Textile Research Journal | Article

Export Conditions of the Chinese Textile Industry: An Analysis in Comparison with Selected ASEAN Countries

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Abstract This paper provides a comprehensive and disaggregated set of elasticity estimates, to date, in the face of MFA abolishment. The estimates made here are at a detailed level of disaggregation and should provide researchers with opportunities for future analysis. We used the gravity model to estimate the trade elasticity of China's apparel cottons in the US market for the period between 1989 and 2009. From the gravity model, two phenomena are observed. First, there exists a unique long-run equilibrium relationship among the import quantity demand, the import price and the US GDP per capita. Second, import price and income elasticity are significant with the expected signs, conditions of which are significant for performing trade–policy analyses.

Key words textile industry, ATC, chinese economy, export demand, error-correction model, gravity model.

Introduction

The Multi Fibre Agreement (MFA), signed in 1974, imposes quota restrictions on textile and apparel items exported to the US from developing countries. However, at the Uruguay Round, a breakthrough occurred with an agreement to bring the MFA-restricted items, under GATT discipline, within the World Trade Organization's (WTO) jurisdiction. The liberalization process of quota restrictions on textiles and apparel items was taken over a 10-year period and scheduled to be completed on 1, January 2005. The *Agreement on Textile* and Clothing (ATC) called for a gradual phase out of the MFA quotas. As Gelb [1] mentions, the ATC called for the reductions of 16% (January 1, 1995), 17% (January 1, 1998), 18% (January 2002), and 49% (January 1, 2005) of the quotas to be eliminated on all trade between WTO countries.

It was expected that 'the gradual transition period would allow apparel manufacturers enough time to prepare for the more competitive global market of the post-ATC era' [2]. The elimination of the last set of quotas of the ATC ostensibly brought about the end of 40 years period of quantitative restrictions on the international trade of textiles and apparel [2]. Thus, the framework resulted in the liberalization for the world trade in textiles and apparel.

A number of papers focus on the impact of the elimination of quotas. For instance, Fox et al. [3] uses the USAGE–ITC model to estimate US welfare gains and sectoral effects of removing all textile and apparel restraints in 2005. Their model estimates that liberalization increases the US welfare, while decreasing US textile and apparel output. Moreover, Elbehri [4] employs a modified version of an applied general equilibrium GTAP model and uses recent estimates of MFA trade restrictiveness in analyzing MFA removal impact. He found that those that are subject

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Textile Research Journal Vol 80(19): 2028–2045 DOI: 10.1177/0040517510373638
Figures 1, 2 appear in color online: http://trj.sagepub.com

to binding MFA-quotas witness significant trade in apparel shift in favor of Asian and South Asian suppliers.

On the other hand, Brambilla et al. [5] investigated China's experience under the US apparel and textile quotas. They found that China experienced more constraint under these regimes than other countries and that, as quotas were lifted, China's exports grew disproportionately. In fact, when the ATC ended in 2005, China's exports surged, while those from nearly all other regions fell. Moreover, Gelb [1] analyzed the effects of the phase-out of the quotas on textiles and apparel that occurred on January 1, 2005 – focusing on the consequences and on implementation issues. The author argues that there will be benefits to the overall US economy from an acceleration of imports of textiles and apparel.

Nordås [6] analyzes the global apparel industry in the post-ATC regime. The author says that 'there is no doubt that both China and India will gain market shares in the European Union, the United States and Canada to a significant extent, but the expected surge in market share may be less than anticipated'.

During the period of this investigation, the US Government imposed non-tariff *barriers on textile* and apparel imports. The US agreed to liberalize 16% of their textile imports on 1st January 1995, 17% in 1998, 18% in 2002, and the remaining 49% at the end of the transition period, on 1st January 2005. A time lag effect might take effect for the consumption and production process in response to such a trade liberalization schedule. Consequently, as Fox et al. [3] mention, imports have increased in the US market, particularly for the apparel industry. From 2002 to 2005, US imports of textiles and apparel increased 23.3% to $100.4 billion. At the same time, 2002 to 2005, US production and employment in these sectors declined by 11.0% and 23.0% respectively.

China, the major player in global textiles and apparel trade, joined the WTO in 2002. At the moment China is the big *winner in the post-quota* era. Fox et al. [3] state that 'China has been the largest beneficiary (by value) from global quota elimination and the resulting market share reallocation'. In this new environment, Chinese exports to the US rose from $12.8 billion to $27.7 billion between 2002 and 2005, an increase of 115.5%. The main reason for this increase was the establishment of 10 safeguards (quantitative restraints) on selected imports of Chinese textile and apparel items in 2005.

The main purpose of this paper is to investigate the behavior of export performance, particularly the role played by income, prices, and trade liberalization in the determination of MFA fibers and cottons (apparel and non-apparel) imported from mainland China, Hong Kong, and four ASEAN countries[2] to the US market. The US continues to be the world's largest importer of textiles and apparel, and it accounted for 17.0% of world imports of these goods in 2005. In other words, as Elbehri [4] states, the US has significant influence on the world textiles and apparel market. Moreover, it is the most important export market for the Chinese textile and apparel industry.

In this paper, we use the gravity model to estimate the trade elasticity of China's apparel cottons in the US market for the period 1989–2009. We use data from the US Department of Commerce, Office of Textiles and Apparel[3]. Covering the period of the 1st quarter of 1989 to the 3rd quarter of 2009, we applied a cointegration and error correction model to the data, examined the sign and extended that real income per capita, prices, and trade liberalization affecting import demand for MFA items exported to the US from mainland China, Hong Kong, and four ASEAN countries. We believe this research is important for international apparel buyers and sellers as well as for trade policy makers.

From the gravity model, we observed two phenomena. First, there exists a unique long-run equilibrium relationship between the import quantity demand, the import price and the US GDP per capita. Second, the import price and income elasticity are significant showing expected signs, the conditions of which are significant for trade–policy analyses. This paper provides a comprehensive and disaggregated set of elasticity estimates to date. The estimates made here are at a detailed level of disaggregation and should provide researchers with opportunities for future analysis.

The paper proceeds as follows, initially the results of previous studies on the import demand function are discussed briefly. Further sections provide econometrics methodology for addressing the issues of estimating trade elasticity. The main findings are presented in the final sections of the paper.

Previous studies

There are numerous empirical studies on the research topic of trade potential, trade determinants, and trade direction employing the gravity model. For instance, Rahman et al. [7] examined trade determinants in Bangladesh using the panel data estimation technique and a generalized gravity model, and Batra [8] applied an Augmented Gravity Model to estimate India's trade potential. Moreover, Christie [9] investigated trade potential for Southeastern Europe.

[2] These countries are Singapore, Malaysia, Thailand, and the Philippines.

[3] Original data is available at http://otexa.ita.doc.gov/msrpoint.htm

The traditional gravity model originates from the notion of Newtonian physics[4]. Trade economists borrowed Newton's gravity theory and since the 1940's there has been a growing literature on the application of the 'gravity trade model'[5]. The economics version of the gravity model proposes that trade flows between two economies are positively related to the product of each economy's 'economic mass', as measured by GDP and negatively related to the distance between the economy's 'economic center's of gravity'. Most estimated gravity equations take the form[6]

$$x_{ij} = \alpha_1 y_i + \alpha_2 y_j + \sum_{m=1}^{M} \beta_m \ln(z_{ij}^m) + \varepsilon_{ij} \tag{1}$$

where x_{ij} is the log of exports from country i to j, y_i and y_j are the log of GDP of the exporter and importer, and z_{ij}^m (m = 1,…, M) is a set of observed variables.

Based on equation (1), McCallum [10] found that trade between Canadian provinces was 22 times (2,200%) more than trade between states in the US and Canadian provinces, after controlling for size and geographical distance. However, Anderson and Wincoop [11] argue that gravity equations can be derived from various different trade theories[7], but none of them leads to the traditional gravity model of equation (1), therefore the result of McCallum [10] is misleading due to model misspecification[8]. This implies that future research using a gravity equation should avoid adopting equation (1). Anderson and Wincoop [12] further proved that given the trade cost function, a micro-founded gravity equation with trade cost can be derived, and the logarithmic form of the empirical gravity equation becomes:

$$\begin{aligned} x_{ij} = {} & \alpha_1 y_i + \alpha_2 y_j + \sum_{m=1}^{M} \beta_m \ln(z_{ij}^m) - (1-\sigma)\ln(\Pi_i) \\ & - (1-\sigma)\ln(p_j) + \varepsilon_{ij} \end{aligned} \tag{2}$$

where $\beta_m = (1 - \sigma)/\gamma_m$, $\sigma > 1$ is the elasticity of substitution across goods. Π_i and p_j are country i's and country j's price indices. p_j is the inward multilateral resistance index (i.e. the supply price), since the law of demand implies that the flow of goods from i into j is stimulated (assuming $\sigma > 1$) by high trade costs from other exporting countries to market j as represented by p_j. On the other hand, higher resistance of exports from i to its alternative foreign markets resulted in more trade back to market i from j, as represented by the outward multilateral resistance index, Π_i. To illustrate this point, we borrow an example from Novy [13] that US–China trade is not only influenced by their bilateral barriers but also by their trade barriers with other countries. Suppose that US trade barriers were decreased with all other countries except for China. This implies that the multilateral trade barrier drops, therefore, part of US trade will be diverted away from China towards other countries although the US–China trade barrier itself remained unchanged.

One practical approach for estimating equation (2) is to use data for the price indices with OLS as suggested by Anderson and Wincoop [12]. Many researchers take this approach.[9] As Baier and Bergstrand [14] emphasize, the drawback of this approach is that it is difficult to measure the theoretical price indices in the data. Also as Anderson and Wincoop [11] mention, the consumer price index, in practice includes nontradables and is affected by local taxes and subsidies. Novy [13] argues that equation (2) derived by Anderson and Wincoop [12] has an upward bias towards the extent of international trade. For the year 1993, the author reports a 31% tariff equivalent of overall US–Canadian trade costs, compared to 46% reported by Anderson and Wincoop [12]. The reason for this bias is because the GDP data includes the services component and this tends to overstate the extent of international trade and thus the level of trade costs [13].

There are several reasons why equation (2) is unsatisfactory for our research purposes. First, we must be aware that the theoretical gravity model is valid only for macroeconomic modeling, because it was derived from a general equilibrium model and trade expenditures function for the whole economy. For researchers who are interested in examining trade issues, which are industry/product specific, equation (2) is inappropriate and will provide misleading results. Second, if researchers are interested in the dynamics of trade flows of the time series or panel data estimation, econometrics tests for stationarity and cointegration are unavoidable. Therefore, we provide a modified model which aims at estimating trade elasticities. The model will be discussed in the following sections.

[4] The theory is based on the late 17th century notion that the Universe is made up of solid objects which are attracted towards each other by a force called 'Gravity'. In sum it proposes that two bodies attract each other proportionally to the product of each body's mass (in kilograms) divided by the square of the distance between their respective centers of gravity (in meters).

[5] Oguledo and Macphee [54] provide detailed literature review on 'gravity trade model'.

[6] We follow exactly the notation used by Anderson and Wincoop [11] here.

[7] For example, the partial equilibrium model of export supply and import demand as developed by Linneman [55]; the trade share expenditure system as proposed by Anderson [56], and a microeconomic foundation model as developed by Bergstrand [57, 58].

[8] Unfortunately, there are large number of studies that follow this type of gravity equation, among others, including McCallum [10] and Wei [59].

[9] For example, Bergstrand [57, 58], and Baier and Bergstrand [14].

Trade Elasticities

Trade elasticities of income and price are important for international economic policy analysis. For instance, the welfare effects of trade liberalization and the impacts of currency appreciation on import quantity/price, and the external balance all depend on estimates of trade elasticity. Thursby and Thursby [15] are among the pioneering authors to estimate different specifications of import demand functions. They use five OECD countries as examples to demonstrate how to find an appropriate aggregate import demand function. They conclude that 'RESET and R^2, which are traditionally used to measure goodness of fit of a model, are statistical indicators that may define unbiased and efficient elasticity estimates'. Moreover, Goldstein and Khan [16] present a detailed review of the import demand functions. They cite some relevant contributions to summarize the model's specification, estimation, and inference decision procedures on estimating 'price' and 'income' elasticities. The authors provide detailed decision rules on how to specify an appropriate import demand function based on the methodology of cross-sectional econometrics. Both papers, however, appeared before the innovation of cointegration technique. The authors use all time series data, which falls in the field of nonstationary econometrics. Therefore, the statistical indicators of 'RESET', 'R^2', and t-statistics, for example, are not relevant for choosing an appropriate import demand function. That is why the R^2 is so high in the estimated models cited by the authors.

More recently, Kee et al. [17] used a data set consisting of an unbalanced panel of data imports for 117 countries at the six-digit level of the HS (around 4900 products) for the period 1988–2001. The authors find that the average price elasticity is –3.12, with wide variation across countries and products. Using this price elasticity, researchers can calculate the trade restiveness index, and ultimately the deadweight loss associated with the existing trade regime. Furthermore, Sheldon et al. [18] estimate the effect of exchange rate volatility on fresh fruit in the US market. The authors use import data from 26 exporting countries covering the period 1976–1999. Using the methodology of fixed effect panel estimation, the authors find that the US bilateral fresh fruit trade has been negatively affected by exchange rate uncertainty.

If nonstationary econometrics techniques are not employed, the authors may incorrectly conclude that a relationship exists between an explained variable and regressions even though they have no relationship at all. In other words, if import quantity, price, and income variables contain stochastic time trends, the elasticity estimates will be biased and inefficient. The cointegration technique is important because of the potential existence of unit root in the related data series. The concept of the cointegration test (pioneered by Clive Granger, the 2003 Nobel Laureate in economics) and the unit root test will be elaborated upon in later sections.

More recent studies have attempted to find evidence of a long-term relationship (cointegration) between levels of import volume, import price and income. However, *results of these studies are mixed*. Clarida [19] use the cointegration technique to estimate the US import elasticity of nondurable goods and concludes that US income and price elasticities of imports were 2.20 and –0.94 respectively. Johnston and Chinn [20] find a unique cointegrating relationship within import demand function by excluding agricultural products and fuels for the 1973–95 period in the US, whereas Chinn [21] obtains evidence of a cointegrating relationship only when computers are excluded. Konno and Fukushige [22] estimate the bilateral US–Canada long-run import demand function in aggregate level taking into account the effects of Canada–US Free Trade Agreement. The results show that the free trade agreement made the US sensitive to import prices and insensitive to its domestic income.

Moreover, Dutta and Ahmed [23] estimate the aggregate import demand function for India using cointegration and error correction approaches and come to three conclusions. First, import quantity cointegrated with import price and real GDP. Second, the import quantity was sensitive to real GDP, and insensitive to import price changes. Third, the trade liberalization program had little effect on import volume.

In contrast, Rose and Yellen [24], and Meade [25] failed to find evidence of cointegration in the data for the period 1960–87 in the US. Furthermore, Tang [26] reports no long-run equilibrium relationship among the Japanese aggregate imports, real income and relative price of imports. However, Abbott et al. [27], Giovannetti [28], Mohammed and Tang [29], and others are critical of the aggregate model in that it suffers from aggregation bias and hence may discount the reliability of policy implications. In this paper, we focus on the textile and apparel sector to minimize this bias.

Lau et al. [30] document the export performance of MFA fibers mainly in cottons exported from mainland China and Hong Kong, to the US during 1989–2005. The authors use the cointegration and error correction approach to investigate whether long-run relationships among variables exist. The empirical results suggest that a unique long-run relationship exists among import price and quantity, real income per capita, and trade liberalization. The short-run dynamics of export demand functions were estimated using an error correction model, in which the error correction term was found correctly signed. The present study extends the research interest to ASEAN countries, and in a panel data framework.

Econometrics Methodology

Long-run Import Demand Function

The natural logarithm of the unit price (US$/m2) and quantity (m2) of imports were plotted in Figures 1a and 1b, and readers may have more information on the behavior of the apparel cottons imported from each importing country. Several preliminary observations were made. First, the unit prices of China and Malaysia were generally cheaper in the whole sample period. The unit price decreased substantially after 2002, while the opposite observation was found for Hong Kong and Singapore. Second, before 2002, the import quantity was roughly the same for Hong Kong and mainland China; however, from 2002 onwards mainland China increased its exports substantially and the gap has

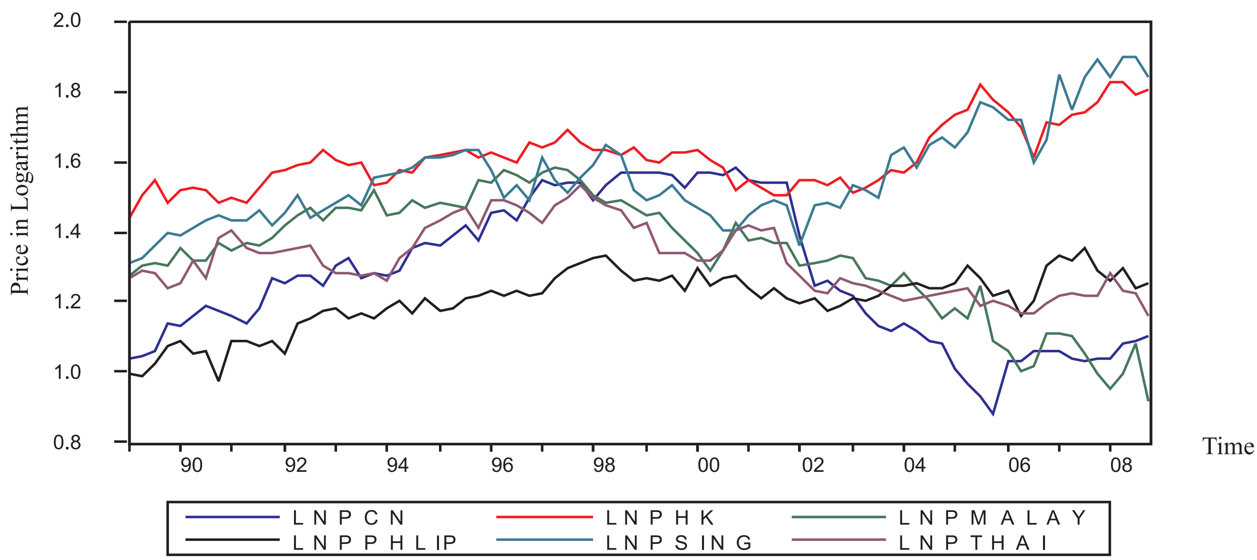

Figure 1a Prices of imports (on a logarithmic scale).

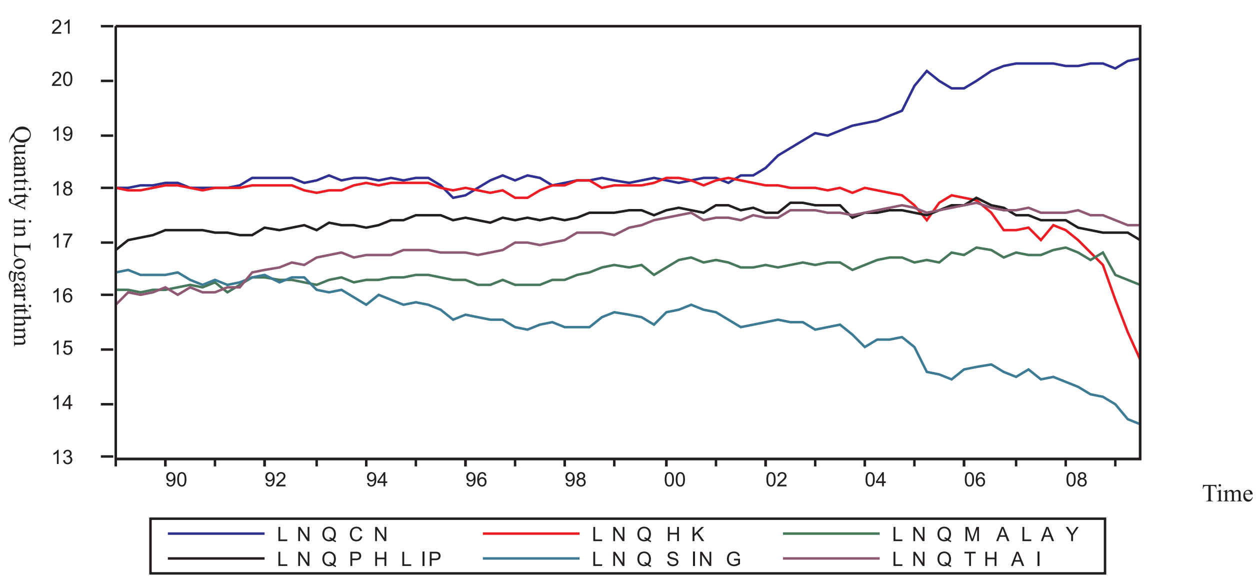

Figure 1b Quantity of imports (on a logarithmic scale).

since further widened. In addition, Singapore's exports decreased substantially after 2002.

These findings are not surprising since Lau et al. [30] apply the Endogenous Break Augmented Dickey–Fuller test of Zivot and Andrews [31], to trace the date on which the structural break of the series would take place in response to shock, like the abolition of MFA quotas. The break date in year 2000 was detected, and it took approximately 1.6–6.5 months for the repercussion of the shock to diminish to half of its initial impulse.

The long-run import demand function of apparel cottons exported to the US for each exporting country:

$$LM_{i,t} = \alpha_{i,0} + \alpha_{i,1}LP_{i,t} + \alpha_{i,2}LGDP_t + \varepsilon_{i,t} \tag{3}$$

where $\alpha_{i,0}$ is the constant intercept term; $\alpha_{i,1}$, the price elasticity; $\alpha_{i,2}$, the income elasticity; $M_{i,t}$ is the import quantity while the lower case i = 1…6 represents exporting countries; $P_{i,t}$ is unit price of apparel cotton imported from mainland China, Hong Kong, and four ASEAN countries; GDP is the nominal GDP per capita of the US; $\varepsilon_{i,t}$ is a random disturbance term with its usual classic assumptions and L the natural logarithm transformation operator.

For each country, we choose the model to ensure that a unique cointegrating relationship exists among price and import quantity. Second, the correct model specification must exhibit the correct sign for price and income elasticity with statistical significance. We believe that when longer time series data was available, a dummy variable for the year 2005 might exhibit the largest effect on import quantity due to the liberalization of 49% of the quota on 1st January 2005.

We expect $\alpha_1 < 0$, $\alpha_2 > 0$. As it is postulated that import volume and import price are negatively related, holding other things constant α_1 is expected to be negative. As the purchasing power of US citizens increases, more MFA items will be imported, subject to other things being constant. Hence, α_2 is expected to be positive. However, it is well known that spurious regression becomes problematic if ordinary least squares (OLS) is used when the time series of LM_{it}, LP_{it}, and $LGDP_t$ are not of the same order of integration. Moreover, if the time series have a unit root, it is necessary to take the first difference of variables in equation (3) to obtain a stationary series:

$$\Delta LM_{i,t} = \alpha_{i,0} + \alpha_{i,1}\Delta LP_{i,t} + \alpha_{i,2}\Delta LGDP_t + \varepsilon_{i,t} \tag{4}$$

For equation (4), Δ is the difference transformation operator; $\alpha_{i,0}$, the constant intercept term; $\alpha_{i,1}$ and $\alpha_{i,2}$ are the estimated coefficients for ΔLP and $\Delta LGDP_t$ respectively. It is to be noted that $\alpha_{i,1}$ and $\alpha_{i,2}$ cannot be viewed as elastic because they are first differenced variables. Maddala [32] argues that 'long-run information' in the data gets ignored in equation (4) once the data is manipulated by taking its first difference. Hence, an error correction (EC) term should be introduced and this is the central idea of cointegration theory. The one period lagged EC term, which integrates the short-run dynamics was introduced in the long-run demand function and equation (4) thus becomes:

$$\Delta LM_{i,t} = \beta_{i,0} + \sum_{j=1}^{j}\beta_{i,j,1}\Delta LM_{i,t-j} + \sum_{j=0}^{j}\beta_{i,j,2}\Delta LP_{i,t-j} + \sum_{j=0}^{j}\beta_{i,j,3}\Delta LGDP_{i,t-j} + \beta_{i,4}EC_{i,t-1} + \varepsilon_{i,t} \tag{5}$$

where $EC_{i,t-1}$ is the one period lagged error-correction term and equation (5) is the error correction model (ECM). The ECM was estimated to determine the short-run dynamic behavior of import demand. Two features of ECM should be mentioned here. First, all variables included in the ECM are stationary and first differenced to avoid superiors outcome. Second, the sign of the $EC_{i,t-1}$ must be negative because the change of import volume can diverge from its long equilibrium in the short-run. However, the error term, $EC_{i,t-1}$ will correct such divergent behavior in the next period once such disequilibrium occurs. This implies that the larger the coefficient ($\beta_{1,4}$) of $EC_{i,t-1}$, the higher would be the speed of convergence toward the equilibrium.

Panel Unit Root Test

Unit root tests can be used to determine whether trending data should be first differenced to render the data stationary. Pretesting for unit roots is generally the first step in cointegration modeling which aims to detect long-run equilibrium relationships among nonstationary time series variables. If the variables in question are I(1), then cointegration techniques can be used to model these long-run relations. Useful surveys on issues associated with unit root testing are given in Stock [33], Maddala and Kim [34], and Phillips and Xiao [35].

Stationarity of a time series can be tested by the augmented Dickey–Fuller (ADF) unit root test pioneered by Dickey and Fuller [36]. They show that under the null hypothesis of a unit root, the ADF statistic does not follow the conventional student's t-distribution; also, they have derived the asymptotic results and simulated critical values for various test and sample sizes. The order of integration of the variables in equation (4) may be determined by applying ADF test. Consider a series at time t,

$$\Delta q_t = \alpha_0 + bq_{t-1} + \sum_{i=1}^{k}\sigma_i\Delta q_{t-i} + \varepsilon_t \tag{6}$$

where q_t can be replaced by time series LM_{it}, LP_{it}, and $LGDP_{it}$, Δq_t is the series of interest in first difference.

Table 1a Panel unit root statistics (unit prices).

	Statistic	Prob.**	Sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin and Chu t-stat	0.12032	0.5479	6	454
Breitung t-stat	2.48998	0.9936	6	448
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	1.25748	0.8957	6	454
ADF – Fisher Chi-square	4.52494	0.972	6	454
PP – Fisher Chi-square	9.50515	0.6593	6	474

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Table 1b Panel unit root statistics (quantity).

	Statistic	Prob.**	Sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin and Chu t-stat	4.07874	1	6	447
Breitung t-stat	4.3921	1	6	441
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	4.50333	1	6	447
ADF – Fisher Chi-square	6.1052	0.9107	6	447
PP – Fisher Chi-square	13.0582	0.3648	6	474

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

$\sum_{i=1}^{k} \sigma_i \Delta q_{t-i}$ is the augmenting term and ε_t the independently and identically distributed (IID) error, that is $\varepsilon_t \sim iid(0,\sigma^2)$. Equation (6) was estimated by the ordinary least square (OLS) technique, and the unit root null hypothesis was rejected when the ADF-statistic was found to be significant for the null: $b = 0$ against the alternative $b < 0$. However, it is well documented in the literature that the ADF test has low power against the stationary alternative. We therefore employ the panel unit root test which can provide more information by combining time (T) and space (N) dimension. These panel unit root tests are advocated by Levin and Lin [37], Im, Pesaran and Shin [38], Maddala and Wu [39], and Taylor and Sarno [40] among others.

The findings presented in Table 1a and 1b show that all variables in this paper are nonstationary. Therefore, cointegration and error correction approaches are appropriate in the coming sections.

Johansen Fisher Panel Cointegration test and ECM

The empirical model that was used in the 1980s was based on the assumption that the variables in these models were stationary. However, the problem is that statistical inference associated with stationary processes is no longer valid if the time series follows nonstationary processes. Granger and Newbold [41] point out that the traditional OLS test may often suggest a statistically significant relationship between variables where none in fact exists. They arrive at this conclusion by generating two independent nonstationary series and regress these series on each other using the traditional OLS. Surprisingly, the coefficient estimated is highly statistically significant despite the fact that the variables in the regression are independent. Subsequently, Engle and Granger [42] considered the problem of testing the null hypothesis of no cointegration between a set of nonstationary variables and provided a rigorous proof for the Granger representation theorem[10].

The term 'cointegration' can be viewed as the statistical expression of the nature of equilibrium relationships. Variables may drift apart in the short-run, but if they diverge without bound, no equilibrium relationship could be said

[10] They won the Nobel Prize in Economics in 2003 for their innovation on the framework of cointegration and error correction.

to have existed. Therefore, economic significance can be defined in terms of testing for equilibrium.

If all series are I(1), the Johansen and Jeuselius [43] cointegration test can be applied to see whether any combinations of the variables in equation (3) are cointegrated. Given a group of nonstationary series, one may be interested in determining whether the series are cointegrated, and if they are, in identifying the cointegrating (long-run equilibrium) relationships. The Vector Auto-Regressive (VAR) based cointegration tests, as developed by Johansen [44, 45], were implemented for the long-run import demand function in equation (3).

Consider a VAR of order p:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + \beta x_t + \varepsilon_t \tag{7}$$

where y_t is a k-vector of nonstationary I(1) variables consisting in this case LM_{it}, LP_{it}, and $LGDP_{it}$; x_t, a vector of deterministic variables; and ε, a vector of innovations.

The VAR can be rewritten as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \beta x_t + \varepsilon_t \tag{8}$$

where $\Pi = \sum_{i=1}^{p} A_i - I$, $\Gamma_i = -\sum_{j=i+1}^{p} A_j$.

Granger's representation theorem asserts that if the coefficient matrix Π has a reduced rank Γ < k, then kxΓ matrices α and β exist, each with rank Γ, such that Π = αβ' and $\beta' y_t$ is I(0). Γ is the number of cointegrating relations (the cointegrating rank) and each column of β is the cointegrating vector. As explained earlier, the elements of α are known as the adjustment parameters in the VEC model. Johansen's method is to estimate the Π matrix from an unrestricted VAR and to test whether one can reject the restrictions imposed by the reduced rank of Π. The empirical findings are presented in Table 2. In the case of a unique cointegrating relationship, equation (5) was estimated to see the short-run dynamic behavior of the import demand function. Empirical findings of ECM are presented in Table 3.

Table 2 Johansen Fisher panel cointegration tests.

Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	22.13	0.0361	23.71	0.0223
At most 1	6.881	0.8654	6.881	0.8654
Individual cross section results				
Cross Section	Trace Test Statistics	Prob.**	Max-Eigen Test Statistics	Prob.**
Hypothesis of no cointegration				
CN	27.3724	0.0323	20.3744	0.0359
HK	22.6377	0.1200	18.1987	0.0737
SING	15.6699	0.5193	13.4201	0.2953
THAI	16.4915	0.4537	11.7949	0.4345
MALAY	13.2006	0.7224	9.8049	0.6397
PHLIP	28.3964	0.0237	20.6416	0.0327
Hypothesis of at most 1 cointegration relationship				
CN	6.9980	0.3447	6.9980	0.3447
HK	4.4390	0.6780	4.4390	0.6780
SING	2.2498	0.9513	2.2498	0.9513
THAI	4.6966	0.6403	4.6966	0.6403
MALAY	3.3957	0.8265	3.3957	0.8265
PHLIP	7.7548	0.2724	7.7548	0.2724

** MacKinnon, Haug, and Michelis (1999) *p*-values. CN, China; HK, Hong Kong; SING, Singapore; THAI, Thailand; MALAY, Malysia; PHLIP, Phillipines.

Table 3 Estimated error-correction model.

Country	China	Hong Kong	Malaysia	Philippines	Singapore	Thailand
Dependent Variable	D(LNQ)	D(LNQ)	D(LNQ)	D(LNQ)	D(LNQ)	D(LNQ)
CointEq1	–0.2806	0.2290	0.0294	–0.0076	0.0044	–0.0109
	[–4.82438]	[4.48194]	[3.23296]	[–0.96402]	[3.20562]	[–1.43713]
D(LNQCN(–1))	0.3080	0.0402	–0.1885	–0.1940	–0.1290	–0.1113
	[3.04879]	[0.27574]	[–1.33822]	[–1.54162]	[–0.91540]	[–0.92840]
D(LNQCN(–2))	–0.1326	–0.1948	–0.1696	0.0241	–0.1354	0.0915
	[–1.28949]	[–1.36885]	[–1.20616]	[0.19369]	[–0.95158]	[0.72751]
D(LNPCN(–1))	0.3232	0.3487	0.1783	0.3772	–0.2363	–0.1452
	[1.21707]	[0.91942]	[0.74592]	[1.52651]	[–0.79481]	[–0.65166]
D(LNPCN(–2))	0.4910	0.4911	–0.1583	0.1911	0.2144	–0.1707
	[1.82813]	[1.23440]	[–0.66231]	[0.70868]	[0.72995]	[–0.74389]
D(LNCCN(–1))	–1.2029	1.0130	2.3001	0.8148	3.7158	2.1246
	[–0.95692]	[0.60215]	[1.94098]	[0.74750]	[2.14924]	[2.20016]
D(LNCCN(–2))	0.8922	–1.1152	4.8323	0.8271	2.9626	1.5850
	[0.71143]	[–0.63149]	[4.06320]	[0.74334]	[1.61631]	[1.66658]
C	0.0269	–0.0458				
	[1.18506]	[–1.40684]				
R-squared	0.3493	0.4559	0.2303	0.1055	0.0960	0.0955

* t-statistics in []. Note: "CointEq1" represents the lagged error term obtained from the long run regression; CN represents China; D denotes the first difference operator; for example D(LNQCN(–1)) means the first difference of one lagged import quantity in logarithm.

Empirical results

Panel Unit root test

Table 1 presents the results for the panel unit root test on variable LM_{it}, LP_{it}, and $LGDP_{it}$. The number of augmenting terms, namely k, was chosen by using Akaike Information Criterion (AIC) as suggested by Elliot, Rothenberg and Stock [46]. The panel unit root tests have shown that all series are nonstationary. The results are along expected lines because the time series dynamics in Figures 1a and 1b do not show mean-reverting properties. Due to the fact that all variables are nonstationary, cointegration techniques can be used to model these long-run relations in the next section.

Johansen Fisher Panel Cointegration test and ECM

Since we will estimate a panel regression in the later stage, we first perform the Johansen Fisher panel cointegration test. It is well known that the asymptotic properties of the estimators in the panel cointegrated regression models are different from those of time series cointegrated regression models, and if the data set is not panel cointegrated, then panel regression or time series regression may generate misleading results.[11]

As suggested by Pesaran and Pesaran [47], a lag of three in level for the Vector Auto-Regressive (VAR) model specification was selected. Table 2 presents the findings for price and quantity in logarithms.[12] The p-value of the maximal eigenvalue test for the null hypothesis of no cointegration (r = 0) among variables is 0.0223, therefore, we reject the null hypothesis of no cointegration (r = 0) and conclude that the results favor the alternative of r = 1 at 5% significant level. As the null hypothesis of $r \leq 1$ cannot be rejected at 5% significant level, we conclude that there exists a unique cointegrating relationship among variables LM_{it}, LP_{it}, and $LGDP_{it}$ in the panel data framework. The trace test also gives strong evidence in support of a unique cointegrating relationship among variables LM_{it}, LP_{it}, and $LGDP_{it}$ at 5% significant level.

[11] For details, see Baltagi [60], Phillips and Moon [61], and Kao and Chiang [62] among others.

[12] We also perform the same testing procedures for price, quantity, and the U.S. per capita income panel data. We find that they also have unique cointegrating relationship but with weaker statistical significance than the relationship between price and quantity.

Estimation of an error-correction model

After confirming that a unique cointegrating relationship existed, we examined the short-run dynamic behavior of the import demand function in equation (5). Three lags for the explanatory variables were selected and of the one period lagged error correction term in the right hand side in equation (5). Table 3 presents the findings. The estimated EC coefficient for China was the most satisfactory and found to have the correct sign. The larger the EC coefficient in absolute values, the higher the speed of convergence of the import volume to the long-run equilibrium. The results in table 3 show that once economic shock occurs, China exhibits the highest speed of convergence to the equilibrium and apparel fibers demonstrate the highest speed of convergence. In mainland China, the EC coefficient was estimated at –0.28, which is statistically significant at 1% level and has the correct sign. The results imply that China is the most competitive because it has a self-adjustment mechanism against external shocks like financial crisis and trade interventions in the long-run.

Impulse Response function

Figures 2a, 2b, 2c, and 2d present the impulse-response functions, which highlight the persistence and impact of one standard deviation shock of price, and GDP per capita on import quantity over a given horizon of 20 years (80 quarters).

Figure 2a examines the price response of Hong Kong and four ASEAN countries to a unit shock in China's change in export volume of MFA items. In response to a unit shock in China's increase in export volume of MFA items (measured as one standard deviation); we can see that it results in an increase of exporting price for Hong

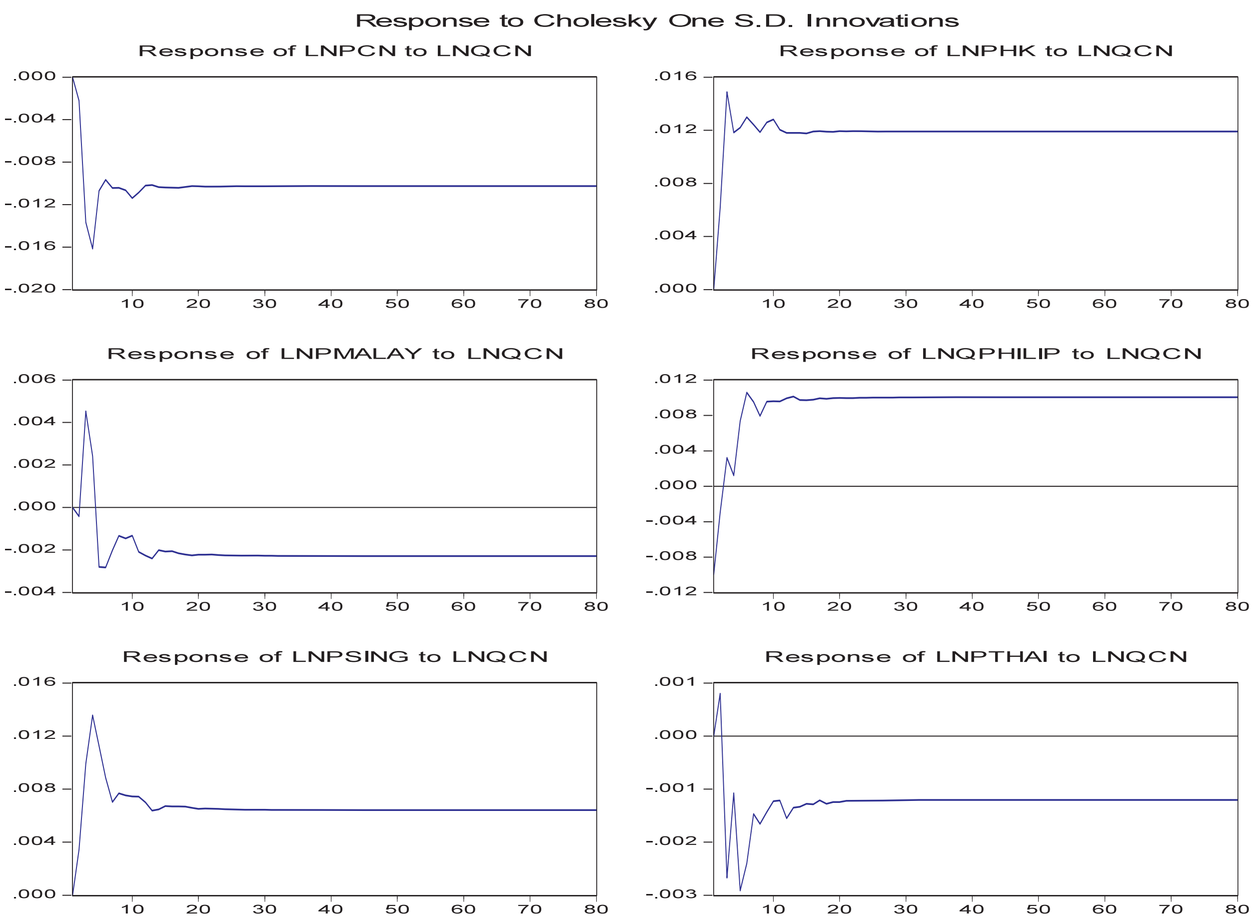

Figure 2a Response of prices to increase in China's export.
Note: Figures in Y-axis multiply 100 proxies percentage change of import price while X-axis denotes the number of quarters. LNPCN denotes import price in logarithm for *China*. LNPHK denotes import price in logarithm for *Hong Kong*. LNPMALAY denotes import price in logarithm for *Malaysia*. LNPPHLIP denotes import price in logarithm for the *Philippines*. LNPSING denotes import price in logarithm for *Singapore*.

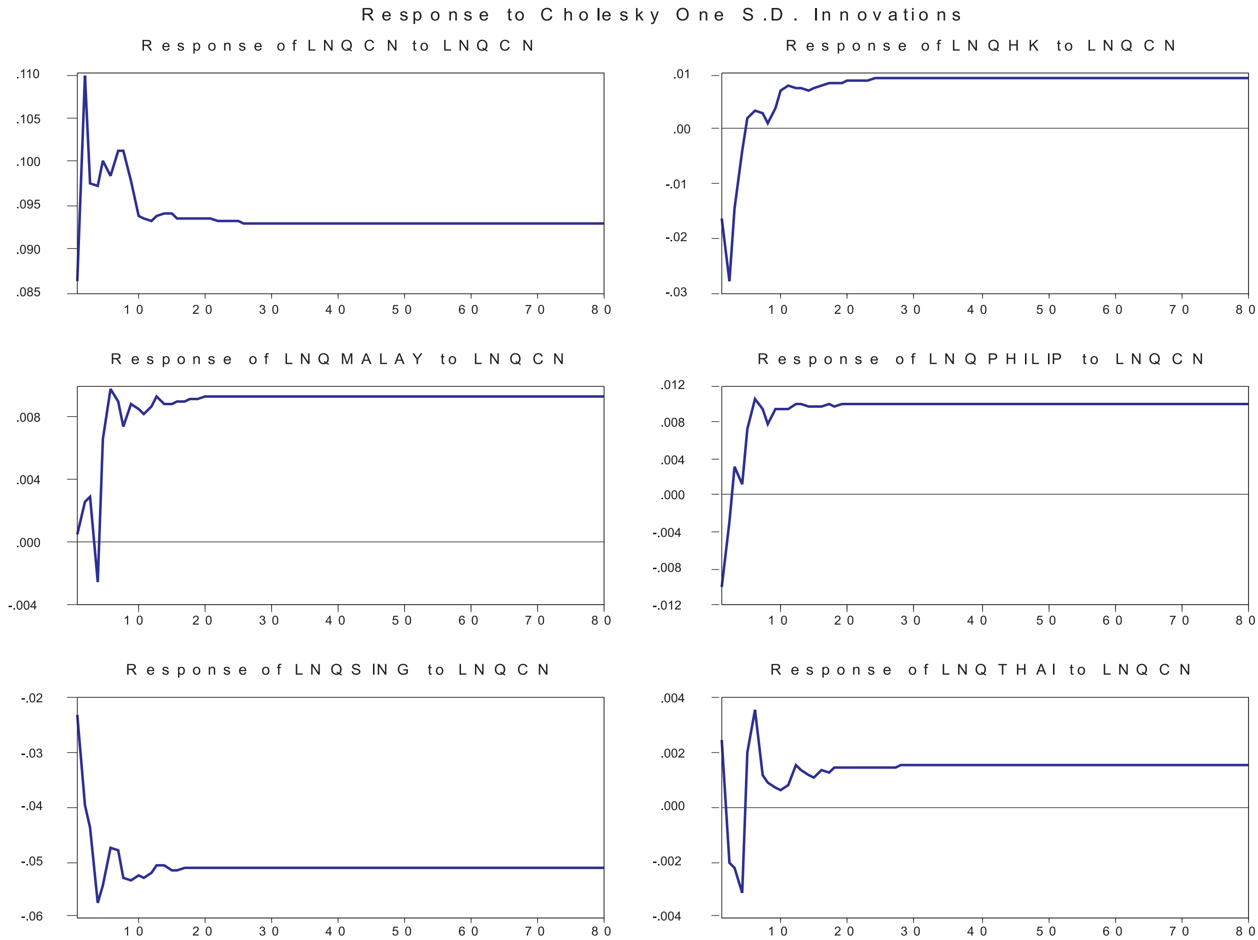

Figure 2b Response of quantities to increase in China's export.

Kong and Singapore, but a decrease in exporting price for other exporting countries.

Figure 2b summarizes the export quantity response of Hong Kong and four ASEAN countries to a unit shock in China's change of export volume. In response to a unit shock in China's change in export volume of MFA items (measured as one standard deviation); we can see that the China's expansion effect is not significant in the long-run. Taking the Philippines as an example in Figure 2b, it is evident that the initial effect of a unit shock of China's export volume (measured as one standard deviation) on import quantity of the Philippines is negative and will have negative impact of 1% on the export volume of the Philippines. However, the subsequent effect of the negative shock eventually disappears by the 10th quarter and remained constant thereafter over the rest of the given horizon.

Figure 2c examines the price response of Hong Kong and four ASEAN countries to a unit shock in China's change in export price of MFA items. Moreover, Figure 2d examines the quantity response of Hong Kong and four ASEAN countries to a unit shock in China's change in export price of MFA items. All the empirical evidence suggests that China's expansion effect on her neighboring countries is insignificant, and therefore will not threaten their survival on the MFA apparel items exporting to the US market.

Long-run price and income elasticity

Table 4 presents the estimates (normalized cointegrating coefficients) for the Johansen cointegration relation such that:

$$LM_{i,t} + \alpha_{i,1}LP_{i,t} + \alpha_{i,2}LGDP_t = I(0) \tag{9}$$

which means that the linear combination of the above variables is stationary.

Rewriting equation (4) one can have:

$$LM_{i,t} = -\alpha_{i,1}LP_{i,t} - \alpha_{i,2}LGDP_t \tag{10}$$

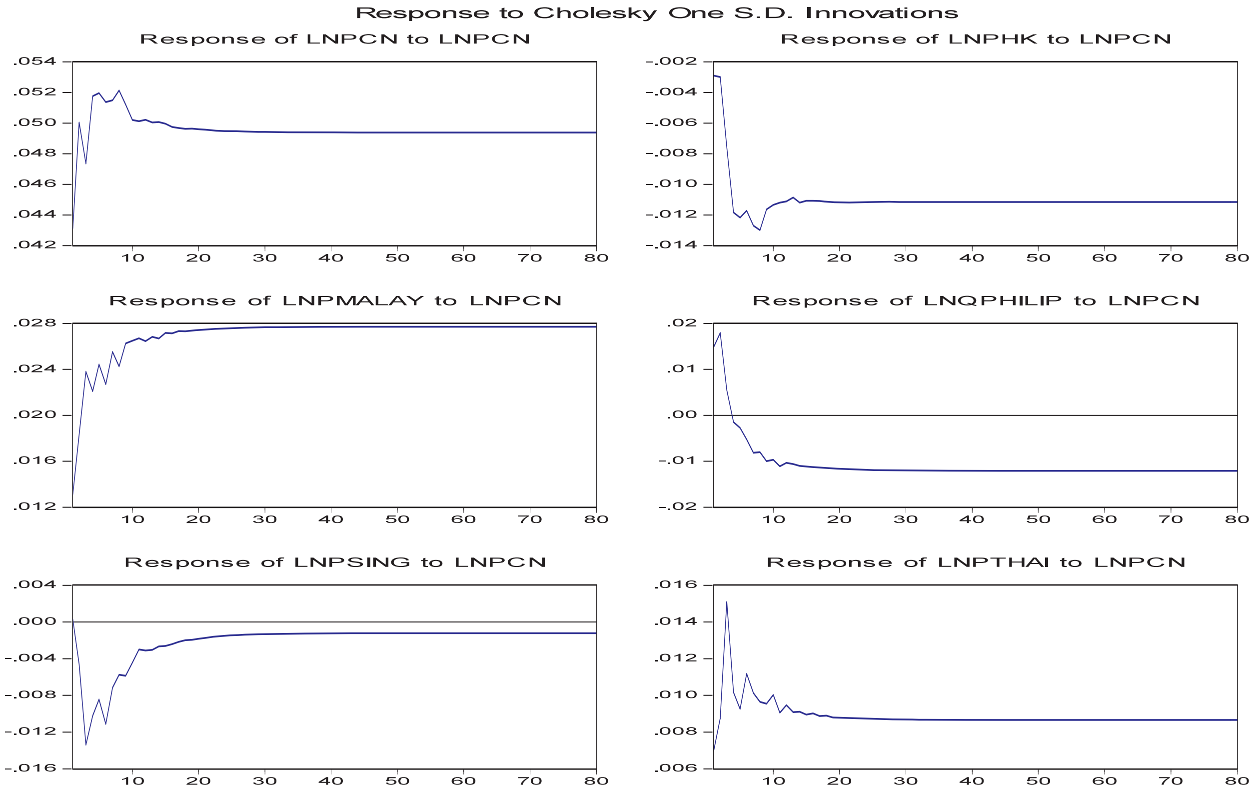

Figure 2c Response of prices to increase in China's export price.
Note: Figures in Y-axis multiply 100 proxies percentage change of import price while X-axis denotes the number of quarters. LNPCN denotes import price in logarithm for *China.* LNPHK denotes import price in logarithm for *Hong Kong.* LNPMALAY denotes import price in logarithm for *Malaysia.* LNPPHLIP denotes import price in logarithm for the *Philippines.* LNPSING denotes import price in logarithm for *Singapore.*

Table 4 Normalized cointegrating coefficients.

Country	China	Hong Kong	Malaysia	Philippines	Singapore	Thailand
Cointegrating Eq:	CointEq1	CointEq1	CointEq1	CointEq1	CointEq1	CointEq1
LNQ(–1)	1	1	1	1	1	1
LNP(–1)	–2.0867	–0.3980	–0.4369	–2.1598	–4.790	0.3088
	[–11.41]	[–0.467]	[– 0.353]	[– 0.636]	[–0.293]	[0.15467]
LNGDP(–1)	2.7887	0.1055	0.2361	0.2691	0.1356	1.1497
	[17.69]	[0.344]	[0.270]	[0.233]	[0.015]	[–1.324]
C	–6.7870	17.4140	16.9566	14.9038	46.4458	2.9390

***** t-statistics in []. Note: "CointEq1" means cointegration equation; C denotes a constant estimate; LNQ(-1) represents the estimate of the one lagged import quantity in logarithm; LNP(-1) represents the estimate of the one lagged import price in logarithm; LNGDP(-1) represents the estimate of the one lagged GDP in U.S. in logarithm.

The restricted price and income elasticity can be represented by α1 and α2 respectively. They all exhibit the correct sign in all MFA items and trading partners except that of Thailand. Taking China as an example, the estimates suggest the following long-run relationship:

$$LM_{t-1} = -6.787 - 2.087 \times LP_{t-1} + 2.789 \times LGDP_{t-1} \quad (11)$$

Estimated equation (10) suggests that the long-run price and income elasticity are highly significant and with the expected sign for China. The long-run price elasticity is –2.087, which

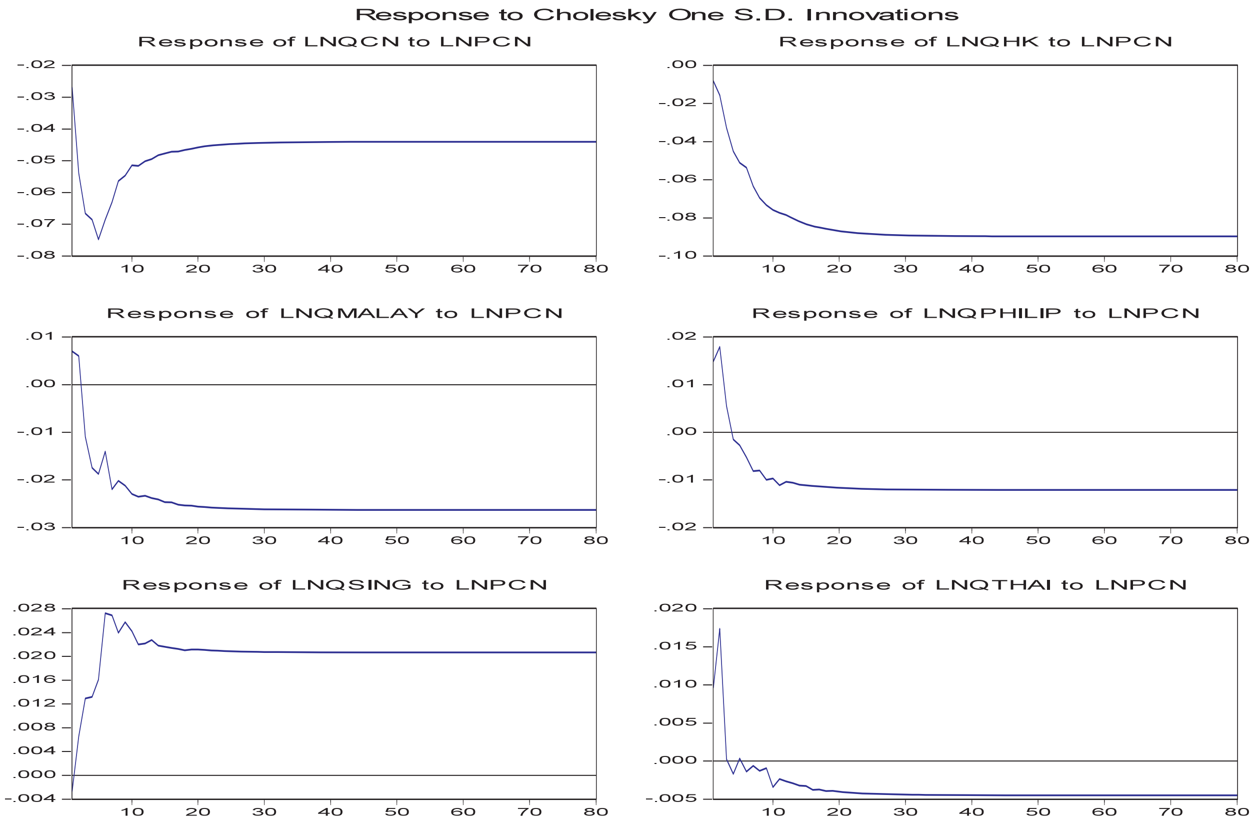

Figure 2d Response of quantities to increase in China's export price.
Note: Figures in Y-axis multiply 100 proxies percentage change of import price while X-axis denotes the number of quarters. LNPCN denotes import price in logarithm for *China*. LNPHK denotes import price in logarithm for *Hong Kong*. LNPMALAY denotes import price in logarithm for *Malaysia*. LNPPHLIP denotes import price in logarithm for the *Philippines*. LNPSING denotes import price in logarithm for *Singapore*.

implies that a reduction of 10% in import prices brings about a 21% rise in imports. The 2.789 long-run income elasticity implies a 10% increase in GDP per capita in the US, which will bring about a 28% rise in imports from China.

Several implications emerge from Table 4 for mainland China. First, income elasticity is elastic for MFA items imported from China, which suggests that an increase of 10% in GDP per capita in the US brings more than a 10% rise in imports. Second, consumers in the US are sensitive to price changes of MFA items imported from China. Since the price elasticity is approximately –2.1, this finding implies that revenue can be increased by cutting price on average, and this is consistent with the authors' observations. The combination of elastic price elasticity and income elasticity suggest that China maintains a competitive position in the US market.

Panel Regression with Fixed Effect

In econometrics the problem of endogeneity occurs once the explanatory variable is correlated with the error term in the regression model because it will provide biased coefficients. Using cross-sectional data for the year 1996, Milgram [48] estimates the impact of MFA abolishment on European apparel imports from 22 countries for 20 categories. The author uses the two stage least squares (2SLS) method to control for an endogeneity bias and finds that the phasing-out of quotas should increase EU imports by 20%. In this paper, the estimation procedure followed here did not suffer from such endogeneity bias, because we find no correlation between explanatory variables and the estimated residuals resulted from the panel regression model. All variables in equation (12) are expressed on a logarithmic scale; a fixed effect model may be constructed as follows:

$$LM_{i,t} = \alpha_{i,0} + \alpha_{i,1}LP_{i,t} + \alpha_{i,2}LGDP_t + \varepsilon_{i,t} \qquad (12)$$

Table 5a Pooled regression.

Independent variable: LNQ

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.8495	0.2408	3.5275	0.0005
LNP_i	–0.7147	0.0998	–7.1649	0.0000
LNGDP	2.6569	0.7120	3.7317	0.0002
$LNQ_i(-1)$	1.0067	0.0042	238.1008	0.0000
LNGDP(–1)	–2.7480	0.7073	–3.8855	0.0001
$LNP_i(-1)$	0.6126	0.1009	6.0727	0.0000
R-squared	0.9933	Durbin-Watson stat		1.7256
Sum squared resid	4.5693			

Note: C denotes a constant estimate; LNQ represents the estimate of the import quantity in logarithm LNQ(-1) represents the estimate of the one lagged import quantity in logarithm; LNP(-1) represents the estimate of the one lagged import price in logarithm; LNGDP(-1) represents the estimate of the one lagged GDP in U.S. in logarithm.

Table 5b Fixed effect regression.

Independent variable: LNQ

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.6041	0.2784	2.1702	0.0305
LNP	–0.6839	0.1008	–6.7817	0.0000
LNGDP	2.3966	0.7242	3.3094	0.0010
LNQ(–1)	1.0223	0.0107	95.4969	0.0000
LNGDP(–1)	–2.4990	0.7184	–3.4788	0.0005
LNP(–1)	0.6414	0.1023	6.2689	0.0000
Fixed Effects (Cross)				
CN—C	–0.0079			
HK—C	–0.0394			
MALAY—C	0.0172			
PHLIP—C	–0.0077			
SING—C	0.0194			
THAI—C	0.0183			
R-squared	0.9934	Durbin-Watson		1.7726
Sum squared resid	4.4877			

Note: C denotes a constant estimate; LNQ represents the estimate of the import quantity in logarithm LNQ(-1) represents the estimate of the one lagged import quantity in logarithm; LNP(-1) represents the estimate of the one lagged import price in logarithm; LNGDP(-1) represents the estimate of the one lagged GDP in U.S. in logarithm. CN denotes China; HK denotes Hong Kong; ALAY denotes Malaysia; PHLIP denotes the Philippines; SING denotes Singapore; THAI; denotes Thailand. For example THAI-C means the constant estimate for Thailand.

α_i captures all unobserved time-constant factors that affect LP_{it}, and $LGDP_{it}$. α_i is called the unobserved effect or simply fixed effects and it does not change over time. Geographical features, such as the country's location, can be included in α_i. Many other factors may not be exactly constant, but they might be roughly constant in the short-run. The model is called the fixed effect model. ε_{it} is the idiosyncratic error or time-varying error, because it represents unobserved factors that change over time, and affect explanatory variables. Alternatively, we may construct a random effect model as follows:

Table 5c Random effect regression.

Independent variable: lnQ

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.800001	0.247674	3.23006	0.0013
LNP	–0.70526	0.099865	–7.06215	0
LNC	2.597854	0.712803	3.644561	0.0003
LNQ(–1)	1.009524	0.005938	170.0071	0
LNGDP(–1)	–2.69101	0.707885	–3.80148	0.0002
LNP(–1)	0.617839	0.100987	6.118025	0
Random Effects (Cross)				
CN—C	0.003986			
HK—C	–0.01197			
MALAY—C	0.003376			
PHLIP—C	–0.00728			
SING—C	0.003709			
THAI—C	0.008187			
R-squared	0.987812	Durbin-Watson stat		1.74185
Sum squared resid	0.987687			

Note: C denotes a constant estimate; LNQ represents the estimate of the import quantity in logarithm LNQ(-1) represents the estimate of the one lagged import quantity in logarithm; LNP(-1) represents the estimate of the one lagged import price in logarithm; LNGDP(-1) represents the estimate of the one lagged GDP in U.S. in logarithm. CN denotes China; HK denotes Hong Kong; ALAY denotes Malaysia; PHLIP denotes the Philippines; SING denotes Singapore; THAI; denotes Thailand. For example THAI-C means the constant estimate for Thailand.

$$LM_{i,t} = \alpha_{i,0} + \alpha_{i,1}LP_{i,t} + \alpha_{i,2}LGDP_t + \mu_{i,t} \tag{13}$$

where the error term, $\mu_{i,t}$ belongs to the i^{th} individual country and is assumed to be constant through the whole sample period.

However, in our import demand function, there is no fixed effect because the export volume should be zero for every exporting country if the export price is zero or the US per capita income is zero. Table 5a, 5b, and 5c present estimation results for pooled regression, fixed effect panel regression, and random effect regression respectively. Essentially, we need to determine between fixed and random effect by running a 'Hausman specification test' as suggested by Hausman [49]. Normally, fixed effect is reasonable to deal with in panel data because it always gives consistent results, however, random effect is a more efficient estimator, so we should run random effects if it is statistically justifiable to do so. The 'Hausman test' checks a more efficient model against a less efficient but consistent model to make sure that the more efficient model also gives consistent results. The chi-square statistics of the 'Hausman test' is 2.78, suggesting that random effect modeling is appropriate as expected. The result suggests that random effect is the appropriate model; it shows that all variables are significant at 5% level. The results also imply that MFA apparel imports will, on average increase 26% as induced by 10% increase in the US's per capita GDP, whereas with a 10% increase/decrease of exporting price there is 7.5% decrease/increase in imports.

Conclusions

This paper provides the most comprehensive and disaggregated set of elasticity estimates to date in the face of MFA abolishment. The estimates made here are at a detailed level of disaggregation and should provide researchers with opportunities for future analysis. In the empirical examination of the MFA apparel items exported to the US from mainland China, Hong Kong, and ASEAN countries during the period of 1989–2009, we apply cointegration and error correction approaches to the US's import demand function for textile items. Several puzzles on the elimination of MFA have been solved. First is the extraction of a unique long-run equilibrium relationship among import quantity demanded, imported price, and the US GDP per capita. This suggests that the existing trade mechanism is capable of ensuring long-run equilibrium of imported quantity, price, and consumer's income.

Second, the long-run price and income elasticity are found to be significant with expected signs, which are important for most trade-policy analyses. In general, MFA abolishment benefits Chinese textile exports; along with elastic price and income elasticity, it is expected that Chinese firms would earn more revenue in the long-run. The imported price of MFA items is subject to downward pressure owing to intensified competition from developing countries after the abolishment of MFA. However, the price elasticity is generally elastic which implies that a 1% decrease in unit price will bring more than a 1% increase in import volume. This, in turn implies that total revenue will increase, given that other things remain constant. Moreover, high-income elasticity also implies that textile items are quite competitive at the current price level.

Third, our research indicates that Chinese textile firms react quicker to trade disturbances. An Error Correction Model was estimated to determine the short-run dynamics around the equilibrium relationship. By impulse response function, we find that the expansion of Chinese MFA items do not threaten the survival of its neighboring countries, because the negative impact of China's emergence is only temporary and insignificant. However, challenges remain in determining elasticity estimates and more advanced models, like those of *Markov regime switching models* (MRS), should be used to endogenize the effect of trade liberalization in future research.

On the other hand, we compare our study with a similar study conducted by Vlontzos and Duquenne [50]. Their study focuses on the determinants of Chinese cotton imports. Vlontzos and Duquenne [50] investigate the determinants of Chinese cotton imports using a gravity equation. Their data set covers 41 trade partners of China and 13 years from 1993 to 2005. The authors find that GDP per capita has no effect on cotton import, and hence conclude that it is difficult to apply the gravity model to these specific trade flows of Chinese cotton imports from other countries. However, we suspect that the incredibility of their model is due to failure of checking for stationary and co-movement among variables in advance to model estimation.

Moreover, our study is comparable with a similar study conducted by Danzinger et al. [51] for Turkish manufacturing industries in terms of econometrics technique. This study examines the determinants of sixteen trade flows from Turkey to the EU based on panel data from the period 1988 to 2002. The authors use the methodology of an extended gravity model with panel data. With regard to the textile and apparel industry, the authors confirm the hypothesis that China should be treated as a serious competitor with Turkish textile exporters. They further find that the price and income elasticity is statistically significant, and with corrected sign. In particular, a 10% improvement in Chinese price competitiveness could lead to a significant deterioration of Turkish exports in the range of 2.1 to 8.7%.

Furthermore, Bilgin and Karabulut [52] analyze the impact of the ATC on Turkish textile and apparel exports for the period of January 2003–September 2006 by using a Chow test method. The authors try to understand if there were any structural changes for the Turkish textile and apparel industry export performance for the period of the last stage of ATC. According to their estimation results, the ATC created serious problems in the Turkish textile and apparel industry. In fact, it led to a negative structural change in the Turkish textile industry. However, the estimation results indicate that there has not been corresponding structural change in the Turkish apparel industry export performance due to last stage of the ATC.

Many studies show that China is a major beneficiary of the *post-quota* era. In fact, from 2004 to 2005, China's share of growth of apparel exports was 74.6% and of textile exports was 100.5% [2]. In this period, however, China also experienced some disadvantages. As Nordås [6] mentions, 'other developing countries are catching up with China in terms of unit labor costs in the apparel sector and China has of yet not shown competitive strength in the design and fashion segments of the markets'. Furthermore, Delpeuch [53] states that, following the phase-out of the ATC, the EU and the US have implemented new restrictions on textile and apparel imports from China. In fact, 'available data suggests that the shortfall thus imposed on China, in terms of textile exports to the EU and to the US, is significant' [53]. The implications from those studies suggest that non-price competitiveness is also important for the sustained growth of Chinese textile and apparel firms. Therefore, further research should be conducted to investigate the perceived factors of competitiveness for Chinese textile and apparel firms.

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