (ROW)), which can be calculated as $s_i = p_i q_i \Big/ \sum_{i=1}^{n} p_i q_i = p_i q_i / x$. p_j is the price of beds from country *j*, *x* is the total expenditure on all of the imported beds. P^* is the Stone's Price Index, which is the linear approximation to original price index P, $\ln p^* = \sum_{i=1}^{n} s_i \ln p_i$. Then *x* is deflated by P^* to get the real total expenditure x / P^*. D_k (k = 1, 2, 3) are the three antidumping investigation dummy variables, and ε_i is the normal disturbance term with zero mean and constant variance. Based on the above description, the AIDS model is formulated as follows:

$$s_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln\left(x / P^*\right) + \sum_{k=1}^{3} \delta_{ik} D_k + \varepsilon_i \tag{3-1}$$

To comply with economic theory, the system of equations (3-1) is required to satisfy the properties of adding-up, homogeneity, symmetry, and negativity. All of them can be tested by Likelihood Ratio (LR) tests. The adding-up property implies that the sum of all import shares equals to one, which requires $\sum_i \alpha_i = 1;\ \sum_i \beta_i = 0;\ \sum_i \gamma_i = 0$. Homogeneity requires $\sum_j \gamma_{ij} = 0$ and suggests that the proportional change in the expenditure and all of the prices has no impact on the quantities purchased or the budget allocation. Symmetry implies that the matrix of the price effects is symmetric, $\gamma_{ij} = \gamma_{ji}$. Negativity requires the matrix of price effects be negative semidefinite, which implies that all the own-price elasticities should be negative to satisfy the law of demand.

The above AIDS model has been applied in various fields with time series data. The expenditures and prices are usually non-stationary, or have unit roots. Import shares ranging from 0 to 1 usually have unit root in empirical studies too. The existence of unit roots can invalidate the asymptotic distribution of the estimators. The statistical inference value such as t, F, and R^2 are not reliable for model explanation. In addition, empirical studies usually find that the applications of AIDS model with time series data cannot satisfy theoretical restrictions, and often lead to auto-correlated residuals (Edgerton et al. 1996). Hence, it is necessary to test for unit roots first using the Augmented Dickey-Fuller (ADF) unit root test.

The static AIDS model implicitly assumes that the consumer behavior is always in equilibrium and there is no difference between short-run and long-run behavior (Anderson and Blundell 1983; Li et al. 2006). In reality, consumers' behavior can be influenced by various factors such as consumption habits (Houthakker and Taylor 1970; Sexauer 1977) , short-run adjustment, and policy intervention (Feleke and Kilmer 2007; Li et al. 2004). Consumption habits[2], including habit persistence and inventory adjustment, happen often because current consumption is usually based on the past consumption. One approach to introducing consumption habit in the model is to incorporate the lagged import share into the right-hand side of equations (3-1).

Cointegration and error correction techniques have been successfully integrated into the AIDS model to consider both long-run and short-run consumer behavior. One of the main cointegration techniques is introduced by Engle and Granger (1987). Following

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[2] Consumption habit first incorporated into dynamic demand model is called Houthakker-Taylor state adjustment model (Houthakker and Taylor 1970). The positive coefficient of the state variable indicates a habit persistence effect, which means that the past consumption has a positive impact on current consumption. The negative coefficient indicates an inventory adjustment effect, which may result from storing the goods. The more in present stock, the less will be needed later. Usually, it is expected to be positive for nondurable goods and negative for durable goods.

Engle and Granger two-step approach[3], a cointegration relationship between the import share and a linear combination of logarithmic prices and total expenditure is examined (Karagiannis et al. 2000). If the residuals in the system of equation (3-1) are stationary, it suggests that a long-run equilibrium relationship exists in this market which is necessary to establish a dynamic AIDS model. Once the cointegration relationship is confirmed, we can move to the second step of short-run adjustment. At this step, the residuals from the long-run system (3-1), called error correction term (*ECT*), are saved and included as variables in the dynamic AIDS model. The coefficients of *ECT* explain the speeds of short-run adjustment to the equilibrium and are theoretically expected to be negative. Based on the above description, dynamic AIDS model can be formulated as follows[4]:

$$\Delta s_{it} = \psi_i \Delta s_{i,t-1} + \sum_{j=1}^{n} \gamma_{ijt} \Delta \ln p_{jt} + \beta_i \Delta \ln(x_t / P_t^*) - \eta_i ECT_{it} + \sum_{k=1}^{3} \delta_{ikt} D_{kt} + u_{it} \tag{3-2}$$

Δ is the first-difference operator and ψ measures the effect of consumption habit. Positive ψ indicates a habit persistence effect and negative ψ indicates an inventory

[3] Johansen and Juselius (1992) cointegration technique (JJ) has been tried to examine the competition among the suppliers in the U.S. wooden bedroom furniture market. Unfortunately, it did not work due to the following reasons. First, the cointegration rank is estimated based on a VAR(*p*) model without *prior* information. This rank is very sensitive to the lag selection of *p*, the number of variables, and the specification of intercept and time trend. Hence, it is difficult to exclude the redundant cointegration vectors whenever spare vectors are found, especially in a big system. Also, it cannot impose theoretical restrictions if the cointegration rank is less than the number of equations. Second, as the number of equations increase, it is hard to reach convergence of the system once the homogeneity and symmetry restrictions are imposed. Therefore, the size of AIDS model is limited with JJ approach. Based on the JJ approach tried previously, only China and Vietnam can be considered in AIDS model but the redundant cointegration rank existed and the system did not converge. To describe a full picture in this market, the major suppliers should be considered. The Engle-Granger two-step approach can avoid the above limitations, and therefore, was employed in this study.

[4] Note that the sign of *ECT* in this formula is negative, which is consistent with original study by Anderson and Blundell (1983). In their study, the matrix form is written as: $\mathbf{\Delta s_t = A\Delta s_t - B(s_{t-1} - \Pi^n(\Theta)s_{t-1}) + \varepsilon_t}$. Where $\mathbf{A}$ and $\mathbf{B}$ are appropriately dimensioned short-run coefficient matrices. The derivation is available upon request.

adjustment effect. *ECT* is calculated as $ECT_i = \hat{\varepsilon}_i = s_i - a_i - \sum_{j=1}^{n} \gamma_{ij} \ln p_j - \beta_i \ln\left(x / P^*\right) - \sum_{k=1}^{3} \delta_{ik} D_k$ and η measures the speed of short-run adjustment. To examine the impacts of antidumping investigation on China on the competition in this market, policy intervention dummy variables D_{kt} were introduced into this dynamic AIDS model.

In the above specification, the adequacy of the models should be examined. The absence of statistical diagnostic testing is a common deficiency in many applied empirical studies (Shukur 2002). To our knowledge, there are few diagnostic tests in AIDS model studies and the empirical results may be inappropriate and invalid. To fill in this gap and examine the robustness of the dynamic model, various misspecification tests are taken in this study. First, the data used in this study are time series data which are often auto correlated. The Breusch-Godfrey (BG) test is used to test the hypothesis of no serial correlation in those variables. Second, the assumption of homoscedasticity means that the variance is constant at each observation point. A failure of this assumption may result in the invalid inferences. The Breusch-Pagan (BP) test is employed to test for heteroscedasticity. The assumption of normally distributed error term is tested using the Jarque-Bera LM test. For the test of functional misspecification, the Ramsey's Regression Specification Error Test (RESET) is adopted. In addition, the assumption of parameter constancy is tested by the cumulated sum of squares (CUSUMSQ) test.

AIDS model can be estimated by Seemingly Unrelated Regression Equations (SURE). Since the sum of all import shares is equal to one, the variance-covariance matrix of residuals is singular. To avoid this problem, one of the equations in the system was dropped for estimation. In order to test the theoretical properties, linear restrictions of homogeneity and symmetry need to be added into the system. The whole process of preliminary data analysis, AIDS model estimation, theoretical and misspecification tests, and elasticity calculation in this study was programmed using software R (R Development Core Team 2009).

Demand elasticities

Researchers and policymakers are usually interested in the demand elasticities such as expenditure elasticity, own-price elasticity, and cross-price elasticity because they can evaluate how consumers behave and how suppliers compete in this market. In this study, all those elasticities were calculated using the estimated parameters from AIDS model and the average import shares (s_i) throughout the whole sample period. The expenditure elasticity η_i measures the change of imported quantity of beds from individual countries in response of the change in total expenditure. Own-price elasticity is used to examine the sensitivity of imported quantity in response to its own price change. Cross-price elasticity can reveal the competitive relationship among those supplier countries. If the sign of cross-price elasticity is positive, the beds from these two countries can be substituted between each other. If negative, they can complement each other to satisfy the different preferences of consumers.

Theoretically speaking, there are two kinds of price elasticities, Marshallian (uncompensated) and Hicksian (compensated). The former one is usually employed for empirical work because the data on prices and nominal incomes are readily available. The latter one is more appropriate for policy implication largely due to its assumption of keeping the utility constant (Nicholson 2008). In other words, the Hicksian elasticities can provide better measurement of substitutability since they only capture the substitution effect and leave out the income effect. Furthermore, the Hicksian elasticities for good *i* with respect to *j* can be derived from the Marshallian price elasticities using the Slutsky equation. The formulas are listed as follows:

Expenditure elasticity: $$\eta_i = 1 + \left(\frac{\beta_i}{s_i}\right) \quad (3\text{-}3)$$

Marshallian price elasticity: $$\varepsilon_{ij}^M = -\delta_{ij} + \frac{\gamma_{ij}}{s_i} - \beta_i\left(\frac{s_j}{s_i}\right) \quad (3\text{-}4)$$

Hicksian price elasticity: $$\varepsilon_{ij}^H = -\delta_{ij} + \frac{\gamma_{ij}}{s_i} + s_j \quad (3\text{-}5)$$

Slutsky equation: $$\varepsilon_{ij}^H = \varepsilon_{ij}^M + \eta_i s_j \quad (3\text{-}6)$$

where $\delta_{ij} = 1$ if $i = j$ and $\delta_{ij} = 0$ if $i \neq j$. In addition, both long-run and short-run elasticities can be calculated by the above formula.

Data sources and variables

To analyze the consumer behavior and competition in this import market, several factors were taken into consideration in this study. The definition of imported wooden bedroom furniture was introduced first. The subject of this study was mainly focused on the specific furniture under HTS9403.50.9040, which is defined as beds by International Trade Commission (ITC). The import of beds grew rapidly and accounted for a large percent of wooden bedroom furniture consumption over the last decade. Due to its high import value from China, beds were the main subject in the antidumping investigation on China.

Monthly disaggregate data of beds were used for the AIDS model analysis in this study. One main reason was that the aggregate data can probably lead to biased results. If using the quantity of aggregate data in the analysis, it will result in the incorrect calculation of unit price. The use of disaggregate data can provide relative accurate estimation of parameters and calculation of elasticities in this market. In addition, to examine the effectiveness of antidumping investigation, data need to be consistent with the treatment by the U.S. ITC. The data under HTS9403.50.9040 can satisfy this requirement. Moreover, empirical evidence on the impacts of antidumping policies has been relatively scarce in the disaggregated form (Durling and Prusa 2006). Therefore, to better analyze the impacts of antidumping investigation at different stages, disaggregated data are the best choice and helpful in providing accurate policy analysis and implication in this study.

The time period covered was from January 2001 to December 2008 due to several reasons. One major reason was that this market has undergone a dramatic change during the past decade. For instance, the import share of beds from Italy decreased from 12.6% in 1996 to 1.2% in 2008. The other traditional suppliers such as Mexico and Taiwan suffered big decreases and accounted for less than 1% import share at present. In contrast, China has become the leading supplier of wooden bedroom furniture from 2001 and gained more than 40% of the import share. Another reason was that Vietnam began to export its beds to the United States from January 2001 and has experienced tremendous growth in this market during the period of 2001 – 2008. The monthly import value from Vietnam surpassed that from China in October 2008. Moreover, the antidumping investigation by the U.S. ITC was during the period of 2001 to 2003.

Hence, to analyze the current market structure and the competition among newly developing countries, this study focused on the period from January 2001 to December 2008.

After identifying the time period, major and representative suppliers need to be selected. According to the statistical data from ITC, there were more than thirty countries exporting their beds to the United States. The aggregate import value of the top seven suppliers represented 85% of the total import during the period of 2001 and 2008. They were China (44.2%), Vietnam (11.7%), Indonesia (7.8%), Malaysia (6.4%), Canada (6.3%), Brazil (4.4%), and Italy (4.2%). All the other countries were aggregated into the Rest-of-world (ROW) (15.0%). The descriptive statistics for import share, import price, and total expenditure from January 2001 to December 2008 were reported in Table 3.2. Next, the monthly cost-insurance-freight (*CIF*) (dollars) and quantity (piece) data were collected from ITC to construct the variables of total expenditure, import shares, and import prices in AIDS model. The total expenditure was the total *CIF* value of imported beds. The import share of each supplier was the percentage of the *CIF* value of that supplier over the total expenditure. The import price of imported bed was calculated as *CIF* value over quantity. All the series except import share were taken logarithms for further unit root test and model estimation.

To examine the impacts of this antidumping investigation in this market, the investigation process was integrated into the AIDS model. Based on the report from U.S. ITC (2004), the whole antidumping investigation took 15 months and experienced several distinct stages. The major events were the announcement of petition in October 2003, the affirmative determination in July 2004, and the final implementation in January 2005.

Table 3.2 Descriptive statistics for import share, import price, and total expenditure from January 2001 to December 2008

Country	Mean	Std. Dev.	Minimum	Maximum
		Import share (%)		
China	44.2	7.0	28.0	58.5
Vietnam	11.7	10.7	0.1	34.3
Indonesia	7.8	1.8	4.7	12.5
Malaysia	6.4	2.4	2.3	10.0
Canada	6.3	3.7	1.4	16.2
Brazil	4.4	1.3	1.8	8.8
Italy	4.2	2.7	0.7	11.8
ROW	15.0	4.1	9.3	26.3
		Import price ($/piece)		
China	150.0	10.4	116.0	178.0
Vietnam	117.3	11.6	90.7	150.7
Indonesia	135.3	21.6	91.1	189.4
Malaysia	104.6	11.5	79.0	142.2
Canada	123.7	12.7	94.2	187.2
Brazil	87.6	11.7	38.0	120.9
Italy	244.0	11.1	137.0	652.0
ROW	112.1	11.4	84.3	145.1
		Total expenditure ($ Million)		
TotExp	83.9	23.4	33.7	121.0

Therefore, these three important decision dates were set as policy intervention dummy variables in AIDS model.

Empirical results

Model estimation and tests

Before estimating the AIDS model, the time series properties of import share, import price, and total expenditure were formally examined by ADF unit root test first (Pfaff 2008). All the results were listed in Table 3.3. As for the import share, the share of different countries had different trends from Figure 3.2. China had an increasing trend but suffered a drop around July in 2004. Vietnam had an obvious growth trend

Table 3.3 ADF unit root test of import share, import price, and total expenditure from January 2001 to December 2008

Variable	Level ADF					First-differenced ADF		
	T & C†	Trend‡	None#	Lag	Order	None	Lag	Order
			Import share					
s.CN*	-2.54	-1.77	-0.92	12	I(1)	-1.68	11	I(0)
s.VN	-1.92	1.50	2.35	11	I(1)	-2.96	10	I(0)
s.ID	-2.22	-2.60	-1.34	10	I(1)	-3.93	9	I(0)
s.MY	-1.93	-1.34	0.22	1	I(1)	-15.81	0	I(0)
s.CA	-2.25	-2.33	-3.90	10	I(1)	-4.73	9	I(0)
s.BR	-1.73	-0.44	-1.08	8	I(1)	-5.97	7	I(0)
s.IT	-3.05	-1.21	-1.94	9	I(1)	-2.90	8	I(0)
s.ROW	-0.01	-2.08	-1.13	11	I(1)	-2.56	10	I(0)
			Import price					
ln(p.CN)	-1.58	-1.96	0.53	11	I(1)	-6.28	10	I(0)
ln(p.VN)	-1.69	-1.40	-0.57	11	I(1)	-6.80	10	I(0)
ln(p.ID)	-2.41	-2.25	0.77	2	I(1)	-11.17	1	I(0)
ln(p.MY)	-4.52	—	—	3	I(0)	—	—	—
ln(p.CA)	-4.06	—	—	6	I(0)	—	—	—
ln(p.BR)	-3.20	-3.36	-0.93	7	I(1)	-6.10	6	I(0)
ln(p.IT)	-2.60	-1.53	0.60	1	I(1)	-15.48	0	I(0)
ln(p.ROW)	-3.98	-3.02	0.28	1	I(1)	-14.58	0	I(0)
			Total expenditure					
ln(TotExp)	-1.49	-2.15	1.97	4	I(1)	-9.03	3	I(0)

† ADF test with trend and constant by equation $\Delta y_t = \beta_1 + \beta_2 t + \pi y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-1} + u_t$, critical value are -4.04 at 1%, -3.45at 5%, and -3.15at 10%, respectively.

‡ ADF test with constant by equation $\Delta y_t = \beta_1 + \pi y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-1} + u_t$, critical value are -3.51 at 1%, -2.89 at 5%, and -2.58 at 10%, respectively.

ADF test without trend and constant by equation $\Delta y_t = \pi y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-1} + u_t$ **,** critical value are -2.60 at 1%, -1.95 at 5%, and -1.61at 10%, respectively.

* CN: China, VN: Vietnam, ID: Indonesia, MY: Malaysia, CA: Canada; BR: Brazil, IT: Italy, ROW: Rest of World.

throughout the whole sample period. In contrast, import shares of Canada and Italy decreased significantly over time. The null hypothesis of unit roots in the import shares failed to be rejected at the 5% significance level, which suggested that all of them had unit roots over 2001 – 2008. All of the import prices were not stationary except Malaysia and Canada[5]. Finally, there was an apparent growth trend of total expenditure on beds over the period 2001 ─ 2008. The ADF test suggested that it also had unit root. However, all the first-difference variables were stationary. These results indicated that the level of data series were integrated in order 1, but the first-difference data were zero.

The next step was to examine the long-run equilibrium relationship in the imported beds market by Engle-Granger cointegration test. First, the system of equation (3-1) was estimated by SURE without the ROW equation and the estimated coefficients were listed in Table 3.4. The residuals of this system were calculated equation by equation, and furthermore, examined for the cointegration relationship. The results in Table 3.5 indicated that all the equations were cointegrated at the 5% significance level. Due to the existence of long-run relationship in this market, the dynamic AIDS model can be further established to consider the short-run consumer behavior. The consumption habit and short-run adjustment were incorporated into the equilibrium model for the dynamic adjustments. After the first-difference of all the variables, the dynamic AIDS model (3-2) were estimated by SURE again. The coefficients in the dynamic AIDS model were listed in Table 3.6.

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[5] Based on the Granger representation theorem, a linear combination of series with different order of integration may consist of a cointegrated regression (Karagiannis and Mergos 2002). In this study, all the variables were I(1) but two were I(0). It was assumed that the existence of I(0) variables make the equations in AIDS model cointegrated.

Table 3.4 The estimated coefficients from static AIDS model for imported beds in the United States from January 2001 to December 2008

Variables	sta.CN†	sta.VN	sta.ID	sta.MY	sta.CA	sta.BR	sta.IT
Intercept	-0.359	-2.631***	0.554***	-0.753***	1.453***	0.127*	0.839***
ln(x/p*)	0.057**	0.204***	-0.034***	0.062***	-0.103***	-0.006	-0.059***
ln(p.CN) ‡	0.245***	-0.048	-0.034**	-0.019	-0.010	-0.003	-0.040***
ln(p.VN)	-0.048	-0.181***	0.008	-0.001	0.024*	0.031***	0.082***
ln(p.ID)	-0.034**	0.008	-0.003	0.019**	0.010	-0.005	-0.012***
ln(p.MY)	-0.019	-0.001	0.019**	-0.001	0.000	0.006	-0.001
ln(p. CA)	-0.010	0.024*	0.010	0.000	-0.009	0.010	-0.016***
ln(p.BR)	-0.003	0.031***	-0.005	0.006	0.010	-0.007	-0.008**
ln(p.IT)	-0.040***	0.082***	-0.012***	-0.001	-0.016***	-0.008**	-0.010**
ln(p.ROW)	-0.091***	0.084***	0.017*	-0.004	-0.008	-0.025***	0.005
Dummy1#	0.042	-0.069	-0.015	-0.007	0.011	0.013	0.006
Dummy 2	-0.063	0.039	0.009	-0.007	-0.014	0.026**	-0.012
Dummy 3	-0.022	-0.005	-0.006	-0.001	-0.001	0.009	0.008

† sta. denotes the equation in static AIDS model.
‡ denotes the logarithmic price of seven countries.
***, **, * denotes significance at 1%, 5%, and 10%, respectively.
Dummy 1: antidumping petition in October 2003; Dummy 2: preliminary determination in July 2004; Dummy 3: final determination in January 2005.
See Table 3.3 for abbreviation of country name.

Table 3.5 Cointegration test of equations in AIDS model for imported beds in the United States from January 2001 to December 2008

Equation	ADF (T & C) †	ADF (T) ‡	ADF (N) #	Lag	Cointegrated?
eq. China*	-2.60	-2.06	-2.07	3	Yes
eq. Vietnam	-2.28	-1.19	-3.07	1	Yes
eq. Indonesia	-2.46	-2.33	-2.33	6	Yes
eq. Malaysia	-3.43	-2.70	-2.70	4	Yes
eq. Canada	-3.31	-3.04	-3.07	4	Yes
eq. Brazil	-5.54	—	—	3	Yes
eq. Italy	-4.81	—	—	9	Yes

* eq. denotes the equation in AIDS model.
†, ‡, # See the footnotes at Table 3.3 for ADF critical values.

Table 3.6 The estimated coefficients from dynamic AIDS model for imported beds in the United States from January 2001 to December 2008

Variables	dyn.CN†	dyn.VN	dyn.ID	dyn.MY	dyn.CA	dyn.BR	dyn.IT
$\Delta s_{i,t-1}$	-0.295***	-0.273***	-0.527***	-0.538***	-0.109	-0.254**	-0.715***
ECT_i	-0.122***	-0.078***	-0.395***	-0.152**	-0.215**	-0.201*	-0.306***
$\ln(x/p^*)$	0.156***	0.042***	-0.032**	-0.018**	-0.071***	-0.011	-0.011
ln(p.CN) ‡	0.119***	-0.002	-0.030**	0.006	-0.037***	-0.012	-0.008
ln(p.VN)	-0.002	0.004	0.007	-0.011*	0.004	-0.003	0.006
ln(p.ID)	-0.030**	0.007	0.000	0.000	0.014**	0.000	-0.003
ln(p.MY)	0.006	-0.011*	0.000	-0.008	0.005	0.003	0.004
ln(p.CA)	-0.037	0.004	0.014**	0.005	-0.007	0.009**	-0.003
ln(p.BR)	-0.012	-0.003	0.000	0.003	0.009**	-0.002	0.003
ln(p.IT)	-0.008	0.006	-0.003	0.004	-0.003	0.003	-0.003
ln(p.ROW)	-0.036**	-0.004	0.012	0.002	0.015**	0.002	0.004
Dummy 1	-0.041	0.016	0.016	0.011	-0.008	0.004	-0.004
Dummy 2	-0.138***	0.054***	0.022*	0.002	-0.004	0.020**	0.000
Dummy 3	0.013	-0.012	0.002	0.013*	-0.013	0.004	-0.003

† dyn. denotes the equation in dynamic AIDS model.
‡ denotes the logarithmic price from seven countries.
***, **, * denotes significance at the 1%, 5%, and 10% level, respectively.
See Table 3.3 for abbreviation of country name.
See Table 3.4 for dummy variable definition.

Theoretical properties were tested by adding linear restrictions into the dynamic system (3-2). Adding-up property was automatically satisfied and used to calculate the coefficients of the ROW equation. The homogeneity, symmetry, and the joint test of them failed to reject at 1% significant level in the dynamic AIDS model, while all these tests were rejected in the static AIDS model. Those tests indicated that the dynamic adjustments were necessary to satisfy the consumer theory and can explain the consumer behavior well.

As mentioned previously, misspecification tests were essential for the parameter explanation and further elasticity calculation. A summary of misspecification tests in dynamic AIDS model were presented in Table 3.7. None of the error terms had serial correlation problems at the 1% significance level by BG test. The results of BP test indicated that all the error terms have constant variance. In addition, all the functions except Italy were correctly specified at the 1% significance level. The error terms in five out of seven equations were normally distributed. The hypothesis of the stable coefficients failed to be rejected in all the equations. Therefore, the superiorities of the dynamic AIDS model were further supported by passing those misspecification tests.

In addition, short-run adjustment played an important role in the market equilibrium. As expected by theory, all the coefficients of *ECT*s were negative and significant at the 10% significance level. The speed of adjustment ranged from -0.078 to -0.395. For instance, the beds from Indonesia had the highest speed -0.395 which took three months to go back to its equilibrium status (1/0.395 ≈ 3). Accordingly, China took 9 months back to the equilibrium (1/0.122 ≈ 9), and Vietnam needed 13 months (1/0.078 ≈ 13). All the above results suggested that this market was stable and the deviations from the long-run equilibrium adjusted back to the equilibrium status. In addition, consumption habit was helpful in explaining the consumer behavior. All the coefficients were negative and significant at the 5% significance level except Canada. They indicated the inventory adjustment effect existed in consumer behavior, ranging from -0.254 to -0.715. Among supplier countries, 71.5% import from Italy can be explained by its inventory adjustment. Moreover, more than half of the import from Indonesia and Malaysia were also due to the inventory adjustment of U.S. consumers. Hence, short-run adjustment and inventory adjustment were helpful to explain the market equilibrium and the consumer behavior.

Table 3.7 Misspecification tests of dynamic AIDS model for imported beds in the United States from January 2001 to December 2008

Equation	BG[a]	BP[b]	RESET[c]	J-B[d]	CUSUMSQ[e]
eq. China	0.01**	0.93	0.76	0.48	0.40
eq. Vietnam	0.10	0.91	0.05	0.00***	0.06
eq. Indonesia	0.06	0.11	0.02**	0.26	0.71
eq. Malaysia	0.31	0.35	0.07	0.43	0.20
eq. Canada	0.02**	0.34	0.10	0.61	0.88
eq. Brazil	0.07	0.74	0.30	0.01**	0.78
eq. Italy	0.09	0.32	0.00***	0.00***	0.02**

[a] H_0 of Breusch-Godfrey test: no serial correlation.
[b] H_0 of Breusch-Pagan test: no heteroscedasticity.
[c] H_0 of RESET Test: no functional misspecification.
[d] H_0 of Jarque-Bera LM Test: normality.
[e] H_0 of CUSUMSQ test: parameters are stable in every period.
***, ** denotes significance at the 1% and 5% level, respectively.

Demand elasticities

In this study, the long-run expenditure, own-price, and cross-price elasticities were calculated by formulas (3-3), (3-4), and (3-5) from the estimated parameters of equilibrium AIDS model. Accordingly, the short-run elasticities were calculated by the coefficients of dynamic AIDS model with the same formula. All the import shares used in the formula were the average of monthly import share over the period 2001 ─ 2008.

Both long-run and short-run expenditure elasticities and their p-values were given in Table 3.8. All the long-run expenditure elasticities were positive and statistically significant at 1% significance level except Canada and Italy. The demand of beds from Vietnam, Malaysia, and China were elastic. Among them, Vietnam had the highest expenditure elasticity of 2.737, followed by Malaysia with 1.977 and China with 1.130. These results indicated that the more expenditure spent on the imported beds, the more beds would be imported from Vietnam, Malaysia, and China in the long-run. This conclusion is consistent with the fact that the import value from Vietnam had exceeded its value from China in October 2008. As for the short-run expenditure elasticities, all of them except Canada were also positive and statistically significant at 1% significance level. Vietnam and China were the major supplier countries in the short-run. Note that imports from Canada, whether in the long-run or the short-run, would decrease as the expenditure spent on the imported beds increased. It was due to the comparative advantages of Asian countries in producing furniture.

With regard to the change of quantity in response of own-price, Marshallian own-price elasticities were calculated and listed in Table 3.9. Both long-run and short-run values were negative and significant at the 1% level, as expected from consumer theory. All the values were elastic and sensitive to the change of its own price except China. Comparing the long-run elasticities with the short-run elasticities, we can see that four of seven countries had higher long-run elasticities in absolute values. This result implied that the consumption on the imported beds from them were more flexible in response of price change in the long-run. Especially, the long-run elasticity of Vietnam was -2.743 which was much higher and more sensitive than the other countries' values. In addition, both long-run and short-run own-price elasticities of China were relatively lower than the other competitors. This result implied that trade policy in order to increase the price of beds from China would have limited impacts on its demand quantities.

To better understand the competition relationship among suppliers as stated previously, Hicksian cross-price elasticities were calculated under the assumption of keeping the utility constant. Both long-run and short-run Hicksian cross-price elasticities were reported in Table 3.10 and 3.11, respectively. The positive value suggested the

Table 3.8 Long-run and short-run expenditure elasticity for imported beds in the United States from January 2001 to December 2008

Country	Long-run		Short-run	
	Estimates	p-value	Estimates	p-value
China	1.130	0.000	1.352	0.000
Vietnam	2.737	0.000	1.358	0.000
Indonesia	0.561	0.000	0.594	0.000
Malaysia	1.977	0.000	0.713	0.000
Canada	-0.636	0.000	-0.126	0.890
Brazil	0.865	0.000	0.762	0.000
Italy	-0.417	0.017	0.745	0.004
ROW	0.197	0.002	0.629	0.000

Table 3.9 Long-run and short-run Marshallian own-price elasticity for imported beds in the United States from January 2001 to December 2008

Country	Long-run		Short-run	
	Estimates	p-value	Estimates	p-value
China	-0.503	0.001	-0.886	0.000
Vietnam	-2.743	0.000	-1.010	0.000
Indonesia	-1.003	0.000	-0.972	0.000
Malaysia	-1.074	0.000	-1.108	0.000
Canada	-1.041	0.000	-1.037	0.000
Brazil	-1.151	0.000	-1.025	0.000
Italy	-1.195	0.000	-1.056	0.000
ROW	-0.741	0.000	-0.909	0.000

substitution effect and the negative value implied the complementary relations of the beds imported from two countries. In the long-run view, the increase of price from any other suppliers can lead to the increase of import from Vietnam ranging 0.01 to 2.11%. In particular, the bed from Italy is a complement to the bed from China, Indonesia, Canada, and Brazil but Vietnam.

Table 3.10 Long-run Hicksian cross-price elasticity for imported beds in the United States from January 2001 to December 2008

Impact on demand	Change in price of							
	China	Vietnam	Indonesia	Malaysia	Canada	Brazil	Italy	ROW
China	—	0.009	0.001	0.021	0.040	0.038	-0.050	-0.056
	—	(0.925)†	(0.981)	(0.548)	(0.321)	(0.206)	(0.079)	(0.257)
Vietnam	0.035	—	0.149	0.055	0.265	0.305	0.744	0.868
	(0.925)	—	(0.148)	(0.600)	(0.027)	(0.001)	(0.000)	(0.000)
Indonesia	0.005	0.223	—	0.302	0.185	-0.019	-0.109	0.371
	(0.981)	(0.148)	—	(0.005)	(0.106)	(0.835)	(0.032)	(0.002)
Malaysia	0.145	0.102	0.374	—	0.061	0.145	0.028	0.094
	(0.548)	(0.600)	(0.005)	—	(0.664)	(0.175)	(0.652)	(0.523)
Canada	0.280	0.492	0.230	0.061	—	0.211	-0.218	0.025
	(0.321)	(0.027)	(0.106)	(0.664)	—	(0.081)	(0.003)	(0.878)
Brazil	0.382	0.808	-0.033	0.206	0.299	—	-0.135	-0.413
	(0.206)	(0.001)	(0.835)	(0.175)	(0.081)	—	(0.090)	(0.025)
Italy	-0.535	2.111	-0.207	0.042	-0.333	-0.145	—	0.278
	(0.079)	(0.000)	(0.032)	(0.652)	(0.003)	(0.090)	—	(0.047)
ROW	-0.163	0.677	0.193	0.039	0.011	-0.122	0.076	—
	(0.257)	(0.000)	(0.002)	(0.523)	(0.878)	(0.025)	(0.047)	—

† p value is in bracket.

In the short-run, if the price of beds from China went up by 1%, the imported quantities from Vietnam and Malaysia would go up by 0.43% and 0.53% respectively. The results suggested that the beds from Vietnam and Malaysia are substitutes for those from China. In contrast, the 1% increase of price from Vietnam and Malaysia resulted in the 0.11% and 0.08% increase of import from China. There were 12 pairs of this kind of substituted products in this market. Moreover, it is interesting that the degrees of substitution were asymmetric. Take the substitution effects between these three countries for example again, Malaysia and Vietnam had higher cross-price elasticities than China to each of them, suggesting that Malaysia and Vietnam had more competitiveness than China in the U.S. market. Cross-price elasticities between China and Canada were negative which indicated they were the complementary goods.

Table 3.11 Short-run Hicksian cross-price elasticity for imported beds in the United States from January 2001 to December 2008

Impact on demand	Change in price of							
	China	Vietnam	Indonesia	Malaysia	Canada	Brazil	Italy	ROW
China	—	0.113	0.011	0.076	-0.021	0.017	0.023	0.069
	—	(0.001)†	(0.733)	(0.000)	(0.402)	(0.428)	(0.298)	(0.092)
Vietnam	0.427	—	0.134	-0.034	0.097	0.016	0.094	0.117
	(0.001)	—	(0.078)	(0.556)	(0.152)	(0.763)	(0.055)	(0.218)
Indonesia	0.061	0.201	—	0.068	0.241	0.043	0.007	0.305
	(0.733)	(0.078)	—	(0.386)	(0.004)	(0.546)	(0.905)	(0.009)
Malaysia	0.530	-0.063	0.084	—	0.148	0.090	0.099	0.174
	(0.000)	(0.556)	(0.386)	—	(0.063)	(0.148)	(0.072)	(0.092)
Canada	-0.150	0.180	0.298	0.148	—	0.193	-0.012	0.387
	(0.402)	(0.152)	(0.004)	(0.063)	—	(0.008)	(0.862)	(0.002)
Brazil	0.174	0.043	0.075	0.128	0.274	—	0.103	0.194
	(0.428)	(0.763)	(0.546)	(0.148)	(0.008)	—	(0.204)	(0.200)
Italy	0.249	0.265	0.014	0.151	-0.018	0.111	—	0.253
	(0.298)	(0.055)	(0.905)	(0.072)	(0.862)	(0.204)	—	(0.115)
ROW	0.202	0.091	0.159	0.073	0.162	0.057	0.069	—
	(0.092)	(0.218)	(0.009)	(0.092)	(0.002)	(0.200)	(0.115)	—

† p value is in bracket.

Antidumping investigation effects

The purpose of antidumping policy on China was to curtail imports from China, and furthermore, to protect the furniture industry in the United States. Figure 3.2 showed that different impacts on major suppliers existed at the stage of the petition announcement, the affirmative determination, and the final implementation during the antidumping investigation against China. Taking the whole investigation process into consideration, we detected both long-run and short-run antidumping effects in the AIDS model. The results were reported in Table 3.12.

In the long-run view, imports from China increased after the antidumping petition filed. This result was consistent with the impacts of antidumping investigation in Chapter 2, which suggested the announcement effect happened. After the preliminary

Table 3.12 Long-run and short-run antidumping investigation effects for imported beds in the United States from January 2001 to December 2008

Antidumping Dummy	China	Vietnam	Indonesia	Malaysia	Canada	Brazil	Italy
			Long-run effect (%)				
Dummy1†	4.2	-6.9	-1.5	-0.7	1.1	1.3	0.6
Dummy 2‡	-6.3	3.9	0.9	-0.7	-1.4	2.6**	-1.2
Dummy 3#	-2.2	-0.5	-0.6	-0.1	-0.1	0.9	0.8
			Short-run effect (%)				
Dummy 1	-4.1	1.6	1.6	1.1	-0.8	0.4	-0.4
Dummy 2	-13.8***	5.4***	2.2*	0.2	-0.4	2.0**	0.0
Dummy 3	1.3	-1.2	0.2	1.3*	-1.3	0.4	-0.3

† Dummy 1: antidumping petition in October 2003.
‡ Dummy 2: preliminary determination in July 2004.
# Dummy 3: final determination in January 2005.
***, **,* denotes significance at the 1%, 5%, and 10% level, respectively.

determination was implemented to collect antidumping duties in July 2004, the import share from China decreased while the import from Vietnam, Indonesia, and Brazil increased. This result indicated that the reduction of import from China diverted to the other countries such as Vietnam, Indonesia, and Brazil. In addition, the final determination had no significant impacts on all the suppliers. All the above long-run impacts were not significant, but imports from Brazil increased by 2.6% was significant at the 5% level.

In the short-run, the antidumping petition had the biggest impact on China and small impacts on the other countries but not statistically significant. As discussed in many studies of antidumping, the market impact began after the preliminary determination. At this stage, imports from China decreased by 13.8%, but the import value from Vietnam, Indonesia, and Brazil increased by 5.4%, 2.2%, and 2.0% at the same time. This effect also can be examined in Figure 3.2. There was a sharp drop of

China's import share and were sudden jumps of Vietnam, Indonesia, and Brazil. In contrast, imports from Canada and Italy decreased at this stage. After the final determination, there were no significant impacts on China and other countries. But imports from Malaysia increased by 1.3%.

In summary, this antidumping investigation on China was not effective at the three typical stages in the long-run. U.S. still increased the import from all over the world but not as rapid as before, as shown in Figure 3.1. In contrast, this antidumping investigation was effective in the short-run to decrease the import from China after the affirmative decision had been made. However, the trade diversion occurred from China to Vietnam, Indonesia, and Brazil. The purpose of reducing total import value was not realized as expected.

Conclusions

The United States has been increasing the import of wooden bedroom furniture to meet its domestic needs. Over the last decade, traditional suppliers have been replaced by the newly developing countries in Asia such as China and Vietnam. The antidumping investigation against China was implemented by ITC during the period of 2003 – 2005 in order to protect the furniture industry in the U.S. To explain this market structure change, dynamic AIDS model was employed to analyze the consumer behavior, and furthermore, evaluate the effectiveness of this antidumping investigation. Monthly disaggregate data of the top seven suppliers from 2001 to 2008 were collected from the ITC.

The empirical results in this study supported several conclusions about the consumer behavior, market competition, and antidumping effectiveness in this market. First, both long-run and short-run consumer choices on the imported wooden bedroom furniture were detected. The existence of a long-run equilibrium status in this market was supported by the Engle-Granger cointegration test. This equilibrium status was regained by the short-run adjustment of individual supplier countries respectively. Current consumption behavior can be explained by inventory adjustment. In addition, expenditure elasticities disclosed that U.S. consumers will spend more on wooden bedroom furniture imported from Vietnam, Malaysia, and China in the long-run. Among these countries, Vietnam has demonstrated a great potential to be the top supplier to the U.S. market. As indicated by the own-price elasticities, the imported quantities from most countries were sensitive to its own price in both short-run and long-run. In particular, Vietnam had the highest own-price elasticity, suggesting that the policy instrument may be used to cut down imports from this country. In particular, both long-run and short-run own-price elasticities of China were inelastic, which indicated the less sensitive change in response of price and further explained the ineffectiveness of antidumping investigation.

Degrees of competition and substitution were revealed by the cross-price elasticities between those supplier countries. On the one hand, this market was very competitive and the products of any two suppliers can be substituted by each other, except the beds from Italy and Canada. There were 8 pairs of long-run substitutes and 12 pairs of short-run substitutes in total. The degrees of substitution among those pairs were not symmetric. The potential of Vietnam to dominate this market was further proved by its significant cross-price elasticities in both long-run and short-run. On the other hand, the cross-price elasticities were relatively small, which were not elastic. The small magnitude of those cross-price elasticities implied that they were far from perfect substitutes. These results further indicated that U.S. consumers do have different preferences on the imported wooden bedroom furniture from all over the world.

As a trade protection instrument, the antidumping investigation against China did not work as it intended to reduce imports. At the stage of petition announcement, the investigation did not generate significant impacts on the import of beds from. The affirmative determination and imposition of antidumping duties led to 13.8% drop on the import value of China. However, the trade diversion took place from China to Vietnam, Indonesia, and Brazil at the same time, which was consistent with the discussion by Brenton (2001). Furthermore, the final determination had no significant impacts on the import from China but resulted in an increase import from Malaysia. In aggregate, this antidumping investigation significantly led to 2.9% decrease in short-run and 2.6% increase long-run. Collectively, the effectiveness of this antidumping investigation was not obvious, which can be further demonstrated by the continuous growth of total import value.

In conclusion, this study analyzed the consumer behavior in purchasing imported wooden bedroom furniture and competition among the top seven suppliers. With the robust and valid model estimation, this study provided more reliable and valuable implications for the trade policymakers and the marketers in the furniture industry. In addition, this study made an empirical contribution to the market analysis of forest products trade with considering the time series properties and dynamic specification. It also provided the empirical evidence of trade diversion in the manufacturing industry and antidumping cases.

This study brings up several interesting questions. For example, the competition among domestic and imported beds can be further studied, which will describe a more accurate picture of this market. However, the same definition of beds and sales data are needed to incorporate into this demand system. The weak separability between imported and domestic beds can also be tested. Moreover, whether this market is integrated or not is also of great interest. Further examining the welfare change after the implementation of antidumping policy can improve our understanding of the benefits of domestic retailers, producers, and consumers.

CHAPTER IV

CONCLUSIONS

The United States has been increasing its imports of wooden bedroom furniture to meet its domestic needs over the last decades. This trade phenomenon has created serious changes to the domestic furniture industry and aroused wide concerns about its future growth. The research goal of this thesis was to comprehend the import pattern, trade disputes, and causes of international wooden furniture trade, provide beneficial information for the U.S. furniture industry, and ultimately help the industry improve its domestic and global competitiveness. To accomplish the overall objective, intervention analysis was employed to assess the impacts of the antidumping investigation on wooden bedroom furniture imports from China. The dynamic AIDS model was employed to examine the consumer behavior and price competition and the impacts of antidumping investigation on the major competitors in this import market.

In Chapter II, antidumping investigation against China was summarized and the intervention analysis was employed to assess its impacts on the import value and unit price. Fist, the rapid growth of wooden bedroom furniture import from China resulted in an antidumping investigation against China in October 2003. Antidumping duties from 0.83% to 198.08% were imposed on individual Chinese firms since January 2005. Next, four wooden bedroom furniture commodities were included in the intervention analysis. The three stages of antidumping policy had different impacts on the import values. The petition announcement generated a positive impact in March 2004, the affirmative decision in the preliminary phase had a negative impact in June 2004, and the final implementation has not shown any significant effect since January 2005. The aggregate impact on import values was approximately equivalent to a one-month reduction. The impact on unit prices was insignificant. Overall, the antidumping investigation and duties had some temporary impacts on imports of wooden bedroom furniture from China.

At present, the total import of wooden bedroom furniture by the United States continues to rise. The antidumping duties implemented on Chinese furniture firms have limited temporary impacts on the import. Furthermore, other developing countries (e.g., Vietnam) with low production costs have also increased their exports rapidly in recent years. Traditional suppliers have been substituted by the developing countries such as China and Vietnam over the past decade.

In Chapter III, the market overview of imported wooden bedroom furniture in the United States was presented first. To explain this market structure change, a dynamic AIDS model was employed to analyze the consumer behavior, and furthermore, evaluate the effectiveness of this antidumping investigation. The Engle-Granger cointegration test showed that the cointegration relationships existed in this demand system. Both homogeneity and symmetry properties failed to be rejected in the dynamic AIDS model. The superiorities of dynamic AIDS model were also revealed in passing several misspecification tests. In addition, the expenditure elasticities suggested that U.S. consumers would spend more money on the wooden bedroom furniture from Vietnam, China, and Malaysia. All the own-price elasticities were significantly negative and the cross-price elasticities indicated the competition among those suppliers. Vietnam and

Malaysia were more competitive than China in the long-run view. Finally, the U.S. antidumping investigation on China was effective in the short-run, but the trade diversion occurred from China to Vietnam, Indonesia, and Brazil. The results from this study were helpful in understanding the competition among suppliers, the consumer behavior in this market, and the impact of antidumping policy.

Overall, the time series technique of unit root test and cointegration, together with dynamic specification and several misspecification tests, were used to provide robust estimation and reliable policy implication. The appraisal of antidumping investigation provided the empirical evidence of petition announcement and trade diversion in the manufacturing industry and antidumping cases. A dynamic AIDS model was also employed to analyze the consumer behavior in purchasing the imported wooden bedroom furniture and examine the price competition among the major suppliers.

This study also brings up several interesting questions. First, what is the price relationship among those suppliers in this furniture import market is of great interest. The law of one price can be used to test whether this market integrates or not. Identifying both long-run and short-run price relationships is essential to understanding the market structure and the ongoing antidumping policy. Second, how does this antidumping policy against China influence the welfare of domestic retailer, producers, consumers, and government is worth paying attention to. A quantitative measure of welfare can provide more implication and evidence for policy analysis.

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APPENDIX A

R CODES FOR CHAPTER II

```
#-------------------------------------------------------------
#   CHAPTER II AN APPRAISAL OF THE ANTIDUMPING INVESTIGATION
#         ON WOODEN BEDROOM FURNITURE IMPORTS FROM CHINA
#-------------------------------------------------------------

# Step 1: Import Data
#     1.1 Import Data & Variables
#     1.2 Libraries Used
#
# Step 2: Inflation, Time Period Selection, Transformation
#     2.1 Inflation consideration
#     2.2 Time period selection
#     2.3 Data transformation and selection
#     2.4 Final data set & graph
#
# Step 3: Variance & Pre-intervention time series
#     3.1 Variance
#     3.2 Pre-intervention time series
#
# Step 4 ARIMA for 6 Individual Series
#     4.1 ACF and PACF graph
#     4.2 ARIMA for two samples
#
# Step 5 Linear Transfer Function (LTF)
#     5.1 Input for three dummy variables LTF model
#     5.2 Create 6 dummy variables & y
#     5.3 LAG: 6 dummy variables set
#     5.4 Same length: dummy set & y
#     5.5 Estimate LTF model
#
# Step 6 Final Intervention Analysis
#     6.1 Input besides for LTF model
#     6.2 Create dummy variables & y
#     6.3 LAG: consider dead time - dummy lost (my.b*) obs
#     6.4 Set same length: adjust time period
#     6.5 Adjust several inputs for IA model
#
#     Figure 1
#     Figure 2
#     Figure 3


#-------------------------------------------------------------
# Step 1 Import Data
#-------------------------------------------------------------

# 1.1 Import Data & Variables

getwd()
setwd("C:/Users/ywan/Desktop/Thesis")
options(prompt="My Code| ", scipen=3)
(sun <- read.table("TariffDataSun.txt",header=TRUE))

# Variable definitions in "Chapter2.xlsx"
# 45 variables, 1989.01-2008.06, 19.5 years = 234 months

# n mydate year month cpi
# custom val, CIF, q, duty-paid val(tv)
```

```
# duties(dt), CIF for all countries, quantity for all
# if5000   if9040   if9080    if7000
# q5000    q9040    q9080@    q7000@

# 1.2 Libraries Used

library(vars)
library(urca)
library(uroot)
library(TSA)
library(forecast)


#-------------------------------------------------------------
# Step 2 Inflation, Time Period Selection, Transformation
#-------------------------------------------------------------

# 2.1 Inflation consideration

# Several studies used real prices(Bohnam 1996;Prestemon 2009)
# To be safe, import values are deflated by CPI for all items

# 2.2 Time period selection: three factors considered

#(1)# Evolving trend of import volumes

sun$aif9080 <- as.numeric(sun$aif9080)

te$sh.if5000 <- 100*te$if5000/te$aif5000
te$sh.if9040 <- 100*te$if9040/te$aif9040
te$sh.if9080 <- 100*te$if9080/te$aif9080
te$sh.if7000 <- 100*te$if7000/te$aif7000

te$fur.china <- (te$if5000 + te$if9040 + te$if9080 +
      te$if7000)/1000000
te$fur.world <- (te$aif5000 + te$aif9040 + te$aif9080 +
      te$aif7000)/1000000
te$sh.china <- 100*te$fur.china/te$fur.world;
names(te); te[,c(1,10:16)]

# Within China's imports: share of CIF values for each HTS
# 9040/9080 import share declined slightly
# 5000/7000 shares increased

if.all = if5000 + if9040 + if9080 + if7000

s5000 = 100 * if5000 / if.all   # 14.2% from 1989 - 2008
s9040 = 100 * if9040 / if.all   # 18.0% from 1989 - 2008
s9080 = 100 * if9080 / if.all   # 46.9% from 1989 - 2008
s7000 = 100 * if7000 / if.all   # 20.9% from 1989 – 2008

sh <- ts(data = data.frame(s5000, s9040, s9080, s7000),
      start=c(1989,1), freq=12)
summary(sh); plot(sh, plot.type=c("multiple"),lab=c(20,6,7))

# Seasonality of import values: both China and US total
# Peaks: 6, 12; bottoms: 3, 9; Seems have a cycle of 3 months
```

```
#(2)# The tariff and trade relation

# US Congress passed MFN status for China in Sept 2000
# China became a WTO member formally on Dec 11, 2001

#(3)# Unit value of 5000 has a new unit since 1997.01

# 2.3 Data transformation and selection

# Transformed in million$: log(x * 1000) = log(x) + log(1000)
# Deflated by CPI
# Use 1997.01-2008.06 for estimation
# 6 variables are used for further analyses

sun$v4 <- (sun$if9040/1000000) / (sun$cpi/154.40)
sun$v8 <- (sun$if9080/1000000) / (sun$cpi/154.40)
sun$v5 <- (sun$if5000/1000000) / (sun$cpi/154.40)
sun$v7 <- (sun$if7000/1000000) / (sun$cpi/154.40)
sun$u4 <- sun$uv9040.m         / (sun$cpi/154.40)
sun$u5 <- sun$uv5000.m         / (sun$cpi/154.40)


# 2.4 Final data set & graph
# 1997.01-2008.06 = 138 obs

f <- sun[97:234,c(2, 51:56)]
f.ts <- ts(data=f[,2:7], start=c(1997,1), freq=12
plot(f.ts)


#-------------------------------------------------------------
# Step 3 Variance, Nonseasonal and Seasonal Unit Root Tests
#-------------------------------------------------------------

# 3.1 Variance: take log to achieve constant variance
# Graphs: v40, v80, v50, v70 increasing variance
#          u40, u50 decreasing variance

#(1)# Raw data in time series format

v4a <- ts(f$v4, start=c(1997,1), freq=12); v4a

#(2)# Take log then create individual ts

v4b <- ts(log(f$v4),start=c(1997,1),freq=12); v4b

#(3)# Regular first difference then create individual TS

v4c <- ts(diff(v4b),start=c(1997,2),freq=12); v4c

#(4)# Seasonal + regular 1st diff then create individual TS

v4d <- ts(diff(v4c,lag=12,differences=1), start=c(1998,2),
      freq=12); v4d

# graph by HTS code
par(mfrow=c(2,2))
plot(v4a,type='l'); abline(v=2004.5,col=3)
```

```
plot(v4b,type='l'); abline(v=2004.5,col=3)
plot(v4c,type='l'); abline(v=2004.5,col=3); abline(h=0,col=3);
plot(v4d,type='l'); abline(v=2004.5,col=3); abline(h=0,col=3);

# Take the same steps for other series

# 3.2 Pre-intervention (1997.01 - 2003.09) for ARIMA

v4as <- ts(v4a, start=c(1997,1), end=c(2003,9),freq=12); v4as
v4bs <- ts(v4b, start=c(1997,1), end=c(2003,9),freq=12); v4bs
v4cs <- ts(v4c, start=c(1997,2), end=c(2003,9),freq=12); v4cs
v4ds <- ts(v4d, start=c(1998,2), end=c(2003,9),freq=12); v4ds

# Take the same steps for other series


#--------------------------------------------------------------
# Step 4 ARIMA for 6 Individual Series
#--------------------------------------------------------------

# 4.1 ACF and PACF graph also can indicate unit root

par(mfcol=c(3,4))
plot(v4a);acf(v4a,36);pacf(v4a,36)
plot(v4b);acf(v4b,36);pacf(v4b,36)
plot(v4c);acf(v4c,36);pacf(v4c,36)
plot(v4d);acf(v4d,36);pacf(v4d,36)

# Take the same steps for other series

# 4.2 ARIMA for two samples: Identify, estimation, diagnostics

# input for ARIMA model
in0 <- u4c
in1 <- c(0,0,4)
in2 <- c(0,0,0)

(am.out <-arima(in0, order=in1, seasonal=list(order=in2,
      period=12),include.mean=T,))


#--------------------------------------------------------------
# Step 5 Linear Transfer Function
#--------------------------------------------------------------

# 5.1 Input for three dummy variables LTF model

(my.yb   <- v8b)      # Input: log value 1997.01 - 2008.06
 my.yr1  <- 2003      # Input: date 1 year
 my.mm1  <- 10        # Input: date 1 month
 my.yr2  <- 2004      # Input: date 2 year
 my.mm2  <- 7         # Input: date 2 month
 my.yr3  <- 2005      # Input: date 3 year
 my.mm3  <- 1         # Input: date 3 month

 my.dim1 <- 9         # Input: N of lagged variables (including V0)
 my.dim2 <- 6
(including V0)
```

```
 my.dim3 <- 15
(including V0)

# 5.2 Create 6 dummy variables & y (raw,differece d=1,d=D=1)

# raw, like v4b, 1997.01 - 2008.06

(loc1 <- (my.yr1-1997)*12 + (my.mm1-1+1))   # obs location
(loc2 <- (my.yr2-1997)*12 + (my.mm2-1+1))
(loc3 <- (my.yr3-1997)*12 + (my.mm3-1+1))

(step1b <- ts(1*(seq(my.yb)>=loc1 & seq(my.yb)<loc2), start=c(1997,1),
      freq=12))
(puls1b <- ts(1*(seq(my.yb)==loc1), start=c(1997,1), freq=12))
(step2b <- ts(1*(seq(my.yb)>=loc2 & seq(my.yb)<loc3), start=c(1997,1),
      freq=12))
(puls2b <- ts(1*(seq(my.yb)==loc2), start=c(1997,1), freq=12))
(step3b <- ts(1*(seq(my.yb)>=loc3), start=c(1997,1), freq=12))
(puls3b <- ts(1*(seq(my.yb)==loc3), start=c(1997,1), freq=12))

# d=1, like v4c, 1997.02-2008.06

(step1c <- diff(step1b))
 puls1c <- diff(puls1b)
 step2c <- diff(step2b)
 puls2c <- diff(puls2b)
 step3c <- diff(step3b)
 puls3c <- diff(puls3b)
(my.yc  <- diff(my.yb))

# d=D=1, like v4d, 1998.02-2008.06

(step1d <- diff(diff(step1b), lag=12, differences=1))
 puls1d <- diff(diff(puls1b), lag=12, differences=1)
 step2d <- diff(diff(step2b), lag=12, differences=1)
 puls2d <- diff(diff(puls2b), lag=12, differences=1)
 step3d <- diff(diff(step3b), lag=12, differences=1)
 puls3d <- diff(diff(puls3b), lag=12, differences=1)
 my.yd  <- diff(diff(my.yb),  lag=12, differences=1)

# 5.3 LAG: 6 dummy variables set (raw, d=1, d=D=1)

# lagged set for each dummy (raw, 1997.01 - 2008.06)

(b.yr1  <- 1997 + floor(my.dim1/12))
(b.mm1  <- 1    - floor(my.dim1/12)*12 + my.dim1 - 1)
(b.yr2  <- 1997 + floor(my.dim2/12))
(b.mm2  <- 1    - floor(my.dim2/12)*12 + my.dim2 - 1)
(b.yr3  <- 1997 + floor(my.dim3/12))
(b.mm3  <- 1    - floor(my.dim3/12)*12 + my.dim3 - 1)

(set.step1b <- ts(embed(step1b, dim=my.dim1), start=c(b.yr1, b.mm1),
      freq=12))
(set.puls1b <- ts(embed(puls1b, dim=my.dim1), start=c(b.yr1, b.mm1),
      freq=12))
(set.step2b <- ts(embed(step2b, dim=my.dim2), start=c(b.yr2, b.mm2),
      freq=12))
```

```
(set.puls2b <- ts(embed(puls2b, dim=my.dim2), start=c(b.yr2, b.mm2),
      freq=12))
(set.step3b <- ts(embed(step3b, dim=my.dim3), start=c(b.yr3, b.mm3),
      freq=12))
(set.puls3b <- ts(embed(puls3b, dim=my.dim3), start=c(b.yr3, b.mm3),
      freq=12))

# lagged set for each dummy (d=1, 1997.02 - 2008.06)

(c.yr1  <- 1997 + floor(my.dim1/12))
(c.mm1  <- 2    - floor(my.dim1/12)*12 + my.dim1 - 1)
(c.yr2  <- 1997 + floor(my.dim2/12))
(c.mm2  <- 2    - floor(my.dim2/12)*12 + my.dim2 - 1)
(c.yr3  <- 1997 + floor(my.dim3/12))
(c.mm3  <- 2    - floor(my.dim3/12)*12 + my.dim3 - 1)

(set.step1c <- ts(embed(step1c, dim=my.dim1), start=c(c.yr1, c.mm1),
      freq=12))
(set.puls1c <- ts(embed(puls1c, dim=my.dim1), start=c(c.yr1, c.mm1),
      freq=12))
(set.step2c <- ts(embed(step2c, dim=my.dim2), start=c(c.yr2, c.mm2),
      freq=12))
(set.puls2c <- ts(embed(puls2c, dim=my.dim2), start=c(c.yr2, c.mm2),
      freq=12))
(set.step3c <- ts(embed(step3c, dim=my.dim3),start=c(c.yr3, c.mm3),
      freq=12))
(set.puls3c <- ts(embed(puls3c, dim=my.dim3), start=c(c.yr3, c.mm3),
      freq=12))

# lagged set for each dummy (d=D=1, 1998.02 - 2008.06)

(d.yr1  <- 1998 + floor(my.dim1/12))
(d.mm1  <- 2    - floor(my.dim1/12)*12 + my.dim1 - 1)
(d.yr2  <- 1998 + floor(my.dim2/12))
(d.mm2  <- 2    - floor(my.dim2/12)*12 + my.dim2 - 1)
(d.yr3  <- 1998 + floor(my.dim3/12))
(d.mm3  <- 2    - floor(my.dim3/12)*12 + my.dim3 - 1)

(set.step1d<- ts(embed(step1d, dim=my.dim1),
      start=c(d.yr1, d.mm1), freq=12))
(set.puls1d<- ts(embed(puls1d, dim=my.dim1),
      start=c(d.yr1, d.mm1), freq=12))
(set.step2d<- ts(embed(step2d, dim=my.dim2),
      start=c(d.yr2, d.mm2), freq=12))
(set.puls2d<- ts(embed(puls2d, dim=my.dim2),
      start=c(d.yr2, d.mm2), freq=12))
(set.step3d<- ts(embed(step3d, dim=my.dim3),
      start=c(d.yr3, d.mm3), freq=12))
(set.puls3d<- ts(embed(puls3d, dim=my.dim3),
      start=c(d.yr3, d.mm3), freq=12))

# 5.4 Same length: dummy set & y
# raw set
(my.dim     <- max(my.dim1, my.dim2, my.dim3))
(b.yr       <- 1997 + floor(my.dim/12))
(b.mm       <- 1    - floor(my.dim/12)*12 + my.dim - 1)

(win.step1b <- window(set.step1b, start=c(b.yr, b.mm), freq=12))
```

```
(win.puls1b <- window(set.puls1b, start=c(b.yr, b.mm), freq=12))
(win.step2b <- window(set.step2b, start=c(b.yr, b.mm), freq=12))
(win.puls2b <- window(set.puls2b, start=c(b.yr, b.mm), freq=12))
(win.step3b <- window(set.step3b, start=c(b.yr, b.mm), freq=12))
(win.puls3b <- window(set.puls3b, start=c(b.yr, b.mm), freq=12))
(win.my.yb  <- window(my.yb,      start=c(b.yr, b.mm), freq=12))

# d=1 set
(c.yr       <- 1997 + floor(my.dim/12))
(c.mm       <- 2    - floor(my.dim/12)*12 + my.dim - 1)
(win.step1c <- window(set.step1c, start=c(c.yr, c.mm), freq=12))
(win.puls1c <- window(set.puls1c, start=c(c.yr, c.mm), freq=12))
(win.step2c <- window(set.step2c, start=c(c.yr, c.mm), freq=12))
(win.puls2c <- window(set.puls2c, start=c(c.yr, c.mm), freq=12))
(win.step3c <- window(set.step3c, start=c(c.yr, c.mm), freq=12))
(win.puls3c <- window(set.puls3c, start=c(c.yr, c.mm), freq=12))
(win.my.yc  <- window(my.yc,      start=c(c.yr, c.mm), freq=12))

# d=D=1 set
(d.yr       <- 1998 + floor(my.dim/12))
(d.mm       <- 2    - floor(my.dim/12)*12 + my.dim - 1)
(win.step1d <- window(set.step1d, start=c(d.yr, d.mm), freq=12))
(win.puls1d <- window(set.puls1d, start=c(d.yr, d.mm), freq=12))
(win.step2d <- window(set.step2d, start=c(d.yr, d.mm), freq=12))
(win.puls2d <- window(set.puls2d, start=c(d.yr, d.mm), freq=12))
(win.step3d <- window(set.step3d, start=c(d.yr, d.mm), freq=12))
(win.puls3d <- window(set.puls3d, start=c(d.yr, d.mm), freq=12))
(win.my.yd  <- window(my.yd,      start=c(d.yr, d.mm), freq=12))

# 5.5. Estimate LTF model

# Must selct reg + y888 in the same group

# raw
# reg <- data.frame(win.step1b, win.step2b, win.step3b)  # b1
# reg <- data.frame(win.step1b, win.step2b, win.puls3b)  # b2
# reg <- data.frame(win.step1b, win.puls2b, win.step3b)  # b3
# reg <- data.frame(win.step1b, win.puls2b, win.puls3b)  # b4
# reg <- data.frame(win.puls1b, win.step2b, win.step3b)  # b5
# reg <- data.frame(win.puls1b, win.step2b, win.puls3b)  # b6
# reg <- data.frame(win.puls1b, win.puls2b, win.step3b)  # b7
# reg <- data.frame(win.puls1b, win.puls2b, win.puls3b)  # b8
# y888 <- win.my.yb

# d=1
# reg <- data.frame(win.step1c, win.step2c, win.step3c)  # c1
# reg <- data.frame(win.step1c, win.step2c, win.puls3c)  # c2
# reg <- data.frame(win.step1c, win.puls2c, win.step3c)  # c3
# reg <- data.frame(win.step1c, win.puls2c, win.puls3c)  # c4
# reg <- data.frame(win.puls1c, win.step2c, win.step3c)  # c5
# reg <- data.frame(win.puls1c, win.step2c, win.puls3c)  # c6
# reg <- data.frame(win.puls1c, win.puls2c, win.step3c)  # c7
# reg <- data.frame(win.puls1c, win.puls2c, win.puls3c)  # c8
# y888 <- win.my.yc

# d=D=1
# reg <- data.frame(win.step1d, win.step2d, win.step3d)  # d1
# reg <- data.frame(win.step1d, win.step2d, win.puls3d)  # d2
```

```
# reg <- data.frame(win.step1d, win.puls2d, win.step3d)  # d3
# reg <- data.frame(win.step1d, win.puls2d, win.puls3d)  # d4
# reg <- data.frame(win.puls1d, win.step2d, win.step3d)  # d5
# reg <- data.frame(win.puls1d, win.step2d, win.puls3d)  # d6
# reg <- data.frame(win.puls1d, win.puls2d, win.step3d)  # d7
  reg <- data.frame(win.puls1d, win.puls2d, win.puls3d)  # d8
  y888 <- win.my.yd

(ltf  <- arimax(y888, order=c(1,0,0), seasonal=list(order=c(1,0,0),
      period=12), reg=data.frame(reg), method='ML') )

## Calculate my residual and plot

(my.dimt  <- my.dim1 + my.dim2 + my.dim3)
(my.x     <- data.frame(interc=1, reg))
 my.x     <- as.matrix(my.x)
(my.coef  <- coef(ltf))
(my.coefs <- as.matrix(my.coef[(3):(3+my.dimt)]))
(y.mat    <- as.matrix(y888))
(my.res   <- y.mat - my.x %*% my.coefs)

win.graph(width=6.5,height=2.5,pointsize=9)
par(mfcol=c(1,2),mai=c(0.8,0.8,0.2,0.2))
acf(my.res,lag=36); pacf(my.res,lag=36)
summary(ltf)
acf(resid(ltf),lag=36, main='model ACF');
pacf(resid(ltf),lag=36,main='model PACF')

## Abstract impulse weight / standard error

(time.lag <- c(1:my.dimt))
 lag1     <- 4
(lag2     <- 3 + my.dimt)  # without intercept
(var.ltf  <- as.matrix(vcov(ltf)))
(var.diag <- diag(var.ltf))
(sd2      <- 2*sqrt(var.diag[lag1:lag2]))
 sd2n     <- -sd2


#------------------------------------------------------------
# Step 6 Final Intervention Analysis
#------------------------------------------------------------

# 6.1 Input besides for LTF model

 my.b1   <- 5         # Input: dead time 1
 my.b2   <- 0         # Input: dead time 2
 my.b3   <- 0         # Input: dead time 3



# 6.2 Create dummy variables & y (raw, d=1, d=D=1)

# The same as step 5.2

# 6.3 LAG: consider dead time - dummy lost (my.b*) obs

# lagged set for each dummy (raw, 1997.01 - 2008.06)
```

```
(ia.step1b <- lag(step1b, -1*my.b1)); step1b
(ia.puls1b <- lag(puls1b, -1*my.b1))
(ia.step2b <- lag(step2b, -1*my.b2))
(ia.puls2b <- lag(puls2b, -1*my.b2))
(ia.step3b <- lag(step3b, -1*my.b3))
(ia.puls3b <- lag(puls3b, -1*my.b3))

# lagged set for each dummy (d=1, 1997.02 - 2008.06)

(ia.step1c <- lag(step1c, -1*my.b1)); step1c
(ia.puls1c <- lag(puls1c, -1*my.b1))
(ia.step2c <- lag(step2c, -1*my.b2))
(ia.puls2c <- lag(puls2c, -1*my.b2))
(ia.step3c <- lag(step3c, -1*my.b3))
(ia.puls3c <- lag(puls3c, -1*my.b3))

# lagged set for each dummy (d=D=1, 1998.02 - 2008.06)

(ia.step1d <- lag(step1d, -1*my.b1)); step1d
(ia.puls1d <- lag(puls1d, -1*my.b1))
(ia.step2d <- lag(step2d, -1*my.b2))
(ia.puls2d <- lag(puls2d, -1*my.b2))
(ia.step3d <- lag(step3d, -1*my.b3))
(ia.puls3d <- lag(puls3d, -1*my.b3))

# 6.4 Set same length: adjust time period because of dead time

(my.b     <- max(my.b1, my.b2, my.b3))
(b.yr     <- 1997 + floor(my.b/12))
(b.mm     <- 1    - floor(my.b/12)*12 + my.b) # No -1

ia.step1b
(f.step1b <- window(ia.step1b, start=c(b.yr, b.mm), end=c(2008,6),freq=12))
(f.puls1b <- window(ia.puls1b, start=c(b.yr, b.mm), end=c(2008,6),freq=12))
(f.step2b <- window(ia.step2b, start=c(b.yr, b.mm), end=c(2008,6),freq=12))
(f.puls2b <- window(ia.puls2b, start=c(b.yr, b.mm), end=c(2008,6),freq=12))
(f.step3b <- window(ia.step3b, start=c(b.yr, b.mm), end=c(2008,6),freq=12))
(f.puls3b <- window(ia.puls3b, start=c(b.yr, b.mm), end=c(2008,6),freq=12))
(f.my.yb  <- window(my.yb,     start=c(b.yr, b.mm), end=c(2008,6),freq=12))

(c.yr     <- 1997 + floor(my.b/12))
(c.mm     <- 2    - floor(my.b/12)*12 + my.b)
(f.step1c <- window(ia.step1c, start=c(c.yr, c.mm), end=c(2008,6),freq=12))
(f.puls1c <- window(ia.puls1c, start=c(c.yr, c.mm), end=c(2008,6),freq=12))
(f.step2c <- window(ia.step2c, start=c(c.yr, c.mm), end=c(2008,6),freq=12))
(f.puls2c <- window(ia.puls2c, start=c(c.yr, c.mm), end=c(2008,6),freq=12))
(f.step3c <- window(ia.step3c, start=c(c.yr, c.mm), end=c(2008,6),freq=12))
(f.puls3c <- window(ia.puls3c, start=c(c.yr, c.mm), end=c(2008,6),freq=12))
(f.my.yc  <- window(my.yc,     start=c(c.yr, c.mm), end=c(2008,6),freq=12))

(d.yr     <- 1998 + floor(my.b/12))
(d.mm     <- 2    - floor(my.b/12)*12 + my.b)

(f.step1d <- window(ia.step1d, start=c(d.yr, d.mm), end=c(2008,6),freq=12))
(f.puls1d <- window(ia.puls1d, start=c(d.yr, d.mm), end=c(2008,6),freq=12))
(f.step2d <- window(ia.step2d, start=c(d.yr, d.mm), end=c(2008,6),freq=12))
(f.puls2d <- window(ia.puls2d, start=c(d.yr, d.mm), end=c(2008,6),freq=12))
```

```
(f.step3d <- window(ia.step3d, start=c(d.yr, d.mm), end=c(2008,6),freq=12))
(f.puls3d <- window(ia.puls3d, start=c(d.yr, d.mm), end=c(2008,6),freq=12))
(f.my.yd  <- window(my.yd,     start=c(d.yr, d.mm), end=c(2008,6),freq=12))

# 6.5 Adjust several inputs for IA model

# Must selct reg.ia + y999 in the same group

# dummy set raw

# reg.ia <- data.frame(f.step1b, f.step2b, f.step3b)  # b1
# reg.ia <- data.frame(f.step1b, f.step2b, f.puls3b)  # b2
# reg.ia <- data.frame(f.step1b, f.puls2b, f.step3b)  # b3
# reg.ia <- data.frame(f.step1b, f.puls2b, f.puls3b)  # b4
# reg.ia <- data.frame(f.puls1b, f.step2b, f.step3b)  # b5
# reg.ia <- data.frame(f.puls1b, f.step2b, f.puls3b)  # b6
# reg.ia <- data.frame(f.puls1b, f.puls2b, f.step3b)  # b7
# reg.ia <- data.frame(f.puls1b, f.puls2b, f.puls3b)  # b8
# y999   <- f.my.yb

# dummy set d=1

# reg.ia <- data.frame(f.step1c, f.step2c, f.step3c);
t5=list(c(1,0),c(1,0),c(1,0)) # c1
# reg.ia <- data.frame(f.step1c, f.step2c, f.puls3c);
t5=list(c(1,0),c(1,0),c(1,0)) # c2
# reg.ia <- data.frame(f.step1c, f.puls2c, f.step3c);
t5=list(c(1,0),c(1,0),c(1,0)) # c3
# reg.ia <- data.frame(f.step1c, f.puls2c, f.puls3c);
t5=list(c(1,0),c(1,0),c(1,0)) # c4
# reg.ia <- data.frame(f.puls1c, f.step2c, f.step3c);
t5=list(c(1,0),c(1,0),c(1,0)) # c5
# reg.ia <- data.frame(f.puls1c, f.step2c, f.puls3c);
t5=list(c(1,0),c(1,0),c(1,0)) # c6
  reg.ia <- data.frame(f.puls1c, f.puls2c, f.step3c);
t5=list(c(1,0),c(1,0),c(1,0)) # c7
# reg.ia <- data.frame(f.puls1c, f.puls2c, f.puls3c);
t5=list(c(1,0),c(1,0),c(1,0)) # c8
# reg.ia <- data.frame(f.puls1c, f.puls2c, f.step3c);
t5=list(c(1,0),c(1,0),c(0,0)) # c7 step
# reg.ia <- data.frame(f.puls1c, f.puls2c, f.puls3c);
t5=list(c(1,0),c(1,0),c(0,0)) # c8 step
    y999   <- f.my.yc

# dummy set d=D=1

# reg.ia <- data.frame(f.step1d, f.step2d, f.step3d);
t5=list(c(1,0),c(1,0),c(1,0)) #d1
# reg.ia <- data.frame(f.step1d, f.step2d, f.puls3d);
t5=list(c(1,0),c(1,0),c(1,0)) #d2
# reg.ia <- data.frame(f.step1d, f.puls2d, f.step3d);
t5=list(c(1,0),c(1,0),c(1,0)) #d3
# reg.ia <- data.frame(f.step1d, f.puls2d, f.puls3d);
t5=list(c(1,0),c(1,0),c(1,0)) #d4
# reg.ia <- data.frame(f.puls1d, f.step2d, f.step3d);
t5=list(c(1,0),c(1,0),c(1,0)) #d5
# reg.ia <- data.frame(f.puls1d, f.step2d, f.puls3d);
t5=list(c(1,0),c(1,0),c(1,0)) #d6
```

```
# reg.ia <- data.frame(f.puls1d, f.puls2d, f.step3d);
t5=list(c(1,0),c(1,0),c(1,0)) #d7
# reg.ia <- data.frame(f.puls1d, f.puls2d, f.puls3d);
t5=list(c(1,0),c(1,0),c(1,0)) #d8
# reg.ia <- data.frame(f.puls1d, f.puls2d, f.step3d);
t5=list(c(1,0),c(1,0),c(0,0)) #d7 step
# reg.ia <- data.frame(f.puls1d, f.puls2d, f.puls3d);
t5=list(c(1,0),c(1,0),c(0,0)) #d8 step

# reg.ia<- data.frame(f.puls1d,f.puls2d,f.puls3d,f.step3d);
t5=list(c(1,0),c(1,0),c(1,0),c(0,0))
# reg.ia<-data.frame(f.puls1d,f.puls2d,f.puls3d,f.step2d);
t5=list(c(1,0),c(1,0),c(1,0),c(0,0))
# reg.ia<-data.frame(f.step1d,f.puls2d,f.puls3d);
t5=list(c(1,0),c(1,0),c(1,0)) #d8
# y999  <- f.my.yd

(ia <- arimax(y999, order=c(4,0,0), seasonal=list(order=c(0,0,0),
period=12), xtransf=reg.ia, transfer=t5, method='ML', include.mean = F ) )

# @@@@@@@@@@@@@@@@@@@ Figure 1 Begin @@@@@@@@@@@@@@@@@@@@@@@@@@@@@

q <- sun[97:234,c(2, 22:25, 47,50)] ; q
(q$mil.v4 <- q$if9040/1000000)
(q$mil.v8 <- q$if9080/1000000)
(q$mil.v5 <- q$if5000/1000000)
(q$mil.v7 <- q$if7000/1000000)

win.graph(width=6,height=3.2,pointsize=9)
par(mai=c(0.4,0.8,0.2,0.8),family="serif")

plot(mill.v8,  lty=1, lwd=1, col=1, xlab='',
      ylab="Import Value ($ Million)")
lines(mill.v4, lty=1, lwd=4, col=8)
lines(mill.v7, lty=1, lwd=1, col=1)
lines(mill.v5, lty=1, lwd=2, col=8)

text(2006.5,99.7,"1"); text(2006.5,60.12,"2")
text(2006.5,31.1,"3"); text(2006.5,11.3,"4")

abline(v=2003+10/12, lty=3)
abline(v=2004+7/12, lty=3)
abline(v=2005+1/12, lty=3)

text(2003.7,5,"a");      text(2004.4,5.5,"b");    text(2004.9,5,"c")

legend(1997,115, c("1 - V9080","2 - V9040","3 - V7000","4 - V5000",
      " ", "a - 2003:10", "b - 2004:07", "c - 2005:01"),box.lty=0)

# @@@@@@@@@@@@@@@@@@@ Figure 1 End @@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@

# @@@@@@@@@@@@@@@@@@@ Figure 2 Begin @@@@@@@@@@@@@@@@@@@@@@@@@@@@@

win.graph(width=6.5,height=2.5,pointsize=9)
par(mfcol=c(1,2),mai=c(0.8,0.8,0.2,0.2),family="serif")
acf( my.res,lag=36, ci.col='black', xlab='Time Lag', ylab='SACF for V80
(d=0, D=0)')
```

```
pacf(my.res,lag=36, ci.col='black', xlab='Time Lag', ylab='SPACF for
V80 (d=0, D=0)')

# @@@@@@@@@@@@@@@@@@@ Figure 2 End @@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@

# @@@@@@@@@@@@@@@@@@@ Figure 3 Begin @@@@@@@@@@@@@@@@@@@@@@@@@@@@@

win.graph(width=6.5,height=4.5,pointsize=9)
par(mai=c(0.8,0.8,0.2,0.2),family="serif")
plot  (my.coef[lag1:lag2],type="h",lend='butt',lwd=6, col='gray35',
       ylim=c(-1.05,0.55), xaxt='n', xlab='Lag Index j',
       ylab=expression(paste("Impulse Response Weights", upsilon[i][j])) )
abline(h=0, col=1)
lines (sd2,  col=1, lty=5, lwd=1)
lines (sd2n, col=1, lty=5, lwd=1)
axis(1, at=c(1:30), labels=c(0:8,0:5,0:14))

arrows(1,-0.85,  9.8,-0.85, code=3, length=0.1, angle=15 )
arrows(10,-0.85, 15.8,-0.85, code=3, length=0.1, angle=20 )
arrows(16,-0.85, 30.8,-0.85, code=3, length=0.1, angle=30 )
text(5, -0.85, "Intervention I\n\n(i = 1, j = 0, 1, ..., 8)")
text(13, -0.85, "Intervention II\n\n(i = 2, j = 0, 1, ..., 5)")
text(22.5, -0.85, "Intervention III\n\n(i = 3, j = 0, 1, ..., 14)")

abline(v=1, col=1,lty=3)
abline(v=10, col=1,lty=3)
abline(v=16, col=1,lty=3)
arrows(1,0.5,  2.5,0.5, code=1, length=0.1, angle=15 )
arrows(10,0.5, 11.5,0.5, code=1, length=0.1, angle=15 )
arrows(16,0.5, 17.5,0.5, code=1, length=0.1, angle=15 )
text(2.55, 0.5, "2003:10", pos=4)
text(11.55, 0.5, "2004:07", pos=4)
text(17.55, 0.5, "2005:01", pos=4)

# @@@@@@@@@@@@@@@@@@@ Figure 3 End @@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@
```

APPENDIX B

R CODES FOR CHAPTER III

```
#-------------------------------------------------------------
#   CHAPTER III COMPETITION OF IMPORTED WOODEN BEDROOM
#                     FURNITURE IN THE U.S.
#-------------------------------------------------------------

# Step 1: Import Data
#      1.1 Import Data & Variables
#      1.2 Libraries Used
#      1.3 Creat Dummy Variables
#      1.4 Time Period Selection
#      1.5 Country Selection
#      1.6 Establish Final Dataset
#
# Step 2: Time Series Analysis
#      2.1 Data Transformation
#      2.2 Unit Root Test for uv, s, and nlxp
#      2.3 Calculate Stone Price Index
#
# Step 3: AIDS Model
#      3.1 AIDS using package[micEcon]
#      3.2 AIDS with Antidumping Dummy
#      3.3 Establish AIDS by Codes
#      3.4 Misspecication Tests
#      3.5 Calculate Elasticities by Codes
#      Summary Output1
#
# Step 4  Dynamic AIDS
#      4.1 Cointegration Test
#      4.2 Dynamic EC_AIDS
#      4.3 Theory Tests by Loop
#      4.4 Misspecication Tests
#      4.5 Calculate Elasticities
#      4.6 EC_AIDS with Antidumping Dummy
#      Summary Output2
#
#      Figure 1
#      Figure 2

#-------------------------------------------------------------
# Step 1 Import Data
#-------------------------------------------------------------

# 1.1 Import Data & Variables

getwd();setwd("C:/Users/ywan/Desktop/Thesis")
options(prompt="Study 2|", scepen=3, digits=4)
wbf <- read.table("fwbf.txt", header=TRUE);names(wbf)

# Variable definitions in "Chapter3.xlsx"
# 38 variables, 1996.01-2008.12, 13 years = 156 months
# All data are based on HTS 9403.50.9040

# Country order:
# 1.Brazil(BR)                 2.Canada(CA)       3.China(CN)
# 4.Denmark(DK)                5.France(FR)       6.Hongkong(HK)
# 7.India(IA)                  8.Indonesia(ID)          9.Italy(IT)
# 10.Malaysia(MY)        11.Mexico(MX)            12.Philippines(PH)
# 13.Taiwan(TW)                14.Thailand(TH)          15.UK(UK)
```

```
# 16.Vietnam(VN)         17.World(WD)

# 1.2 Libraries Used

library(urca)
library(tseries)
library(lmtest)
library(strucchange)
library(micEcon)
library(systemfit)

# 1.3 Creat Dummy Variables

TotExp <- wbf$cif.WD

(pulse1 <- ts(1*(seq(TotExp)== 94), start=c(1996,1), freq=12))
(pulse2 <- ts(1*(seq(TotExp)==103), start=c(1996,1), freq=12))
(pulse3 <- ts(1*(seq(TotExp)==109), start=c(1996,1), freq=12))

(step1  <- ts(1*(seq(TotExp) >= 94 & seq(TotExp) <= 156),
      start=c(1996,1), freq=12))
(step2 <- ts(1*(seq(TotExp) >= 103 & seq(TotExp) <= 156),
      start=c(1996,1), freq=12))
(step3 <- ts(1*(seq(TotExp) >= 109 & seq(TotExp) <= 156),
      start=c(1996,1), freq=12))

(dummy <- data.frame(pulse1, pulse2, pulse3,
      step1, step2, step3))
ts.dummy <- ts(data.matrix(dummy), start=c(1996,1),freq=12)

# 1.4 Time Period Selection

sh <- 100 * wbf[,c(5:20)]/wbf[,37]
colnames(sh) <- c(
      "sh.BR", "sh.CA", "sh.CN", "sh.DK", "sh.FR", "sh.HK",
      "sh.IA", "sh.ID",  "sh.IT", "sh.MY", "sh.MX", "sh.PH",
      "sh.TW", "sh.TH", "sh.UK","sh.VN")
sh <- cbind(wbf[,1:4],sh);summary(sh[,5:20])

# 1.5 Country Selection

sh.01 <- summary(sh[61:156,5:20]);sh.01

# 1.6 Establish Final Dataset for Further Analysis

cif.top7 <- (wbf$cif.CN + wbf$cif.VN + wbf$cif.ID + wbf$cif.MY
           + wbf$cif.CA + wbf$cif.BR + wbf$cif.IT)
wbf$cif.ROW <- wbf$cif.WD - cif.top7

q.top7 <- (wbf$q.CN + wbf$q.VN + wbf$q.ID + wbf$q.MY
         + wbf$q.CA + wbf$q.BR + wbf$q.IT)

wbf$q.ROW <- wbf$q.WD - q.top7

uv.CN <- wbf$cif.CN / wbf$q.CN
s.CN <- wbf$cif.CN / wbf$cif.WD

final <- data.frame(
```

```
  uv.CN, uv.VN, uv.ID, uv.MY, uv.CA, uv.BR, uv.IT, uv.ROW,
  s.CN,  s.VN,  s.ID,  s.MY,  s.CA,  s.BR,  s.IT,  s.ROW,
  TotExp, dummy)

# Time period: 2001.1 ~ 2008.12
f.01 <- data.frame(final[61:156,])

# Average budget share for calculating elasticities
as.01 <- round(mean(f.01[,9:16]),5);as.01

cif <- data.frame(wbf[,1:4],  wbf$cif.CN, wbf$cif.VN,
                   wbf$cif.ID, wbf$cif.MY, wbf$cif.CA,
                   wbf$cif.BR, wbf$cif.IT, wbf$cif.ROW)
sum.cif <- aggregate(x = cif[,c(5:12)]/1000000,
      by=list(YEAR = cif$year),FUN = "sum")


#-------------------------------------------------------------
# Step 2 Time Series Analysis
#-------------------------------------------------------------

# 2.1 Data Transformation

#(1)# Raw data f.01 in time series format
#(2)# Take log then create individual ts
#(3)# Regular difference then create individual ts
#(4)# Total expenditure

# 2.2 Unit Root Test for log(uv)

summary(t.uv.CN <- ur.df(b.uv.CN, type=c("trend"), lags=11))
summary(d.uv.CN <- ur.df(b.uv.CN, type=c("drift"), lags=11))
summary(n.uv.CN <- ur.df(b.uv.CN, type=c("none"), lags=11))
summary(dd.uv.CN <- ur.df(diff(b.uv.CN), type=c("drift"),
      lags=10))

summary(t.s.CN <- ur.df(a.s.CN, type=c("trend"), lags=12))
summary(d.s.CN <- ur.df(a.s.CN, type=c("drift"), lags=12))
summary(n.s.CN <- ur.df(a.s.CN, type=c("none"), lags=12))
summary(dn.s.CN <- ur.df(diff(a.s.CN), type=c("none"),
      lags=11))

summary(t.TotExp <- ur.df(b.TotExp, type=c("trend"), lags=10))
summary(d.TotExp <- ur.df(b.TotExp, type=c("drift"), lags=10))
summary(n.TotExp <- ur.df(b.TotExp, type=c("none"), lags=10))
summary(dn.TotExp <- ur.df(diff(b.TotExp), type=c("none"),
      lags=9))

# Take the same steps for other countries

# 2.3 Calculate Stone Price Index for dynamic AIDS

shareNames <- c( "s.CN", "s.VN", "s.ID", "s.MY",
                 "s.CA", "s.BR", "s.IT", "s.ROW")
priceNames <- c( "uv.CN", "uv.VN", "uv.ID", "uv.MY",
                 "uv.CA", "uv.BR", "uv.IT", "uv.ROW")
totExpName <- c( "TotExp" )
```

```
(nGoods <- length(priceNames))  # 8
(nObs <- nrow(f.01))                  # 96
(lnp <- numeric(nObs))                # 96 zeros

# Stone Price Index
for(i in 1:nGoods)
lnp <- lnp + f.01[[shareNames[i]]]*log(f.01[[priceNames[i]]])
n.lxp <- log(f.01$TotExp) - lnp


#-------------------------------------------------------------
# Step 3 Static AIDS Model
#-------------------------------------------------------------

# 3.1 Static AIDS with antidumping dummy

p123.ai <- aidsEst(priceNames, shareNames, "TotExp",
      data = f.01, hom = TRUE, sym = TRUE, priceIndex = "S",
      shifterNames = c("pulse1","pulse2","pulse3"))

summary(p123.ai);(p123.elas <- elas(p123.ai))


# 3.2 Establish Static AIDS by codes

sta.CN <- (s.CN ~ pulse1 + pulse2 + pulse3 + n.lxp +
      log(uv.CN) + log(uv.VN) + log(uv.ID) + log(uv.MY) +
      log(uv.CA) + log(uv.BR) + log(uv.IT) + log(uv.ROW))
sta.VN <- (s.VN ~ pulse1 + pulse2 + pulse3 + n.lxp +
      log(uv.CN) + log(uv.VN) + log(uv.ID) + log(uv.MY) +
      log(uv.CA) + log(uv.BR) + log(uv.IT) + log(uv.ROW))
sta.ID <- (s.ID ~ pulse1 + pulse2 + pulse3 + n.lxp +
      log(uv.CN) + log(uv.VN) + log(uv.ID) + log(uv.MY) +
      log(uv.CA) + log(uv.BR) + log(uv.IT) + log(uv.ROW))
sta.MY <- (s.MY ~ pulse1 + pulse2 + pulse3 + n.lxp +
      log(uv.CN) + log(uv.VN) + log(uv.ID) + log(uv.MY) +
      log(uv.CA) + log(uv.BR) + log(uv.IT) + log(uv.ROW))
sta.CA <- (s.CA ~ pulse1 + pulse2 + pulse3 + n.lxp +
      log(uv.CN) + log(uv.VN) + log(uv.ID) + log(uv.MY) +
      log(uv.CA) + log(uv.BR) + log(uv.IT) + log(uv.ROW))
sta.BR <- (s.BR ~ pulse1 + pulse2 + pulse3 + n.lxp +
      log(uv.CN) + log(uv.VN) + log(uv.ID) + log(uv.MY) +
      log(uv.CA) + log(uv.BR) + log(uv.IT) + log(uv.ROW))
sta.IT <- (s.IT ~ pulse1 + pulse2 + pulse3 + n.lxp +
      log(uv.CN) + log(uv.VN) + log(uv.ID) + log(uv.MY) +
      log(uv.CA) + log(uv.BR) + log(uv.IT) + log(uv.ROW))

(sta.system <- list(sta.CN, sta.VN, sta.ID,
                     sta.MY, sta.CA, sta.BR, sta.IT))

aids <- systemfit(sta.system, method="SUR", data=f.01)
summary(aids)

n = 5
BSName <- c("s.CN", "s.VN", "s.ID", "s.MY",
             "s.CA", "s.BR", "s.IT", "s.ROW")
nBS <- length(BSName);nBS
npr <- n + nBS; npr
```

```
tpr <- (nBS - 1) * npr; tpr

# 3.3 Theory Tests by codes

#(1)# Homogeneity
homo <- NULL
homo <- matrix(0, (nBS - 1), tpr)
for (i in 1:(nBS -1)) {
for (j in 1:nBS) {
homo[i, (i-1)*npr + n + j] <- 1}};homo
(rhomo <- rep(0, nrow(homo)))

h.aids <- systemfit(sta.system, method="SUR", data=f.01,
             restrict.matrix=homo, restrict.rhs=rhomo)
summary(h.aids)
lrtest(aids,h.aids)

#(2)# Symmetry
ns <- (nBS - 1) * (nBS - 2)/2;ns
sym <- NULL
sym <- matrix(0, ns, tpr)
k <- 0
for (i in 1:(nBS-2)){
for (j in (i+1):(nBS-1)) {
k <- k + 1
sym[k, (i-1)*npr + n + j] <- 1
sym[k, (j-1)*npr + n + i] <- -1}};sym
(rsym <- rep(0, nrow(sym)))

s.aids <- systemfit(sta.system, method="SUR", data=f.01,
      restrict.matrix=sym, restrict.rhs=rsym)
summary(s.aids)
lrtest(aids,s.aids)

#(3)# Homogeneity & Symmetry
hs <- NULL
hs <- matrix(0, (nBS -1), tpr);hs

for (i in 1:(nBS -1)) {
for (j in 1:nBS) {
hs[i, (i-1)*npr + n + j] <- 1}};hs

hs <- rbind(hs, matrix(0, ns, tpr))

k <- 0
for (i in 1:(nBS-2)){
for (j in (i+1):(nBS-1)) {
k <- k + 1
hs[k + (nBS -1), (i-1)*npr + n + j] <- 1
hs[k + (nBS -1), (j-1)*npr + n + i] <- -1}};hs
(rhs <- rep(0, nrow(hs)))

p123.aids <- systemfit(sta.system, method="SUR", data=f.01,
      restrict.matrix=hs, restrict.rhs=rhs)
summary(p123.aids)
lrtest(aids,p123.aids)

# 3.4 Misspecication Tests
```

```
#(1)# Autocorrelation Test (Breusch-Godfrey)
# H0: There is no serial correlation of any order up to p

bgtest(sta.CN, order=1, order.by=NULL, type = c("Chisq"), data = f.01)

#(2)# Hetroscedasticity Test (Breusch-Pagan)
# H0: no heteroscedasticity

bptest(sta.CN, varformula = NULL, studentize = TRUE, data = f.01)

#(3)# Functional Misspecification (RESET)
# H0: no functional misspecification

resettest(sta.CN, power=2:3, type = c("fitted"),
      data = f.01)

#(4)# Normality (Jarque-Bera LM Test)
# H0: normality

jarque.bera.test(residuals(p123.aids$eq[[1]]))

#(5)# Parameter Stability (efp)

ps.sCN <- efp(sta.CN, data=f.01, h=0.15, dynamic=FALSE,
      rescale=FALSE); plot(ps.sCN);sctest(ps.sCN)

# Take the same steps for other countries

# 3.5 Calculate elasticities by codes

co.aids <- coef(p123.aids);co.aids
vc.aids <- vcov(p123.aids);vc.aids
df <- df.residual(p123.aids)

#(1)# Expenditure elasticities

e.exp <- NULL      # elaticity
t.exp <- NULL      # t-value
p.exp <- NULL      # p-value

for(i in 1:(nBS-1)){
e.exp[i] <- 1 + co.aids[(i-1)*npr + n]/as.01[i]
t.exp[i] <- as.01[i]*e.exp[i]/sqrt(vc.aids[(i-1)*npr+n,
      (i-1)*npr+n])
p.exp[i] <- 2*(1- pt(abs(t.exp[i]), df))}
round(e.exp,3);round(t.exp,3);round(p.exp,3)

#(2)# Marshallian Own- & Hicksian cross-price elasticity

e.oc <- matrix(NA, nBS, nBS)
t.oc <- matrix(NA, nBS, nBS)
p.oc <- matrix(NA, nBS, nBS)

for(i in 1:(nBS-1)){k <- 1
for(j in 1:nBS){
if(i==j){
e.oc[i,i] <- (-1 + co.aids[(i-1)*npr + n + k]/as.01[i]
```

```
            - co.aids[(i-1)*npr + n])
t.oc[i,i] <- e.oc[i,i]/sqrt(
  vc.aids[(i-1)*npr + n + k,(i-1)*npr + n + k]/(as.01[i]^2) +
  vc.aids[(i-1)*npr + n,(i-1)*npr + n] -
  2 * vc.aids[(i-1)*npr + n + k,(i-1)*npr + n]/as.01[i])
p.oc[i,i] <- 2*(1- pt(abs(t.oc[i,i]), df))}
else{
e.oc[i,j] <- co.aids[(i-1)*npr + n + k]/as.01[i] + as.01[j]
t.oc[i,j] <- e.oc[i,j]/(sqrt(
      vc.aids[(i-1)*npr + n + k,(i-1)*npr + n + k])/as.01[i])
p.oc[i,j] <- 2*(1- pt(abs(t.oc[i,j]), df))}
k <- k + 1}}
round(e.oc,3);round(t.oc,3);round(p.oc,3)


#-------------------------------------------------------------
# Step 4 Dynamic AIDS
#-------------------------------------------------------------

# 4.1 Engle & Granger test for cointegration

rd.CN <- residuals(p123.aids)[1]      # eq.CN residual
a.rd.CN <- ts(rd.CN, start=c(2001,1), freq=12)

par(mfcol=c(3,4))
plot(a.rd.CN);acf(a.rd.CN,24);pacf(a.rd.CN,24)

# ADF Cointegration Test
summary(t.rd.CN <- ur.df(a.rd.CN, type=c("trend"), lags=3))
summary(d.rd.CN <- ur.df(a.rd.CN, type=c("drift"), lags=3))
summary(n.rd.CN <- ur.df(a.rd.CN, type=c("none"),  lags=3))

# Take the same steps for other countries

# 4.2 Dynamic AIDS without restrictions (daids)

#(1)# Data transformation

ts.01 <- ts(f.01[,1:24],start=c(2001,1), freq=12)

ds <- diff(ts.01[,9:15], k=1)   # 2001.2-2008.12
colnames(ds) <- c('ds.CN', 'ds.VN', 'ds.ID', 'ds.MY',
                    'ds.CA','ds.BR', 'ds.IT')

s.l <- lag(ts.01[,9:15], k=1)   # 2000.12-2008.11
ds.l <- diff(s.l, k=1)          # 2001.1-2008.11
colnames(ds.l) <- c('ds.CN.l', 'ds.VN.l', 'ds.ID.l',
      'ds.MY.l', 'ds.CA.l', 'ds.BR.l', 'ds.IT.l')

luv <- log(ts.01[,1:8])
dluv <- diff(luv, k=1)   # 2001.2-2008.12
colnames(dluv) <- c('dluv.CN', 'dluv.VN', 'dluv.ID',
      'dluv.MY', 'dluv.CA', 'dluv.BR', 'dluv.IT', 'dluv.ROW')

lxp <- ts.01[,"n.lxp"]
dlxp <- diff(lxp, k=1)   # 2001.2 - 2008.12

rd <- cbind(a.rd.CN*(-1), a.rd.VN*(-1), a.rd.ID*(-1),
```

```
            a.rd.MY*(-1), a.rd.CA*(-1), a.rd.BR*(-1),
            a.rd.IT*(-1))      # 2001.1-2008.12
rd.l <- lag(rd, k=1)     # 2000.12-2008.11
colnames(rd.l) <- c('rd.CN.l', 'rd.VN.l', 'rd.ID.l',
      'rd.MY.l', 'rd.CA.l','rd.BR.l', 'rd.IT.l')

#(2)# Cut data into the same length

ds     <- window(ds,   start=c(2001,2), end=c(2008,11))
ds.l   <- window(ds.l, start=c(2001,2), end=c(2008,11))
dluv   <- window(dluv, start=c(2001,2), end=c(2008,11))
dlxp   <- window(dlxp, start=c(2001,2), end=c(2008,11))
rd.l   <- window(rd.l, start=c(2001,2), end=c(2008,11))
ts.dum <- window(ts.dummy, start=c(2001,2), end=c(2008,11))

dyn.data <- data.frame(ds, ds.l, dluv, dlxp, rd.l, ts.dum)
names(dyn.data)

#(3)# Dynamic Model by codes

dyn.CN <- (ds.CN ~ 0 + pulse1 + pulse2 + pulse3 + ds.CN.l
      + rd.CN.l + dlxp + dluv.CN + dluv.VN + dluv.ID
      + dluv.MY + dluv.CA + dluv.BR + dluv.IT + dluv.ROW)
dyn.VN <- (ds.VN ~ 0 + pulse1 + pulse2 + pulse3 + ds.VN.l
      + rd.VN.l + dlxp + dluv.CN + dluv.VN + dluv.ID
      + dluv.MY + dluv.CA + dluv.BR + dluv.IT + dluv.ROW)
dyn.ID <- (ds.ID ~ 0 + pulse1 + pulse2 + pulse3 + ds.ID.l
      + rd.ID.l + dlxp + dluv.CN + dluv.VN + dluv.ID
      + dluv.MY + dluv.CA + dluv.BR + dluv.IT + dluv.ROW)
dyn.MY <- (ds.MY ~ 0 + pulse1 + pulse2 + pulse3 + ds.MY.l
      + rd.MY.l + dlxp + dluv.CN + dluv.VN + dluv.ID
      + dluv.MY + dluv.CA + dluv.BR + dluv.IT + dluv.ROW)
dyn.CA <- (ds.CA ~ 0 + pulse1 + pulse2 + pulse3 + ds.CA.l
      + rd.CA.l + dlxp + dluv.CN + dluv.VN + dluv.ID
      + dluv.MY + dluv.CA + dluv.BR + dluv.IT + dluv.ROW)
dyn.BR <- (ds.BR ~ 0 + pulse1 + pulse2 + pulse3 + ds.BR.l
      + rd.BR.l + dlxp + dluv.CN + dluv.VN + dluv.ID
      + dluv.MY + dluv.CA + dluv.BR + dluv.IT + dluv.ROW)
dyn.IT <- (ds.IT ~ 0 + pulse1 + pulse2 + pulse3 + ds.IT.l
      + rd.IT.l + dlxp + dluv.CN + dluv.VN + dluv.ID
      + dluv.MY + dluv.CA + dluv.BR + dluv.IT + dluv.ROW)

(dyn.system <- list(dyn.CN, dyn.VN, dyn.ID,  dyn.MY,
                     dyn.CA, dyn.BR, dyn.IT ))
p123.dai <- systemfit(dyn.system, method="SUR",
      data=dyn.data)
summary(p123.dai)

n = 6
BSName <- c("s.CN", "s.VN", "s.ID", "s.MY", "s.CA", "s.BR", "s.IT",
      "s.ROW")
nBS <- length(BSName);nBS
npr <- n + nBS; npr
tpr <- (nBS - 1) * npr; tpr

# 4.3 Theory Tests by codes (daids)
# Similar to step 3.3
```

```
# 4.4 Diagnostic Tests
# Similar to step 3.4

# 4.5 Calculate Elasticities
# Similar to step 3.5

# @@@@@@@@@@@@@@@@@@@@ Figure 1 Begin @@@@@@@@@@@@@@@@@@@@@@@

ImVal <- read.table("wbf_6.txt", header = TRUE);names(ImVal)
iv.96 <- ts(ImVal[,5:6]/1000000, start=c(1996,1), freq=12)

win.graph(width=6, height=3.2, pointsize=9)
par(mai=c(0.4,0.8,0.2,0.8), family="serif")
ts.plot(iv.96, lty=1, lwd=c(1,4), col=c(1,8), xlab='',
      ylab="Import Value ($ Million)")

abline(v=2003+10/12, lty=3)
abline(v=2004+7/12, lty=3)
abline(v=2005+1/12, lty=3)
text(2003.7, 120, "a");  text(2004.4, 120, "b")
text(2004.9, 120, "c");  text(2006.6,280,"1");
text(2006.6,125,"2")

legend(1996, 350, c("1 Value - wooden bedroom furniture",
      "2 Value - bed", " ", "a Oct. 2003", "b Jul. 2004",
      "c Jan. 2005"), box.lty=0)
# @@@@@@@@@@@@@@@@@@@@ Figure 1 End @@@@@@@@@@@@@@@@@@@@@@@@@

# @@@@@@@@@@@@@@@@@@@@ Figure 2 Begin @@@@@@@@@@@@@@@@@@@@@@@

CN <- ts(f.01[,9],  start=c(2001,1), freq=12)
TExp <- ts(f.01[,17]/1000000, start=c(2001,1),freq=12)

# China
win.graph(width=2.9, height=2.4, pointsize=9)
par(mai=c(0.3, 0.6, 0.3, 0.6), family="serif")
plot(CN, lty=1, lwd=1, col=1, xlab='', ylab="Budget Share",
      main='(a) China')
abline(v=2003+10/12, lty=3)
abline(v=2004+7/12, lty=3)
abline(v=2005+1/12, lty=3)
text(2003.7, 0.3, "a");  text(2004.4, 0.3, "b");text(2004.9, 0.3, "c")
legend(2004.7, 0.60, c( "a Oct. 2003",
      "b Jul. 2004", "c Jan. 2005"), box.lty=0)

# @@@@@@@@@@@@@@@@@@@@ Figure 2 End @@@@@@@@@@@@@@@@@@@@@@@@@
```