PANEL DATA ECONOMETRIC MODELS: THEORY AND APPLICATION

A Dissertation

by

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ABSTRACT

This dissertation contains two essays studying panel data econometric models. First, we consider the problem of estimating a nonparametric panel data models with fixed effects. We propose using the profile least squares method to concentrate out the fixed effects and then estimate the unknown function by the kernel method. We show that our proposed estimator is consistent and has an asymptotically normal distribution. Monte Carlo simulations show that our proposed estimator performs well compared with several existing estimators.

Second, we study the effects of Hong Kong's fixed exchange rate against U.S. dollar using a novel panel data method. After the 1997 Asian Financial Crisis, many of the Asia countries adopted flexible exchange rate policies while Hong Kong still keeps its fixed exchange rate. By comparing Hong Kong versus its major trading partners, we show that if like other Asian countries, Hong Kong had adopted a float exchange rate policy in October 1998, Hong Kong's (counterfactual) total value of exports would increase by 14.65 %. Similarly, Hong Kong's total value of imports would increase about 31%. We conclude that Hong Kong dollar is overvalued by 9.34% due to its fixed exchange rate policy.

To my parents and my husband

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1. INTRODUCTION

In this thesis, we first consider the problem of estimating a nonparametric panel data models with fixed effects. Panel data records information on each individual unit over time, the rich information contained in panel data allows researchers to estimate complex models and answer questions that may not be possible using time series or cross sectional data alone. As a result of the increased availability of panel data, longitudinal data analysis becomes a popular subject of theoretical and applied study. Arellano (2003), Baltagi (2005) and Hsiao (2003) provided excellent overviews of parametric panel data model analysis. The early literatures on nonparametric estimation of panel models focused on semiparametric and nonparametric estimation of *random effects* models, see Li and Stengos (1996) and Lin and Carroll (2001), among others. However, most economists believe that it is more likely that the correlation between the individual effects and the regressors follows an unknown pattern. If that is the case, one should specify the true model as a *fixed effects* model rather than a *random effects* model.

Second, we study the effects of Hong Kong's fixed exchange rate against U.S. dollar using a novel panel data method. The Asian Financial Crisis began in July 1997, when China just resumed soverei-gnty of Hong Kong. Indonesia, Republic of Korea (hereafter, Korea), Thailand, Malaysia, Philippines and Hong Kong were affected by the Asian Financial Crisis. Before 1999, aforementioned countries have changed their exchange rate policy, except for Hong Kong. We examine (I) the effects of switching Hong Kong's exchange rate policy on Hong Kong's external trade, and (II) the overvaluation of Hong Kong dollar. For part (I), there is numerous factors affects external trade. And these factors are hard to control for. Hsiao, Ching and Wan (2011;

henceforth, HCW) proposed a simple-to-implement panel data method to construct a counterfactual to measure the treatment effects, without identifying variations in other factors. Motivated by HCW's method, we use external trade for other countries to control for the potential changes in those of Hong Kong. By regressing the treatment group with the control groups before the exchange rate policy change, we estimate the hypothetical external trade under a float Hong Kong exchange rate policy using those of the control group. Comparing the hypothetical value with the actual value, we can identify the changes in Hong Kong's import/export prices. Using purchasing power parity (PPP), we evaluate the changes in Hong Kong's exchange rate to measure whether Hong Kong dollar is overvalued under its fixed exchange rate policy as part (II).

2. NONPARAMETRIC ESTIMATION OF FIXED EFFECTS PANEL DATA MODELS

2.1 Introduction

Panel data records information on each individual unit over time, the rich information contained in panel data allows researchers to estimate complex models and answer questions that may not be possible using time series or cross sectional data alone. As a result of the increased availability of panel data, longitudinal data analysis becomes a popular subject of theoretical and applied study. Arellano (2003), Baltagi (2005) and Hsiao (2003) provided excellent overviews of parametric panel data model analysis. The early literatures on nonparametric estimation of panel models focused on semiparametric and nonparametric estimation of *random effects* models, see Li and Stengos (1996) and Lin and Carroll (2001), among others. However, most economists believe that it is more likely that the correlation between the individual effects and the regressors follows an unknown pattern. If that is the case, one should specify the true model as a *fixed effects* model rather than a *random effects* model.

There are various estimation methods for estimating a fixed effects nonparametric panel data model. We describe five estimation methods which can be classified into two approaches. Three of the methods are based on the first difference approach which removes the fixed effects completely and estimates the nonparametric component by kernel method. The remaining two methods, along with our proposed method, use profile least square method to (asymptotically) concentrate out the fixed effect and estimate the nonparametric component by kernel method.

Herderson, Carroll and Li (2008; henceforth, HCL) introduced an iterative nonparametric kernel estimator assuming large n and fixed T, and derived the rate of convergence of their estimator. One important advantage of HCL's estimator and other estimators based on first differencing method is that they all completely remove the fixed effect parameter. However, HCL failed to obtain asymptotic distribution results of their estimator due to the complication of iterative estimation procedure.

Qian and Wang (2012) proposed to estimate the nonparametric component by marginal integration method assuming fixed T and large n. One problem of marginal integration method is that it is computational very costly. To evaluate a marginal integration based estimator, one must compute $(nT)^2$ regression, each of which requires $O(nTh_1...h_q)$ operations, where h_s is the bandwidth associated with the sth component of the covariate in the nonparametric regression model. Thus, the marginal integration estimator takes $O((nT)^3h_1...h_q)$ operations to compute.

Kim, Linton and Hengartner (1999; henceforth, KLH) proposed an estimator that is computationally more efficient than the marginal integration based estimator by exploiting conditional density estimation from the marginal integration estimator proposed by Linton and Nielsen (1995). This estimator is computationally less costly than a marginal integration based estimator. However, the simulation results reported in section 2.4 suggests that this estimator is less efficient than our proposed estimator.

Su and Ullah (2006; henceforth, SU) proposed a local linear kernel estimator based on a partial linear nonparametric panel data model with fixed effect. With fixed T and large n, they derived the asymptotic distribution of their proposed estimator by imposing a strong identification condition, namely, that $\sum_{i=1}^{n} \mu_i = 0$, where $\{\mu_i\}$ are the unobserved individual fixed effects. In this chapter we replace the strong identification condition of Su and Ullah (2006) by a much weaker condition that $E(\mu_i) = 0$. We derive the asymptotic distribution of our proposed estimator under this weak identification condition.

Li and Sun (2011; henceforth, LS) proposed a local constant kernel estimator using nonparametric least squares dummy variables (LSDV) method requiring large n and large T. However, their estimator has large estimation errors when T is small. This is because their estimator is near singular when T is small. This problem is indeed revealed by the simulation results reported in section 2.4. In contrast, our proposed estimator does not suffer the near singular problem when T is small as we will show in section 2.2.

In this chapter we proposed an alternative estimator in the spirit of Li and Sun (2011). The main contribution of our chapter is that our estimator does not suffer the near singular problem when T is small. For example, the simulation results reported in section 2.4 show that when $T = 2$, Li and Sun's (2011) estimator's estimation mean squared errors does not decrease as n increases from 200 to 500, while our proposed estimator's estimation mean squared errors is halved when n increases from 200 to 500.

The remaining parts of the chapter are organized as follows. We introduce the model and our estimator in section 2.2. We develop the limiting distribution of the proposed estimator in Section 2.3. Section 2.4 reports Monte Carlo simulation results to compare the performance of our proposed estimator with some of the existing estimators. We conclude the chapter in Section 2.5. Mathematical proofs are postponed to the Appendix.

2.2 Model and Estimation Method

We consider the following nonparametric fixed effects panel data model

$$Y_{it} = m(X_{it}) + \mu_i + \nu_{it}, \qquad i = 1, ..., n;\ t = 1, ..., T \tag{2.2.1}$$

where $X_{it} \in \mathbb{R}^q$ $(q \geq 1)$, and Y_{it}, μ_i, and ν_{it} are all scalars. $m(\cdot)$ is an unknown smooth function. For the nonparametric fixed effects model (2.2.1), as in Li and Sun (2011), we allow $E\left(\mu_i | X_{it,1}, ..., X_{it,q}\right) \neq 0$.

Rewriting model (2.2.1) in a matrix form gives

$$Y = m(X) + D_0\mu + V,$$

where $m(X) = [m(X_1), m(X_2), \ldots, m(X_n)]'$ with $m(X_i) = [m(X_{i1}), \ldots, m(X_{iT})]'$ for $i = 1, 2, \ldots, n$. Y and V are similarly defined. $\mu = [\mu_1, \mu_2, \ldots, \mu_n]'$. $D_0 = I_n \otimes \iota_T$ is an nT by n matrix, '$\otimes$' denotes the Kronecker product, I_n denotes the identity matrix of dimension n, ι_T denotes a $T \times 1$ column vector of ones, and A' denotes the transpose of the matrix A.

To estimate the unknown function $m(x)$, we will use the profile least squares method - an extremely powerful method in the estimation of nonparametric/semi-parametric models in statistics. Specifically, we treat the fixed effects as unknown parameters and estimate $m(\cdot)$ as a function of these unknown parameters. Substituting the estimated nonparametric function into a least-square type objective function to minimize the objective function over the fixed effects parameters, we obtain an expression of the fixed effect parameters in terms of nonparametric regression function. Finally, replacing the fixed effects parameters by the function obtained in the previous step yields the consistent estimator for $m(\cdot)$.

For any given value of μ, we estimate the unknown function $m(x)$ by (x is an interior point in the support of X)

$$m_\mu(x) = \arg\min_{m \in \mathbb{R}} [Y - \iota_{nT} m(x) - D_0\mu]' K_h(x) [Y - \iota_{nT} m(x) - D_0\mu], \qquad (2.2.2)$$

where $K_h(x) = \text{diag}\{K_h(X_{11}, x), \cdots, K_h(X_{1T}, x), K_h(X_{21}, x), \cdots, K_h(X_{nT}, x)\}$ is an $nT \times nT$ diagonal matrix, $K_h(X_{it}, x) = \prod_{s=1}^{q} h_s^{-1} k((X_{it,s} - x_s)/h_s)$ is the product kernel function, and $k(\cdot)$ is the univariate kernel function.

Taking derivatives of the objective function in equation (2.2.2) with respect to $m(x)$ gives

$$\iota'_{nT} K_h(x)[Y - \iota_{nT}\tilde{m}(x) - D_0\mu] = 0.$$

Rearranging terms in the above equation and solve for $\tilde{m}(x)$ yields

$$\begin{aligned} \tilde{m}_\mu(x) &= \left[\iota'_{nT} K_h(x) \iota_{nT}\right]^{-1} \iota'_{nT} K_h(x)[Y - D_0\mu] \\ &= \frac{\sum_{i=1}^{n}\sum_{t=1}^{T}(y_{it} - \mu_i) K_h(X_{it}, x)}{\sum_{i=1}^{n}\sum_{t=1}^{T} K_h(X_{it}, x)}. \end{aligned} \tag{2.2.3}$$

Note that $\tilde{m}_\mu(x)$ defined in equation (2.2.3) is not feasible because $\{\mu_i\}$ is unobservable. Next, we estimate the fixed effects vector μ by

$$\widehat{\mu} = \arg\min_{\mu}(Y - D_0\mu - \tilde{m}_\mu(X))'(Y - D_0\mu - \tilde{m}_\mu(X)), \tag{2.2.4}$$

where $\tilde{m}_\mu(X) = [\tilde{m}_\mu(x_{11}), \ldots, \tilde{m}_\mu(x_{nT})]'$ is defined in equation (2.2.3). Equation (2.2.4) shows that $\widehat{\mu}$ is a standard least-squares dummy variables (LSDV) estimator of μ when $m(x)$ is replaced by $\tilde{m}_\mu(x)$ defined in equation (2.2.3).

Substituting equation (2.2.3) into equation (2.2.4), we obtain

$$\widehat{\mu} = \arg\min_{\mu}(Y - D_0\mu)' P (Y - D_0\mu), \tag{2.2.5}$$

where $P = [I_{nT} - S]'[I_{nT} - S]$ with $S = (s_h(x_{11}), \ldots, s_h(x_{nT}))'$ being an $nT \times nT$ matrix. Each argument of S is an $nT \times 1$ vector of $s_h(x)' = \left[\iota'_{nT} K_h(x)\iota_{nT}\right]^{-1} \iota'_{nT} K_h(x)$. From equation (2.2.5) one may conclude that $\widehat{\mu} = [D_0' P D_0]^{-1} D_0' P Y$, but this estimator is not feasible since $D_0'PD_0$ is singular. We need to replace D_0 by another matrix D such that D removes the unobserved fixed effects asymptotically and $D'PD$ is non-singular. Following the practice in Su and Ullah (2006), Li and Sun (2011) and Sun, Carroll and Li (2009), we use $D\widehat{\mu}$ to replace $D_0\mu$, where $D = [-\iota_{n-1}\ \ I_{n-1}]' \otimes \iota_T$ is an $nT \times (n-1)$ matrix. Then $D\hat{\mu} = (\hat{\mu}_1, \tilde{\mu}')'$ with $\hat{\mu}_1 = -\sum_{i=2}^{n} \hat{\mu}_i$, and

$$\tilde{\mu} \equiv (\widehat{\mu}_2, \ldots, \widehat{\mu}_n)' = \left[D'PD\right]^{-1} D'PY.$$

Replacing $D_0\mu$ in equation (2.2.3) by $D\widehat{\mu}$, we obtain a feasible estimator of $m(x)$ given by

$$\widehat{m}(x) = s_h(x)'MY \equiv \left[\iota_{nT}' K_h(x)\iota_{nT}\right]^{-1} \iota_{nT}' K_h(x) MY, \tag{2.2.6}$$

where $M = I_{nT} - D[D'PD]^{-1}D'P$.

From equation (2.2.6) we see that our estimator requires the inverse of $\iota_{nT}' K_h(x)\iota_{nT} = \sum_{i=1}^{n}\sum_{t=1}^{T} K_h(X_{it}, x)$. Even when $T = 2$, as long as n is large, $\sum_{i=1}^{n}\sum_{t=1}^{T} K_h(X_{it}, x)$ will be positive[1] (with probability one) so that unlike Li and Sun's (2011) estimator, our estimator does not suffer the near singular problem when T is small.

We derive the asymptotic distribution of $\widehat{m}(x)$ in the next section.

2.3 Asymptotic Distribution for the Estimator

In order to derive the asymptotic distribution of $\widehat{m}(x)$, we fisrt list some regularity conditions and definitions.

(A1) (Y_i, X_i) are independently and identically distributed (i.i.d.) continuous random variables, where $Y_i = (Y_{i1}, \ldots, Y_{iT})'$ and $X_i = (X_{i1}, \ldots, X_{iT})'$. X_{it} is a strictly stationary α-mixing process with mixing coefficients $\alpha_k = O\left(k^{-(\delta+2)/\delta}\right)$

[1] This is because $(nT)^{-1}\sum_{i=1}^{n}\sum_{t=1}^{T} K_h(X_{it}, x) \overset{a.s.}{\to} f(x) > 0$, where $f(x)$ is the density function of X_{it} evaluated at $X_{it} = x$.

and $E\left(\|X_{it}\|^{2+\delta'}\right) < \infty$ for some $\delta' > \delta > 0$. Let $f(x)$ denote the density function of X_{it} and $f_{t,s}(x_1, x_2) = f_{t,s}(X_{it} = x_1, X_{is} = x_2)$ denote the joint density function of (X_{it}, X_{is}). Let $\mathcal{S}$ denote the support of X_{it}; then, $f(x) > 0$ at any interior point $x \in \mathcal{S}$. $m(x)$, $f(x)$, and $f_{t,s}(x_1, x_2)$ are all twice continuously differentiable in the neighborhood of $x \in \mathcal{S}$. X, the $nT \times q$ matrix defined in equation (2.2.1), has full rank q.

(A2) The unobserved fixed effects μ_i are i.i.d., with $E(\mu_i) = 0$, $E(\mu_i^2) = \sigma_\mu^2 > 0$, and $E(\mu_i|X_{it}) \neq 0$. The idiosyncratic errors $\{\nu_{it}\}$ are i.i.d. across all i and t and $E(\nu_{it}|\{(\mu_i, X_{it})\}) = 0$, $E(\nu_{it}^2|\{(\mu_i, X_{it})\}) = \sigma_v^2$, and $E\left(|\nu_{it}|^{2+\delta'}|\{(\mu_i, X_{it})\}\right) < \infty$ for all i and t.

(A3) The product kernel function is $K(u) = \prod_{s=1}^{q} k(u_s)$, where the univariate kernel function $k(\cdot)$ is a bounded, symmetric (around zero) probability density function with compact support on $\mathbb{R}$.

(A4) As $n \to \infty$ and $T \to \infty$, $h_j \to 0$ for all $j = 1, 2, \cdots, q$, $nTh_1...h_q \to \infty$, and $\sqrt{nTh_1...h_q}\sum_{j=1}^{q} h_j^2 = O(1)$.

(A5) As $n \to \infty$ and $T \to \infty$, $h_j \to 0$ for all $j = 1, 2, \cdots, q$, $nTh_1...h_q \to \infty$ and $n\sum_{j=1}^{q} h_j^4 = O(1)$.

The above assumptions are quite standard and are commonly seen in the literature on nonparametric estimation. The conditional homoskedastic error Assumption A2 can be relaxed to allow for conditional heteroskedasticity. Assumption A4 is satisfied when one chooses bandwidths $h_1, ..., h_q$ by the least squares cross-validation method.

We present the limiting distribution of $\widehat{m}(x)$ below and delay the proofs to the Appendix.

THEOREM 2.3.1. *Define* $\zeta_0 = \int K(v)^2 dv$ *and* $B_h(x) = \kappa_2 \sum_{s=1}^{q} h_s^2 [m_s(x) f_s(x) / f(x) + \frac{1}{2} m_{ss}(x)]$, *where* $m_s(x) = \frac{\partial m(x)}{\partial x_s}$, $m_{ss}(x) = \frac{\partial^2 m(x)}{\partial x_s^2}$, $f_s(x) = \frac{\partial f(x)}{\partial x_s}$ *and* $\kappa_2 = \int k(v) v^2 dv$. *Then at an interior point* $x \in \mathcal{S}$, *the limiting distribution of* $\widehat{m}(x)$ *depends on the behavior of* $Th_1 ... h_q$ *and are given as follows.*

1. *Under Assumptions A1-A4, when* $Th_1...h_q \to 0$,

$$\sqrt{nTh_1...h_q}\left[\widehat{m}(x) - m(x) - B_h(x)\right] \xrightarrow{d} N\left(0, \frac{\zeta_0 \sigma_v^2}{f(x)}\right).$$

2. *Under Assumptions A1-A4, when* $Th_1...h_q \to a_0$, *where* a_0 *is some constant,*

$$\sqrt{nTh_1...h_q}\left[\widehat{m}(x) - m(x) - B_h(x)\right] \xrightarrow{d} N\left(0, a_0 \sigma_\mu^2 + \frac{\zeta_0 \sigma_v^2}{f(x)}\right).$$

3. *Under Assumptions A1-A3 and A5, when* $Th_1...h_q \to \infty$,

$$\sqrt{n}\left[\widehat{m}(x) - m(x) - B_h(x)\right] \xrightarrow{d} N\left(0, \sigma_\mu^2\right).$$

Theorem 2.3.1 requires that both n and T are large. For the case of large n and a fixed value of T, deriving the asymptotic distribution of $\widehat{m}(x)$ is a challenging task. However, Monte Carlo Simulations show that our estimator performances well when T is small.

It may seem that the above asymptotic result of our estimator is similar to that of Li and Sun (2011). However, there is a major difference between our proposed estimator and the estimator of Li and Sun (2011). It can be shown, after some simplifications, that Li and Sun's estimator (Li and Sun, 2011, p.18) can be represented by

$$\widehat{m}_{LS}(x) = \frac{1}{n} \sum_{i=1}^{n} \frac{\sum_{t=1}^{T} K_h(X_{it}, x) y_{it}}{\sum_{t=1}^{T} K_h(X_{it}, x)}. \tag{2.3.1}$$

From equation (2.3.1), we can see that when T is small, say $T = 2$, there is a high chance that the denominator $\sum_{t=1}^{2} K_h(X_{it}, x) = K_h(X_{i1}, x) + K_h(X_{i2}, x)$ is zero (or near zero) for some i, which leads to a large value of $\widehat{m}_{LS}(x)$. Consequently, Li and Sun's estimator can yield a large estimation mean squared error when T is small. Our estimator does not suffer this problem as the denominator of our estimator is in the form of $(nT)^{-1} \sum_{i=1}^{n} \sum_{t=1}^{T} K_h(X_{it}, x)$, which converges to $f(x) > 0$ as long as n is large for any value of T. The simulations reported in section 2.4 confirms our above analysis, i.e., the simulations show that Li and Sun's (2011) estimator has large estimation mean squared error (MSE) when T is small, while our estimator has relatively small estimation MSE as long as n is large, T can be small or large.

2.4 Monte Carlo Simulations

In this section we use simulations to assess the performance of our proposed estimator and compare its behavior with the five existing estimators reviewed in section 2.1. We consider the following Data Generating Processes (DGP). Specifically, we generate Y_{it} by

$$
\begin{aligned}
DGP1 : Y_{it} =& \sin(2X_{it}) + \mu_i + \nu_{it}, \\
DGP2 : Y_{it} =& X_{it} - 0.5X_{it}^2 + \mu_i + \nu_{it},
\end{aligned}
$$

where X_{it} is i.i.d. uniform[-1,1], ν_{it} is i.i.d. $N(0, 1)$, v_i is i.i.d. uniform[-1,1], and μ_i $= v_i + c_0 T^{-1} \sum_{s=1}^{T} X_{is}$. Also, X_{it}, ν_{it}, and v_i are mutually independent of each other. We take $c_0 = 0.5,\ 1$ and 2 so that μ_i and $\{X_{it} : t = 1, \ldots, T\}$ are correlated. We take $n = 50, 100,\ 200,$ and $\ 500$ and $T = 2, 3, 4, 5, 10, 20$. The number of Monte Carlo replications is $M = 1,000$. We use the standard normal kernel function to compute the proposed estimator, and the bandwidth used is selected via $h = c\hat{\sigma}_x(nT)^{-1/5}$, where $\hat{\sigma}_x$ is the sample standard deviation of $\{X_{it}\}_{i=1,...,n;t=1,...,T}$, and without losing generality, c is 1. DGP1 is used in Li and Sun (2011) and Henderson, Carroll and Li (2008). DGP2 is a quadratic function, which is a commonly used specification in empirical applications.

To compare the different estimators, we report the average mean squared error (AMSE) of our proposed estimator along with the five estimators reviewed in section 2.1. AMSE for $\hat{m}(x)$ is defined as

$$AMSE(\widehat{m}) = \frac{1}{M}\sum_{j=1}^{M}\frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left[\widehat{m}_j(X_{it}) - m(X_{it})\right]^2,$$

where j refers to the jth simulation replication.

The simulation results are reported in Tables C.1-C.8. Tables C.1-C.3 report simulation results for DGP1 with $c_0 = 0.5$, 1, 2, respectively. Tables C.4-C.6 report simulation results for DGP2 with $c_0 = 0.5$, 1, 2, respectively. Because the marginal integration based estimator is computationally very costly, we only computed it for cases $T \leq 5$ and $n \leq 200$ and report the results, along with our proposed estimator, in Table C.7. Table C.7 also reports the computation times of the marginal integration (MI) estimator and our estimator. Finally, Table C.8 compares computation times for different estimators.

We observe several patterns comparing Tables C.1-C.7. First, for any c_0, the AMSEs of all estimators decrease as both n and T grow, indicating that all the estimators are consistent. Second, for given c_0, n and T, our proposed estimator $\widehat{m}_{LC}(x)$ performs well compared with all the other estimators for all cases. Third, for fixed n and T, the larger c_0 is, the larger the AMSEs of $\widehat{m}_{LC}(x)$, $\widehat{m}_{SU}(x)$ and $\widehat{m}_{LS}(x)$ are. The pattern arises because as c_0 increases, the variance of the fixed effects increases. The simulation results show that the AMSEs of the three estimators vary as c_0 changes, suggesting that the estimators can be sensitive to the unknown fixed effects in finite sample applications, although asymptotically, the fixed effects is removed and does not affect the consistency and the asymptotic distribution of these estimators. In contrast, HCL, KLH and the marginal integration method remove the fixed effects completely. In all three tables, for small T, the ASMEs of $\widehat{m}_{LS}(x)$ are much larger than other estimators, suggesting the near singular problem of LS's estimator for small T.

The last two columns of Table C.7 and Table C.8 report the computation time in seconds for different estimators. The estimators proposed by KLH and LS are relatively computationally less costly. HCL's estimator is time consuming in most cases due to the iterative procedure. The marginal integration estimator is extremely time consuming.

2.5 Conclusions

We propose using the profile least square method to estimate a nonparametric panel data fixed effects model. We derive the asymptotic distribution of our proposed estimator when both n and T are large. Our proposed estimator has an asymptotically normal distribution with different variances depending on the order of magnitude of $Th_1...h_q$. When n is large and T is small, the asymptotic analysis of our proposed estimator is quite complex and we leave the asymptotic analysis of our estimator for the small T case as a future research topic. Monte Carlo simulations show that in finite sample applications our proposed estimator performs well compared with existing estimators.

3. IS HONG KONG DOLLAR OVERVALUED? EVIDENCE FROM HONG KONG'S TRADE PRICES POST FINANCIAL CRISIS

3.1 Introduction

The Asian Financial Crisis began in July 1997, when China just resumed sovereignty of Hong Kong. Indonesia, Republic of Korea (hereafter, Korea), Thailand, Malaysia, Philippines and Hong Kong were affected by the Asian Financial Crisis. Before 1999, aforementioned countries have changed their exchange rate policy, except for Hong Kong.

This chapter examines (I) the effects of switching Hong Kong's exchange rate policy on Hong Kong's external trade, and (II) the overvaluation of Hong Kong dollar. For part (I), there is numerous factors affects external trade. And these factors are hard to control for. Hsiao, Ching and Wan (2011; henceforth, HCW) proposed a simple-to-implement panel data method to construct a counterfactual to measure the treatment effects, without identifying variations in other factors. Motivated by HCW's method, we use external trade for other countries to control for the potential changes in those of Hong Kong. By regressing the treatment group with the control groups before the exchange rate policy change, we allow for the impact of underlying factors to change by countries. Also, unlike difference-in-difference (DID) method, the weights for more relevant control countries are higher than those of less relevant control countries in our method. In a word, we estimate the hypothetical external trade under a float Hong Kong exchange rate policy using those of the control group. Comparing the hypothetical value with the actual value, we can identify the changes in Hong Kong's import/export prices. Using purchasing power parity (PPP), we evaluate the changes in Hong Kong's exchange rate to measure whether Hong Kong dollar is overvalued under its fixed exchange rate policy as part (II).

There are two vital choices for part (I). One is the choice of control groups. Since exchange rate is mostly affected by international trade, we use Hong Kong's major trading partners as control groups, shown in Table C.9[1]. For Hong Kong's imports, there are 11 major suppliers that supply more than 85% of Hong Kong's imports. About 83% of Hong Kong's exports are shipped to its 10 major export destinations. Among Hong Kong's major trading partners, Korea, Thailand and Malaysia are the countries changed their exchange rate policy after the Asian Financial Crisis. Based on Table C.9, the control groups for this chapter are: Canada, the mainland of China (hereafter, China), France, Federal Republic of Germany (hereafter, Germany), Italy, Japan, Korea, Malaysia, Netherlands, Singapore, Taiwan, Thailand, United Kingdom (hereafter, UK), and United States (hereafter, US). The other vital choice is the effective time of switching exchange rate regime. Table C.10[2] shows the exchange rate policy for countries we examined in this chapter before and after the Asian Financial Crisis.

A few definitions are important for understanding the changes in exchange rate regime. *Fixed exchange rates*, or pegged exchange rate, indicates that there are no fluctuations from the central rate. One advantages of fixed exchange rate is its stability. Hong Kong exchange rate is fixed to 7.80 per US dollar. France, Germany, Italy, and Netherlands have an exchange rate fixed to euro. Malaysia (after September 1998) also has a pegged exchange rate to US dollar. *Managed floating exchange rate* suggests that value of the currency is determined by market demand

[1] Sources: Hong Kong Annual Yearbook (1997-1999), Appendix 20: Hong Kong's External Trade by Major Trading Partner.

[2] Sources: World Currency Yearbook (WCY), IMF Annual Report on Exchange Arrangement and Exchange Restriction (IMF) , and European Central Bank. The currency of France, Germany, Italy and Netherlands became the euro after December 1998. The conversion rate between the euro and the countries' currency was set irrevocably.

and supply. However, some intervention might be taken on currency demand. For example, the government may desire for a lower currency to increase exports. The exchange rate policy for Korea (March 1980- November 1997) and Malaysia (December 1992-September 1998) are managed floating. In the 1990s, Chinese exchange rate regime is on more market-oriented basis. Since 1994, China has been maintaining a controlled float foreign exchange regime. *Free floating exchange rate* means that the value of a currency is determined purely by demand and supply of the currency. The central bank neither sets target, nor takes intervention for the exchange rate in the market. In our sample, Canada, Japan, Korea (after 1997), Singapore, Taiwan, Thailand (after July 1997) and UK (after 1992) use free floating exchange rate policy. Based on Table C.10, we use October 1998 as the time of the hypothetical policy invention on Hong Kong's exchange rate policy. That is, hypothetically, Hong Kong changed its exchange rate policy from fixed to float on October 1998.

For part (II), one could apply HCW's method on Hong Kong fixed exchange rate to evaluate the overvaluation of Hong Kong dollar. However, regressions on Hong Kong's exchange rate using Hong Kong's trading partners' exchange rates are not useful, since that first, Mussa (1986) showed that exchange rates behaved very differently under fix and flexible exchange rate system; second, it is not, mechanically, very meaningful to regress a fixed number on a set of random variables. Then, to evaluate the overvaluation of Hong Kong dollar, we use purchasing power parity (PPP) to examine Hong Kong's exchange rate. In PPP,

$$s_t = a + b_1 p_t + b_2 p_t^* + e_t, \tag{3.1.1}$$

where s_t, p_t, and p_t^* are the logarithm of the nominal exchange rate, domestic prices and foreign prices, correspondingly, and e_t is the error term. In PPP theory, $a = 0$,

$b_1 = 1$, and $b_2 = -1$. The choices of prices using in PPP is important. Xu (2003) demonstrated that trade price index (TPI) is a more appropriate price index for exchange rate forecasting than consumer price index (CPI) or wholesale price index (WPI), where TPI is a weighted average of export price and import price using total value of exports and imports as weights. Thus, we examine the behavior of total value of imports/exports and the import/export volume to measure the movements of Hong Kong's trade price. And Hong Kong's exchange rate increases if Hong Kong's trade price increases.

Using HCW's approach, we find that Hong Kong's exports prices would increase by about 9.54% if Hong Kong uses float exchange rate policy after October 1998. And Hong Kong's import price increases by 9.14%. Both indicate that Hong Kong's TPI is increasing, which suggests increasing Hong Kong's exchange rate. Therefore, we conclude that Hong Kong dollar is overvalued by 9.34% if Hong Kong keeps using fixed exchange rate policy.

This chapter is organized as following. Section 3.2 reviews HCW's method and presents our estimation strategy. We describe the data in Section 3.3. Section 3.4 reports the estimation results. Section 3.5 concludes the chapter.

3.2 The Model

In this section we first review a panel data model estimation method proposed by Hsiao, Ching and Wan (2011, HCW) which is related to the method we will propose to evaluate the effect of Hong Kong's fixed exchange rate policy.

3.2.1 HCW Method

HCW proposed using a panel data model to estimate average treatment effects (ATE). Let y^1_{it} and y^0_{it} denote country i's economic measurements in period t before and after October 1998. y represents for total value of imports/exports and import/export volume index. The policy change effect to Hong Kong ($i = 1$)'s value at time t is

$$\Delta_{1t} = y_{1t}^1 - y_{1t}^0.$$

However, since Hong Kong's value for float exchange rate policy, y_{1t}^1, is not observable. We need to predicted $\widehat{y}_{1t}^1$ using the observed data. Based on HCW (2011), we assume that there exists a $K \times 1$ vector of *unobservable* common factors f_t that drives external trade of all countries to change over time. These factors can be global economic growth, technology innovation, environmental improvements, etc. Therefore, for Hong Kong's external trade before and after October 1998 (T_1), we have

$$y_{1t} = \begin{cases} y_{1t}^0 = \alpha_1 + \beta_1' f_t + u_{1t}, & t < T_1, \\ y_{1t}^0 = \alpha_1 + \beta_1' f_t + u_{1t}, & t > T_1, \end{cases}$$

where α_1 is a country specific intercept, β_1' is a factor loading vector of dimension $K \times 1$, u_{1t} is the error term. y_{1t} has the same equation format before and after October 1998 since Hong Kong uses the same exchange rate policy. For those of Hong Kong's major trading partners ($i = 2, ..., N$) before and after October 1998 (T_1), we have

$$y_{it} = \begin{cases} y_{it}^0 = \alpha_i + \beta_i' f_t + u_{it}, & t < T_1, \\ y_{it}^1 = \alpha_i + \beta_i' f_t + \Delta_{it} + u_{it}, & t > T_1, \end{cases}$$

where α_i, β_i' and u_{it} are similarly defined. Δ_{it} are the treatment effects of switching exchange rate policy for country i's external trade after October 1998. The error term can be I(0) or I(1), according to Bai, Li, and Ouyang (2012; henceforth, BLO). Unlike DID method, β_i can be different among i. We assume that there are only a few common factors affect different countries' external trade, i.e., $K < N$.

Again, since y_{1t}^1 is not observable for $t > T_1$, we need to estimate the counterfactual value $\widehat{y}^1_{1t}$ after October 1998. HCW (2011) suggests using $Y_t = (y_{2t}, ..., y_{Nt})'$ in lieu of f_t to predict y^1_{1t} for post-treatment period. In particular, we estimate the linear regression model

$$y^1_{1t} = \alpha_1 + \beta' Y_t + \epsilon_{1t}, \quad \text{for} \quad t < T_1,$$

where α_1 is a scalar parameter, $\beta = (\beta_2, ..., \beta_N)'$ is an $(N-1)\times 1$ vector of parameters, and ϵ_{1t} is the error term. Estimating equation (3.2.1) by OLS regression, we have the consistent estimates $\widehat{\alpha}_1$ and $\widehat{\beta}$. According to Assumption 6 of HCW and Proposition 2.1 of BLO, y^1_{1t} can be predicted by

$$\widehat{y}^1_{1t} = \widehat{\alpha}_1 + \widehat{\beta}' Y_t, \quad \text{for} \quad t > T_1.$$

Then, the possible treatment effects that Hong Kong changed its exchange rate policy from flat to float are

$$\widehat{\Delta}_{1t} = \widehat{y}^1_{1t} - y^0_{1t}, \quad \text{for} \quad t > T_1,$$

and the average treatment effect is

$$\widehat{\Delta}_1 = \frac{1}{T - T_1} \sum_{t=T_1+1}^{T} \widehat{\Delta}_{1t},$$

where T is the total number of observations. Based on Lemma 2 and Lemma 4 of HCW and Proposition 2.2 and Proposition 2.3 of BLO, it is easy to show that $\widehat{\Delta}_1$ converges to the true average treatment effects Δ_1 in probability, under the condition that both T_1 and $T - T_1$ are large.

3.2.2 Our Estimation Strategy

We study Hong Kong's fixed exchange rate effect on its economic outcomes. Different from the treatment-control case considered in HCW, here Hong Kong's fixed exchange rate policy remains effective throughout the sample period. In this sense there is no 'treatment' occurred to Hong Kong in the middle of our sample. However, there was a significant event, the Asia Financial Crisis that occurred in 1997-1998. During this period, several countries changed their foreign exchange rate policy, such as Korea, Malaysia and Thailand. We conjecture that Hong Kong's dollar would depreciate significantly against US dollar if Hong Kong had adopted a flexible exchange rate policy during that time. The purpose of this chapter is to investigate, since the 1997 Asian Financial Crisis, whether Hong Kong dollar is overvalued (against US dollar) due to its fixed exchange rate policy after. For this purpose we need to estimate the counterfactual Hong Kong's exchange rate under the scenario of a flexible exchange rate regime. Our problem is much more difficulty than the standard treatment effects estimation problems such as considered in HCW (2011) or in the usual difference in difference (DID). One major difficulty in our analysis is that Hong Kong's exchange rate is fixed throughout, hence, regressing Hong Kong's exchange on other countries' exchange rate is meaningless. We have to seek alternative estimation strategies. We use import/export price and purchasing power parity to examine the counterfactual effects of Hong Kong exchange rate. Our estimation procedure consists of the following steps. To facilitate the discussion we will call October 1998 as the treatment date (denote as T_1).

1. Hong Kong's export price.

   (a) Similar to HCW (2011), we regress (logarithm of) Hong Kong's total value of exports on that of its major trading partners using data prior to

October 1998 (pre-treatment data),

$$y_{1t} = \alpha_1 + \beta' Y_t + \epsilon_{1t} \quad \text{for} \quad t < T_1, \tag{3.2.1}$$

where y_{1t} is Hong Kong's total value of exports at time t, $Y_t = (y_{2t}, ..., y_{Nt})'$ a vector of other countries' total value of exports. Then, we use the estimate coefficients of equation (3.2.1), along with the major trading partners' total value of exports, to compute Hong Kong's counterfactual of total value of exports for the post-treatment period. Let $\widehat{y}^1_{1t}$ denote this counterfactual value.

$$\widehat{y}^1_{1t} = \widehat{\alpha}_1 + \widehat{\beta}' Y_t, \quad \text{for} \quad t > T_1. \tag{3.2.2}$$

Then, the average treatment effects (ATE) for Hong Kong's total value of exports (TVE) is

$$\bar{\widehat{\Delta}}_{TVE} = \frac{1}{T - T_1} \sum_{t=T_1+1}^{T} \widehat{\Delta}_{TVE,1t} = \frac{1}{T - T_1} \sum_{t=T_1+1}^{T} \left(\widehat{y}^1_{1t} - y^0_{1t} \right),$$

where $\widehat{\Delta}_{TVE,1t}$ represents the estimated treatment effects for Hong Kong total value of exports (TVE) at time t and y^0_{1t} are the observed Hong Kong's total value of exports.

(b) Repeat step 1 (a) for Hong Kong's export volume (EV), i.e., replace total value of exports by export volume index in step 1 (a), we estimate the ATE for Hong Kong's export volume, i.e., $\bar{\widehat{\Delta}}_{EV}$ after October 1998.

Based on step 1 (a) and 1 (b), we can measure the change in Hong Kong's export price as follows. Let EP denote export price. Recall that TVE and

EV represent for total value of exports and export volume, respectively, we have

$$EP_{1t}^j = \frac{TVE_{1t}^j}{EV_{1t}^j}, \qquad \text{for } j = 0, 1.$$

Hence, the change in Hong Kong's export price (EP) can be computed by

$$\begin{aligned} \widehat{\Delta}_{EP,1t} = \ln\left(\frac{EP_{1t}^1}{EP_{1t}^0}\right) &= \ln(EP_{1t}^1) - \ln(EP_{1t}^0) \\ &= \ln(TVE_{1t}^1) - \ln(TVE_{1t}^0) - \left[\ln(EV_{1t}^1) - \ln(EV_{1t}^0)\right] \\ &= \widehat{\Delta}_{TVE,1t} - \widehat{\Delta}_{EV,1t}. \end{aligned}$$

Then, the average estimated treatment effects for export price is

$$\bar{\widehat{\Delta}}_{EP} = \frac{1}{T - T_1} \sum_{t=T_1+1}^{T} \widehat{\Delta}_{EP,1t} = \frac{1}{T - T_1} \sum_{t=T_1+1}^{T} \left[\widehat{\Delta}_{TVE,1t} - \widehat{\Delta}_{EV,1t}\right] = \bar{\widehat{\Delta}}_{TVE} - \bar{\widehat{\Delta}}_{EV}.$$

2. Hong Kong's import price.

   Similar to the calculation of export price, we only need to change 'E' (export) to 'I' (import) as follows: replacing EP, TVE and EV by IP, TVI and IV in step 1 respectively, where IP, TVI and IV represent for import price, total value of imports, and import volume, respectively. This gives us the estimated change in Honk Kong's import price (IP), i.e., $\bar{\widehat{\Delta}}_{IP}$.

3. Generate the change in trade price index (TPI) as a weighted average of the change in Hong Kong's export price and import price, using Hong Kong's total value of exports and imports as weights.

$$\Delta TPI = \frac{TVE \times \bar{\widehat{\Delta}}_{EP} + TVI \times \bar{\widehat{\Delta}}_{IP}}{TVE + TVI}.$$

4. According to PPP, $s_t = p_t - p_t^* + e_t$, where s_t, p_t, and p_t^* are the logarithm of the bilateral exchange rate, Hong Kong's trade prices and US trade prices, respectively, and e_t is the error term. Under the assumption that US price level is not affected by the treatment of 1997 Asia Financial Crisis. We obtain the treatment effects on the bilateral exchange rate (Δs_t) given by $\Delta s_t = \Delta TPI$.

   That is, the percentage (counterfactual) change in Hong Kong's exchange rate equals to the percentage (counterfactual) change in Hong Kong's trade price index. Then, a positive (negative) ΔTPI implies a overvalued (undervalued) Hong Kong dollar.

3.3 The Data

The data sample for this chapter includes Hong Kong and Hong Kong's 14 major trading partners: Canada, China, France, Germany, Italy, Japan, Korea, Malaysia, Netherlands, Singapore, Taiwan, Thailand, UK, and US. We use the monthly data from IMF's *International Financial Statistics* (IFS) (1991-2002). Total value of imports/exports measured in national currency in log level and import/export volume index (2005=100) for the 14 trading partners are used in lieu of the common factors f_t to predict those of Hong Kong after October 1998. IFS reports the data for most of the countries.

Available for all the countries, the total value of imports/exports in national currency is reported in IFS. We use the *log level* of the total value of imports/exports in the regression.

The monthly data of import/export volume index are available in IFS, except for China, Malaysia and Taiwan. These data reported in IFS use the trading volume of 2005 as baseline. The Taiwanese data are from the Department of Statistics of Taiwan. We change the baseline of the data from year 2011 to 2005. Chinese and

Malaysian data are the linear interpolation of the annual data from UNCTD[3]. The baseline is changed from year 2000 to 2005.

Hong Kong's total value of imports/exports and import/export volume index are all non-seasonal adjusted. We use these data to examine the treatment effects of changing Hong Kong's exchange rate policy from fixed to float and the overvaluation of Hong Kong dollar. The empirical results are reported in the next section.

3.4 Results

Using HCW's method, we regress Hong Kong's economic measurements (y_{1t}) with those (Y_t) of Hong Kong's major trading partners from January 1991 to October 1998. The economic measurements are: total value of imports/exports and import/export volume index. The regression model is as following. Since all of Hong Kong's economic measurements are non-seasonal adjusted data. We add seasonal dummies in equation (3.2.1):

$$y_{1t} = \alpha_1 + \beta' Y_t + \sum_{j=1}^{11} \gamma_{1j} D_{jt} + \epsilon_{1t} \quad \text{for } \ t < T_1, \tag{3.4.1}$$

where D_{jt} for $j = 1, ..., 11$ are the monthly dummies and i may be different for different regression. For instance, the control groups for section 3.4.1 are the countries of domestic exports destinations, shown in Table C.9. Section 3.4.2 uses the imports supplier in Table C.9.

3.4.1 Exports

In this section, y_{1t} in equation (3.4.1) is the Hong Kong's total value of exports, Y_t is the vector of the total value of exports for Hong Kong's major domestic export destinations. Table C.11 shows the OLS regression results, with very high adjusted

[3] United Nations Conference on Trade and Development, Handbook of Statistics and data files

R-square and the p-value of F-statistics being 0.0000. Both suggest that the major export destinations' export values are good predictors for Hong Kong's total value of exports.

Figure B.1 plots the actual and the predicted total value of exports before and after October 1998. We reports the estimated treatment effects after October 1998 in Table C.12. The autocorrelation functions for the treatment effects after October 1998 are plotted in Figure B.2 [4]. Based on Figure B.2, it seems that there is no serial correlation for the treatment effects of Hong Kong total value of exports. Then, the long-run effect is 0.1465, with t-statistic being 18.96, which is statistically significant. This means that changing Hong Kong's exchange rate policy from fixed to float will significantly increase Hong Kong's total value of exports by 14.65%.

For the regression of export volume, y_{1t} in equation (3.4.1) is the Hong Kong's export volume index, Y_t is the vector of the export volume indices for Hong Kong's major domestic export destinations. Table C.13 reports the regression results for Hong Kong's export volume index. The actual and the predicted export volume index before and after October 1998 are plotted in Figure B.3. The estimated treatment effects after October 1998 are reported in Table C.14. Figure B.4 plots the autocorrelation functions for the treatment effects after October 1998, which suggests fitting an AR(4) model to the estimated treatment effects for export volume index after October 1998.

$$\begin{aligned}\widehat{\Delta}_{1t} = &0.9802 + 0.3490\Delta_{1t-1} + 0.3549\Delta_{1t-2} - 0.1234\Delta_{1t-3} + 0.3046\Delta_{1t-4}.\\ &(1.31) \quad (2.37) \qquad\quad (1.91) \qquad\quad (-0.90) \qquad\quad (1.72)\end{aligned}$$

[4] The shade area uses Bartlett's formula for MA(q) 95% confidence bands. The shade areas for the rest autocorrelation functions figures use the same formula.

This indicates the long-run effect is 8.5262, with t-statistic being 1.15, which is statistically insignificant. However, based on Table C.14, the average treatment effects for Hong Kong's exports volume is 5.11% with large t-statistics being 6.69. Notice that the increase in export volume is smaller than the increase in total value of exports, indicating that Hong Kong's export price increases by $14.65\% - 5.11\% = 9.54\%$.

3.4.2 Imports

This section uses y_{1t} in equation (3.4.1) as the Hong Kong's total value of imports and Y_t as the vector of the total value of imports for Hong Kong's major imports suppliers. The OLS regression results are shown in Table C.15. Adjusted R-square is very high. The p-value of F-statistics is 0.0000. Both suggest that the major suppliers' imports values are good predictors for Hong Kong's total value of imports.

Figure B.5 plots the actual and the predicted total value of imports before and after October 1998. We reports the estimated treatment effects after October 1998 in Table C.16. The autocorrelation functions for the treatment effects after October 1998 are plotted in Figure B.6, suggesting that there is serial correlation in the treatment effects. Then, we fit an AR(3) model to the treatment effects of Hong Kong total value of imports.

$$\begin{aligned}\widehat{\Delta}_{1t} =& \underset{(3.02)}{0.0972} + \underset{(0.26)}{0.0375}\Delta_{1t-1} + \underset{(2.06)}{0.2725}\Delta_{1t-2} + \underset{(4.15)}{0.4176}\Delta_{1t-3}.\end{aligned}$$

This indicates the long-run effect is 0.3567, with t-statistic being 8.60, which is statistically very significant. Based on Table C.16, the average treatment effects for Hong Kong's total value of imports in 31.04% with t-statistics being 21.11.

Now, we change y_{1t} in equation (3.4.1) to the Hong Kong's import volume index and Y_t to the vector of import volume indices for Hong Kong's major suppliers. Table C.17 reports the regression results for Hong Kong's import volume index. The actual and the predicted import volume index before and after October 1998 are plotted in Figure B.7. The estimated treatment effects after October 1998 are reported in Table C.18. Figure B.8 plots the autocorrelation functions for the treatment effects after October 1998. Based on Figure B.8, we fit an AR(4) model to the treatment effects of Hong Kong import volume index.

$$\begin{aligned}\widehat{\Delta}_{1t} =& 1.7014 + 0.4961\Delta_{1t-1} + 0.4757\Delta_{1t-2}.\\ & (1.33) \quad\; (3.47) \qquad\qquad (3.65)\end{aligned}$$

This indicates the long-run effect is 60.2695, with t-statistic being 0.80, which is statistically insignificant. However, based on Table C.18, the average treatment effects for Hong Kong's imports volume is 21.90% with large t-statistics being 16.02. Similarly, t the increase in import volume is smaller than the increase in total value of imports, indicating that Hong Kong's import price increases by $31.04\% - 21.90\% = 9.14\%$.

3.4.3 Overvaluation

Combining the results for Hong Kong's external trade from November 1998 to December 2002, we find that if Hong Kong uses float exchange rate, Hong Kong's export (import) price increases by 9.54% (9.14%), since Hong Kong's total value of exports (imports) increases by 14.65% (31.04%) and Hong Kong's export (import) volume index increases by 5.11% (21.90%). Also, the average Hong Kong's total value of exports (imports) is about 15.9 (16.6) billions after October 1998. Hong

Kong's trade price (TPI) increases by

$$\Delta TPI = \frac{TVE \times \bar{\bar{\hat{\Delta}}}_{EP} + TVI \times \bar{\bar{\hat{\Delta}}}_{IP}}{TVE + TVI}$$
$$= \frac{15.9 \times (14.65\% - 5.11\%) + 16.6 \times (31.04\% - 21.90\%)}{15.9 + 16.6} = 9.34\%,$$

which indicates that Hong Kong dollar is overvalued by 9.34% if Hong Kong keeps using fixed exchange rate policy.

3.5 Conclusions

Using a simple-to-implement panel data method proposed by Hsiao, Ching and Wan (2011), we examine Hong Kong's imports/exports changes as a result of different exchange rate policies. That is, we regress the external trade on those of other countries before October 1998 and exploit the dependence among countries to construct a counterfactual for Hong Kong's external trade assuming Hong Kong's exchange rate policy being float after October 1998.

Using the data for Hong Kongs 14 major trading partners, we find that changing Hong Kong exchange rate policy from pegging to US dollar to float rate would increase Hong Kong's total value of exports by 14.65%, which is larger than the increase in the export volume (5.11%). Hong Kong's total value of imports increases significantly by 31.04%, larger than the increase in the import volume (21.90%). All of which indicates an increase in Hong Kong's trade price, which is a more appropriate price index for exchange rate forecasting than CPI or WPI. Based on purchasing power parity (PPP), we conclude that Hong Kong dollar is overvalued by 9.34% if Hong Kong continues using fixed exchange rate policy.

4. CONCLUSIONS

In this thesis, we first propose using the profile least square method to estimate a nonparametric panel data fixed effects model. We derive the asymptotic distribution of our proposed estimator when both n and T are large. Our proposed estimator has an asymptotically normal distribution with different variances depending on the order of magnitude of $Th_1...h_q$. When n is large and T is small, the asymptotic analysis of our proposed estimator is quite complex and we leave the asymptotic analysis of our estimator for the small T case as a future research topic. Monte Carlo simulations show that in finite sample applications our proposed estimator performs well compared with existing estimators.

Second, we examine Hong Kong's imports/exports changes as a result of different exchange rate policies, using a simple-to-implement panel data method proposed by Hsiao, Ching and Wan (2011). That is, we regress the external trade on those of other countries before October 1998 and exploit the dependence among countries to construct a counterfactual for Hong Kong's external trade assuming Hong Kong's exchange rate policy being float after October 1998. Using the data for Hong Kongs 14 major trading partners, we find that changing Hong Kong exchange rate policy from pegging to US dollar to float rate would increase Hong Kong's total value of exports by 14.65%, which is larger than the increase in the export volume (5.11%). Hong Kong's total value of imports increases significantly by 31.04%, larger than the increase in the import volume (21.90%). All of which indicates an increase in Hong Kong's trade price. Based on purchasing power parity (PPP), we conclude that Hong Kong dollar is overvalued by 9.34% if Hong Kong continues using fixed exchange rate policy.

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APPENDIX A

PROOF OF THEOREM 2.3.1

Throughout the Appendix, we use the following notations: '$\xrightarrow{d}$' and '$\xrightarrow{p}$' refer to convergence in distribution and convergence in probability, respectively. For a function $g : \mathbb{R}^q \to \mathbb{R}$, we use $g^{(1)}(x) = \partial g(x)/\partial x$ (a $q \times 1$ vector) and $g^{(2)}(x) = \partial^2 g(x)/\partial x \partial x'$ (a $q \times q$ matrix) to represent g's first- and second- order partial derivatives, respectively.

Rewriting $\widehat{m}(x)$, we obtain,

$$\begin{aligned}\widehat{m}(x) &= s_h(x)'MY \\ &= s_h(x)'M(m(X) + D_0\mu + V) \\ &\equiv \widehat{m}_1(x) + \widehat{m}_2(x) + \widehat{m}_3(x),\end{aligned}$$

where $\widehat{m}_1(x) = s_h(x)'Mm(X)$, $\widehat{m}_2(x) = s_h(x)'MD_0\mu$ and $\widehat{m}_3(x) = s_h(x)'MV$.

We derive the limiting results of $\widehat{m}_1(x)$, $\widehat{m}_2(x)$ and $\widehat{m}_3(x)$ in the following subsections.

A.1 Limiting result of $\widehat{m}_1(x)$

Recall that $s_h(x)' = [\iota_{nT}' K_h(x)\iota_{nT}]^{-1}\iota_{nT}' K_h(x)$ is a 1 by nT vector with a typical element given by $s_{h,it}(x)$.

Lemma A.1. *Under Assumptions A1-A4,*

$$s_{h,it}(x) = \frac{K_h(X_{it}, x)}{\sum_{i=1}^n \sum_{t=1}^T K_h(X_{it}, x)} = \frac{K_h(X_{it}, x)}{nTf(x)}[1 + o_p(1)]. \qquad \text{(A.1)}$$

Proof: It follows from $(nT)^{-1}\sum_{i=1}^{n}\sum_{t=1}^{T}K_h(X_{it},x)=f(x)+o_p(1)$.

We decompose $\widehat{m}_1(x)$ into different parts next. By Taylor expansion, we have $m(X_{it})-m(x)=(X_{it}-x)'m^{(1)}(x)+\frac{1}{2}(X_{it}-x)'m^{(2)}(x)(X_{it}-x)+R(X_{it}-x)$, where $R(X_{it}-x)=m(X_{it})-m(x)-(X_{it}-x)'m^{(1)}(x)-\frac{1}{2}(X_{it}-x)'m^{(2)}(x)(X_{it}-x)$. Then,

$$\begin{aligned}
\widehat{m}_1(x) &= s_h(x)'(I_{nT}-D[D'PD]^{-1}D'P)m(X)\\
&= s_h(x)'[\iota_{nT}m(x)+m(X)-\iota_{nT}m(x)-D[D'PD]^{-1}D'Pm(X)]\\
&= s_h(x)'\iota_{nT}m(x)+\sum_{i=1}^{n}\sum_{t=1}^{T}s_{h,it}(x)(X_{it}-x)'m^{(1)}(x)\\
&+\frac{1}{2}\sum_{i=1}^{n}\sum_{t=1}^{T}s_{h,it}(x)(X_{it}-x)'m^{(2)}(x)(X_{it}-x)+R(x)\\
&- s_h(x)D[D'PD]^{-1}D'Pm(X)\\
&= m(x)+\sum_{i=1}^{n}\sum_{t=1}^{T}s_{h,it}(x)(X_{it}-x)m^{(1)}(x)\\
&+\frac{1}{2}\sum_{i=1}^{n}\sum_{t=1}^{T}s_{h,it}(x)(X_{it}-x)'m^{(2)}(x)(X_{it}-x)+R(x)\\
&- s_h(x)'D[D'PD]^{-1}D'Pm(X)\\
&\equiv m(x)+A_{11}+A_{12}+R(x)-A_{14},
\end{aligned}$$

where

$$A_{11}=\sum_{i=1}^{n}\sum_{t=1}^{T}s_{h,it}(x)(X_{it}-x)m^{(1)}(x) \tag{A.2}$$

$$A_{12}=\frac{1}{2}\sum_{i=1}^{n}\sum_{t=1}^{T}s_{h,it}(x)(X_{it}-x)'m^{(2)}(x)(X_{it}-x), \tag{A.3}$$

$$R(x)=\sum_{i=1}^{n}\sum_{t=1}^{T}s_{h,it}(x)R(X_{it}-x) \tag{A.4}$$

$$A_{14} = s_h(x)'D[D'PD]^{-1}D'Pm(X). \tag{A.5}$$

By recalling that the leading term of $s_{h,it}(x)$ is $\frac{K_h(X_{it},x)}{nTf(x)}[1+o_p(1)]$, it is easy to show that $R(x) = O_p(\sum_{s=1}^q h_s^4)$.

Lemma A.2. *Under Assumptions A1-A4,*

$$A_{11} = B_h(x) + O_p\left(\sum_{s=1}^q h_s^4\right) + O_p\left((nTh_1...h_q)^{-1/2}\sum_{s=1}^q h_s\right), \tag{A.6}$$

where $B_h(x) = \kappa_2 \sum_{s=1}^q h_s^2[m_s(x)f_s(x)/f(x) + \frac{1}{2}m_{ss}(x)] = O\left(\sum_{s=1}^q h_s^2\right)$ *and* $\kappa_2 = \int_{\mathbb{R}^q} v^2 k(v)dv$*, where* $m_s(x) = \frac{\partial m(x)}{\partial x_s}$, $m_{ss}(x) = \frac{\partial^2 m(x)}{\partial x_s^2}$ *and* $f_s(x) = \frac{\partial f(x)}{\partial x_s}$.

Proof: By Lemma A.1, we obtain

$$\begin{aligned}
A_{11} &= m^{(1)}(x)'\sum_{i=1}^n\sum_{t=1}^T s_{h,it}(x)(X_{it}-x) + \frac{1}{2}\sum_{i=1}^n\sum_{t=1}^T s_{h,it}(x)(X_{it}-x)'m^{(2)}(x)(X_{it}-x)\\
&= m^{(1)}(x)'\sum_{i=1}^n\sum_{t=1}^T (nT)^{-1}f^{-1}(x)K_h(X_{it},x)(x_{it}-x)\\
&+ \frac{1}{2}\sum_{i=1}^n\sum_{t=1}^T (nT)^{-1}f^{-1}(x)K_h(X_{it},x)(X_{it}-x)'m^{(2)}(x)(X_{it}-x)\\
&= f^{-1}(x)m^{(1)}(x)'(nT)^{-1}\sum_{i=1}^n\sum_{t=1}^T K_h(X_{it},x)(X_{it}-x)\\
&+ f^{-1}(x)\frac{1}{2}(nT)^{-1}\sum_{i=1}^n\sum_{t=1}^T K_h(X_{it}-x)(X_{it}-x)'m^{(2)}(x)(X_{it}-x).
\end{aligned}$$

Therefore,

$$
\begin{aligned}
E(A_{11}) &= f^{-1}(x)m^{(1)}(x)'E(K_h(X_{it},x)(X_{it}-x)) \\
&\quad + f^{-1}(x)\frac{1}{2}E(K_h(X_{it},x)(X_{it}-x)'m^{(2)}(x)(X_{it}-x)) \\
&= \kappa_2\sum_{s=1}^{q} h_s^2[m_s(x)f_s(x)/f(x)+\frac{1}{2}m_{ss}(x)] + O(\left(\sum_{s=1}^{q} h_s^4\right).
\end{aligned}
$$

Using the same methods, it is easy to show that $Var(A_{11}) = O\left((nTh_1...h_q)^{-1}\sum_{s=1}^{q} h_s^2\right)$. Hence, we have $A_{11} = B_h(x) + O_p\left(\sum_{s=1}^{q} h_s^4\right) + O_p\left((nTh_1...h_q)^{-1/2}\sum_{s=1}^{q} h_s\right)$. This completes the proof of Lemma A.2.

Lemma A.3. *For two square matrices A and B, if AA=A, BB=B, AB=BA=0, and A+B=I, then*

$$
C^{-1} = (aA+bB)^{-1} = \frac{1}{a}A + \frac{1}{b}B, \qquad (a,b\neq 0) \tag{A.7}
$$

Proof:

$$
\begin{aligned}
CC^{-1} =& (aA+bB)(aA+bB)^{-1} = (aA+bB)(\frac{1}{a}A+\frac{1}{b}B) \\
=& AA + \frac{b}{a}BA + \frac{a}{b}AB + BB = A+B = I.
\end{aligned}
$$

Lemma A.4.

$$
(D'D)^{-1} = \frac{1}{T}I_{n-1} - \frac{1}{nT}J_{n-1},
$$

where $J_{n-1} = \iota_{n-1}\iota_{n-1}'$.

Proof: Since $D = [-\iota_{n-1} \ \ I_{n-1}]' \otimes \iota_T$,

$$\begin{aligned} D'D =& ([-\iota_{n-1} \ \ I_{n-1}]' \otimes \iota_T)'([-\iota_{n-1} \ \ I_{n-1}]' \otimes \iota_T) \\ =& ([-\iota_{n-1} \ \ I_{n-1}][-\iota_{n-1} \ \ I_{n-1}]') \otimes \iota_T'\iota_T = T[\iota_{n-1}\iota_{n-1}' + I_{n-1}]. \end{aligned}$$

Let $\bar{J}_{n-1} \equiv \frac{1}{n-1} J_{n-1} = \frac{1}{n-1}\iota_{n-1}\iota_{n-1}'$ and $E_{n-1} \equiv I_{n-1} - \bar{J}_{n-1}$, we have

$$D'D = T(I_{n-1} + J_{n-1}) = T[I_{n-1} + (n-1)\bar{J}_{n-1}] = T[n\bar{J}_{n-1} + E_{n-1}]. \tag{A.8}$$

By Lemma A.3, we have $a = n$, $b = 1$ $A = \bar{J}_{n-1} = \frac{1}{n-1} J_{n-1}$, $B = E_{n-1} = I_{n-1} - \bar{J}_{n-1}$, $AA = \frac{1}{n-1} J_{n-1} \frac{1}{n-1} J_{n-1} = \frac{1}{(n-1)^2}\iota_{n-1}\iota_{n-1}'\iota_{n-1}\iota_{n-1}' = \frac{1}{(n-1)}\iota_{n-1}\iota_{n-1}' = A$, $BB = (I_{n-1} - \bar{J}_{n-1})(I_{n-1} - \bar{J}_{n-1}) = B$ and $AB = \bar{J}_{n-1}(I_{n-1} - \bar{J}_{n-1}) = 0 = BA$. Therefore,

$$\begin{aligned} (D'D)^{-1} =& \frac{1}{T}\left[\frac{1}{n}\bar{J}_{n-1} + E_{n-1}\right] = \frac{1}{T}\left[\frac{1}{n}\bar{J}_{n-1} + I_{n-1} - \bar{J}_{n-1}\right] \\ =& \frac{1}{T}\left[\frac{1-n}{n}\bar{J}_{n-1} + I_{n-1}\right] = \frac{1}{T}\left[\frac{1-n}{n}\frac{1}{n-1} J_{n-1} + I_{n-1}\right] = \frac{1}{T} I_{n-1} - \frac{1}{nT} J_{n-1}. \end{aligned}$$

Lemma A.5. *Under Assumptions A1-A4, as $n \to \infty$ and $T \to \infty$,*

$$(D'PD)^{-1} = (D'D)^{-1} - O_p(\delta_n),$$

where $\delta_n = h^2 + \frac{1}{\sqrt{nTh}}$.

Proof: Recall that $D = [-\iota_{n-1} \ \ I_{n-1}]' \otimes \iota_T$ and $P = [I_{nT} - S]'[I_{nT} - S]$, we have that $D'PD = D'D - D'S'D - D'SD + D'S'SD = T[\iota_{n-1}\iota_{n-1}' + I_{n-1}] - \Delta$, where the

$(n-1)$ square matrix Δ is

$$\Delta = \begin{pmatrix} s_{h,2,2} - s_{h,1,2} - s_{h,2,1} + s_{h,1,1} & \cdots & s_{h,n,2} - s_{h,1,2} - s_{h,n,1} + s_{h,1,1} \\ & \ddots & \\ s_{h,2,n} - s_{h,1,n} - s_{h,2,1} + s_{h,1,1} & \cdots & s_{h,n,n} - s_{h,1,n} - s_{h,n,1} + s_{h,1,1} \end{pmatrix}$$
$$+ \begin{pmatrix} s_{h,2,2} - s_{h,1,2} - s_{h,2,1} + s_{h,1,1} & \cdots & s_{h,2,n} - s_{h,1,n} - s_{h,2,1} + s_{h,1,1} \\ & \ddots & \\ s_{h,n,2} - s_{h,1,2} - s_{h,n,1} + s_{h,1,1} & \cdots & s_{h,n,n} - s_{h,1,n} - s_{h,n,1} + s_{h,1,1} \end{pmatrix}$$
$$- \begin{pmatrix} \sum_{j=1}^n \{s_{h,2,j} - s_{h,1,j}\}^2 & \cdots & \sum_{j=1}^n \{s_{h,2,j} - s_{h,1,j}\}\{s_{h,n,j} - s_{h,1,j}\} \\ & \ddots & \\ \sum_{j=1}^n \{s_{h,2,j} - s_{h,1,j}\}\{s_{h,n,j} - s_{h,1,j}\} & \cdots & \sum_{j=1}^n \{s_{h,2,j} - s_{h,1j}\}^2 \end{pmatrix}$$

where $s_{h,i,j} = \sum_{s=1}^T \sum_{t=1}^T s_{h,it}(X_{js})$ and $s_{h,it}(X_{js})$ is a typical element of $s_h(x)' = [\iota'_{nT} K_h(x) \iota_{nT}]^{-1}\ \iota'_{nT} K_h(x)$ when $x = X_{js}$. Rewrite $s_{h,i,j}$ and by Lemma A.1, we have

$$s_{h,i,j} = \sum_{s=1}^T \sum_{t=1}^T s_{h,it}(X_{js}) = \sum_{s=1}^T \frac{\sum_{t=1}^T K_h(X_{it}, X_{js})}{\sum_{i=1}^n \sum_{t=1}^T K_h(X_{it}, X_{js})}.$$

As $n \to \infty$ and $T \to \infty$,

$$s_{h,i,j} = \sum_{s=1}^T \frac{Tf(X_{js})}{nTf(X_{js})}[1+\delta_n] = \frac{T}{n}[1+\delta_n],$$

where $\delta_n = O_p\left(h^2 + \frac{1}{\sqrt{nTh}}\right)$. Then, $D'PD = D'D - \Delta = D'D - \delta_n J_{n-1}$. This completes the proof of Lemma A.5.

Let (s.o.) denotes small order terms, which means if $A = B[1 + o_p(1)]$, then $A = B + (s.o.)$, where B is the leading term, and (s.o.) represents the terms that have smaller order than B.

Lemma A.6. *Under Assumption A1-A4 and by Lemma A.4 and Lemma A.5, for any nT by 1 vector $\Pi_{nT} = (\pi_{11}, \pi_{12}, \cdots, \pi_{1T}, \pi_{21}, \cdots, \pi_{nT})'$, we have*

$$\begin{aligned}
&s_h(x)'D[D'PD]^{-1}D'P\Pi_{nT} \\
=&\frac{1}{n^2T}\sum_{i=2}^{n}\sum_{t=1}^{T}\pi_{it}[1+\delta_n] - \frac{2}{n^3T^2}\sum_{i=1}^{n}\sum_{t=1}^{T}\pi_{it}[1+\delta_n] + \frac{1}{n^4T^3}\sum_{i=1}^{n}\sum_{t=1}^{T}\pi_{it}[1+\delta_n],
\end{aligned}$$

where $e_1 = (0, \ldots, 0, 1, \ldots, 1)$ is a 1 by nT row vector with the first T elements being zeros and the rest elements being ones.

Proof: By Lemma A.5, we have

$$\begin{aligned}
& s_h(x)'D[D'PD]^{-1}D'P\Pi_{nT} = s_h(x)'D[D'D]^{-1}D'P\Pi_{nT} + (s.o.) \\
= \;& s_h(x)'D[D'D]^{-1}D'[I_{nT} - S' - S + S'S]\Pi_{nT} + (s.o.) \\
= \;& s_h(x)'D[D'D]^{-1}D'\Pi_{nT} - s_h(x)'D[D'D]^{-1}D'S'\Pi_{nT} - s_h(x)'D[D'D]^{-1}D'S\Pi_{nT} \\
& + s_h(x)'D[D'D]^{-1}D'S'S\Pi_{nT} + (s.o.) \\
\equiv \;& B_1 - B_2 - B_3 + B_4 + (s.o.),
\end{aligned}$$

where the definitions of B_j, $j = 1, ..., 4$, should be apparent.

Recall that $D = [-\iota_{n-1} \;\; I_{n-1}]' \otimes \iota_T$ and by Lemma A.4,

$$\begin{aligned}
D[D'D]^{-1}D' =& D\left[\frac{1}{T}I_{n-1} - \frac{1}{nT}J_{n-1}\right]D' \\
=& \frac{1}{nT}\left(\begin{array}{c|cccc}
\mathbf{0}_{T\times T} & & \mathbf{0}'_{(n-1)T\times T} & & \\
\hline
 & (n-1)J_T & -1 & \cdots & -1 \\
\mathbf{0}_{(n-1)T\times T} & & \ddots & & \\
 & -1 & \cdots & -1 & (n-1)J_T
\end{array}\right),
\end{aligned}$$

where $\mathbf{0}_{T\times T}$ is a T by T square matrix with all elements being zeros. The diagonal

T by T elements of the low left part of the matrix are $(n-1)$, and the rest elements are -1.

Since $s_h(x)' = [\iota_{nT}' K_h(x)\iota_{nT}]^{-1}\iota_{nT}' K_h(x)$, we have

$$
\begin{aligned}
B_1 &= s_H(x)' D[D'D]^{-1}D'\Pi_{nT} \\
&= \frac{1}{nT}\left(0, \cdots, 0, (n-1)s_{h,2}(x) - \sum_{i=3}^{n} s_{h,i}(x), \cdots, (n-1)s_{h,n}(x) - \sum_{i=2}^{n-1} s_{h,i}(x)\right)\Pi_{nT} \\
&= \frac{1+\delta_n}{n^2T^2 f(x)}\left(\mathbf{0}_{1\times T}, (n-1)\sum_{t=1}^{T} K_h(X_{2t}, x)\right. \\
&\left. - \sum_{i=3}^{n}\sum_{t=1}^{T} K_h(X_{it} - x), \cdots, (n-1)\sum_{t=1}^{T} K_h(X_{nt}, x) - \sum_{i=2}^{n-1}\sum_{t=1}^{T} K_h(X_{it} - x)\right)\Pi_{nT} \\
&= \frac{1}{n^2T^2 f(x)}\left(\mathbf{0}_{1\times T}, Tf(x), \cdots, Tf(x)\right)\Pi_{nT}[1+\delta_n] = \frac{1}{n^2T} e_1 \Pi_{nT}[1+\delta_n] \\
&= \frac{1}{n^2T}\sum_{i=2}^{n}\sum_{t=1}^{T} \pi_{it}[1+\delta_n],
\end{aligned}
$$

where $s_{h,i}(x) = \sum_{t=1}^{T} s_{h,it}(x)$ is the same defined in the proof of Lemma A.5. Lemma A.1 is used in the second equality. The same derivation is used in the second term.

$$
\begin{aligned}
B_2 =& s_h(x)' D[D'D]^{-1}D'S'\Pi_{nT} = \frac{1}{n^2T} e_1 S'\Pi_{nT}[1+\delta_n] \\
&= \frac{1}{n^2T}\left(\frac{\sum_{i=2}^{n}\sum_{t=1}^{T} K_h(X_{11}, X_{it})}{\sum_{i=1}^{n}\sum_{t=1}^{T} K_h(X_{11}, X_{it})}, \cdots, \frac{\sum_{i=2}^{n}\sum_{t=1}^{T} K_h(X_{nT}, X_{it})}{\sum_{i=1}^{n}\sum_{t=1}^{T} K_h(X_{nT}, X_{it})}\right)\Pi_{nT}[1+\delta_n] \\
&= \frac{1}{n^2T}\left(\frac{f(X_{11})}{nTf(X_{11})}, \cdots, \frac{f(X_{nT})}{nTf(X_{nT})}\right)\Pi_{nT}[1+\delta_n] + (s.o.) \\
&= \frac{1}{n^3T^2}\iota_{nT}'\Pi_{nT}[1+\delta_n] + (s.o.) = \frac{1}{n^3T^2}\sum_{i=1}^{n}\sum_{t=1}^{T}\pi_{it}[1+\delta_n] + (s.o.).
\end{aligned}
$$

For the third term,

$$
\begin{aligned}
B_3 &= s_h(x)'D[D'D]^{-1}D'S\Pi_{nT} = \frac{1}{n^2T}e_1 S\Pi_{nT}[1+\delta_n] \\
&= \frac{1}{n^2T}\left(\sum_{i=2}^{n}\sum_{t=1}^{T}\frac{K_h(X_{11},X_{it})}{\sum_{j=1}^{n}\sum_{s=1}^{T}K_h(X_{js},X_{it})},\cdots,\right. \\
&\qquad\qquad \left.\sum_{i=2}^{n}\sum_{t=1}^{T}\frac{K_h(X_{nT},X_{it})}{\sum_{j=1}^{n}\sum_{s=1}^{T}K_h(X_{js},X_{it})}\right)\Pi_{nT}[1+\delta_n] \\
&= \frac{1}{n^2T}\left(\sum_{i=2}^{n}\sum_{t=1}^{T}\frac{K_h(X_{11},X_{it})}{nTf(X_{it})},\cdots,\sum_{i=2}^{n}\sum_{t=1}^{T}\frac{K_h(X_{nT},X_{it})}{nTf(X_{it})}\right)\Pi_{nT}[1+\delta_n].
\end{aligned}
$$

For a typical elements in the above vector, we have

$$
\begin{aligned}
\frac{K_h(X_{js},X_{it})}{f(X_{it})} &= \frac{K_h(X_{js},X_{it})}{f(X_{it})-f(X_{js})+f(X_{js})} = \frac{K_h(X_{js},X_{it})}{f(X_{js})[1-\frac{f(X_{it})-f(X_{js})}{f(X_{js})}]} \\
&= \frac{K_h(X_{js},X_{it})}{f(X_{js})}[1+\varsigma_{it,js}+\varsigma_{it,js}^2+\cdots],
\end{aligned}
$$

where $\varsigma_{it,js}=\frac{f(X_{it})-f(X_{js})}{f(X_{js})}$ and the fact that $\frac{1}{1-x}=1+x+x^2+\cdots$ is used in the last equality. Further calculation gives that

$$
\begin{aligned}
& s_h(x)'D[D'D]^{-1}D'S\Pi_{nT} \\
=\; & \frac{1}{n^2T}\left(\sum_{i=2}^{n}\sum_{t=1}^{T}\frac{K_h(X_{11},X_{it})}{nTf(X_{11})},\cdots,\right. \\
& \qquad \left.\sum_{i=2}^{n}\sum_{t=1}^{T}\frac{K_h(X_{nT},X_{it})}{nTf(X_{nT})}\right)\Pi_{nT}[1+\varsigma_{it,js}+\varsigma_{it,js}^2+\cdots][1+\delta_n] \\
=\; & \frac{1}{n^2T}\left(\frac{f(X_{11})}{nTf(X_{11})},\cdots,\frac{f(X_{nT})}{nTf(X_{nT})}\right)\Pi_{nT}[1+\delta_n]+(s.o.) \\
=\; & \frac{1}{n^3T^2}\iota_{nT}'\Pi_{nT}[1+\delta_n]+(s.o.) = \frac{1}{n^3T^2}\sum_{i=1}^{n}\sum_{t=1}^{T}\pi_{it}[1+\delta_n]+(s.o.).
\end{aligned}
$$

Using the same method in deriving the second and the third terms above, we have

$$
\begin{aligned}
B_4 =& s_h(x)'D[D'D]^{-1}D'S'S\Pi_{nT} = \frac{1}{n^3T^2}\iota_{nT}'S\Pi_{nT}[1+\delta_n] \\
&= \frac{1}{n^3T^2}\left(\sum_{i=1}^{n}\sum_{t=1}^{T}\frac{K_h(X_{11},X_{it})}{nTf(X_{11})},\cdots,\sum_{i=1}^{n}\sum_{t=1}^{T}\frac{K_h(X_{nT},X_{it})}{nTf(X_{nT})}\right)\Pi_{nT}[1+\delta_n] \\
&= \frac{1}{n^3T^2}\left(\frac{f(X_{11})}{nTf(X_{11})},\cdots,\frac{f(X_{nT})}{nTf(X_{nT})}\right)\Pi_{nT}[1+\delta_n]+(s.o.) \\
&= \frac{1}{n^4T^3}\iota_{nT}'\Pi_{nT}[1+\delta_n]+(s.o.) = \frac{1}{n^4T^3}\sum_{i=1}^{n}\sum_{t=1}^{T}\pi_{it}[1+\delta_n]+(s.o.).
\end{aligned}
$$

Summarizing the above, we have shown that

$$
\begin{aligned}
& s_h(x)'D[D'PD]^{-1}D'P\Pi_{nT} \\
&= s_h(x)'D[D'D]^{-1}D'\Pi_{nT} - s_h(x)'D[D'D]^{-1}D'S'\Pi_{nT} - s_h(x)'D[D'D]^{-1}D'S\Pi_{nT} \\
&+ s_h(x)'D[D'D]^{-1}D'S'S\Pi_{nT} + (s.o.) \\
&= \frac{1}{n^2T}e_1\Pi_{nT}[1+\delta_n] - \frac{1}{n^3T^2}\iota_{nT}'\Pi_{nT}[1+\delta_n] - \frac{1}{n^3T^2}\iota_{nT}'\Pi_{nT}[1+\delta_n] \\
&+ \frac{1}{n^4T^3}\iota_{nT}'\Pi_{nT}[1+\delta_n] + (s.o.) \\
&= \frac{1}{n^2T}\sum_{i=2}^{n}\sum_{t=1}^{T}\pi_{it}[1+\delta_n] - \frac{2}{n^3T^2}\sum_{i=1}^{n}\sum_{t=1}^{T}\pi_{it}[1+\delta_n] + \frac{1}{n^4T^3}\sum_{i=1}^{n}\sum_{t=1}^{T}\pi_{it}[1+\delta_n] + (s.o.).
\end{aligned}
$$

This completes the proof of Lemma A.6.

Lemma A.7. *Under Assumptions A1-A4, Lemma A.4, A.5 and A.6,*

$$A_{14} = s_h(x)'D[D'PD]^{-1}D'Pm(X) = \frac{1}{n}\left[E[m(X_{it})] + O_p\left(\frac{1}{\sqrt{nT}}\right)\right].$$

Proof: By Lemma A.6, it is easy to show that

$$\begin{aligned}
&s_h(x)'D[D'PD]^{-1}D'Pm(X) \\
&= s_h(x)'D[D'D]^{-1}D'Pm(X) + (s.o.) \\
&= \left\{ \frac{1}{n^2T} e_1[1+\delta_n] - \frac{2}{n^3T^2} \iota_{nT}'[1+\delta_n] + \frac{1}{n^4T^3} \iota_{nT}'[1+\delta_n] \right\} m(X) \\
&= \frac{1}{n^2T} \sum_{i=2}^{n} \sum_{t=1}^{T} m(X_{it})[1+\delta_n] - \frac{2}{n^3T^2} \sum_{i=1}^{n} \sum_{t=1}^{T} m(X_{it})[1+\delta_n] \\
&+ \frac{1}{n^4T^3} \sum_{i=1}^{n} \sum_{t=1}^{T} m(X_{it})[1+\delta_n] \\
&= \frac{1}{n} \left[E[m(X_{it})] + O_p\left(\frac{1}{\sqrt{nT}} \right) \right] + (s.o.).
\end{aligned}$$

A.2 Limiting result of $\widehat{m}_2(x)$

Define an $(n-1)$ by 1 vector $\tilde{\mu}$ by $\tilde{\mu} = (\mu_2, \ldots, \mu_n)'$. Then it is easy to check that $MD\tilde{\mu} \equiv 0$, where $M = I_{nT} - D[D'PD]^{-1}D'P$. Hence, by adding and subtracting terms, we obtain

$$\begin{aligned}
\widehat{m}_2(x) &\equiv s_h(x)'MD_0\mu \\
&= s_h(x)'(I_{nT} - D[D'PD]^{-1}D'P)D_0\mu \\
&= s_h(x)'(I_{nT} - D[D'PD]^{-1}D'P)(D_0\mu + D\tilde{\mu} - D\tilde{\mu}) \\
&= s_h(x)'(D_0\mu - D\tilde{\mu}) - s_h(x)'D[D'PD]^{-1}D'P(D_0\mu - D\tilde{\mu}) \\
&= s_h(x)'(D_0\mu - D\tilde{\mu}) - s_h(x)'D[D'D]^{-1}D'P(D_0\mu - D\tilde{\mu}) + (s.o.),
\end{aligned}$$

where $MD\tilde{\mu} \equiv 0$ is used in the second to the last equality and Lemma A.5 is used in the last equality.

Recall that

$$D_0\mu - D\tilde{\mu} = \begin{pmatrix} \mu_1 \\ \vdots \\ \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{pmatrix} - \begin{pmatrix} -\sum_{i=2}^n \mu_i \\ \vdots \\ -\sum_{i=2}^n \mu_i \\ \mu_2 \\ \vdots \\ \mu_n \end{pmatrix} = \begin{pmatrix} n\bar{\mu} \\ \vdots \\ n\bar{\mu} \\ 0 \\ \vdots \\ 0 \end{pmatrix},$$

where $n\bar{\mu} = \sum_{i=1}^n \mu_i$. We obtain $D_0\mu - D\tilde{\mu} = n\bar{\mu}e_2$, where $e_2 = (1, \ldots, 1, 0, \ldots, 0)'$ is an nT by 1 vector with the first T elements being ones and all other elements being zeros.

By Lemma A.6, it is easy to show that

$$\begin{aligned}
&\widehat{m}_2(x) = s_h(x)'(D_0\mu - D\tilde{\mu}) - s_h(x)'D[D'D]^{-1}D'P(D_0\mu - D\tilde{\mu}) + (s.o.) \\
&= n\bar{\mu}s_h(x)'e_2 - \left\{ \frac{1}{n^2T}e_1[1+\delta_n] - \frac{2}{n^3T^2}\iota_{nT}'[1+\delta_n] + \frac{1}{n^4T^3}\iota_{nT}'[1+\delta_n] \right\} n\bar{\mu}e_2 \\
&= \frac{n\bar{\mu}}{nTf(x)}\sum_{t=1}^T K_h(X_{1t}, x) - \frac{n\bar{\mu}}{n^2T}e_1e_2[1+\delta_n] + \frac{2n\bar{\mu}}{n^3T^2}[1+\delta_n]\iota_{nT}'e_2 - \frac{n\bar{\mu}}{n^4T^3}[1+\delta_n]\iota_{nT}'e_2 \\
&= n\bar{\mu}\sum_{t=1}^T s_{h,1t}(x) - 0 + \frac{2\bar{\mu}[1+\delta_n]}{n^2T^2} - \frac{\bar{\mu}[1+\delta_n]}{n^3T^3} \\
&\equiv \bar{\mu}\widehat{m}_{21}(x) + (s.o.),
\end{aligned}$$

where $\widehat{m}_{21}(x) = n\sum_{t=1}^T s_{h,1t}(x) = \frac{\sum_{t=1}^T K_h(X_{1t},x)}{Tf(x)}$.

Lemma A.2.1. *Under Assumptions A1-A4,*

$$\widehat{m}_{21}(x) = 1 + o_p(1),$$

since $\frac{1}{T}\sum_{t=1}^{T} K_h(X_{1t}, x) \xrightarrow{p} f(x)$ *as* $T \to \infty$ *and* $n \to \infty$.

Recall that $\widehat{m}_2(x) = \bar{\mu}\widehat{m}_{21}(x) + (s.o.) = \bar{\mu}[1 + o_p(1)]$ and $\sqrt{n}\bar{\mu} \xrightarrow{d} N(0, \sigma_\mu^2)$, as $T \to \infty$ and $n \to \infty$.

Lemma A.2.2. *1. Under Assumption A1-A4, when* $Th_1...h_q \to 0$,

$$\sqrt{nTh_1...h_q}\widehat{m}_2(x) = \sqrt{Th_1...h_q}\sqrt{n}\bar{\mu} \xrightarrow{p} 0.$$

2. Under Assumption A1-A4, , when $Th_1...h_q \to a_0$, *where* a_0 *is a constant,*

$$\sqrt{nTh_1...h_q}\widehat{m}_2(x) = \sqrt{Th_1...h_q}\sqrt{n}\bar{\mu} \xrightarrow{d} N(0, a_0\sigma_\mu^2).$$

3. Under Assumption A1-A3 and A5, when $Th_1...h_q \to \infty$,

$$\sqrt{n}\widehat{m}_2(x) = \sqrt{n}\bar{\mu} \xrightarrow{d} N(0, \sigma_\mu^2),$$

and

$$\sqrt{n}B_h(x) = \sqrt{n}O(\sum_{s=1}^{q} h_s^2) = \sqrt{n\sum_{s=1}^{q} h_s^4} = O(1).$$

A.3 Limiting result of $\widehat{m}_3(x)$

Lemma A.3.1. *Under Assumptions A1-A4, Lemma A.4, A.5 and A.6,*

$$\sqrt{nTh_1...h_q}\widehat{m}_3(x) \xrightarrow{d} N\left(0, \frac{\zeta_0\sigma_\nu^2}{f(x)}\right). \quad \text{(A.1)}$$

Proof: Let $\zeta_0 = \int K(v)^2 dv$, by CLT and the same methods we prove A_{11},

$$
\begin{aligned}
&\sqrt{nTh_1...h_q}\widehat{m}_3(x) \\
&= \sqrt{nTh_1...h_q}s_h(x)'MV = \sqrt{nTh_1...h_q}s_h(x)'(I_{nT} - D[D'PD]^{-1}D'P)V \\
&= \sqrt{nTh_1...h_q}s_h(x)'V - \sqrt{nTh_1...h_q}s_h(x)'D[D'PD]^{-1}D'PV \\
&= \sqrt{nTh_1...h_q}\left\{s_h(x)'V - \frac{1}{nT^2}e_1V[1+\delta_n] - \frac{2}{n^2T^3}\iota_{nT}'V[1+\delta_n] + \frac{1}{n^3T^4}\iota_{nT}'V[1+\delta_n]\right\} \\
&+ (s.o.) \\
&= \sqrt{nTh_1...h_q}\sum_{i=1}^{n}\sum_{t=1}^{T}s_{h,it}(x)\nu_{it} - \frac{\sqrt{nTh_1...h_q}}{nT^2}\sum_{t=1}^{T}\nu_{1t} + (s.o.) \\
&\xrightarrow{d} N\left(0, \frac{\zeta_0\sigma_\nu^2}{f(x)}\right).
\end{aligned}
$$

Remark A.3.2. *When $Th_1...h_q \to \infty$, $\sqrt{n}(nTh_1...h_g)^{-1/2} = \frac{1}{\sqrt{Th_1...h_q}} \to 0$, which gives the result of Theorem 2.3.1 part 3.*

We have now completed the proof of Theorem 2.3.1.

APPENDIX B

FIGURES

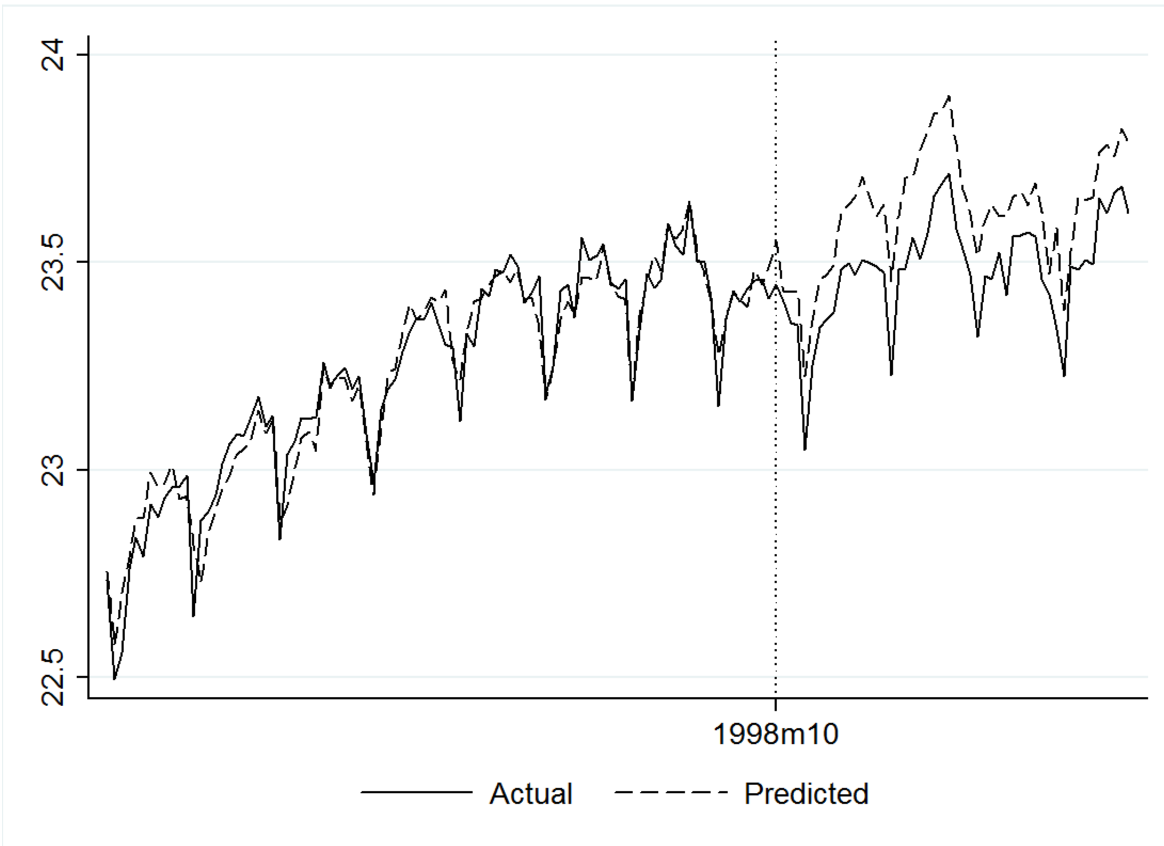

Figure B.1: Treatment Effects of Hong Kong Total Value of Exports

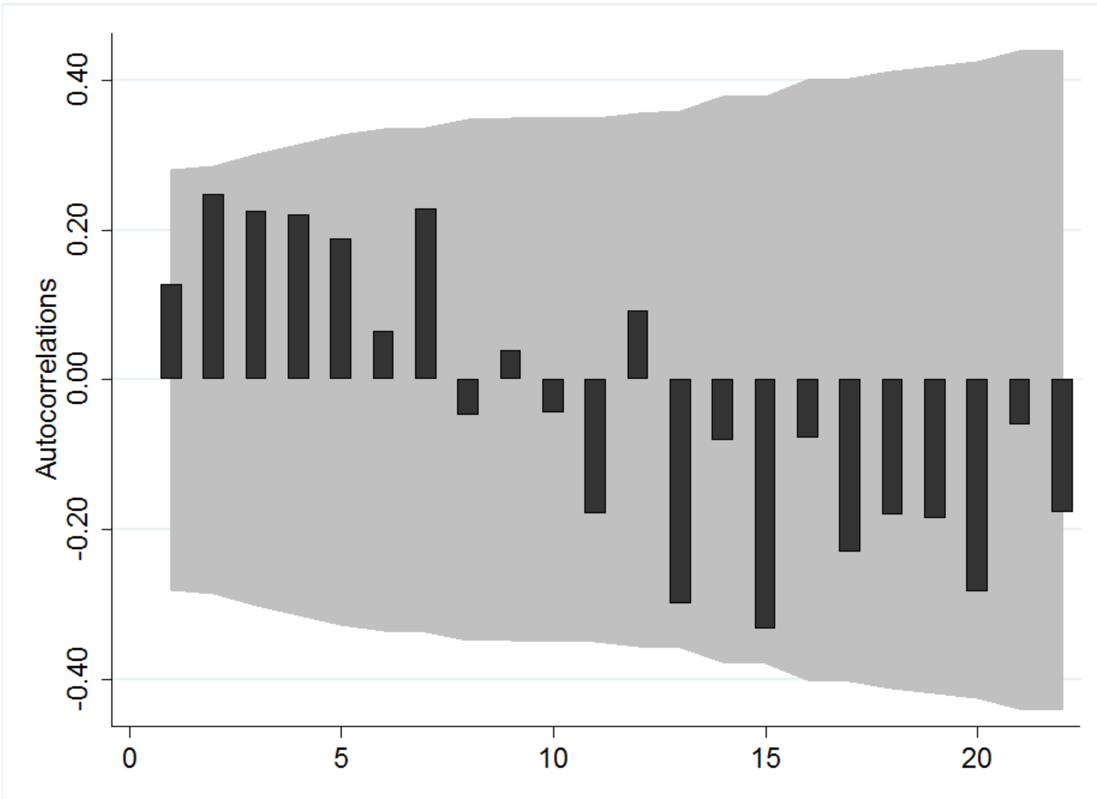

Figure B.2: Autocorrelations of Treatment Effects for Hong Kong Total Value of Exports

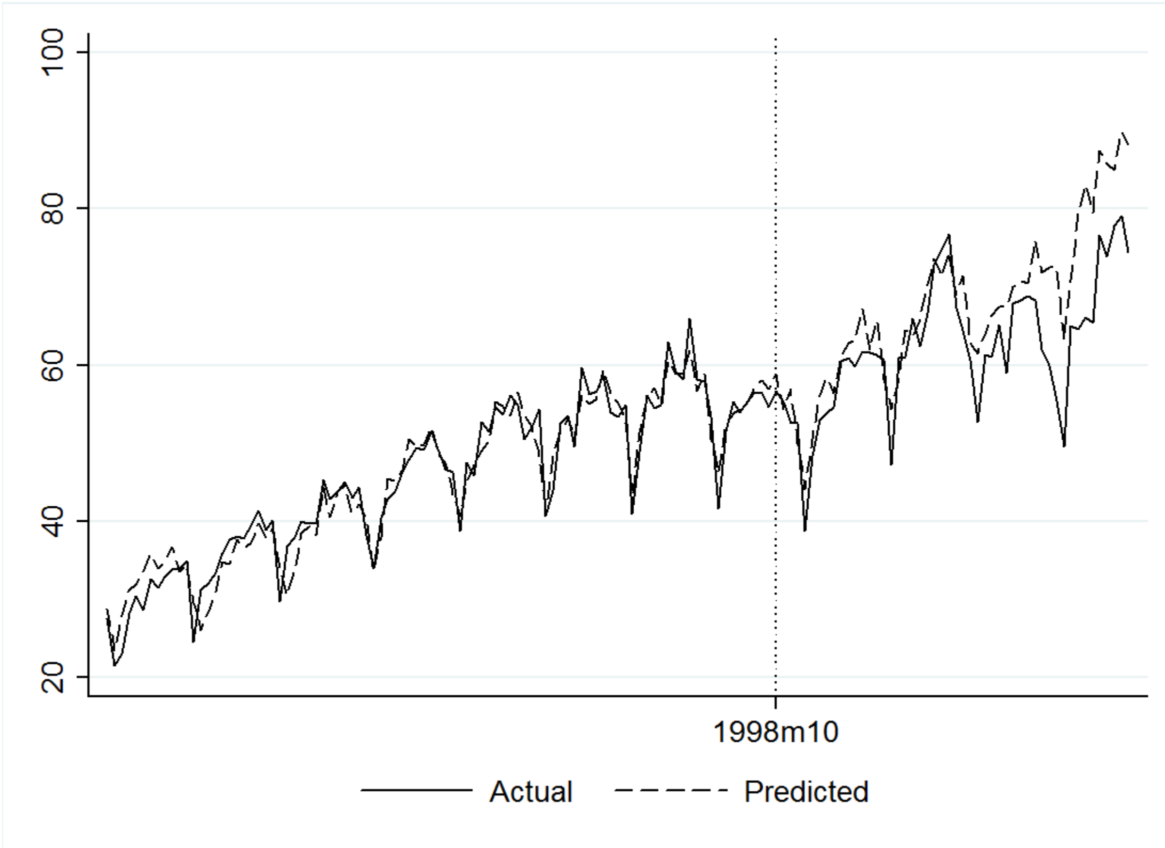

Figure B.3: Treatment Effects of Hong Kong Export Volume Index

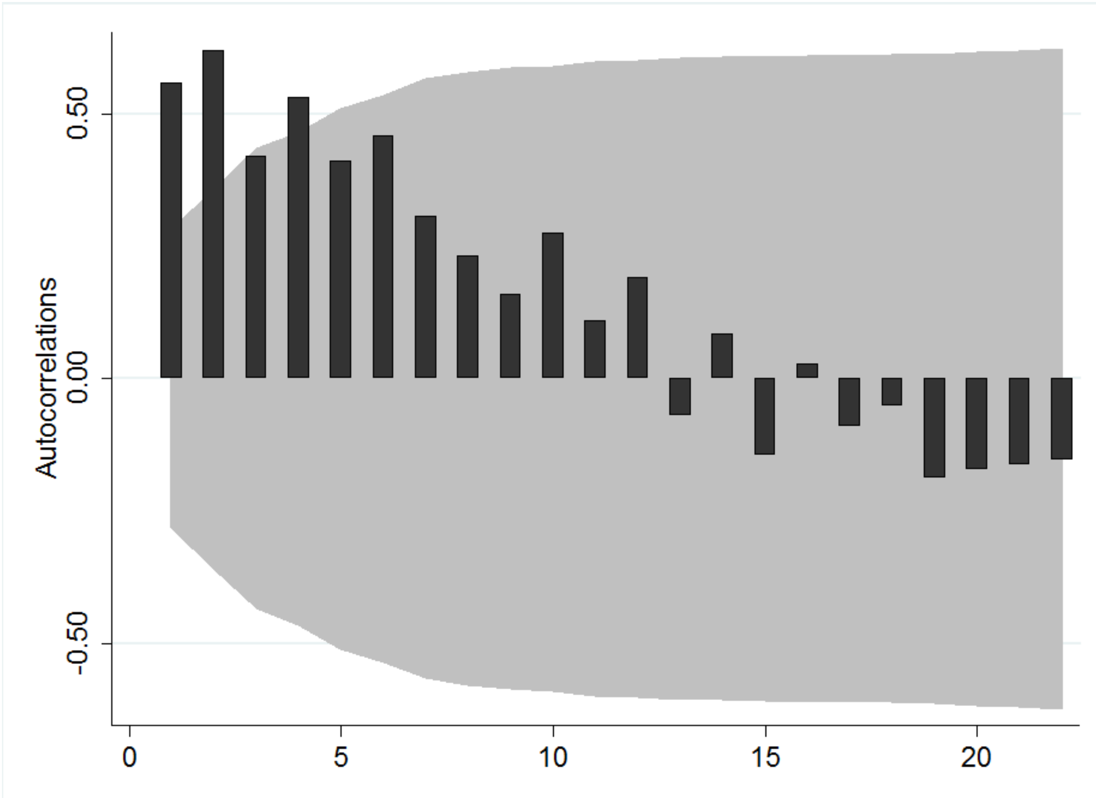

Figure B.4: Autocorrelations of Treatment Effects for Hong Kong Export Volume Index

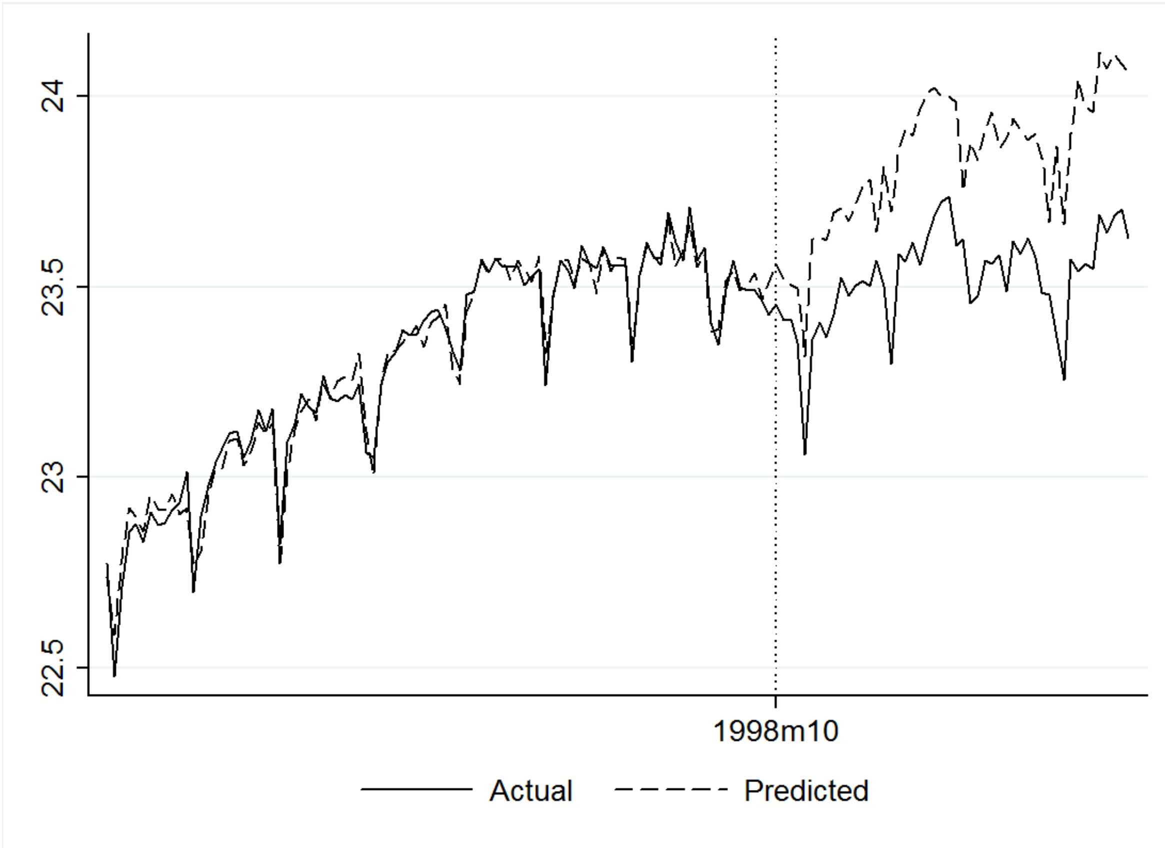

Figure B.5: Treatment Effects of Hong Kong Total Value of Imports

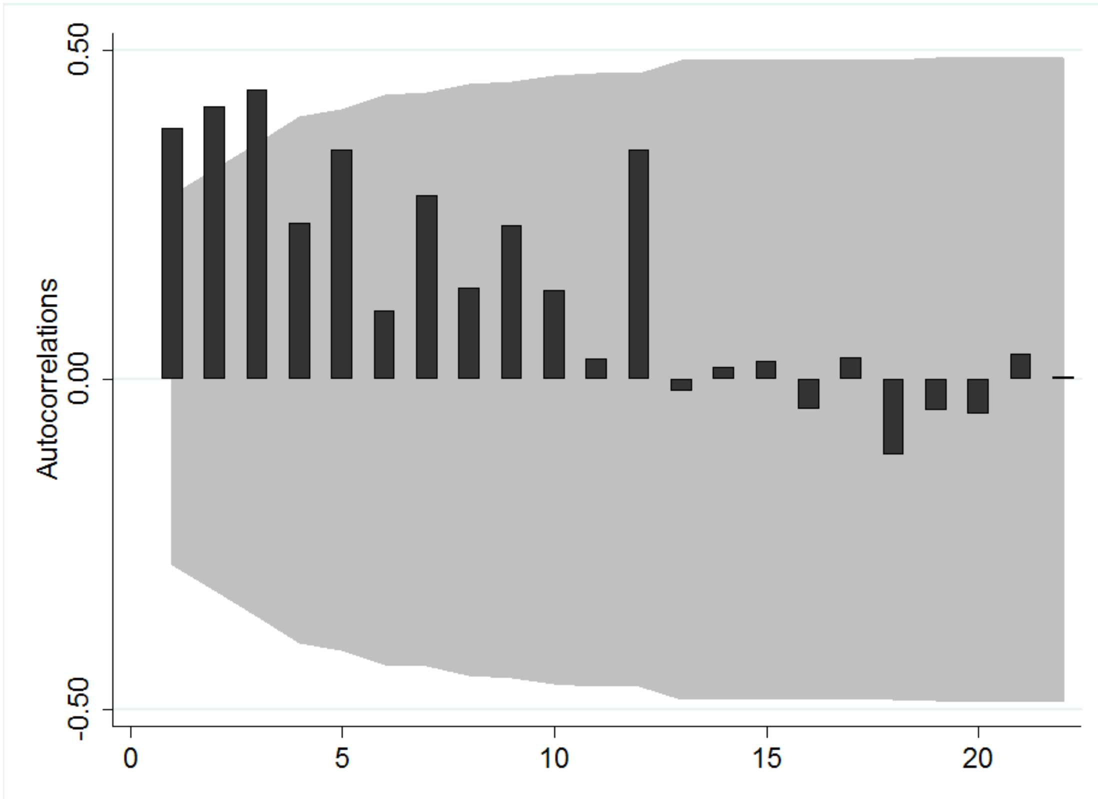

Figure B.6: Autocorrelations of Treatment Effects for Hong Kong Total Value of Imports

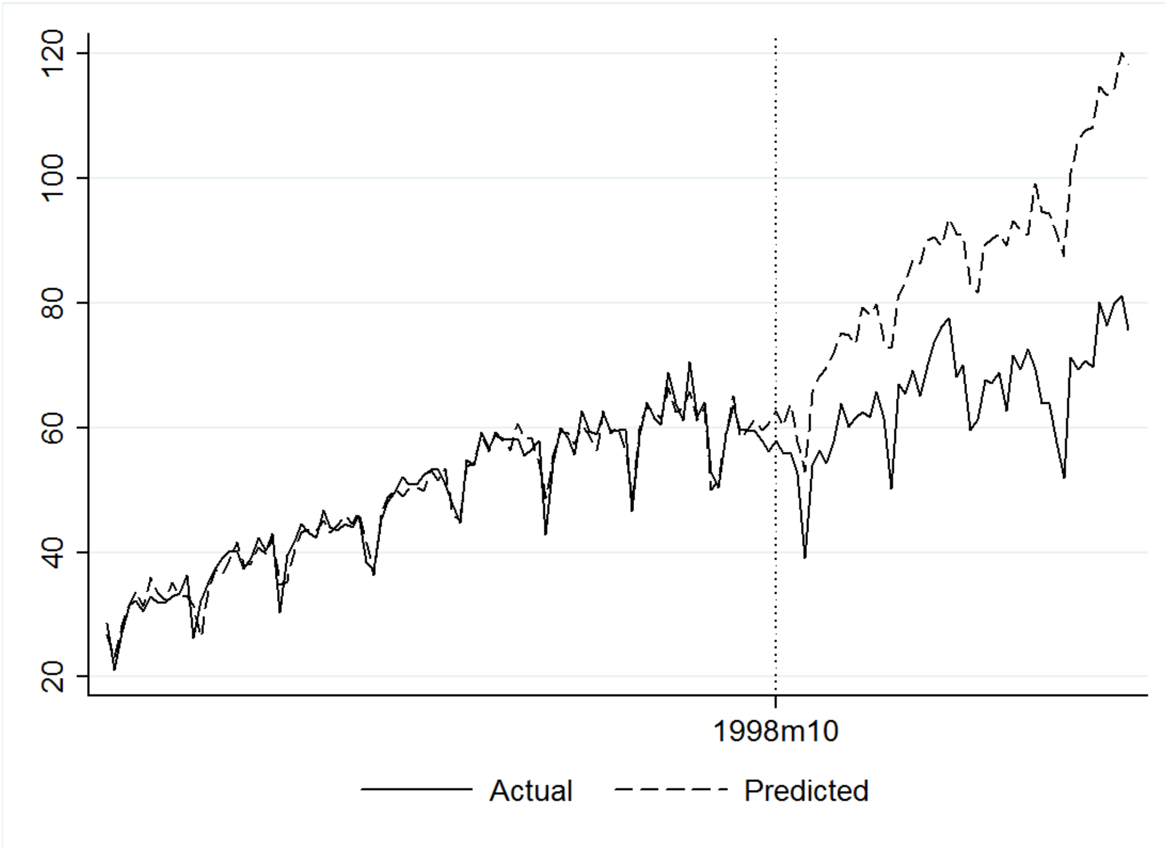

Figure B.7: Treatment Effects of Hong Kong Import Volume Index

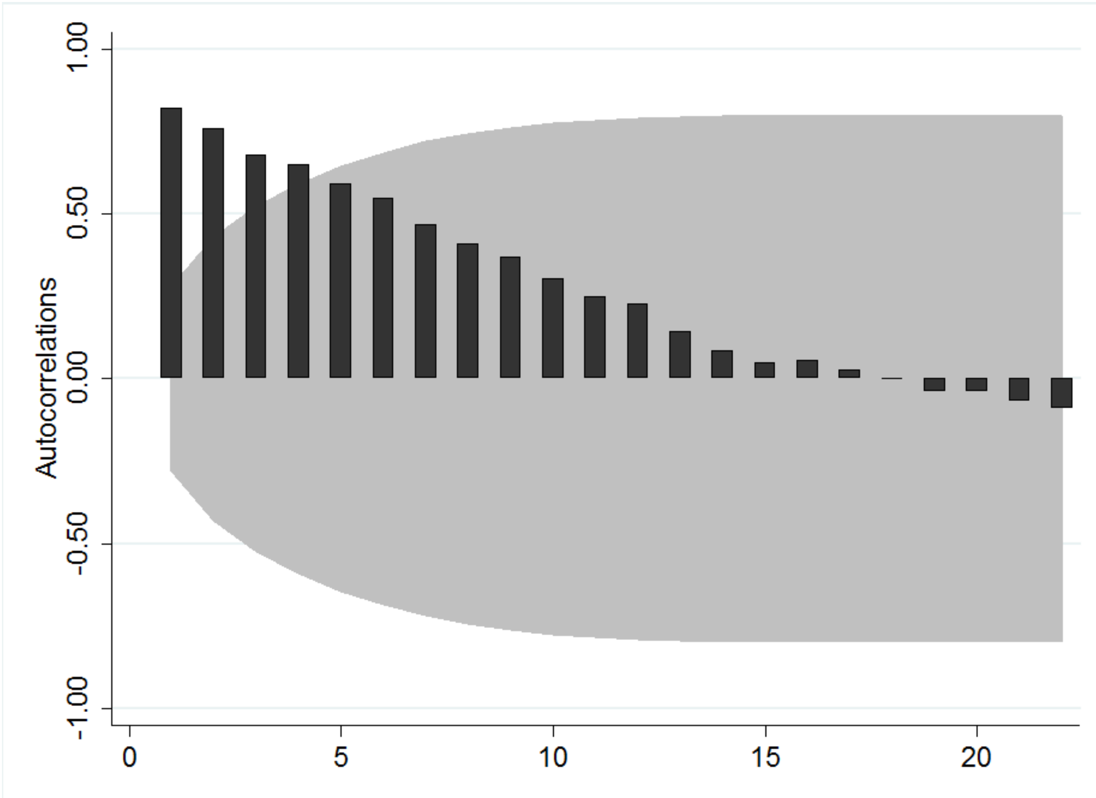

Figure B.8: Autocorrelations of Treatment Effects for Hong Kong Import Volume Index

APPENDIX C

TABLES

Table C.1: AMSE of $\hat{m}(x)$ for Different Estimators (DGP1, $c_0 = 0.5$)

T	n	$\widehat{m}_{HCL}(x)$	$\widehat{m}_{KLH}(x)$	$\widehat{m}_{LS}(x)$	$\widehat{m}_{SU}(x)$	$\widehat{m}_{LC}(x)$
2	50	0.0833	0.1478	0.2052	0.0725	0.0567
	100	0.0462	0.0863	0.1874	0.0415	0.0332
	200	0.0253	0.0460	0.1767	0.0217	0.0177
	500	0.0115	0.0240	0.1709	0.0102	0.0087
3	50	0.0670	0.0697	0.0912	0.0432	0.0372
	100	0.0363	0.0394	0.0739	0.0252	0.0198
	200	0.0191	0.0243	0.0682	0.0135	0.0119
	500	0.0086	0.0136	0.0615	0.0063	0.0055
4	50	0.0630	0.0486	0.0525	0.0339	0.0298
	100	0.0336	0.0267	0.0376	0.0196	0.0160
	200	0.0176	0.0174	0.0313	0.0104	0.0089
	500	0.0079	0.0097	0.0264	0.0048	0.0042
5	50	0.0570	0.0375	0.0354	0.0275	0.0242
	100	0.0306	0.0219	0.0239	0.0155	0.0139
	200	0.0168	0.0140	0.0174	0.0084	0.0075
	500	0.0076	0.0084	0.0133	0.0038	0.0036
10	50	0.0552	0.0194	0.0178	0.0167	0.0164
	100	0.0278	0.0124	0.0098	0.0094	0.0087
	200	0.0158	0.0083	0.0056	0.0054	0.0048
20	50	0.0533	0.0118	0.0126	0.0127	0.0120
	100	0.0291	0.0079	0.0067	0.0067	0.0062

Table C.2: AMSE of $\hat{m}(x)$ for Different Estimators (DGP1, $c_0 = 1$)

T	n	$\widehat{m}_{HCL}(x)$	$\widehat{m}_{KLH}(x)$	$\widehat{m}_{LS}(x)$	$\widehat{m}_{SU}(x)$	$\widehat{m}_{LC}(x)$
2	50	0.0843	0.1478	0.2091	0.0749	0.0597
	100	0.0462	0.0863	0.1895	0.0424	0.0327
	200	0.0262	0.0460	0.1778	0.0222	0.0186
	500	0.0113	0.0240	0.1713	0.0105	0.0087
3	50	0.0066	0.0697	0.0939	0.0463	0.0379
	100	0.0370	0.0394	0.0752	0.0244	0.0219
	200	0.0199	0.0243	0.0688	0.0141	0.0118
	500	0.0089	0.0136	0.0618	0.0064	0.0059
4	50	0.0595	0.0486	0.0545	0.0358	0.0321
	100	0.0325	0.0267	0.0386	0.0192	0.0169
	200	0.0178	0.0174	0.0317	0.0106	0.0098
	500	0.0082	0.0097	0.0266	0.0049	0.0045
5	50	0.0596	0.0375	0.0366	0.0292	0.0258
	100	0.0325	0.0219	0.0246	0.0165	0.0141
	200	0.0170	0.0140	0.0178	0.0087	0.0078
	500	0.0078	0.0084	0.0135	0.0040	0.0036
10	50	0.0564	0.0194	0.0183	0.0188	0.0173
	100	0.0297	0.0124	0.0101	0.0098	0.0093
	200	0.0161	0.0083	0.0058	0.0054	0.0041
20	50	0.0546	0.0118	0.0128	0.0130	0.0117
	100	0.0300	0.0079	0.0068	0.0068	0.0064

Table C.3: AMSE of $\hat{m}\,(x)$ for Different Estimators (DGP1, $c_0 = 2$)

T	n	$\widehat{m}_{HCL}(x)$	$\widehat{m}_{KLH}(x)$	$\widehat{m}_{LS}(x)$	$\widehat{m}_{SU}(x)$	$\widehat{m}_{LC}(x)$
2	50	0.0838	0.1478	0.2217	0.0845	0.0697
	100	0.0467	0.0863	0.1963	0.0476	0.0403
	200	0.0242	0.0460	0.1811	0.0248	0.0212
	500	0.0117	0.0240	0.1726	0.0114	0.0099
3	50	0.0659	0.0697	0.1028	0.0530	0.0462
	100	0.0356	0.0394	0.0793	0.0276	0.0240
	200	0.0195	0.0243	0.0707	0.0156	0.0139
	500	0.0088	0.0136	0.0626	0.0070	0.0063
4	50	0.0612	0.0486	0.0610	0.0409	0.0368
	100	0.0328	0.0267	0.0419	0.0218	0.0194
	200	0.0176	0.0174	0.0333	0.0118	0.0106
	500	0.0079	0.0097	0.0272	0.0054	0.0049
5	50	0.0591	0.0375	0.0412	0.0328	0.0289
	100	0.0313	0.0219	0.0273	0.0187	0.0168
	200	0.0174	0.0140	0.0189	0.0096	0.0088
	500	0.0077	0.0084	0.0140	0.0045	0.0041
10	50	0.0533	0.0194	0.0204	0.0207	0.0189
	100	0.0307	0.0124	0.0111	0.0107	0.0099
	200	0.0158	0.0083	0.0064	0.0059	0.0055
20	50	0.0559	0.0118	0.0139	0.0140	0.0133
	100	0.0297	0.0079	0.0074	0.0073	0.0069

Table C.4: AMSE of $\hat{m}(x)$ for Different Estimators (DGP2, $c_0 = 0.5$)

T	n	$\widehat{m}_{HCL}(x)$	$\widehat{m}_{KLH}(x)$	$\widehat{m}_{LS}(x)$	$\widehat{m}_{SU}(x)$	$\widehat{m}_{LC}(x)$
2	50	0.0758	0.1724	0.1531	0.0693	0.0596
	100	0.0425	0.1150	0.1378	0.0390	0.0357
	200	0.0222	0.0767	0.1288	0.0202	0.0195
	500	0.0106	0.0548	0.1241	0.0096	0.0098
3	50	0.0521	0.1017	0.0867	0.0423	0.0394
	100	0.0285	0.0716	0.0713	0.0226	0.0216
	200	0.0158	0.0569	0.0661	0.0127	0.0131
	500	0.0073	0.0446	0.0606	0.0059	0.0065
4	50	0.0438	0.0810	0.0592	0.0326	0.0316
	100	0.0242	0.0592	0.0454	0.0174	0.0174
	200	0.0131	0.0487	0.0397	0.0096	0.0101
	500	0.0062	0.0397	0.0353	0.0044	0.0050
5	50	0.0398	0.0692	0.0440	0.0268	0.0256
	100	0.0227	0.0537	0.0330	0.0150	0.0151
	200	0.0123	0.0455	0.0270	0.0079	0.0085
	500	0.0057	0.0380	0.0230	0.0037	0.0042
10	50	0.0332	0.0518	0.0222	0.0174	0.0177
	100	0.0190	0.0441	0.0141	0.0091	0.0096
	200	0.0100	0.0387	0.0097	0.0049	0.0055
20	50	0.0324	0.0433	0.0143	0.0122	0.0129
	100	0.0169	0.0383	0.0081	0.0063	0.0070

Table C.5: AMSE of $\hat{m}\,(x)$ for Different Estimators (DGP2, $c_0 = 1$)

T	n	$\widehat{m}_{HCL}(x)$	$\widehat{m}_{KLH}(x)$	$\widehat{m}_{LS}(x)$	$\widehat{m}_{SU}(x)$	$\widehat{m}_{LC}(x)$
2	50	0.0783	0.1724	0.1564	0.0687	0.0622
	100	0.0439	0.1150	0.1397	0.0398	0.0372
	200	0.0229	0.0767	0.1297	0.0209	0.0202
	500	0.0109	0.0548	0.1245	0.0098	0.0100
3	50	0.0539	0.1017	0.0890	0.0437	0.0412
	100	0.0293	0.0716	0.0724	0.0244	0.0225
	200	0.0162	0.0569	0.0665	0.0133	0.0134
	500	0.0075	0.0446	0.0608	0.0058	0.0067
4	50	0.0452	0.0810	0.0609	0.0329	0.0331
	100	0.0249	0.0592	0.0463	0.0187	0.0181
	200	0.0135	0.0487	0.0401	0.0097	0.0104
	500	0.0063	0.0397	0.0354	0.0044	0.0051
5	50	0.0406	0.0692	0.0451	0.0281	0.0264
	100	0.0233	0.0537	0.0337	0.0160	0.0157
	200	0.0125	0.0455	0.0272	0.0079	0.0087
	500	0.0058	0.0380	0.0231	0.0037	0.0043
10	50	0.0336	0.0518	0.0227	0.0178	0.0181
	100	0.0192	0.0441	0.0144	0.0094	0.0099
	200	0.0102	0.0387	0.0099	0.0050	0.0057
20	50	0.0326	0.0433	0.0145	0.0120	0.0132
	100	0.0170	0.0383	0.0083	0.0067	0.0071

Table C.6: AMSE of $\hat{m}\,(x)$ for Different Estimators (DGP2, $c_0 = 2$)

T	n	$\widehat{m}_{HCL}(x)$	$\widehat{m}_{KLH}(x)$	$\widehat{m}_{LS}(x)$	$\widehat{m}_{SU}(x)$	$\widehat{m}_{LC}(x)$
2	50	0.0882	0.1724	0.1679	0.0817	0.0723
	100	0.0492	0.1150	0.1459	0.0458	0.0427
	200	0.0255	0.0767	0.1327	0.0236	0.0229
	500	0.0119	0.0548	0.1256	0.0109	0.0111
3	50	0.0608	0.1017	0.0971	0.0509	0.0483
	100	0.0325	0.0716	0.0762	0.0266	0.0258
	200	0.0178	0.0569	0.0681	0.0147	0.0150
	500	0.0081	0.0446	0.0616	0.0066	0.0073
4	50	0.0505	0.0810	0.0670	0.0393	0.0386
	100	0.0276	0.0592	0.0492	0.0208	0.0208
	200	0.0148	0.0487	0.0416	0.0112	0.0117
	500	0.0068	0.0397	0.0360	0.0050	0.0056
5	50	0.0443	0.0692	0.0493	0.0313	0.0301
	100	0.0256	0.0537	0.0361	0.0179	0.0180
	200	0.0135	0.0455	0.0283	0.0091	0.0097
	500	0.0062	0.0380	0.0236	0.0042	0.0047
10	50	0.0356	0.0518	0.0247	0.0198	0.0201
	100	0.0201	0.0441	0.0153	0.0102	0.0108
	200	0.0108	0.0387	0.0105	0.0056	0.0062
20	50	0.0336	0.0433	0.0155	0.0135	0.0142
	100	0.0175	0.0383	0.0088	0.0070	0.0076

Table C.7: AMSE and computation time (seconds) for $\widehat{m}_{MI}(x)$ and $\widehat{m}_{LC}(x)$

		DGP1				DGP2				Time (seconds)	
		$c_0 = 1$		$c_0 = 2$		$c_0 = 1$		$c_0 = 2$			
T	n	MI	LC	MI	LC	MI	LC	MI	LC	MI	LC
2	50	0.1528	0.0597	0.1528	0.0697	0.1488	0.0622	0.1488	0.0723	102	2
	100	0.0805	0.0327	0.0805	0.0403	0.0783	0.0372	0.0783	0.0427	1197	12
	200	0.0400	0.0186	0.0400	0.0212	0.0387	0.0202	0.0387	0.0229	26600	84
3	50	0.0744	0.0379	0.0744	0.0462	0.0723	0.0412	0.0723	0.0483	1204	3
	100	0.0394	0.0219	0.0394	0.0240	0.0382	0.0225	0.0382	0.0258	47028	22
	200	0.0222	0.0118	0.0222	0.0139	0.0210	0.0134	0.0210	0.0150	70078	155
4	50	0.0512	0.0321	0.0512	0.0368	0.0494	0.0331	0.0494	0.0386	5637	5
	100	0.0262	0.0169	0.0262	0.0194	0.0248	0.0181	0.0248	0.0208	28584	35
5	50	0.0396	0.0258	0.0396	0.0289	0.0379	0.0264	0.0379	0.0301	27121	8
	100	0.0215	0.0141	0.0215	0.0168	0.0208	0.0157	0.0208	0.0180	59348	50

Table C.8: Computation Time (seconds) for Different Estimators

T	n	$\widehat{m}_{HCL}(x)$	$\widehat{m}_{KLH}(x)$	$\widehat{m}_{LS}(x)$	$\widehat{m}_{SU}(x)$	$\widehat{m}_{LC}(x)$
2	50	15	1	2	3	2
	100	44	2	6	16	12
	200	145	9	21	107	84
	500	756	48	126	1331	1279
3	50	25	2	3	6	3
	100	78	9	11	32	22
	200	265	31	42	190	155
	500	1409	185	254	2452	2201
4	50	37	5	5	10	5
	100	121	18	18	51	35
	200	415	68	70	307	241
	500	2274	409	428	3772	3495
5	50	53	9	7	15	8
	100	174	31	27	77	50
	200	616	119	106	448	345
	500	3376	710	645	5564	4839
10	50	172	39	26	55	29
	100	599	150	102	281	176
	200	2101	585	400	1580	1144
20	50	626	166	98	218	108
	100	2188	650	396	1088	641

Table C.9: Hong Kong External Trade by Major Trading Partner (1996-1999)

	1996		1997		1998		1999	
	Million $	%	Million $	%	Million $	%	Million $	%
Imports (Supplier)								
China	570,442	37.1	608,372	37.7	580,614	40.6	607,546	43.6
Japan	208,239	13.6	221,646	13.7	179,947	12.6	162,652	11.7
US	121,058	7.9	125,381	7.8	106,537	7.5	98,572	7.1
Taiwan	123,202	8.0	124,547	7.7	104,075	7.3	100,426	7.2
Korea	73,302	4.8	73,226	4.5	68,836	4.8	65,432	4.7
Singapore	81,495	5.3	79,186	4.9	61,457	4.3	60,017	4.3
Germany	33,884	2.2	38,518	2.4	32,639	2.3	28,114	2.0
Malaysia	33,994	2.2	38,008	2.4	32,479	2.3	30,010	2.2
UK	33,264	2.2	36,285	2.2	29,671	2.1	26,961	1.9
Italy	31,799	2.1	31,018	1.9	23,500	1.6		
Thailand			26,070	1.6	22,234	1.6	22,798	1.6
Others	224,903	14.6	212,834	13.2	187,102	13.0	167,392	13.7
Total	1,535,582	100	1,615,090	100	1,429,092	100	1,392,718	100
Domestic Exports (Destination)								
China	61,620	29.0	63,867	30.2	56,066	29.8	50,414	29.6
US	53,860	25.4	55,073	26.1	54,842	29.1	51,358	30.1
UK	10,597	5.0	10,723	5.1	10,058	5.3	10,392	6.1
Germany	11,388	5.4	10,321	4.9	9,805	5.2	8,543	5.0
Taiwan	6,705	3.2	7,029	3.3	6,505	3.5	5,101	3.0
Japan	11,335	5.3	10,641	5.0	6,435	3.4	5,459	3.2
Singapore	10,009	4.7	8,404	4.0	5,103	2.7	3,682	2.2
Netherlands	4,674	2.2	5,138	2.4	4,736	2.5	4,119	2.4
Canada	3,885	1.8	3,872	1.8	3,598	1.9	3,151	1.8
France	2,947	1.4	3,210	1.5	3,171	1.7	3,081	1.8
Others	35,139	16.6	33,131	15.7	28,137	14.9	25,300	14.8
Total	212,160	100	211,410	100	188,454	100	170,600	100

Table C.10: Counties' Exchange Rate Policy

Country	Effective Time	Exchange Rate Policy
Hong Kong		Fixed, 1 US$ = 7.80 HK$
China		Crawling Peg
France	January 1999	1 euro= 6.55957 French Franc
Germany	January 1999	1 euro= 1.95583 Deutsche Mark
Italy	January 1999	1 euro= 1936.27 Italian Lira
Netherlands	January 1999	1 euro= 2.20371 Dutch Guilders
Korea	March 1980	Managed Floating
	November 1997	Free Floating
Malaysia	March 1990	Fixed
	December 1992	Managed Floating
	September 1998	Fixed, 1 US$=3.80 RM
Thailand	January1970	Fixed
	July 1997	Free Floating
Canada		Free Floating
Japan		
Singapore		
Taiwan		
UK	September 1992	

Table C.11: Hong Kong's Total Value of Exports: Weights of Control Countries Before 1998m10

Hong Kong	Weights	t
China	0.2346	3.39
Germany	0.0832	0.41
Singapore	0.1599	1.46
France	-0.0612	-0.75
Japan	0.4964	3.13
US	0.1374	0.57
UK	-0.1095	-0.56
Canada	0.2796	1.76
Taiwan	0.0976	0.75
Netherlands	-0.3771	-1.36
M1	0.1932	2.88
M2	0.0013	0.02
M3	-0.0594	-1.14
M4	0.0532	1.21
M5	0.1074	2.65
M6	0.0716	1.90
M7	0.1641	4.14
M8	0.1381	3.30
M9	0.1285	3.68
M10	0.1631	4.64
M11	0.1109	3.52
Constant	0.7143	0.18
R^2	0.9480	
P-value of F-statistic	0.0000	

Table C.12: Treatment Effects for Hong Kong Total Value of Exports

Time	Actual	Predicted	Treatment
1998m11	23.4048	23.4307	0.0260
1998m12	23.3536	23.4275	0.0739
1999m1	23.3476	23.4282	0.0805
1999m2	23.0470	23.2242	0.1772
1999m3	23.2514	23.3582	0.1068
1999m4	23.3445	23.4556	0.1112
1999m5	23.3629	23.4695	0.1066
1999m6	23.3804	23.4952	0.1148
1999m7	23.4837	23.6176	0.1339
1999m8	23.4970	23.6396	0.1426
1999m9	23.4695	23.6564	0.1869
1999m10	23.5046	23.7051	0.2005
1999m11	23.4992	23.6560	0.1568
1999m12	23.4908	23.6099	0.1191
2000m1	23.4754	23.6390	0.1636
2000m2	23.2272	23.4553	0.2281
2000m3	23.4814	23.6109	0.1295
2000m4	23.4840	23.7029	0.2189
2000m5	23.5595	23.7041	0.1446
2000m6	23.5078	23.7706	0.2628
2000m7	23.5708	23.8152	0.2444
2000m8	23.6596	23.8582	0.1986
2000m9	23.6883	23.8642	0.1759
2000m10	23.7129	23.9004	0.1875
2000m11	23.5791	23.7849	0.2058
2000m12	23.5322	23.6752	0.1430
Mean	23.4815	23.6258	0.1465(19.15)***

Table C.13: Hong Kong's Export Volume Index: Weights of Control Countries Before 1998m10

Hong Kong	Weights	t
China	1.0039	2.04
Germany	-0.2244	-1.52
Singapore	0.6337	4.65
France	-0.0579	-0.43
Japan	0.0526	0.36
US	0.1215	0.60
UK	0.2277	1.32
Canada	-0.1498	-0.88
Taiwan	0.0037	0.05
Netherlands	-0.2306	-1.03
M1	-2.5376	-0.89
M2	-5.7926	-2.19
M3	-5.3114	-2.53
M4	-1.2674	-1.02
M5	-0.4259	-0.22
M6	-0.8228	-0.53
M7	2.4749	1.61
M8	-1.1925	-0.61
M9	1.2509	0.96
M10	4.4323	2.90
M11	0.9015	0.55
Constant	14.4125	1.75
R^2	0.9432	
P-value of F-statistic	0.0000	

Table C.14: Treatment Effects for Hong Kong Export Volume Index

Time	Actual	Predicted	Treatment
1998m11	55.3571	54.2933	-1.0639
1998m12	52.5510	56.9067	4.3557
1999m1	52.5510	50.0348	-2.5162
1999m2	38.7755	44.1475	5.3720
1999m3	48.3418	50.4637	2.1218
1999m4	52.9337	56.0718	3.1381
1999m5	53.8265	58.3421	4.5155
1999m6	54.5918	56.4490	1.8572
1999m7	60.4592	61.2715	0.8123
1999m8	60.8418	62.8125	1.9706
1999m9	59.8214	63.2130	3.3916
1999m10	61.7347	67.2121	5.4774
1999m11	61.6071	61.8713	0.2642
1999m12	61.3520	65.7518	4.3997
2000m1	60.5867	58.1757	-2.4111
2000m2	47.1939	54.3382	7.1443
2000m3	60.8418	58.1160	-2.7258
2000m4	60.9694	64.4621	3.4927
2000m5	65.9439	63.6532	-2.2907
2000m6	62.3724	65.9294	3.5570
2000m7	66.5816	70.3450	3.7634
2000m8	72.8316	73.5534	0.7218
2000m9	74.7449	71.2659	-3.4790
2000m10	76.7857	74.4737	-2.3120
2000m11	67.3469	68.9245	1.5775
2000m12	64.4133	71.3758	6.9625
Mean	62.5969	67.9365	5.1149(6.69)***

Table C.15: Hong Kong's Total Value of Imports: Weights of Control Countries Before 1998m10

Hong Kong	Weights	t
China	0.4319	5.83
Taiwan	0.1662	2.10
Germany	-0.0475	-0.35
Italy	0.1068	0.82
Singapore	-0.0111	-0.10
Japan	-0.0632	-0.47
US	0.3045	2.10
UK	-0.0974	-0.70
Korea	0.0836	1.01
Malaysia	0.0462	0.49
Thailand	0.0987	1.25
M1	0.2705	4.11
M2	0.1926	2.87
M3	0.1427	2.63
M4	0.2243	4.55
M5	0.2021	4.31
M6	0.1850	3.72
M7	0.2344	4.80
M8	0.2483	3.43
M9	0.1951	3.62
M10	0.2145	3.79
M11	0.1681	3.72
Constant	-0.5152	-0.34
R^2	0.9777	
P-value of F-statistic	0.0000	

Table C.16: Treatment Effects for Hong Kong Total Value of Imports

Time	Actual	Predicted	Treatment
1998m11	23.4111	23.5219	0.1107
1998m12	23.4147	23.5052	0.0904
1999m1	23.3538	23.4974	0.1436
1999m2	23.0605	23.3182	0.2577
1999m3	23.3606	23.6247	0.2641
1999m4	23.4059	23.6308	0.2248
1999m5	23.3660	23.6210	0.2550
1999m6	23.4259	23.6948	0.2689
1999m7	23.5242	23.7048	0.1806
1999m8	23.4774	23.6716	0.1943
1999m9	23.5004	23.7148	0.2144
1999m10	23.5159	23.7612	0.2453
1999m11	23.5018	23.7804	0.2786
1999m12	23.5679	23.6448	0.0769
2000m1	23.5016	23.8153	0.3137
2000m2	23.2971	23.6975	0.4004
2000m3	23.5865	23.8506	0.2641
2000m4	23.5660	23.9153	0.3494
2000m5	23.6170	23.8947	0.2777
2000m6	23.5567	23.9672	0.4106
2000m7	23.6294	24.0084	0.3789
2000m8	23.6830	24.0209	0.3380
2000m9	23.7222	23.9987	0.2765
2000m10	23.7376	24.0003	0.2628
2000m11	23.6075	23.9819	0.3745
2000m12	23.6245	23.7506	0.1261
Mean	23.5268	23.8363	0.3104(21.11)***

Table C.17: Hong Kong Import Volume Index: Weights of Control Countries Before 1998m10

Hong Kong	Weights	t
China	1.1172	2.50
Taiwan	0.1303	1.43
Germany	0.0415	0.27
Italy	-0.0085	-0.08
Singapore	0.2540	3.75
Japan	0.0383	0.37
US	0.0487	0.22
UK	0.0119	0.05
Korea	0.1082	1.33
Malaysia	-0.0549	-0.38
Thailand	0.1455	2.15
M1	-4.3319	-2.41
M2	-5.2545	-2.63
M3	-3.4722	-3.02
M4	0.1442	0.14
M5	0.9286	0.73
M6	-0.9503	-0.76
M7	0.9823	0.83
M8	-0.1353	-0.06
M9	0.0043	0.00
M10	1.2273	0.78
M11	-1.0021	-0.89
Constant	-12.8731	-2.35
R^2	0.9671	
P-value of F-statistic	0.0000	

Table C.18: Treatment Effects for Hong Kong Import Volume Index

Time	Actual	Predicted	Treatment
1998m11	55.8981	60.2199	4.3218
1998m12	55.8981	63.8210	7.9229
1999m1	52.5469	57.6976	5.1506
1999m2	39.1421	52.9610	13.8189
1999m3	53.8874	65.5029	11.6155
1999m4	56.3003	68.3525	12.0522
1999m5	54.2895	69.6045	15.3149
1999m6	57.7748	71.9842	14.2094
1999m7	63.8070	75.2182	11.4113
1999m8	60.0536	74.7970	14.7434
1999m9	61.5281	73.3604	11.8322
1999m10	62.4665	79.2055	16.7390
1999m11	61.6622	78.1730	16.5108
1999m12	65.8177	79.8527	14.0350
2000m1	61.5281	73.3862	11.8580
2000m2	50.1340	72.7511	22.6171
2000m3	66.8901	81.2485	14.3585
2000m4	65.4156	83.5058	18.0903
2000m5	69.1689	86.9800	17.8111
2000m6	65.0134	86.3323	21.3189
2000m7	70.1072	90.0004	19.8931
2000m8	73.5925	90.5679	16.9755
2000m9	76.1394	89.1935	13.0541
2000m10	77.6139	93.5601	15.9461
2000m11	68.2306	91.0625	22.8320
2000m12	70.1072	90.6889	20.5816
Mean	65.4531	87.7900	21.9039(16.02)***