

ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
Bachelor Thesis Economics & Business
Specialization: Financial Economics

The Effect of Mainland China's Capital Liberalization on Hong Kong's Stock Market: A Synthetic Control Approach

Stakes for Investors in Developed Markets

Author: [Runlin Liang]
Student number: [478378]
Thesis supervisor: [Dr. Rex Wang Renjie]
Second reader: [Prof. Dr. Mary A. Pieterse-Bloem]
Finish date: [26-06-2024]

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second reader, Erasmus School of Economics or Erasmus University Rotterdam.

ABSTRACT

The recent partial liberalization of China's stock market offers new opportunities to study the impact of the market liberalization in capital-abundant emerging economies on developed markets. This thesis investigates the effects of the first two phases of China's multistage capital liberalization policy on Hong Kong's stock market using the Synthetic Control Method. The results show significant and transitory effects, with approximately 7-10% changes in the market index that tracks large- and mid-cap stocks. The direction of these changes depends on capital flows after the integration, which are influenced by the relative attractiveness of investments and investor preferences. The findings are consistent with studies on demand shock in stock markets and implications of mainstream research on investor behavior. The conclusion provides insights for policy makers and general investors in markets that may undergo market integration with emerging markets.

Keywords: Capital Liberalization, Market Integration, Stock Connect Program, Synthetic Control Method, Developed Markets

TABLE OF CONTENTS

ABSTRACT	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	iv
LIST OF FIGURES.....	v
CHAPTER 1 Introduction	1
CHAPTER 2 Theoretical Framework	5
2.1 Institutional Background.....	5
2.2 Significant but Transitory Effect.....	5
2.3 Effect Heterogeneity	6
CHAPTER 3 Data	7
3.1 Outcome Variable	7
3.2 Covariates	8
CHAPTER 4 Method	9
4.1 Modelling.....	9
4.2 Estimation	10
4.3 Inference & Diagnostics	11
4.4 Alternative Models.....	12
CHAPTER 5 Results & Discussion	14
5.1 Results for the Shanghai – Hong Kong Stock Connect Program.....	14
5.2 Results for the Shenzhen – Hong Kong Stock Connect Program.....	19
5.3 Discussion.....	23
5.4 Limitation.....	24
CHAPTER 6 Conclusion.....	26
REFERENCES	27
APPENDIX A Figures and Tables	32

LIST OF TABLES

Table 1	[An Overview of Models]	[page 13]
Table 2	[Predictor Balance of the SCM Analysis for the Shanghai – Hong Kong Stock Connect Program]	[page 15]
Table 3	[Country Weights in the Synthetic Control for the Shanghai – Hong Kong Stock Connect Program]	[page 16]
Table 4	[Predictor Balance of the SCM Analysis for the Shenzhen – Hong Kong Stock Connect Program]	[page 19]
Table 5	[Country Weights in the Synthetic Control for the Shenzhen – Hong Kong Stock Connect Program]	[page 20]

LIST OF FIGURES

Figure 1	[Synthetic MSCI Hong Kong Index in the Period from November 2013 to November 2015]	[page 16]
Figure 2	[Estimated Treatment and Placebo Effects of the Shanghai – Hong Kong Stock Connect Program]	[page 17]
Figure 3	[P-Value for the Standardized Treatment Effect of the Shanghai – Hong Kong Stock Connect Program]	[page 18]
Figure 4	[Synthetic MSCI Hong Kong Index in the Period from December 2015 to December 2017]	[page 21]
Figure 5	[Estimated Treatment and Placebo Effects of the Shenzhen – Hong Kong Stock Connect Program]	[page 22]
Figure 6	[P-Value for the Standardized Treatment Effect of the Shanghai – Hong Kong Stock Connect Program]	[page 23]
Figure A1	[Standard MSCI Country Index]	[page 32]
Figure A2	[Export Value on a Free-on-Board Basis]	[page 33]
Figure A3	[Import Value on a Cost-Insurance-Freight Basis]	[page 34]
Figure A4	[Unemployment Rates in the Labor Markets]	[page 35]
Figure A5	[Consumer Price Index for all Items]	[page 36]
Figure A6	[Real Broad Effective Exchange Rates]	[page 37]

CHAPTER 1 Introduction

The effect of stock market liberalization has been extensively discussed since financial liberalization policies became popular in emerging markets around 1990. One constructive study by Henry (2000) concludes a monthly aggregate abnormal return of 3.3 percent on average in real dollar terms during an event-window of eight months prior to the liberalization date, using a sample of 12 emerging countries. Henry's (2000) finding is consistent with one of the implications of standard international asset pricing models (IAPMs), which indicates a country's equity price index is expected to increase with the reduction in the aggregate cost of equity capital due to stock market liberalization, with an assumption of unchanged future cash flows.

Following the significant wave of capital liberalization among emerging economies in the 1990s, research on capital liberalization appeared to pause, probably due to a lack of new events. However, over the past decade, China's endeavors to unlock its financial markets with multistage reform policies have provided new and valuable natural experiments for the study of stock market liberalization (Carpenter & Whitelaw, 2017). With the implementation of the Shanghai-Hong Kong, Shenzhen-Hong Kong, Shanghai-London, and Shenzhen-London Stock Connect programs in 2014, 2016, 2019, and 2023 (Chen et al., 2022; London Stock Exchange, 2024), China's stock market has been gradually integrated with the global financial market and has experienced more than a fivefold increase in its total market capitalization (Carpenter & Whitelaw, 2017).

Following Henry's (2000) pioneering research, recent literature studying the stock connect programs have been primarily centered around the liberalization effects on mainland China's stock markets and identified different effects. For example, Ma et al. (2019) use firm-level data and find downward adjustment of overvalued Chinese stocks, which can be explained by increased market efficiency. This finding contrasts with prior studies, which typically suggest an upward adjustment of asset prices with market liberalization (Henry, 2000). Ma et al. (2019) attribute this difference in liberalization effects to capital abundance, a distinctive feature of China that sets it apart from other emerging economies that liberalized around 1990. They argue that large and state-owned firms in China's mainland market with no financial constraint cannot benefit from the traditional funding cost channel. This characteristic of capital abundance of China is one reason to revisit the existing findings on liberalization effects. However, some other researches do observe value appreciation of connected stocks with high market beta in mainland China's markets within a short period after liberalization due to speculative activities (Liu et al., 2021). Besides focusing on asset pricing, other effects of the stock connect programs are also identified, such as the "learning channel" (Ma et al., 2019), which is similar to the indirect effects of liberalization on corporate governance, market outlook, and macroeconomic environment (Kose et al., 2009).

It is naturally to follow the tradition of stock market liberalization studies to examine the expected positive liberalization effect on the liberalizing market, mainland China's stock market, as done by many studies (Bai & Chow, 2017; Liu et al., 2021; Ma et al., 2019). However, a recent news about financial companies relocating their Asia-Pacific headquarters from Hong Kong to other Asian counties, with a subtitle "the commercial hub's ties to mainland China, which global companies once considered an asset, have become a liability" (Yu, 2023), has aroused my interest in the potential side effects of these multistage liberalization policies on Hong Kong's stock market. Hong Kong is the first developed market connected to mainland China's markets through these liberalization policies.

Therefore, this research on Hong Kong's market serves as a pioneering groundwork for subsequent studies on other developed markets connected or to be connected to mainland China's markets. Given the successful implementation of Shanghai-London and Shenzhen-London Stock Connect programs, and the efforts to establish the Sino-Swiss corridor (the China – Switzerland Stock Connect program), China is accelerating its liberalization process after 2022 (Ku, 2024). The results and implications from this research could provide immediate and important insights for financial practitioners in developed markets likely to be influenced from the liberalization of mainland China's capital markets. Additionally, this research design could offer valuable experience for future studies on the effects of liberalization policies in other capital-abundant economies on developed markets, such as the gradual easing of capital controls in India (Perez-Gorozpe et al., 2023).

The potential effects of liberalizing capital-abundant economies could be related to the mutual liberalization nature of the stock connect programs. Unlike the liberalization policies around 1990 studied by prior research, the stock connect programs not only remove the restrictions for most foreign investors but also allow previously trapped domestic savings to invest offshore (He et al., 2023). Given this two-way nature of the stock connect program, it is reasonable to investigate these liberalization policies from a different perspective, to study their potential effects on foreign markets. Bai and Chow (2017) conclude that there is heterogeneity in investor reactions between domestic and foreign markets. Mainland investors reacted positively to the program announcement, while foreign investors responded differently at the initiation of the Shanghai – Hong Kong Stock Connect program. They also mentioned herding behavior in both inexperienced mainland retail investors trading Hong Kong stocks and less-informed foreign investors trading mainland stocks, in the short term. Such herding behavior is expected to bring noise instead of new information into both markets. However, the noise brought by foreign investors appears insignificant and is neutralized by other positive effects on mainland China's market, given the overall increased efficiency and the downward adjustment of overvalued stock prices (Chen et al., 2022; Ma et al., 2019). Given the observed heterogeneity in investor reactions between local and foreign markets, it is plausible that such heterogeneity might also exist in asset pricing. However, the effects of the stock connect programs initiated by the Chinese government on the performance of foreign developed markets require further examination. Therefore,

this thesis is motivated to lay the ground work for further studies and investigate the multistage liberalization policies initiated by the Chinese government on foreign developed markets, focusing on the first two phases of these policies, the Shanghai – Hong Kong and Shenzhen – Hong Kong stock connect programs, with the following research question: *What is the effect of mainland China's multi-stage capital liberalization policy on the performance of Hong Kong's stock market?*

Following pioneering studies, this research about the effect on stock market performance will be conducted on an aggregate level (Henry, 2000; Liu et al., 2021). Given the eligible stocks in the Hong Kong Stock Exchange that are directly tradable by investors in mainland China through the stock connect programs are mostly mid- and large-cap stocks (Liu et al., 2021), it is justifiable to conduct an aggregate-level study to avoid endogeneity issues in an individual-level study, such as substantial differences between connected(treated) and unconnected(untreated) individual stocks. However, consideration is given to the traditional event study method, which might generate biased estimates (Borusyak et al., 2024). The selection of model specification, the assumption of linearity, and the existence of potential cofounders are all sources of bias. To improve the traditional event study method, Borusyak et al. (2024) incorporate Difference-in-Difference(DiD) designs into the upgraded method, which generates better results but still relies on parallel trend assumption, like other DiD designs. Therefore, the Synthetic Control Method (SCM) proposed by Abadie and Gardeazabal (2003) is preferred over other techniques used for causal inference for its transparency and interpretability. The SCM shares similarity with the DiD design but relaxes the parallel trend assumption (Galiani & Quistorff, 2017). Given its advantages, it has been utilized in many empirical comparative studies about financial markets and economic liberalization (Billmeier & Nannicini, 2013; Opatrny, 2021). With the SCM, a counterfactual state of the treated unit could be constructed by a weighted combination of a group of untreated units, which is known as a ‘donor pool’ (Abadie, 2021). This weighted combination of untreated units is referred to as a synthetic control.

To analyze stock market performance, the standard MSCI country index is used as a proxy. The index tracks the performance of large- and mid-cap stocks in a specific market, and provides classification for different markets (MSCI, 2024), making it suitable for an aggregate-level study. The treated unit is the MSCI Hong Kong index within the Developed Markets category, representing stocks in the Hong Kong Stock Exchange that are traded in the stock connect programs. As suggested by Abadie (2021), the controls in the donor pool should be comparable to the treated unit. Given this, the donor pool is a subset of the Developed Markets (DM) MSCI index category, excluding the MSCI Hong Kong index and indexes that are significantly different from it. The liberalization effect is computed as the difference between the actual and the synthetic MSCI Hong Kong index.

While Hong Kong's status as a developed market suggests a certain level of resilience, the precise effects of liberalization remain unclear before a thorough investigation. Recent news articles suggest

that Hong Kong's stock market could potentially suffer from negative impacts of the stock connect programs (Yu, 2023). With the gradual liberalization of China's stock markets, other capital-fluent countries may reallocate their investment portfolio away from Hong Kong towards mainland China (Ma et al., 2019). Moreover, increased passive capital inflows into China's mainland market are expected, after the inclusion of mainland China stocks into the MSCI emerging market index in 2017, which serves as a crucial benchmark for fund management (Ma et al., 2019). As major fund managers rebalance their portfolio to include stocks listed in both mainland China and Hong Kong, passive capital inflows into Hong Kong's market are decreasing. However, the extent to which the event in 2017 can effectively apply to the liberalization effects in 2014 and in 2016 remains a subject for further discussion.

The remaining chapters of this thesis are as follows. The theoretical framework will introduce hypotheses to be examined and relate them to existing theories. The data chapter will detail the data collection and transformation process and introduce the variables used for subsequent analysis. The method chapter will explain the design and implementation of the SCM analysis. The results chapter will present the estimated findings derived from the analysis and provide interpretations of these results in relation to the hypotheses. Additionally, limitations of the results and proposed solutions to improve validity will be discussed. Finally, the conclusion chapter will summarize the main findings, discuss their broader implications, and suggest directions for further research.

CHAPTER 2 Theoretical Framework

2.1 Institutional Background

Before formulating hypotheses for the research question, it is beneficial to review the main characteristics of the stock exchanges involved in the stock connect programs. The Shanghai Stock Exchange is the oldest and largest stock market in mainland China, which mainly large state-owned firms active in traditional and industrial industries, such as manufacturing, energy, and banking (Pistor & Xu, 2005). The Shenzhen Stock Exchange has a shorter history, being the main hub for high-tech start-ups and innovative firms with substantial growth potential (Peng et al., 2014). The Hong Kong Stock Exchange is recognized as one of the most developed and efficient stock market in the world and a leading financial hub in Asia, known for its diversified range of listed firms and high standard of market regulation and transparency, which makes it attractive for international investors (Chan et al., 2007; Hung & Cheung, 1995).

The Shanghai – Hong Kong and Shenzhen – Hong Kong stock connect programs are the first and second episodes of the multistage capital liberalization initiative launched by the Chinese government. These stock connect programs allow local investors to directly trade on foreign stocks through their respective stock exchanges without having to adapt to foreign systems (Shanghai Stock Exchange, 2021; Shenzhen Stock Exchange, 2024). Essentially, these programs create channels for bidirectional capital flows. Given that the research question focuses on the impact of these stock connect programs on Hong Kong’s stock markets, this thesis mainly discusses the capital inflows into and capital outflows from Hong Kong’s market though these stock connect programs.

2.2 Significant but Transitory Effect

Firstly, the additional demand for stocks in the Hong Kong Stock Exchange due to capital inflows from mainland investors could potentially generate significant but short-lasting effects on Hong Kong’s market. Before the initiation of the stock connect programs, other pilot programs were in place serving similar purposes. The major differences between those pilot programs and the stock connect programs is the shift in focus from institutional investors to retail investors (Bai & Chow, 2017). The initiation of the stock connect programs relaxes the previously strict capital control regulations in mainland China, encouraging the mainland investors, mostly retail investors, to invest offshore (Carpenter & Whitelaw, 2017). As mainstream theories suggest, retail investors tend to behave speculatively and irrationally (Barber & Odean, 2000). These speculative and irrational behaviors can lead to asset price bubbles and subsequent corrections (Hong et al., 2006). The short-term price spikes caused by demand shock are expected to be corrected when more information becomes available and after arbitrageurs get involved. Empirical evidence of these short-time significant price spikes is found in research on the effect of the stock connect programs on mainland China’s markets (Liu et al.,

2021). Given the recognized level of efficiency of Hong Kong's market, the correction of the price spikes is expected to be faster than in the mainland markets, likely within a month. Therefore, the first hypothesis is that the stock connect programs generate significant but transitory effects on Hong Kong's stock market.

2.3 Effect Heterogeneity

Besides the capital inflows from mainland investors being a potential driver of the effects of the stock connect programs on Hong Kong's market, investment strategies adopted by Hong Kong investors could also influence Hong Kong's market. The initiation of the stock connect programs provides new opportunities for both Hong Kong and mainland investors to diversify and rebalance their portfolios. As the Arbitrage Pricing Theory suggests, the risk factors are key components in return expectations of investors (Ross, 1976). Given the substantial difference in the composition between the Shanghai Stock Exchange and Shenzhen Stock Exchange, risk factors in the two markets are expected to be different for Hong Kong investors. Therefore, it is expected that the Shanghai market and the Shenzhen market have different attractiveness to Hong Kong investors. Compared to the Shanghai market, innovative firms listed in the Shenzhen market with high growth potential might receive more attention from experienced investors in Hong Kong, given the attractiveness of growth and innovation has been well discussed in the literature (Fama & French, 1992; Ritter, 1991). Additionally, different market characteristics, such as sectoral compositions, can influence investor preferences, meaning mainland investors in the Shanghai market and the Shenzhen market might react differently to the two stock connect programs (Chui & Kwok, 1998).

Therefore, whether the effects of the stock connect programs on Hong Kong's stock market are positive or negative depends on the relative attractiveness of the two markets in each of the stock connect programs. If the Hong Kong market is more attractive than the connected mainland market, which means more capital inflows into Hong Kong and a higher demand, a positive effect on the Hong Kong market might be observed. Otherwise, there would be more capital outflow from Hong Kong as its investors rebalance their portfolios towards the connected mainland market, leading to a lower demand for Hong Kong stocks. Therefore, the second hypothesis is that the effects of the Shanghai – Hong Kong and Shenzhen – Hong Kong stock connect programs differ in both direction and magnitude.

CHAPTER 3 Data

This chapter explains the process of collecting and consolidating all the data used in the subsequent analysis. Additionally, it describes the transformations applied to the raw data to prepare it for the analysis.

All variables are collected at a monthly frequency for the period from November 2013 to December 2017. Specifically, data for the period from November 2013 to November 2015 and the period from December 2015 to December 2017 are used in the analysis for the Shanghai – Hong Kong stock connect program and the Shenzhen – Hong Kong stock connect program, respectively. The main variable of interest, “MSCI”, and three covariates, “Exports”, “Imports”, and “EER”, form a strongly balanced panel dataset. Missing values are present for the remaining covariates, “Unemployment”, and “CPI”, meaning certain countries will be excluded from the controls if one of these two variables is included as predictors.

3.1 Outcome Variable

First of all, the MSCI Global Investable Market Indexes (GIMI) are utilized to measure the general performance of the stock markets in Hong Kong and 14 other control countries: Australia, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, United Kingdom, and USA. These countries were selected based on their classification as Developed Markets in MSCI's market classification framework (MSCI, 2024). Additionally, to ensure comparability in term of stock market size, all of these control countries have total market capitalization sizes exceeding one tenth of Hong Kong's market capitalization (CEIC Data, 2024).

MSCI, a leading provider of investment decision-making tools, creates indexes frequently used as benchmarks in the financial industry. The MSCI GIMI is constructed at an individual market level using a consistent methodology established in May 2008 (MSCI, 2024). These market-specific indexes provide a reliable basis for making fair comparisons of stock market performance across different countries and regions. Consequently, they are well-suited for this research, enabling the construction of a counterfactual state of Hong Kong's stock market using comparable controls.

Specifically, the standard MSCI country index, which captures the performance of large- and mid-cap stocks in a specific market, is used. The end-of-day indexes for the last trading day of each month will be retrieved from the publicly accessible MSCI online data query portal. These end-of-month indexes will be normalized by setting the end-of-month index of March 2009 to 100, marking the lowest point of the S&P 500 after the 2008 financial crisis (Yahoo! Finance, 2024)). Figure A1 provides an overview of these monthly indexes for the stock markets in Hong Kong and the 14 control areas

within the donor pool. The monthly market index, referred to as “MSCI,” will be the primary variable of interest.

3.2 Covariates

Apart from the main variable of interest, five other variables are used as indicators of general macroeconomic and financial environments. These variables are a subset of the covariates used in another comparative case study on the influence of Brexit on the British financial market, which is similar to the setting of this research (Opatrny, 2021). Some variables from the original covariate list are excluded due to unavailability. Figure A2 - 6 give an overview of these covariates.

These covariates include “Exports” and “Imports”, the value of goods exported and imported, expressed in million US dollars on a free on board (FOB) and cost, insurance, and freight (CIF) basis, respectively (Figure A2 and Figure A3). Besides, the variable “Unemployment”, the unemployment rate, reported as a percentage, provides insight into the labor market conditions (Figure A4). When the “Unemployment” variable is used as a predictor, Singapore will be excluded from the donor pool because the monthly unemployment rate series of Singapore labor market starts from April 2020 (Singapore Ministry of Manpower, 2024). Lastly, the variable “CPI”, the Consumer Price Index for all items, normalized by setting the 2010 index as 100, measures inflation by reflecting changes in the price level of a basket of consumer goods and services (Figure A5). When the “CPI” variable is used as predictor, Australia will be excluded from the donor pool because the monthly CPI series of Australia starts from April 2020 (Australian Bureau of Statistics, 2024). The data for these 4 variables, “Exports”, “Imports”, “Unemployment”, and “CPI” are retrieved from the International Financial Statistics datasets available on the International Monetary Fund's online database.

Additionally, the data for the variable “EER”, the real (broad) effective exchange rates (EER) for Hong Kong Dollar and other currencies in the 14 controls, are obtained from the online data portal of the Bank for International Settlements (BIS) (Figure A6). The EER measures the international competitiveness of the currency in an economy and reflects the transmission of external shocks (Bank for International Settlements, 2024). Nominal EER is geometric time-varying trade-weighted average of a basket of bilateral exchange rates in 64 economies, while real EER adjusts the nominal EER by relative consumer prices (Bank for International Settlements, 2024). This double-weighting process reflects both direct bilateral trade and third-market competition, which qualifies EER to be a good indicator for macroeconomic situation. The real broad EER is expressed as an index, normalized in a way that the 2020 index is 100.

CHAPTER 4 Method

The synthetic control methodology (SCM) is utilized to estimate the effect of mainland China's multistage liberalization policy on Hong Kong's stock market. Given the interpretability and transparency of this method, it has been utilized in multiple influential aggregate-level comparative case studies (Abadie & Gardeazabal, 2003; Abadie et al., 2010; Abadie et al., 2015; Billmeier & Nannicini, 2013). In this chapter, a detailed description of the utilization and adaptation of this method in the context of the Hong Kong stock connect programs is included.

4.1 Modelling

The general framework of the modelling process follows the classic comparative case study for California's tobacco control program, in which the counterfactual untreated state of California is estimated by a weighted average of untreated regions in the donor pool (Abadie et al., 2010). In the Hong Kong case, the counterfactual MSCI Hong Kong index with the absence of the stock connect programs will be estimated using the same methodology, which can be specified by the following general factor model:

$$\begin{aligned} MSCI_{jt} &= \alpha_{jt} D_{jt} + MSCI_{jt}^N \\ &= \alpha_{jt} D_{jt} + (\delta_t + \boldsymbol{\theta}_t \mathbf{Z}_j + \boldsymbol{\lambda}_t \boldsymbol{\mu}_j + \varepsilon_{jt}) \end{aligned} \quad (1)$$

where $MSCI_{jt}$ is the observed (de facto) MSCI country index for unit j at time t , D_{jt} is a dummy indicator for treatment for unit j at time t , $\alpha_{jt} D_{jt}$ is a time-varying treatment effect, and $MSCI_{jt}^N$ is the counterfactual untreated MSCI country index for unit j at time t . The observed index equals to the sum of the treatment effect and the estimated counterfactual untreated index. Furthermore, the estimated counterfactual index can be specified into the sum of δ_t , $\boldsymbol{\theta}_t \mathbf{Z}_j$, $\boldsymbol{\lambda}_t \boldsymbol{\mu}_j$, and ε_{jt} , where δ_t is an unknown time effect that common to all units, $\boldsymbol{\theta}_t$ is a $(1 \times r)$ vector of unknown parameters, \mathbf{Z}_j is a $(r \times 1)$ vector of observed covariates unaffected by the treatment (such as the variable "EER", "Imports", etc. described in the previous chapter), $\boldsymbol{\lambda}_t$ is a $(1 \times F)$ vector of unknown factors, $\boldsymbol{\mu}_j$ is an $(F \times 1)$ vector of unknown factor loadings, and the zero-mean error term ε_{jt} is transitory shocks independent across units and time.

This SCM model shares similarity with a traditional fixed-effect model and a difference-in-differences (DiD) design (Abadie et al., 2010; Galiani & Quistorff, 2017). However, unlike the assumption of time invariant individual-specific effects in the fixed-effect model, the term $\boldsymbol{\lambda}_t \boldsymbol{\mu}_j$ allows for unobserved heterogeneity (Galiani & Quistorff, 2017). When comparing to a DiD design, the SCM model also exploits the similarities between treated and untreated units in the pretreatment period and the

differences between them in the posttreatment period, but relaxes the parallel trend assumption, which is critical for a DiD design. To approximate a close match for the pretreatment trend of the treated unit, the SCM model assigns different weights for the untreated unit, while a DiD design assigns the same weight (Galiani & Quistorff, 2017).

Suppose unit 1 is Hong Kong, the treated unit, and the pretreatment trend of unit 1 is approximated by a weighted average of untreated units in the donor pool (a synthetic control), with ω_j , a $(J \times 1)$ weighting matrix, where $\sum_{j>2} \omega_j = 1$ and $\omega_j > 0 \forall j \in \{2, \dots, J+1\}$, the estimated treatment effect can be calculated by projecting the synthetic control into the posttreatment period using the same weighting matrix:

$$\widehat{\alpha_{1t}} = MSCI_{1t} - \sum_{j>1} \omega_j MSCI_{jt} \quad (2)$$

The modelling process, as well as the subsequent estimation, inferencing, and illustrating process are performed with the utilization of the Synth_Runner package in STATA (Galiani & Quistorff, 2017).

4.2 Estimation

In this section, the estimation process of the weighting matrix W will be introduced. For each of the stock connect programs, a separate estimation process will be performed. To demonstrate, the following explanation uses the Shanghai – Hong Kong stock connect program as an example.

To begin with, the dataset containing variables “Exports”, “Imports”, “EER”, and “MSCI” in the period from November 2013 to November 2015 will be used. Let unit 1 be Hong Kong, the treated unit, and unit $\{2, \dots, 15\}$ be the “donors” (14 control countries, Australia, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, United Kingdom, and USA). There are 25 periods (from November 2013 to November 2015) in the data set, so $MSCI_1$ is a (25×1) vector of Hong Kong’s outcomes. Let $MSCI_0$ be the (25×14) matrix of outcomes for all donors (unit 2 – 15). The treatment happened in November 2014. Therefore, there are 12 periods in the pretreatment period, and 13 periods in the posttreatment period (considering the treatment month as the first posttreatment period). Separate the $MSCI_j$ variable into pretreatment and posttreatment vectors $MSCI_j = \overleftarrow{MSCI_j} \setminus \overrightarrow{MSCI_j}$. Then, $\overleftarrow{MSCI_1}$ is a (12×1) vector of Hong Kong’s pretreatment outcomes and $\overrightarrow{MSCI_0}$ is a (13×14) matrix of pretreatment outcomes for all donors.

The set of predictors (“pretreatment characteristics”) is denoted as X , which comprises 3 observed covariates, “Exports”, “Imports”, and “EER” (elements of the Z matrix mentioned in equation (1)), augmented by 12 periods of pretreatment values of the outcome variable ($\{MSCI_{jt}: t = 1, 2, \dots, 12\}$).

Let \mathbf{X}_1 be a (15×1) predictor vector for the treated unit, Hong Kong, and \mathbf{X}_0 be a (15×14) matrix of donor predictors. The inclusion of all pretreatment outcomes is suggested in one of the STATA conferences, as it could improve estimation precision (Lu, 2021). The deliberation of the predictor set will be discussed again in the diagnostics and alternatives section below.

Lastly, let V be a (15×15) predictor-weighting matrix which reflects the relative predicting power of the predictors (Abadie et al., 2010; Galiani & Quistorff, 2017). Given a V , a weighting matrix W is estimated to minimize the differences between \mathbf{X}_1 and $\mathbf{X}_0 W$, that is the root mean squared prediction error (RMSPE) of the predictor variables, $\|\mathbf{X}_1 - \mathbf{X}_0 W\|_V = \sqrt{(\mathbf{X}_1 - \mathbf{X}_0 W)' V (\mathbf{X}_1 - \mathbf{X}_0 W)}$ (Abadie et al., 2010; Galiani & Quistorff, 2017). Then, the RMSPE for the pretreatment outcomes, $\|\widehat{\mathbf{MSCI}}_1 - \widehat{\mathbf{MSCI}}_0 W\|$ will be determined by this estimated W . The optimal V will be selected when its associated W provides the lowest RMSPE for the pretreatment outcome, which ideally satisfies the condition, $\|\widehat{\mathbf{MSCI}}_1 - \widehat{\mathbf{MSCI}}_0 W\| = \|\mathbf{Z}_1 - \mathbf{Z}_0 W\| = 0$ (Abadie & Gardeazabal, 2003; Abadie et al., 2010; Galiani & Quistorff, 2017). But this convex hull solution is hardly found in empirical data, normally the optimal $W(V)$, a function of V , is just an approximate estimation (Abadie et al., 2010; Abadie, 2021). If $\sum_{t=1}^{12} \boldsymbol{\lambda}_t' \boldsymbol{\lambda}_t$ is nonsingular, the estimated treatment effect $\widehat{\alpha}_{1t}$ calculated using equation(2) with the optimal $W(V)$ will have a bias towards zero, given the pretreatment period (12 months) is rather large compared to the transitory shocks ε_{jt} (assumed to be very small and last for maximum one period) (Abadie et al., 2010; Galiani & Quistorff, 2017).

The example above is a thorough description of estimating the counterfactual state of Hong Kong's stock market and the treatment effect of the Shanghai – Hong Kong stock connect program.

Analogically, the estimation process for the Shenzhen – Hong Kong stock connect program follows the same steps, except the dataset in the period from December 2015 to December 2017 will be used. And in this second estimation process, the treatment period is December 2016, which will also be the first posttreatment period.

4.3 Inference & Diagnostics

To evaluate the statistical significance of the estimated treatment effect, a permutation test is performed by iteratively performing the SCM estimation on each of the 14 countries in the donor pool. In each iteration of these placebo tests, Hong Kong, the actual treated unit, will be excluded from the donor pool (Galiani & Quistorff, 2017). The significances of posttreatment effects depend on the probability of the placebo posttreatment effects being as large as the estimated posttreatment effects for the treated unit (p-value). For accurate interpretation, all the raw estimated treatment and placebo effects will be standardized by their corresponding standard errors before calculating the p-values.

These p-values for the standardized effects are associated with “a pseudo t-statistic” and will be used to determine the significance of the results (Galiani & Quistorff, 2017).

Given a distribution of placebo posttreatment effects, if the p-value is lower than 5 percent ($\alpha = 0.05$), the estimated posttreatment effect is considered significant, indicating that the estimated difference between the treated unit and the synthetic control is unlikely to be observed by chance. Otherwise, the estimated posttreatment effect is deemed insignificant and possibly occurs by chance.

Let $\widehat{\alpha}_{1t} = \{\widehat{\alpha}_{1t}: t > 12\}$ be the estimated posttreatment effect and $\widehat{\alpha}_{1t}^{PL} = \{\widehat{\alpha}_{jt}: j > 1, t > 12\}$, the

raw two-sided p-value is $\Pr(|\widehat{\alpha}_{1t}^{PL}| \geq |\widehat{\alpha}_{1t}|) = \frac{\sum_{j>1} 1(|\widehat{\alpha}_{1t}^{PL}| \geq |\widehat{\alpha}_{1t}|)}{14}$ (Abadie, 2021; Galiani &

Quistorff, 2017). The p-values can be inverted to calculate confidence intervals. However, they will not be included in the results sections because they lack standard interpretation given that the treatment in this analysis is not randomly assigned (Abadie, 2021; Galiani & Quistorff, 2017).

There are generally two approaches to check the validity of the estimated counterfactual outcome in the pretreatment period: one is to visually compare the pretreatment series of the synthetic control with the actual pretreatment outcome series, while the other one is to check the reliability of the estimated synthetic control by changing the number of pretreatment outcomes in the predictor set (Cavallo et al., 2013; Galiani & Quistorff, 2017). As discussed in the previous section, the predictor set in the model includes all pretreatment outcomes, in total 12 periods (matrixes) of the outcomes. For diagnosing, only a restricted set of lagged MSCI index values will be in the predictor set, $\{MSCI_{jt}: t = 3, 6, 9, 12\}$ (in total 4 periods). Such a model with only part of the pretreatment outcomes in the predictor set will be referred to as a diagnostic model.

4.4 Alternative Models

Besides the standard model described above, which is used with the dataset containing variables “Exports”, “Imports”, “EER”, and “MSCI” in the period from November 2013 to November 2015 or in the period from December 2015 to December 2017, other alternative models with different covariates and donor pools are used to check the reliability of the results, given the sensitivity and importance of the construction of donor pools described by the originator of this method (Abadie, 2021). Table 1 summarizes all the combinations of different covariate sets and donor pools.

Table 1

An Overview of Models

Model No.	Covariates	Donor Pool	Donor Pool Size
1	“Exports”, “Imports”, “EER”	Standard	14
2	“Exports”, “Imports”, “EER”, “Unemployment”	Standard excluding Singapore	13
3	“Exports”, “Imports”, “EER”, “CPI”	Standard excluding Australia	13
4	“Exports”, “Imports”, “EER”, “Unemployment”, “CPI”	Standard excluding Australia and Singapore	12
5	-	Standard	14

Note. This table summarizes all the models used in this paper. Model (1) is the standard model. Model (5) excludes all covariates. The standard donor pool with 14 control countries: Australia, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, United Kingdom, and USA.

Model (1) is the standard model, which is used as the example in section 4.2. Its donor pool is the standard donor pool with 14 control countries: Australia, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, United Kingdom, and USA. Model (5) excludes all covariates and only includes pretreatment outcomes in the predictor set, as suggested by Lu (2021) for potentially better estimation precision.

CHAPTER 5 Results & Discussion

As shown in Figure A1, no single MSCI index adequately represents the MSCI Hong Kong index before the initiation of the first stock connect program. Consequently, no single MSCI index could serve as a reliable indicator of the counterfactual MSCI Hong Kong index during the posttreatment periods (13 months following the initiation month). To construct the counterfactual MSCI Hong Kong index (a weighted combination of controls in the donor pool) and compare it with its actual counterpart to estimate the treatment effect, separate estimations were conducted for the two stock connect programs using the models summarized in Table 1. This chapter presents the detailed results of the models that best estimate the counterfactual state after the initiation of the Shanghai – Hong Kong and Shenzhen – Hong Kong stock connect programs and briefly discusses the results of alternative models.

5.1 Results for the Shanghai – Hong Kong Stock Connect Program

Among the SCM analyses for the Shanghai – Hong Kong stock connect program, Model (1) and Model (5) yield almost identical results and share the lowest RMSPE. However, Model (5) is less reliable due to a significant difference between its results and those of its diagnostic model. Therefore, Model (1) is considered the best model for estimating the treatment effect of the Shanghai – Hong Kong stock connect program.

Table 2 demonstrates the similarities between real Hong Kong and the synthetic Hong Kong, provides important indications for selecting the predictor-weighting matrix V . For example, the diagonal element of V determining the relative predictive power of the “Exports” variable is very low to achieve the lowest RMSPE during the estimation process, as explained in Section 4.2. The same applies to the variables “Imports” and “EER”. Consequently, the optimal predictor-weighting matrix V assigns relatively low predictive power to all three covariates. Such a predictor-weighting matrix V explains the almost identical results between Model (1) and Model (5), given Model (5) excludes all three covariates from Model (1).

Table 3 demonstrates the optimal control weights \mathbf{W} used to construct the synthetic Hong Kong, given the selected optimal predictor-weighting matrix V . As shown, the MSCI Hong Kong index series during the pretreatment periods of the Shanghai – Hong Kong Stock Connect program is best replicated by a weighted combination of Australia, Canada, Japan, Singapore, and the United States. In this convex combination of control countries, Japan and the US hold the majority of weights (around 60%), similar to the results of models (2), (3), and (4), while Canada has the lowest weight (around 5%). Australia and Singapore have relatively low weights compared to Japan and the US but are important components in the estimated synthetic control, as indicated by the results of models (2),

(3), and (4). When Singapore is excluded from the donor pool in Model (2), Australia's weight increases by nearly the same amount as Singapore's weight in the synthetic control of Model (1). Similarly, when Australia is excluded from the donor pool in Model (3), Singapore's weight increases by nearly the same amount as Australia's weight in the synthetic control of Model (1), with a slight increase in Canada's weight and a subtle decrease in the combined weight of Japan and the US. When both Australia and Singapore are excluded from the donor pool in Model (4), Canada's weight rises significantly, and the combined weight of Japan and the US increases slightly. In terms of RMSPE, the prediction error monotonically increases from Model (2) to Model (4), reflecting the importance of retaining Australia and Singapore in the donor pool.

Table 2

Predictor Balance of the SCM Analysis for the Shanghai – Hong Kong Stock Connect Program

Predictors	Hong Kong	
	Real	Synthetic
Exports	43571.92	69916.98
Imports	50104.17	92300.53
EER	85.82333	99.61912
MSCI(2014m10)	225.999	218.6252
MSCI(2014m09)	211.75	216.2212
MSCI(2014m08)	229.397	225.8512
MSCI(2014m07)	232.268	224.4323
MSCI(2014m06)	218.864	222.6191
MSCI(2014m05)	218.099	218.3284
MSCI(2014m04)	210.026	214.1619
MSCI(2014m03)	205.071	212.7552
MSCI(2014m02)	210.423	210.7996
MSCI(2014m01)	201.28	203.5726
MSCI(2013m12)	213.229	213.2831
MSCI(2013m11)	212.997	212.3171

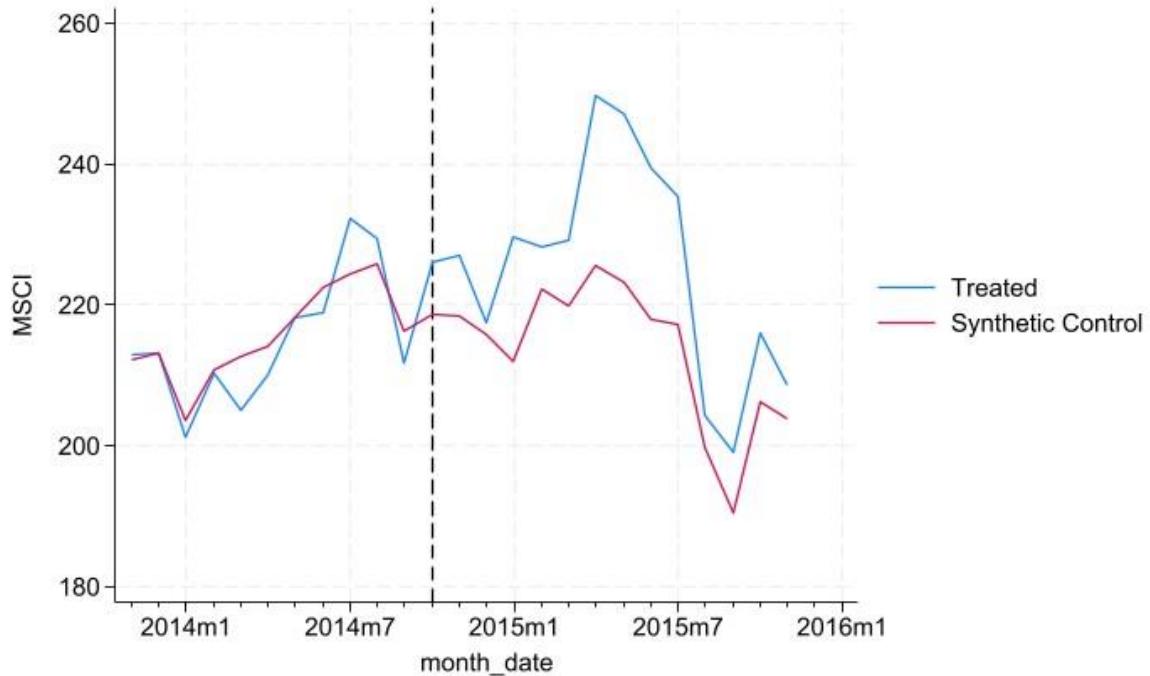
Note. The variables “Exports”, “Imports”, and “EER” are averaged for the whole pretreatment periods (from November 2013 to October 2014). The variables “Exports” and “Imports” are measured in million USD. The variables “EER” and “MSCI” are indexes, and their detailed descriptions are included in the data chapter and the figures in the appendix.

Table 3

Country Weights in the Synthetic Control for the Shanghai – Hong Kong Stock Connect Program

Country	Weight
Australia	0.176
Canada	0.055
Denmark	0
France	0
Germany	0
Italy	0
Japan	0.298
Netherlands, The	0
Singapore	0.169
Spain	0
Sweden	0
Switzerland	0
United Kingdom	0
United States	0.303

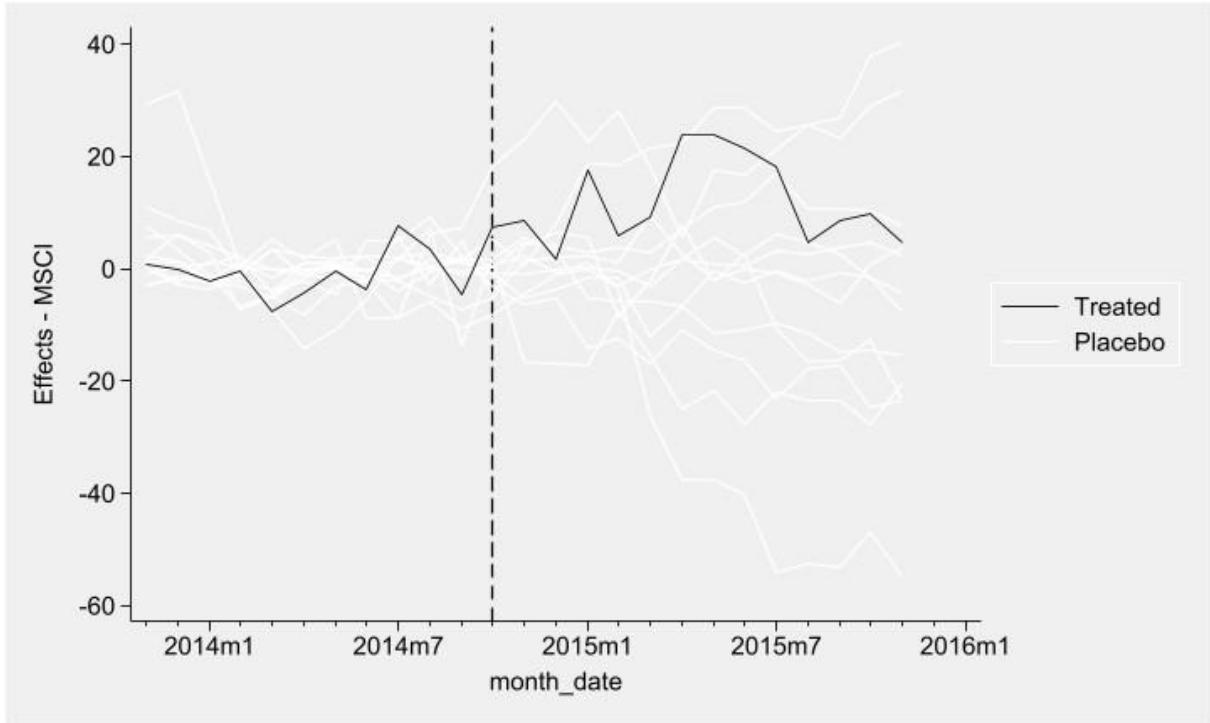
Figure 1

Synthetic MSCI Hong Kong Index in the Period from November 2013 to November 2015

Note. This figure illustrates the real MSCI Hong Kong index (the blue series) and its synthetic counterpart (the red series) in the period from November 2013 to November 2015. The vertical line partition the time frame into the pretreatment period and the posttreatment period.

Figure 2

Estimated Treatment and Placebo Effects of the Shanghai – Hong Kong Stock Connect Program



Note. This figure illustrates the estimated treatment effect (the black series) and placebo effects (the white series) for the Shanghai – Hong Kong stock connect program in the period from November 2013 to November 2015. 14 placebo tests are performed in total but only 12 placebo effects are included in the graph, because results from 2 placebo tests are excluded due to rather poor approximation in the pretreatment periods. The vertical line partition the time frame into the pretreatment period and the posttreatment period.

Figure 1 displays the real and synthetic MSCI Hong Kong index from November 2013 to November 2015, obtained from Model (1). The synthetic MSCI Hong Kong index closely follows the trajectory of the real MSCI Hong Kong index, with a few acceptable gaps, making it a reasonable approximation of the counterfactual state of the real MSCI Hong Kong index had the stock connect program not been initiated.

Figure 2 displays the estimated treatment and placebo effects of the Shanghai – Hong Kong stock connect program from November 2013 to November 2015, obtained from Model (1). The black series represents the estimated treatment effect, the gap between the real and synthetic MSCI Hong Kong index, equal to the vertical distance between the two series in Figure 1. The white series represents the placebo effects from the permutation test described in Section 4.3. These effects fluctuate around 0 during the pretreatment period with a few exceptions, suggesting that the synthetic controls are a good approximation to the real outcomes in most cases. In the posttreatment period, large and extreme treatment effects are observed around January and May 2015 (around leads of 3 and 7 periods).

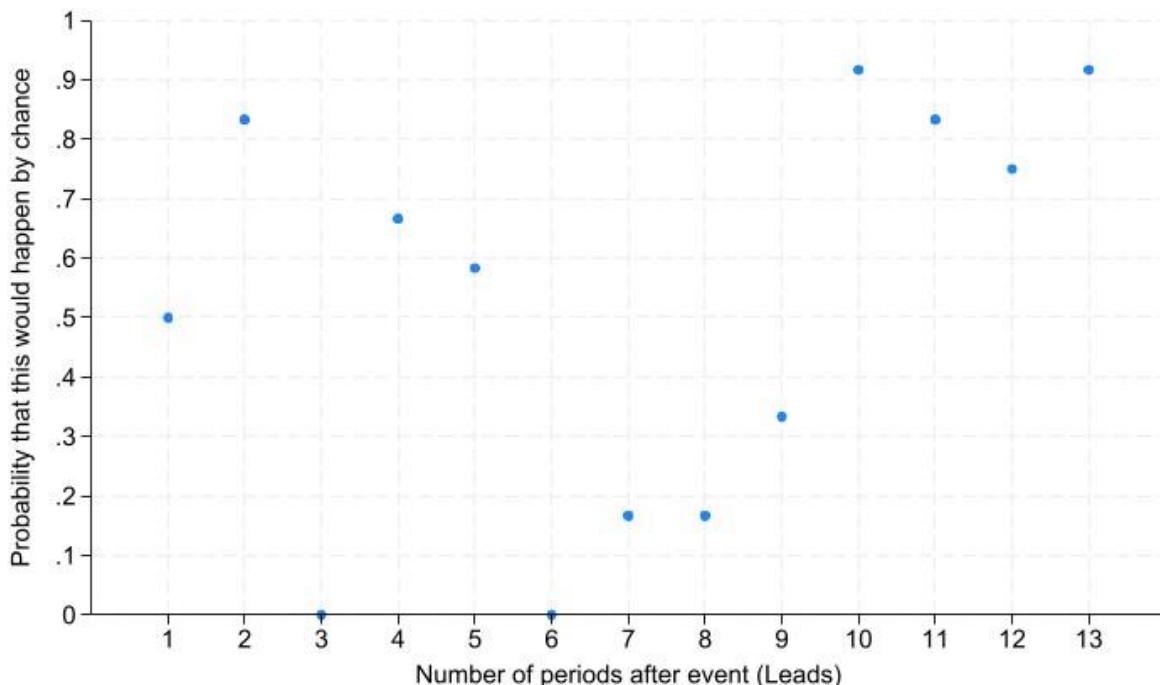
Figure 3 displays the p-values for the standardized estimated treatment effects in each posttreatment period of the Shanghai – Hong Kong Stock Connect program, obtained from Model (1). The graph shows that only the p-values for the estimated treatment effects at leads of 3 and 6 months (in January 2015 and April 2015) are below the 5% significance level (α), also supported by the results from the diagnostic model of Model (1).

The significant estimated treatment effect at leads of 6 periods is observed in all five models, while significance at leads of 3 periods is observed in 3 out of 5 models. The diagnostic models of Models (1), (2), and (3) also indicate significance at leads of 7 periods. For a conservative interpretation, the discussion will focus primarily on the significant estimated treatment effect at leads of 6 periods and briefly include the significance at lead of 3 periods.

According to the results from Model (1), the synthetic MSCI Hong Kong index is valued at 225.6765 (211.9938) at leads of 6 (3) periods, with estimated treatment effects of 24.04055 (17.58317), indicating an approximate 10.7% (8.3%) increase in the valuation of the MSCI Hong Kong index 6 (3) months after the initiation of the Shanghai – Hong Kong Stock Connect program.

Figure 3

P-Value for the Standardized Treatment Effect of the Shanghai – Hong Kong Stock Connect Program



Note. This figure displays the p-values of the standardized estimated treatment effect of the Shanghai – Hong Kong stock connect program in the posttreatment period.

5.2 Results for the Shenzhen – Hong Kong Stock Connect Program

For estimating the treatment effect of the Shenzhen – Hong Kong Stock Connect program, Models (1), (2), and (5) yield similar results and share the lowest RMSPE. Among these, Model (2) is more reliable, given that its diagnostic model produces the same low RMSPE. Therefore, Model (2) is considered the best model for estimating the treatment effect.

Table 4 indicates the optimal predictor-weighting matrix V. The variables “Imports” and “Unemployment” receive very little weight due to their low predictive power. Similarly, the variables “Exports” and “EER” also have relatively low weights compared to the pretreatment outcomes. As in the previous section, the resulting optimal predictor-weighting matrix V assigns most of the weights to pretreatment outcome predictors, explaining the similar results among Models (1), (2), and (5).

Table 4

Predictor Balance of the SCM Analysis for the Shenzhen – Hong Kong Stock Connect Program

Predictors	Hong Kong	
	Real	Synthetic
Exports	42990.58	58134.54
Imports	45196.75	81382.83
Unemployment	3.391667	5.007528
EER	97.85333	102.4939
MSCI(2016m11)	222.369	220.411
MSCI(2016m10)	226.768	218.0824
MSCI(2016m09)	229.439	221.7738
MSCI(2016m08)	222.304	219.7159
MSCI(2016m07)	220.771	222.8771
MSCI(2016m06)	206.643	210.5623
MSCI(2016m05)	205.643	211.2333
MSCI(2016m04)	209.47	212.7696
MSCI(2016m03)	207.946	208.796
MSCI(2016m02)	190.312	192.3701
MSCI(2016m01)	190.768	194.8714
MSCI(2015m12)	210.33	209.6701

Note. The variables “Exports”, “Imports”, “Unemployment”, and “EER” are averaged for the whole pretreatment periods (from December 2015 to October 2014). The variables “Exports” and “Imports” are measured in million USD. The variable “Unemployment” are reported in percentage. The variables “EER” and “MSCI” are index, and their detailed descriptions are included in the data chapter and the figures in the appendix.

Table 5

Country Weights in the Synthetic Control for the Shenzhen – Hong Kong Stock Connect Program

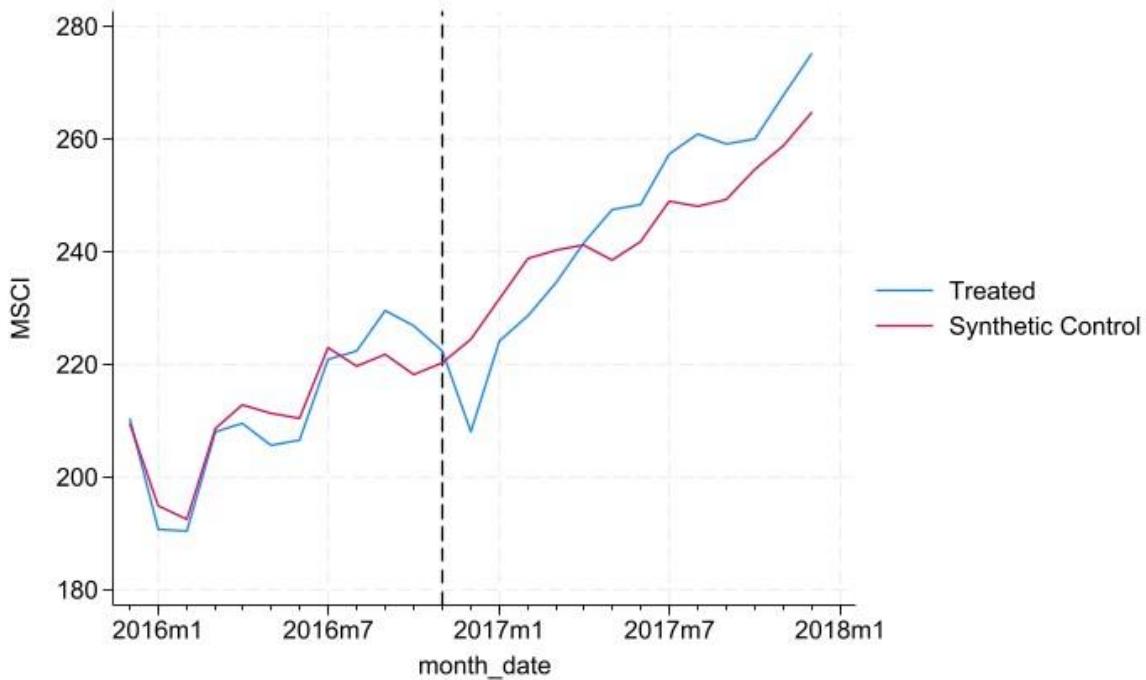
Country	Weight
Australia	.489
Canada	0
Denmark	0
France	0
Germany	0
Italy	0
Japan	.163
Netherlands, The	0
Spain	0
Sweden	0
Switzerland	0
United Kingdom	0
United States	0.348

Table 5 shows that the synthetic control best capturing the pretreatment trend of the Shenzhen – Hong Kong Stock Connect program is a weighted combination of Australia, Japan, and the US. This combination is similar to that used in the previous section, with the US and Japan receiving the majority of the weights. However, unlike the previous section, Singapore and Canada receive zero weight, while Australia now has the highest weight, indicating its importance in the donor pool. Excluding Australia from the donor pool results in poorer estimation, as reflected in the results of Models (3) and (4). Notably, the control weights are sparser in this synthetic control than in the previous analysis, indicating a better counterfactual estimation and a closer approximation to the convex hull of the predictors (Abadie, 2021). The lower RMSPE in this section compared to the previous section reflects this improvement in estimation validity.

Figure 4 plots the synthetic MSCI Hong Kong index from December 2015 to December 2017, obtained from Model (1), versus the actual MSCI Hong Kong index in the same period. The synthetic series closely follows the actual series during the pretreatment period, making it a reasonable approximation of what the MSCI Hong Kong index would have been in the absence of the Shenzhen – Hong Kong Stock Connect program.

Figure 4

Synthetic MSCI Hong Kong Index in the Period from December 2015 to December 2017

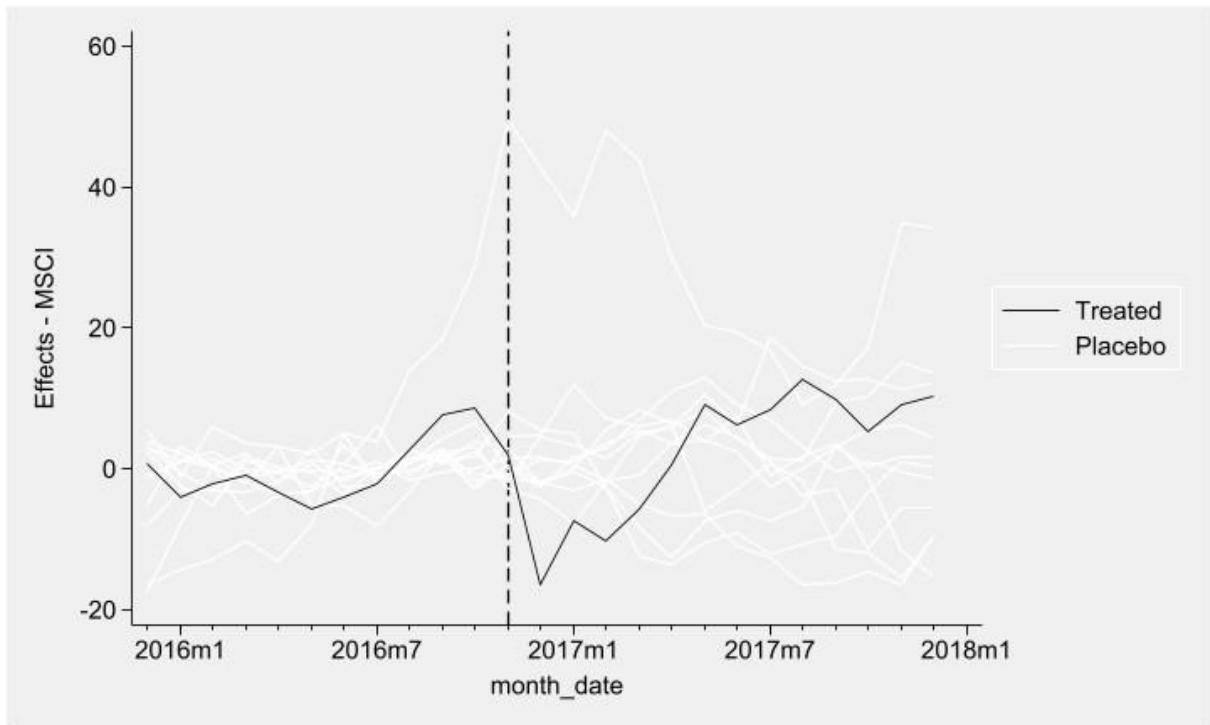


Note. This figure illustrates the real MSCI Hong Kong index (the blue series) and its synthetic counterpart (the red series) in the period from December 2015 to December 2017. The vertical line partition the time frame into the pretreatment period and the posttreatment period.

The vertical distance between the synthetic and actual MSCI Hong Kong index in Figure 4 represents the estimated treatment effect of the Shenzhen – Hong Kong Stock Connect program, displayed in Figure 5 (the black series) along with the placebo effects from the permutation test (described in Section 4.3). As shown, the estimated treatment and placebo effects in the pretreatment periods are mainly around 0, indicating good approximation. In the posttreatment period, the estimated treatment effect is significantly larger than all placebo effects in December 2016 (the treatment month and the first posttreatment period).

Figure 5

Estimated Treatment and Placebo Effects of the Shenzhen – Hong Kong Stock Connect Program



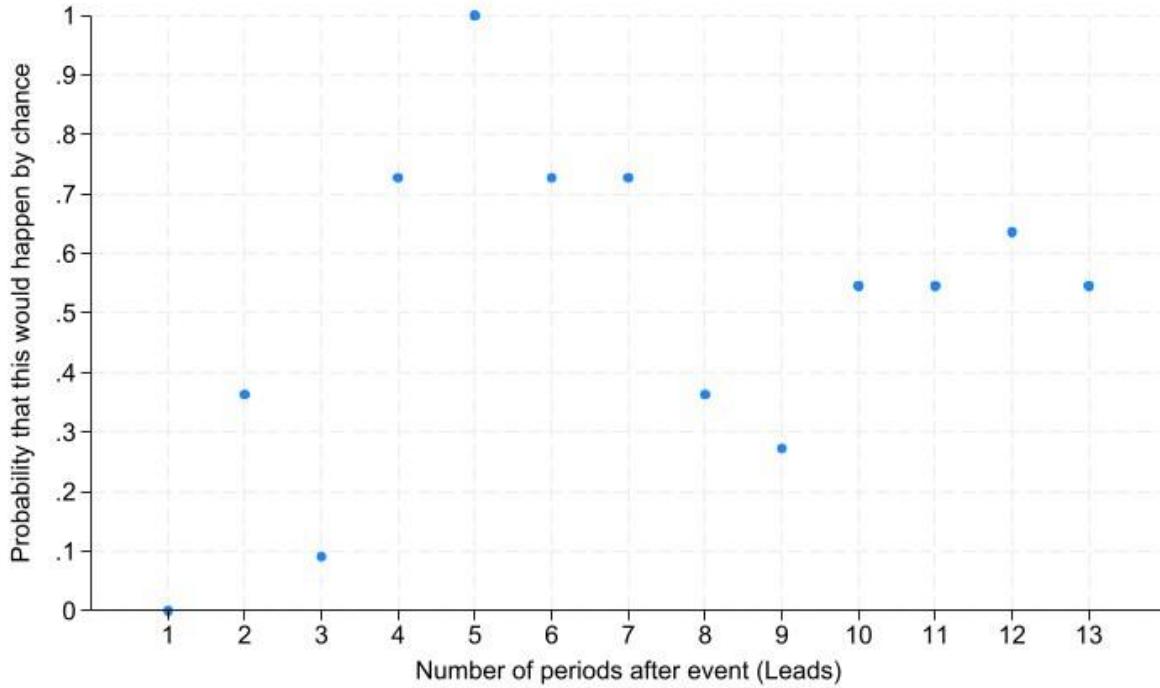
Note. This figure illustrates the estimated treatment effect (the black series) and placebo effects (the white series) for the Shenzhen – Hong Kong stock connect program in the period from December 2015 to December 2017. 13 placebo tests are performed in total but only 11 placebo effects are included in the graph, because results from 2 placebo tests are excluded due to rather poor approximation in the pretreatment periods. The vertical line partition the time frame into the pretreatment period and the posttreatment period.

Unsurprisingly, the p-value for the standardized estimated treatment effect in the first period after the stock connect program's initiation is 0, as shown in Figure 6. This significant estimated treatment effect in December 2016 is supported by the results of all five models and is therefore reliable.

According to the results from Model (2), the synthetic MSCI Hong Kong index is valued at 224.5232, with an estimated treatment effect of -16.43121, indicating an approximate 7.3% decrease in the valuation of the MSCI Hong Kong index one month after the initiation of the Shenzhen – Hong Kong Stock Connect program.

Figure 6

P-Value of the Standardized Treatment Effect of the Shenzhen – Hong Kong Stock Connect Program



Note. This figure displays the p-values of the standardized estimated treatment effect for the Shenzhen – Hong Kong stock connect program in the posttreatment period.

5.3 Discussion

To compare the estimated treatment effects of the two stock connect programs on Hong Kong's stock market, this section focuses on 4 main aspects: magnitude, duration, direction, and timing.

Firstly, the effects have similar magnitudes and durations, ranging from 7% to 10% and lasting about a month. These significant but short-lasting effects are supported by the demand shock theories (Hong et al., 2006; Liu et al., 2021), allowing us to reject the null hypothesis of no effect from the two stock connect programs. Secondly, the difference in the directions of the effects can be attributed to the varying attractiveness of the connected mainland markets for Hong Kong investors and the differing investor preferences in the two mainland markets. The positive effect of the Shanghai – Hong Kong Stock Connect program indicates a spike in demand for Hong Kong stocks, likely due to mainland investors finding the Hong Kong market more appealing for portfolio diversification, whereas the Shanghai market lacks attractiveness for Hong Kong investors. Conversely, the negative effect of the Shenzhen – Hong Kong Stock Connect program suggests Hong Kong investors are rebalancing their portfolios towards the Shenzhen market. Therefore, the null hypothesis that the effects of the two stock connect programs are the same can be rejected.

Lastly, the difference in timing of the effects can be explained by varying investor behaviors and the herding phenomenon (Bai & Chow, 2017). The significant effects observed three and six months after the initiation of the Shenzhen – Hong Kong Stock Connect program, primarily induced by capital inflows from mainland retail investors, provide evidence for herding behaviors among these inexperienced retail investors. As shown in Figure 2 (the black series), the estimated positive effects appear in waves during the posttreatment period, with values in leads 3 and 6 months being significantly high before slowly reverting to around 0 after lead 6. This fluctuating pattern reflects the uncertainty and herding behavior behind investment decisions. In contrast, the immediate effect after the initiation of the Shenzhen – Hong Kong Stock Connect program, likely driven by experienced professional Hong Kong investors rebalancing their portfolios, reflects more informed and decisive investment decisions.

5.4 Limitation

The findings are subject to several limitations. Firstly, the selection of predictors and controls in the donor pool for the SCM specification is directly related to the estimation of the optimal weighting matrix W for the synthetic control. In this research, the included covariates have minimal predictive power for the outcome variable, the MSCI index, similar to the results in Opatrny's (2021) study on the FTSE 100 Index. For future research, pretreatment matching could be improved by considering alternative predictors and donor pools to obtain a synthetic control closer to the convex hull solution. Alternatively, using a vector autoregressive (VAR) model with time-varying coefficients, which is more suitable for high-frequency, autocorrelated time series like stock indices, could eliminate the need for covariates. Furthermore, a VAR model with an SCM design allows for shortening the pretreatment period without compromising estimation validity (Abadie et al., 2010). Data closer to the treatment date in the pretreatment period offers more relevant and timely information for forecasting trends, whereas a longer pretreatment period could potentially introduce more noise than valuable information into the model. Therefore, future research could model the daily MSCI index with a VAR model and conduct SCM analysis on data from 120 trading days prior to the treatment date. The results could provide insights into the validity of the results in this research.

Additionally, this research did not examine the observed difference between the synthetic outcome and the actual outcome in the pretreatment periods, which may involve (potentially insignificant) pretreatment effects. This discrepancy could be attributed to insider trading, warranting further investigation due to its potential to dilute the estimated treatment effect. Several studies have found evidence of insider trading by mainland investors through foreign custodians, due to regulatory inefficiencies, and have examined how stock connect programs reduce these behaviors (He, 2023; He et al., 2023; Yang et al., 2022). Although these studies focus on insider trading in mainland China's markets, it is logical to assume similar behaviors may exist in Hong Kong's market, particularly with

the Shanghai – Hong Kong Stock Connect program, where the effects on Hong Kong’s market are likely driven by capital inflows from mainland China.

It is plausible that some mainland investors with private information about the stock connect programs could speculate and trade in Hong Kong’s market, explaining the surge in the MSCI index before the program’s initiation. However, this effect is hypothesized to be insignificant because these insider trading activities are expected to be small in volume. To test this hypothesis, sensitivity analyses can be conducted by using different treatment dates in the SCM analysis. For instance, assuming the treatment month for the Shanghai – Hong Kong Stock Connect program is October 2014 instead of November 2014, one can evaluate the significance of the treatment effect in October. Alternatively, event studies can detect any abnormal trading volume in the pretreatment periods.

Some other disadvantages include the acceptable difference between \mathbf{X}_1 and $\mathbf{X}_0\mathbf{W}$, indicating a less reliable synthetic control, especially in the case of Shanghai – Hong Kong Stock Connect program. This issue is common in SCM analyses but is less concerning if the synthetic control weights are sparse in the weighting matrix \mathbf{W} (Abadie, 2021). Another disadvantage concerns the timeframe in the posttreatment period. Only one year of posttreatment data is available for each stock programs because their initiation dates are too close to each other. The short posttreatment timeframe limit the findings to only immediate effects, whereas structural changes might take years to become observable. Future research should consider a new research design to investigate the longer-term impacts of these stock connect programs. One potential solutions for the above two disadvantages is using the AllSynth design (Wiltshire, 2021). This upgraded SCM package provides bias-corrected treatment effect estimations that account for inexact matches in the pretreatment periods and offers options to estimate the treatment effects of multiple events. This method can reduce the estimation imprecision due to a poor match between the treated unit and its synthetic control and allows for the estimation of the long-term synthesized effects of the two stock connect programs on Hong Kong’s stock market.

CHAPTER 6 Conclusion

This thesis investigates the effects of the first two phases of China's multistage capital liberalization policy on Hong Kong's stock market, using the Synthetic Control Method (SCM). Evidence supports the positive effects of the Shanghai – Hong Kong stock connect program and the negative effects of the Shenzhen – Hong Kong stock connect program, with both resulting in approximately 7-10% changes in the MSCI Hong Kong index. These effects are short-lasting, but the effect of connecting to the Shanghai market exhibits waving patterns. The findings are subject to several limitations, such as the selection of predictors in the SCM specifications and the influence of potential insider trading in the pretreatment periods. Possible solutions include considering a vector autoregressive model to get rid of the covariates and conducting sensitivity analyses to detect insider trading.

Further research could explore the latter stages of China's capital liberalization policy, such as the Shanghai – London and Shenzhen – London stock connect programs, to evaluate the reliability of the results presented here. Given the difference between Hong Kong's market and other developed markets, the treatment effects might vary in significance, magnitude, duration, direction, or timing. Nevertheless, the findings of this thesis have broad implications for financial practitioners, policymakers, and general investors. With China accelerating the opening of its financial markets, investors in developed markets can draw on the experiences discussed in this paper to prepare for upcoming risks and opportunities. As further integration occurs between other developed markets and China, or other capital-abundant emerging economies like India, it is crucial to critically assess the differences between local markets and emerging markets to understand potential capital flows and make informed decisions. For risk-averse investors, strategically hedging against potential short-term volatility associated with market integration is a sensible option.

REFERENCES

- Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, 59(2), 391-425. <https://doi.org/10.1257/jel.20191450>
- Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, 105(490), 493-505. <https://doi.org/10.1198/jasa.2009.ap08746>
- Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science*, 59(2), 495-510.
<https://doi.org/10.1111/ajps.12116>
- Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque country. *The American Economic Review*, 93(1), 113-132. <http://www.jstor.org/stable/3132164>
- Australian Bureau of Statistics. (2024). *Monthly consumer price index indicator*. Australian Bureau of Statistics. Retrieved June 23, 2024, from <https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/monthly-consumer-price-index-indicator/latest-release>
- Bai, Y., & Chow, D. Y. P. (2017). Shanghai-Hong Kong stock connect: An analysis of Chinese partial stock market liberalization impact on the local and foreign markets. *Journal of International Financial Markets, Institutions & Money*, 50, 182-203.
<https://doi.org/10.1016/j.intfin.2017.09.006>
- Bank for International Settlements. (2024). *Effective exchange rates*. Retrieved June 16, 2024, from <https://data.bis.org/topics/EER>
- Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance*, 55(2), 773-806.
<https://doi.org/10.1111/0022-1082.00226>

Billmeier, A., & Nannicini, T. (2013). Assessing economic liberalization episodes: A synthetic control approach. *Review of Economics and Statistics*, 95(3), 983-1001.
https://doi.org/10.1162/rest_a_00324

Borusyak, K., Jaravel, X., & Spiess, J. (2024). Revisiting event study designs: Robust and efficient estimation. *The Review of Economic Studies*, <https://doi.org/10.1093/restud/rdae007>

Carpenter, J. N., & Whitelaw, R. F. (2017). The development of China's stock market and stakes for the global economy. *Annual Review of Financial Economics*, 9, 233-257.

Cavallo, E., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic natural disasters and economic growth. *The Review of Economics and Statistics*, 95(5), 1549-1561.

https://doi.org/10.1162/REST_a_00413

CEIC Data. (2024). *Hong Kong SAR, China market capitalization*. Retrieved June 16, 2024, from
<https://www.ceicdata.com/en/indicator/hong-kong/market-capitalization>

Chan, K., Menkveld, A. J., & Yang, Z. (2007). The informativeness of domestic and foreign investors' stock trades: Evidence from the perfectly segmented Chinese market. *Journal of Financial Markets*, 10(4), 391-415. <https://doi.org/10.1016/j.finmar.2007.07.001>

Chen, Y., Huang, J., Li, X., & Yuan, Q. (2022). Does stock market liberalization improve stock price efficiency? evidence from China. *Journal of Business Finance & Accounting*, 49(7-8), 1175-1210. <https://doi.org/10.1111/jbfa.12586>

Chui, A. C. W., & Kwok, C. C. Y. (1998). Cross-autocorrelation between A shares and B shares in the Chinese stock market. *The Journal of Financial Research*, 21(3), 333-353.
<https://doi.org/10.1111/j.1475-6803.1998.tb00689.x>

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2), 427-465.

Galiani, S., & Quistorff, B. (2017). The Synth_Runner package: Utilities to automate synthetic control estimation using synth. *The Stata Journal: Promoting Communications on Statistics and Stata*, 17(4), 834-849. <https://doi.org/10.1177/1536867x1801700404>

He, Z. (2023). *Homemade foreign trading*. SSRN. <https://doi.org/10.2139/ssrn.4318182>

He, Z., Wang, Y., & Zhu, X. (2023). The stock connect to China. *SSRN Electronic Journal*, <https://doi.org/10.2139/ssrn.4342392>

Henry, P. B. (2000). Stock market liberalization, economic reform, and emerging market equity prices. *The Journal of Finance*, 55(2), 529-564. <https://doi.org/10.1111/0022-1082.00219>

Hong, H., Scheinkman, J., & Xiong, W. (2006). Asset float and speculative bubbles. *The Journal of Finance*, 61(3), 1073-1117. <https://doi.org/10.1111/j.1540-6261.2006.00867.x>

Hung, B. W., & Cheung, Y. (1995). Interdependence of Asian emerging equity markets. *Journal of Business Finance & Accounting*, 22(2)

Kose, M. A., Prasad, E., Rogoff, K., & Wei, S. (2009). Financial globalization: A reappraisal. *IMF Staff Papers*, 56(1), 8-62. <https://doi.org/10.1057/imfsp.2008.36>

Ku, L. (2024, January 23.). *Why the China-Switzerland stock connect never quite took off*. EUROMONEY. Retrieved July 01, 2024, from <https://www.euromoney.com/article/2cr360z010c1qmtnl9h4w/capital-markets/why-the-china-switzerland-stock-connect-never-quite-took-off>

Liu, C., Wang, S., & Wei, K. C. J. (2021). Demand shock, speculative beta, and asset prices: Evidence from the shanghai-Hong Kong stock connect program. *Journal of Banking & Finance*, 126, 106102. <https://doi.org/10.1016/j.jbankfin.2021.106102>

London Stock Exchange. (2024). *London stock exchange stock connect*. London Stock Exchange.

Retrieved May 3, 2024, from <https://www.londonstockexchange.com/raise-finance/equity/london-stock-connect>

Lu, J. (2021). *Synthetic control method*. 2021 Chinese Stata Conference. Retrieved June 16, 2024, from https://www.stata.com/meeting/china21-Uone-Tech/slides/China21_Jiaxuan.pdf

Ma, C., Rogers, J., & Zhou, S. (2019). The effect of the China Connect. Available at SSRN <http://dx.doi.org/10.2139/ssrn.3432134>

MSCI. (2024). *MSCI global investable market indexes methodology*. Retrieved June 16, 2024, from <https://www.msci.com/index/methodology/latest/GIMI>

Opatrny, M. (2021). The impact of the Brexit vote on UK financial markets: A synthetic control method approach. *Empirica*, 48(2), 559-587. <https://doi.org/10.1007/s10663-020-09481-7>

Peng, R., Zhao, M., & Wang, L. (2014). Financial inclusion in the people's republic of China: Achievements and challenges. *Financial Inclusion in Asia*, 7, 7-43.

Perez-Gorozpe, J., Lawson, B., Lam, A. & Poon, A. (2023, August 3.). *Unlocking India's capital markets potential*. S & P Global. Retrieved July 01, 2024, from <https://www.spglobal.com/en/research-insights/special-reports/look-forward/unlocking-india-s-capital-markets-potential>

Pistor, K., & Xu, C. (2005). Governing stock markets in transition economies: Lessons from China. *American Law and Economics Review*, 7(1), 184-210. <https://doi.org/10.1093/aler/ahj008>

Ritter, J. R. (1991). The long-run performance of initial public offerings. *The Journal of Finance*, 46(1), 3-27. <https://doi.org/10.1111/j.1540-6261.1991.tb03743.x>

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of economic theory*, 13(3), 341-360. Retrieved from <http://www.econis.eu/PPNSET?PPN=484090550>

Shanghai Stock Exchange. (2021). *Shanghai-Hong Kong stock connect*. Shanghai Stock Exchange.

[https://english.sse.com.cn/access/stockconnect/introduction/#:~:text=The%20Shanghai%2DHong%20Kong%20Stock, and%20Clearing%20Limited%20\(HKEX\).](https://english.sse.com.cn/access/stockconnect/introduction/#:~:text=The%20Shanghai%2DHong%20Kong%20Stock, and%20Clearing%20Limited%20(HKEX).)

Shenzhen Stock Exchange. (2024). *Definition & development*. SZHK STOCK CONNECT.

<https://www.szse.cn/enSzhk/index/index.html>

Singapore Ministry of Manpower. (2024). *Statistical table: Unemployment*. Labour Market Statistics and Publications. Retrieved June 23, 2024, from

<https://stats.mom.gov.sg/Pages/UnemploymentTimeSeries.aspx>

Yahoo! Finance. (2024). *S&P 500*. Retrieved June 16, 2024, from

<https://finance.yahoo.com/quote/%5EGSPC/>

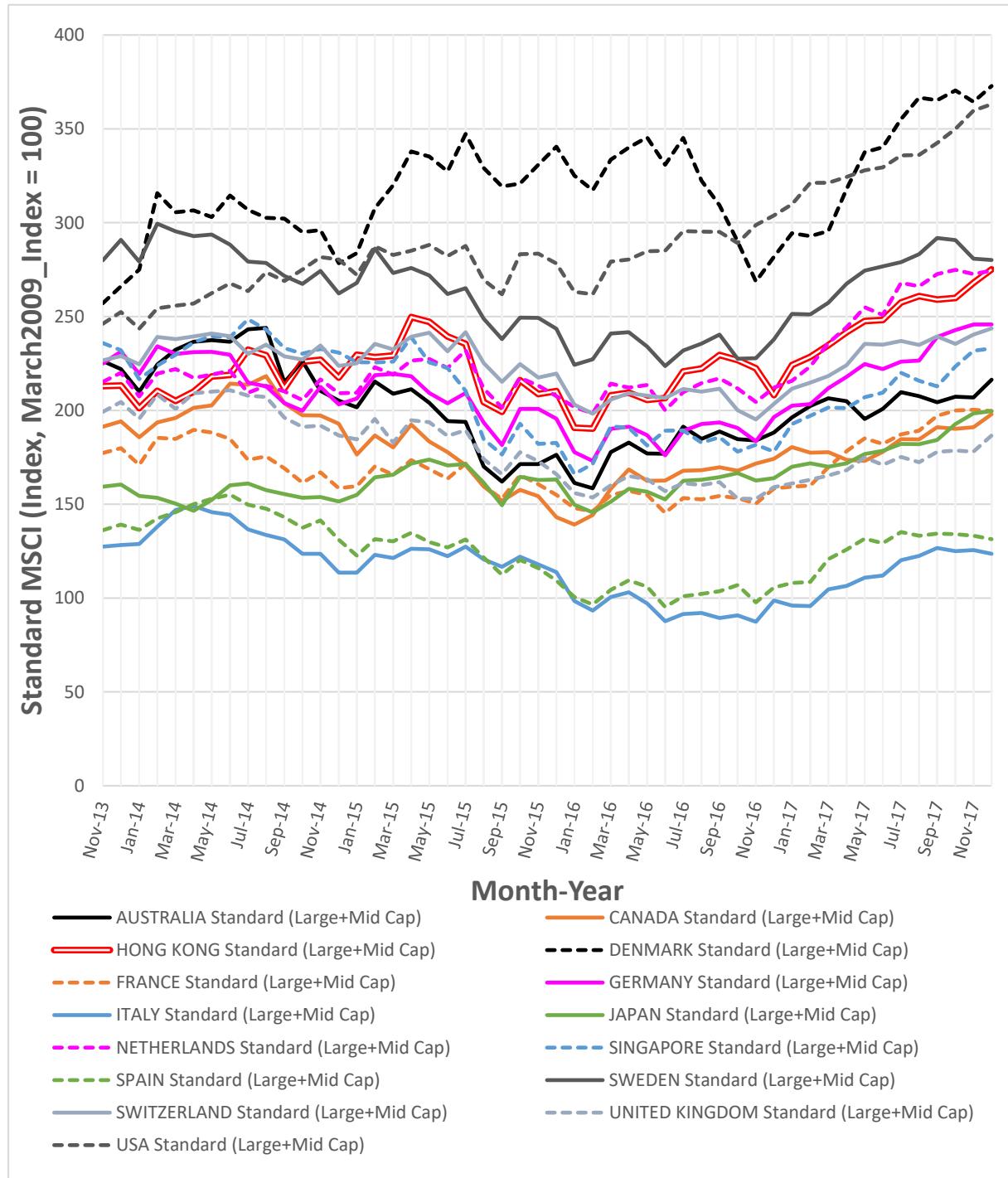
Yang, X., Lu, C., & Yang, Z. (2022). Capital-market liberalization and controlling shareholders' tunneling-experimental research in the context of "mainland China-Hong Kong stock connect". *Applied Economics*, 54(45), 5241-5256. <https://doi.org/10.1080/00036846.2022.2041183>

Yu, E. (2023, Oct 24,). *The corporate retreat from Hong Kong is accelerating*. The Wall Street Journal Online. Retrieved May 3, 2024, from <https://www.wsj.com/world/asia/hong-kong-china-corporate-headquarters-retreat-10454a9a>

APPENDIX A Figures and Tables

Figure A1

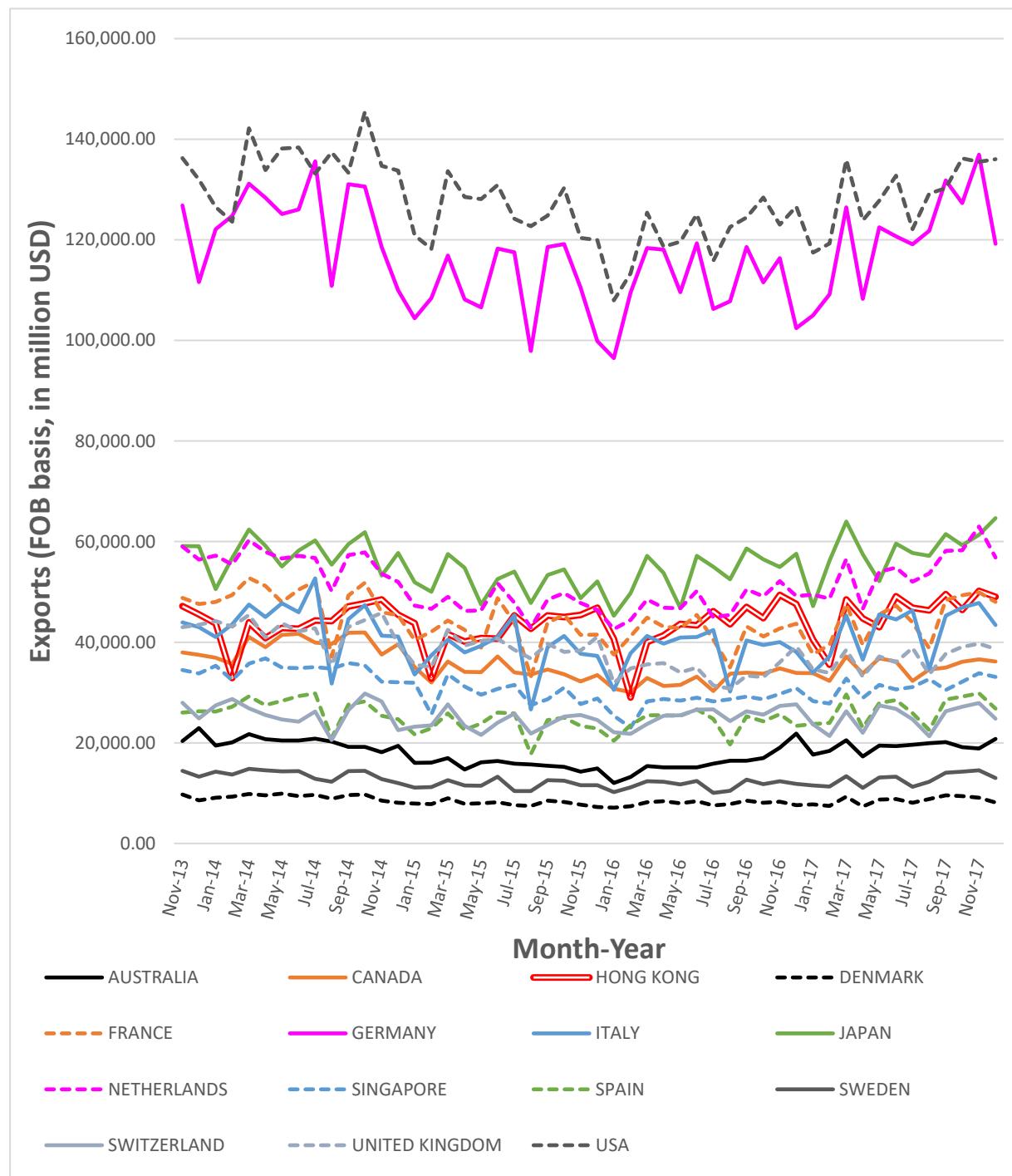
Standard MSCI Country Index



Note. This figure demonstrates the MSCI country index for Hong Kong and the 14 control countries (Australia, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, United Kingdom, and USA) in the period from November 2013 to December 2017. The values are normalized by setting the end-of-month index of March 2009 to 100. Data are retrieved from MSCI online data query portal (<https://www.msci.com/end-of-day-data-search>) on June 04, 2024.

Figure A2

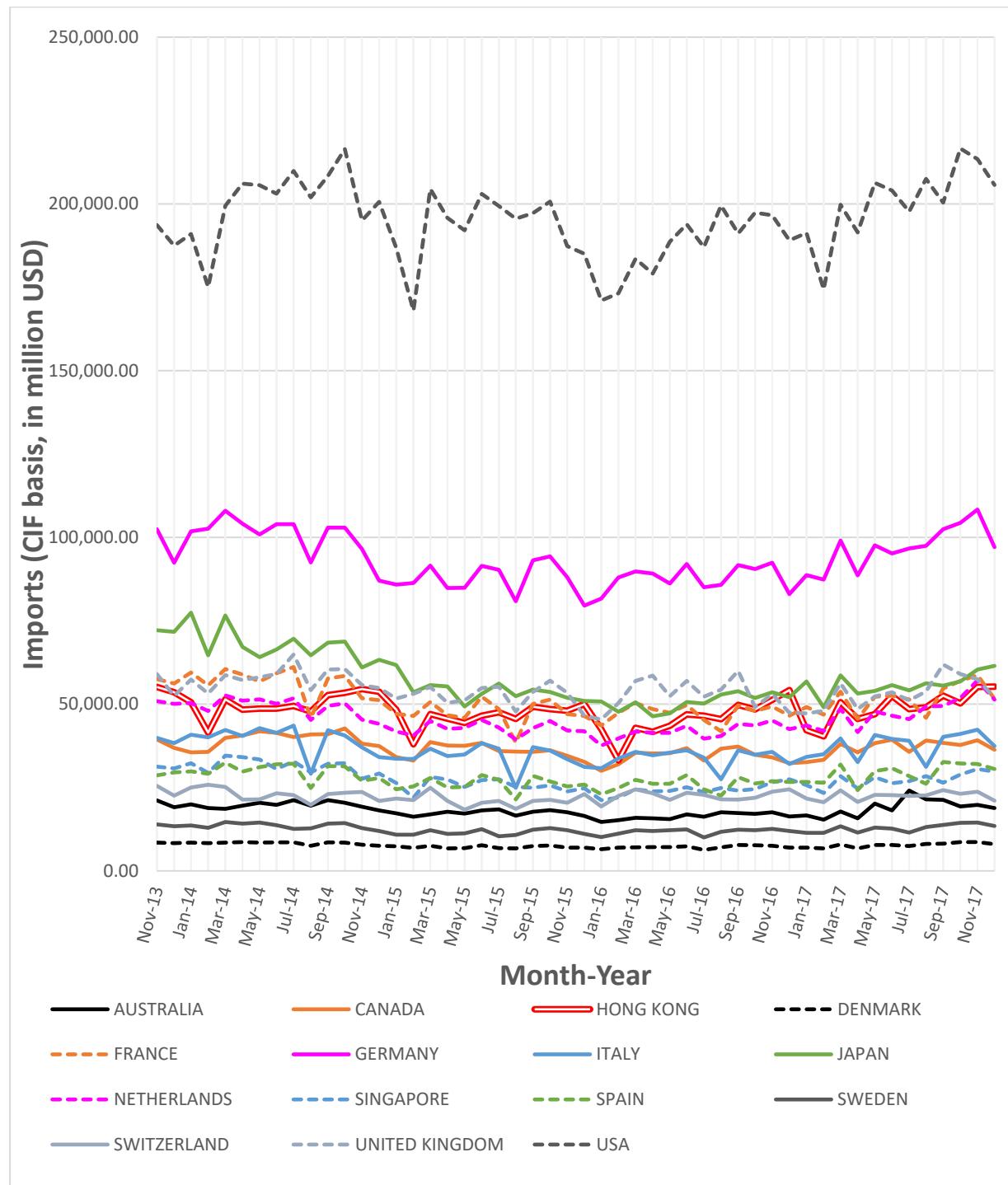
Export Value on a Free-on-Board Basis



Note. This figure demonstrates the export value on an FOB basis for Hong Kong and the 14 control countries (Australia, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, United Kingdom, and USA) in the period from November 2013 to December 2017. The values are expressed in million USD. Data are retrieved from the International Financial Statistics datasets available on the International Monetary Fund's online database (<https://data.imf.org/?sk=4c514d48-b6ba-49ed-8ab9-52b0c1a0179b&sid=1390030341854>) on May 14, 2024.

Figure A3

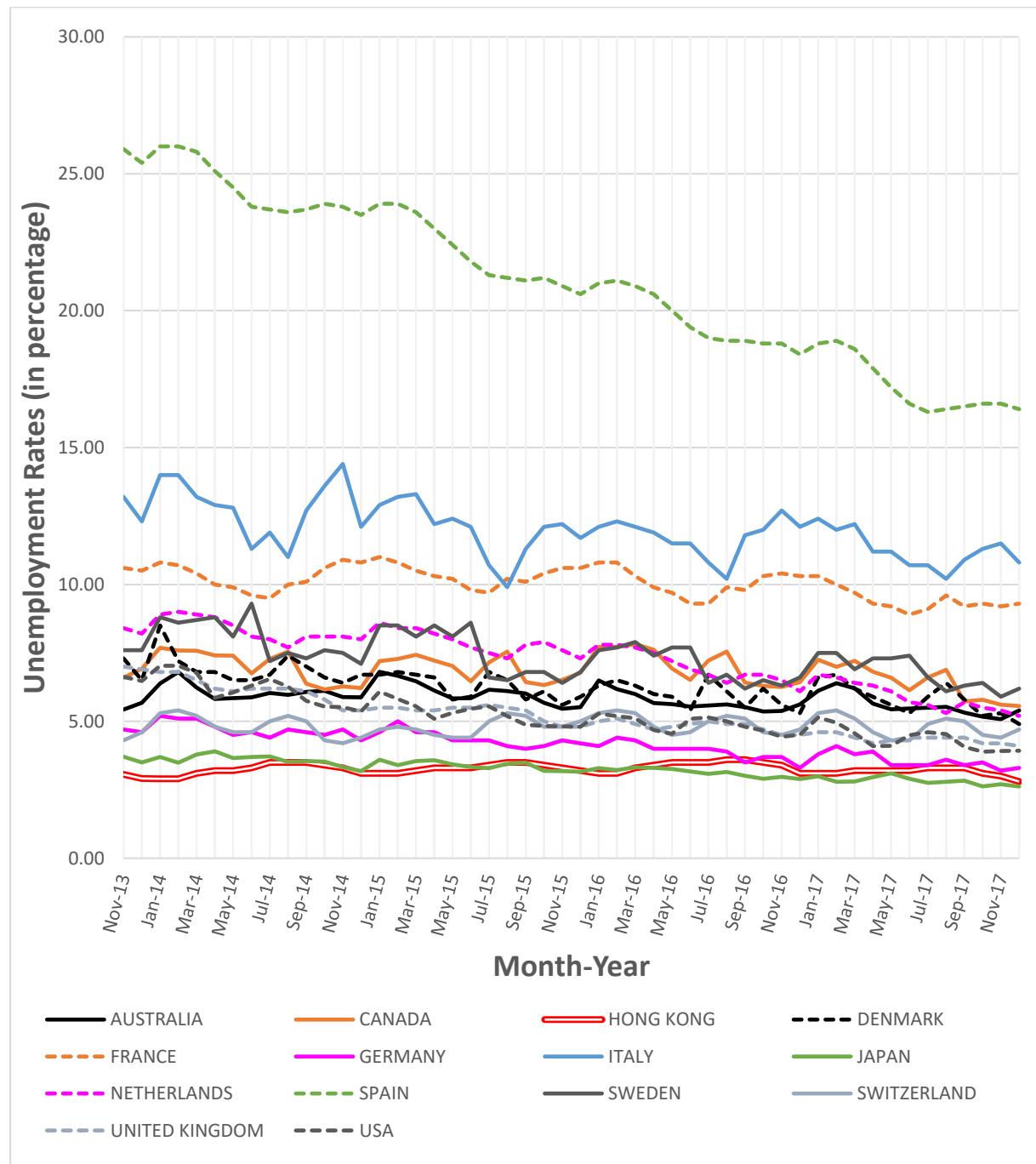
Import Value on a Cost-Insurance-Freight Basis



Note. This figure demonstrates the import value on a CIF basis for Hong Kong and the 14 control countries (Australia, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, United Kingdom, and USA) in the period from November 2013 to December 2017. The values are expressed in million USD. Data are retrieved from the International Financial Statistics datasets available on the International Monetary Fund's online database(<https://data.imf.org/?sk=4c514d48-b6ba-49ed-8ab9-52b0c1a0179b&sid=1390030341854>) on May 14, 2024.

Figure A4

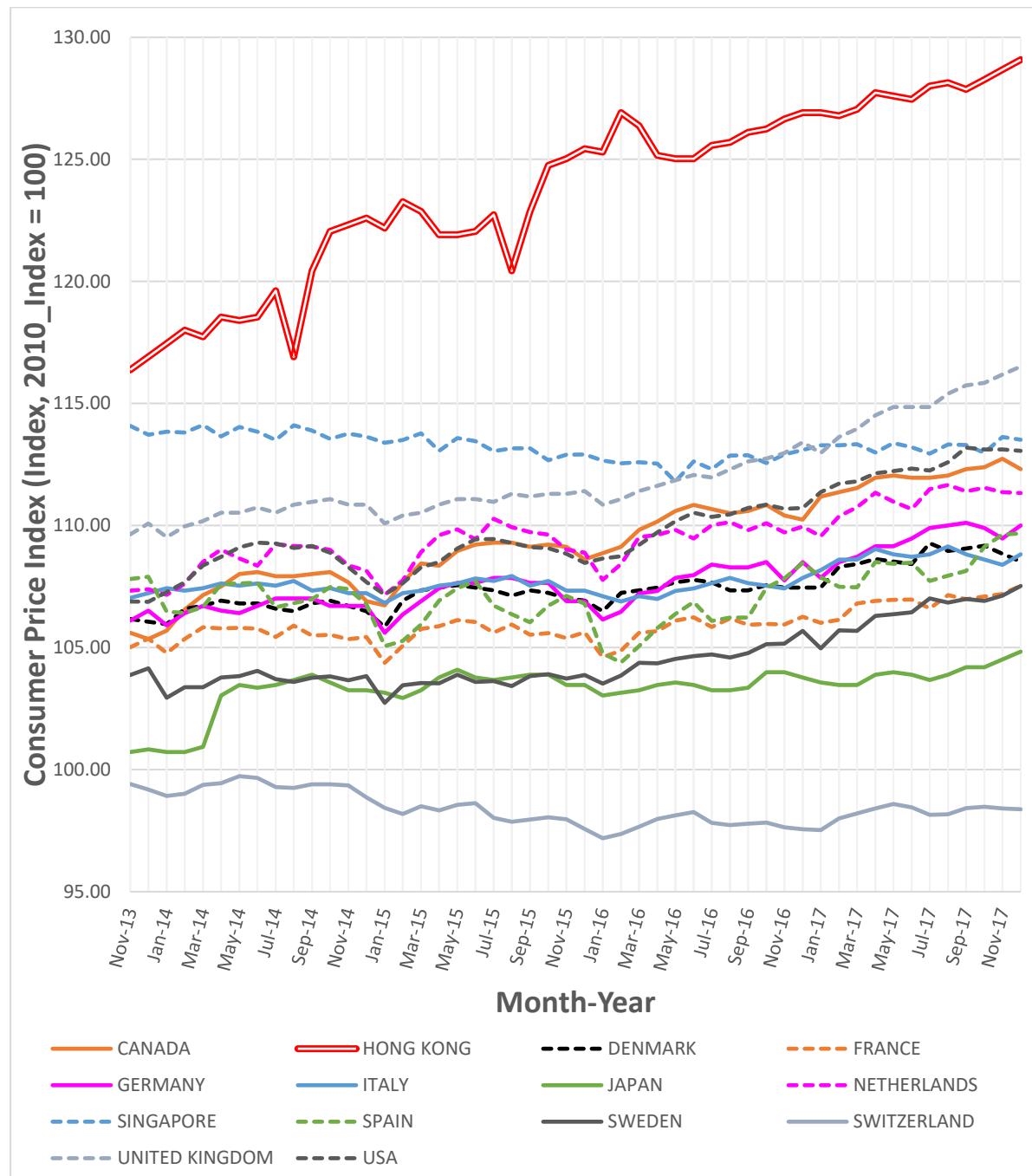
Unemployment Rates in the Labor Markets



Note. This figure demonstrates the unemployment rates in the labor markets of Hong Kong and 13 control countries (Australia, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, United Kingdom, and USA) in the period from November 2013 to December 2017. Singapore is excluded from the controls because the monthly unemployment rate series of Singapore labor market starts from April 2020 (Singapore Ministry of Manpower, 2024). The values are reported in percentage. Data are retrieved from the International Financial Statistics datasets available on the International Monetary Fund's online database (<https://data.imf.org/?sk=4c514d48-b6ba-49ed-8ab9-52b0c1a0179b&sid=1390030341854>) on May 14, 2024.

Figure A5

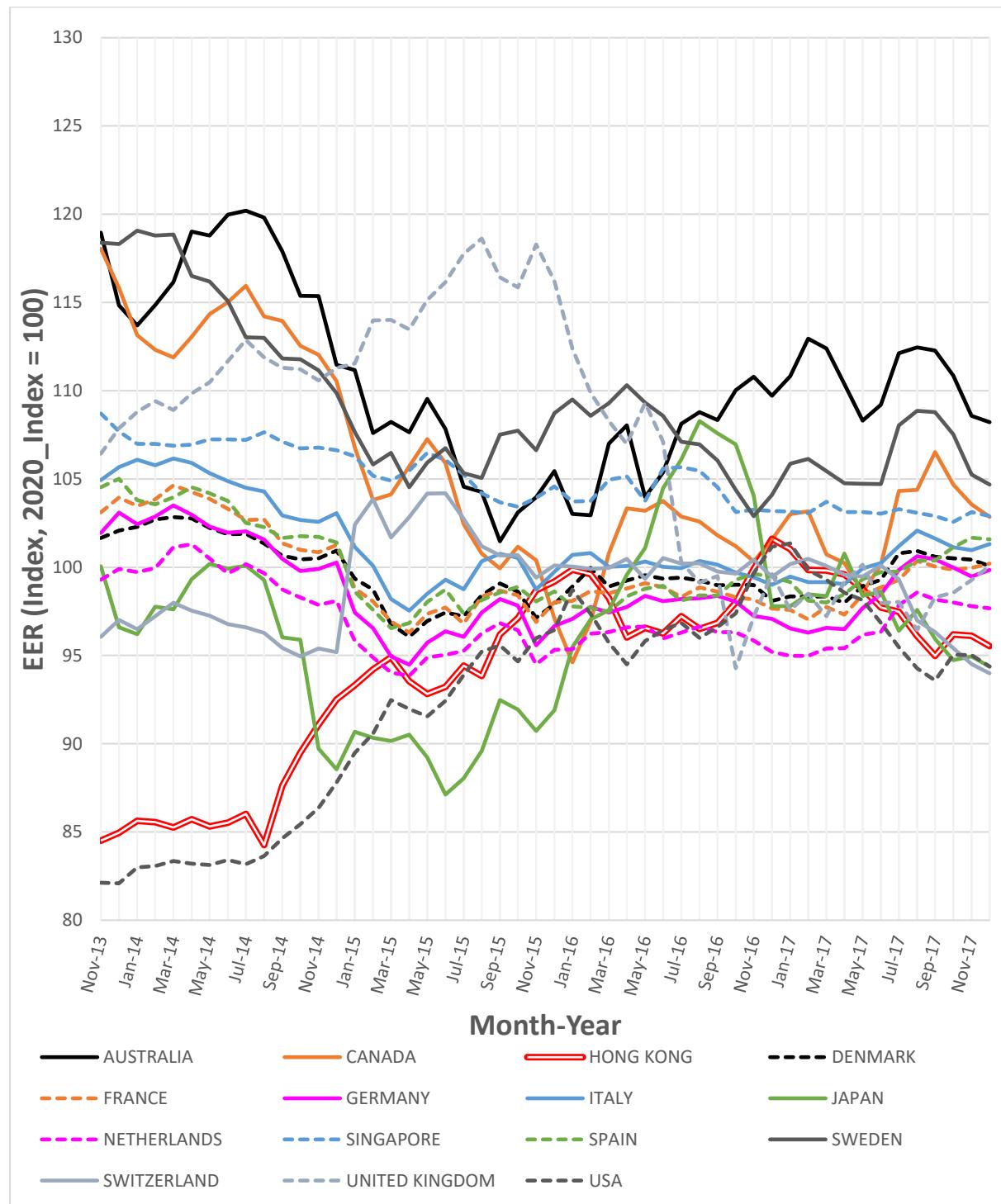
Consumer Price Index for all Items



Note. This figure demonstrates the consumer price index for Hong Kong and 13 control countries (Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, United Kingdom, and USA) in the period from November 2013 to December 2017. Australia is excluded from the controls because the monthly CPI series of Australia starts from April 2020 (Australian Bureau of Statistics, 2024). The values are reported in percentage and normalized by setting the 2010 index as 100. Data are retrieved from the International Financial Statistics datasets available on the International Monetary Fund's online database (<https://data.imf.org/?sk=4c514d48-b6ba-49ed-8ab9-52b0c1a0179b&sid=1390030341854>) on May 14, 2024.

Figure A6

Real Broad Effective Exchange Rates



Note. This figure demonstrates the real broad effective exchange rates for currencies in Hong Kong and the 14 control countries (Australia, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, United Kingdom, and USA) in the period from November 2013 to December 2017. The values are expressed as an index, normalized by setting the 2020 index to 100. Data are retrieved from online data portal of the Bank for International Settlements (BIS) (<https://data.bis.org/topics/EER/data>) on May 15, 2024.