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The causality link between political risk and stock prices: A counterfactual study in an emerging market

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Abstract

Purpose – Prior studies have paid close attention to the impact of political risk on financial markets. Following this strand of literature, this paper aims to focus on the causality link between political shocks and their impacts on emerging stock markets.

Design/methodology/approach – This paper highlights an innovative counterfactual model for political risk assessment. Based on a natural experiment, i.e. the Taiwan Strait Crisis in 1995-1996, this study utilizes one data-driven approach, e.g. the synthetic control methods (SCMs), to estimate causal impact of this political shock on Taiwan's stock market.

Findings – Major findings in this study are consistent with existing literature on the price of political risk, e.g. political uncertainty commands a risk premium. The SCM estimations suggest that Taiwan's stock prices dramatically underperformed its newly industrialized peers and other developed markets during the crisis. The SCM results are statistically significant and robust to various cross-validation tests.

Research limitations/implications – Findings in this study indicate that political risks could generate enormous impacts on emerging financial markets. In particular, political uncertainty following new geopolitical dynamics requires proper identification and assessment.

Originality/value – To the author's knowledge, this paper is the first rigorous counterfactual study to the causality relationship between political uncertainty and stock prices in emerging markets. This paper is distinct from previous studies in applying a data-driven approach to combine the features of learning from others (cross-sectional) and learning from the past (time series).

Keywords International finance, Forecasting and simulation

Paper type Research paper

1. Introduction

Country risk has been one determinant of international trade and offshore investment, particularly when emerging markets are added into capital allocation decisions. Following global geopolitical dynamics in the 1980s, emerging markets became an alternative option for international investors to improve their risk-return frontiers (Divecha *et al.*, 1992; Cosset and Suret, 1995; Claessens *et al.*, 1995). Although being attractive to capital flows, professionals and academics have noticed that emerging markets are risker to invest due to certain risk factors (Oetzel, 2005). These country risks can be either economic-specific or market-specific. Interest rate and exchange rate uncertainties are examples of economic risks. Market-specific risks include social, environmental and political risk. All these risks have been major barriers for emerging markets to be fully integrated into global capital markets (Bekaert and Harvey, 1995, 2003; Bekefi and Epstein, 2008).

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Compared with conventional country risks, investors found that political uncertainty is particularly challenging to manage. Thus, accurate political risk assessments have become one critical component for international investment (Lambsdorff, 1999; Rios-Morales *et al.*, 2009). Political risk can be a broad concept, including but not limited to political resolutions, political circumstances or other events in a country which could affect the financial and material assets of a firm or threaten returns on investment (Kobrin, 1979; Fatehi-Sedeh and Safizadeh, 1989; Nawaz and Hood, 2005). In reality, financial markets have told us political risks do not have a potential to cause losses, but they actually do cause losses (West, 1999). To reflect the degree of country risks, professionals usually apply discount rate adjustments to their investments in unfamiliar emerging markets (Lessard, 1996). However, compared with using arbitrary discount rate adjustments, accurate forecast and measurement of potential impact of political risk would be more helpful for adopting proper risk management strategies.

Over years, there is a rising trend of applying more quantitative methods in political risk analysis. In particular, the inextricable linkage between political uncertainty and financial markets has generated enormous impacts on global investing, lending and trading (Saunders and Cornett, 2007; Wagner, 2012). Recently, new and different forms political uncertainties raised some new issues. For example, in some Asia-Pacific emerging markets, the probability of traditional political risks, such as expropriation, industrial policy changes, civil turmoil and military conflicts, have become lower. In contrast, democratization, geopolitics and the "Great Gaming" between regional powers have brought new challenges in capital markets[1]. Thus, researchers are expected to use innovative methods to identify, quantify and visualize risk factors and extract insights for business decisions. As a cutting-edge area, causal estimation has been increasingly applied in country studies. More than ex post estimation, a causality relationship also provides researchers useful predictive and prescriptive evidence for analysis.

In financial markets, both investors and scholars have paid close attention to the severity of political risks' potential impacts to emerging economies. For example, Bilson *et al.* (2002) found that political risks had a larger effect on stock prices in emerging markets than in developed markets since the 1990s, especially in the Asia-Pacific region. Similarly, a number of empirical studies have tried to explain how political uncertainties would affect stock markets (Bekaert *et al.*, 2005; Le and Zak, 2006; Boutchkova *et al.*, 2011; Julio and Yook, 2012; Belo *et al.*, 2013; Jens, 2017). In particular, centering on the price of political risk, Pastor and Veronesi (2012, 2013) pointed out a mechanism through which political uncertainty affects asset prices. Their model suggested that political uncertainty would generate a risk premium whose magnitude may vary in different economic conditions. During political shocks, stock prices should fall to reflect the higher required returns commanded for political uncertainty. Later, some empirical studies, such as Brogaard and Detzel (2015), Kelly *et al.* (2016) and Liu *et al.* (2017), presented consistent evidence as the political risk pricing model predicted.

Unlike prior studies, this paper introduces a counterfactual approach for capturing causal impact of political risk on stock prices. This approach is distinctive in setting up a proper benchmark for fair comparisons, which is an optimally weighted combination of peer units. The counterfactual model also combines the advantages of "learning from others" and "learning from the past" (Bekefi and Epstein, 2008). In fact, more than political risks, this approach can also be used for estimating the impacts of other exogenous events (such as natural disasters). Compared with conventional methods, predictive and prescriptive modeling raised some new issues for both data and empirical strategies. On the data side, advances in data science give analysts more options to combine cross-sectional and inter-temporal data for analysis. Big Data methods have played a critical role in deriving business intelligence. But "small data" methods still have their unique contribution, as a lot of informative variables are only available at aggregate (city, country and region) levels. On the empirical strategy side, researchers have noticed that simple statistical correlation may have certain limitations in decision-making. Without randomization in a lab-controlled experiment, confounding factors or endogenous variables cannot be used for causal estimations. With the advances in econometrics during the past two decades, several quasi-experimental techniques have been developed for causality estimation. Meanwhile, researchers become more active in exploring data from natural experiments. In a natural experiment setting, a causal exogenous variable can change independently with respect to other covariates. Moreover, the counterfactual model is a convenient way for an explicit causal relationship. If we have a proper benchmark, the causal impact of a political risk factor can be measured as the difference between the actual outcomes and their unobserved counterfactual outcomes. Without endogeneity concern in natural experiments, analysts just need to focus on selecting an appropriate peer group for comparison.

Based on the above concerns, this study focuses on one nonconventional estimator, the synthetic control methods (SCMs). The SCM was formally introduced in the paper of Abadie *et al.* (2010). One distinct feature of SCM is it can generate an optimally weighted counterfactual for evaluating policy interventions. For measuring the impact of political shock, SCM can generate an appropriate peer benchmarking for comparison. In the real world, it is difficult, even for experienced researchers, to customize peer group and perform meaningful comparison. Given a large number of predictors (and their combinations), analysts could obtain hundreds of benchmarks. However, SCM could automatically conduct model selection. Another desirable property, SCM combines cross-sectional evidence (learning from others) and time series evidence (learning from the past) for quantifying and visualizing potential impact of a political shock. SCM provide analysts an alternative solution to identify, estimate and present potential risk exposure. Last but not least, more than an ex post model, SCM also has implications in forecasting. Analysts can forecast risk scenarios based on in-sample information and variables in our risk metrics. This point may have more potential for risk hedging strategies in the future, for example constructing international portfolio and diversifying unit-specific systematic risks. Following the work of Abadie *et al.* (2010), SCM became popular in empirical policy evaluations. Some recent SCM applications include Billmeier and Nannicini (2013), Bassok *et al.* (2014), El-Shagi *et al.* (2016), Castillo *et al.* (2017), Chamon *et al.* (2017) and Saia (2017). Even with its popularity, a few issues of SCM's application are still open to discussion. Clarifying these issues would make the SCM model become more applicable for empirical researchers.

More than finding evidence for the price of political risks, this paper also discusses some methodological issues of SCM. Specifically, I concern two issues. First, this study stresses the effectiveness of SCM as an innovative estimator. The paper explains why SCM is a good supplement to conventional regression-based estimators, for example the difference-in-difference (DD) model. Second, I will showcase some technical details of applying SCM in practice, e.g. how SCM implements an automatic model selection. In essence, given a set of predictors, SCM uses the convex combination of peer units to provide a good fit for the unit under political shock. Moreover, this case study explains how to use SCM for scenario visualization. After fitting the trajectory of actual outcomes and its counterfactual in the pre-crisis period, the magnitude of the crisis can be directly measured as the actual-counterfactual gap in the post-crisis period.

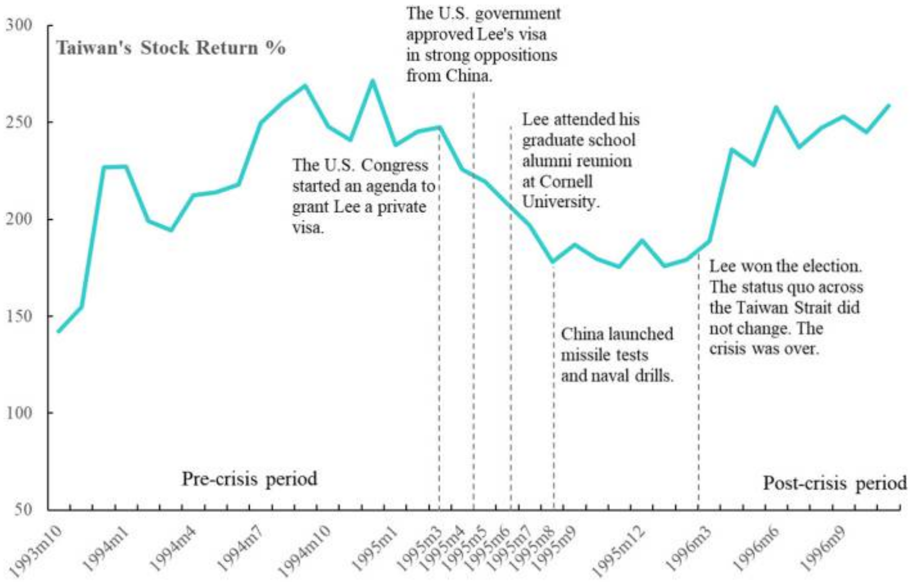
For illustration, this paper chooses a natural experiment of the 1995-1996 Taiwan Strait Crisis, and explains how to implement persuasive causal inference via proper model selection and cross-validations. The choice of Taiwan's stock market and the natural experiment is three-fold. First, the study of Taiwan could add new evidence to existing literature of long-run performance of emerging markets relative to the developed markets.

Researchers and investors have long noticed the rising role of East Asian markets in global capital market. Historical data show that a country's share in the world equity index depends on relative performance of its stock market. Moreover, the dynamics of world index actually reflect some fundamental factors in the long-run, such as the sustainability of economic growth and shifts of national wealth across countries (Dimson *et al.*, 2003, 2009). This study offers us a unique chance to make proper comparison of the historical performance of an emerging Asian market with its developed counterparts via an optimal benchmark. Second, a better understanding Taiwan's market could be helpful for researchers and investors who are interested to equity markets in mainland China. This point is particularly interesting. Because of the strong cultural, economic and geographic connections, as the integration of Greater China financial markets (China, Hong Kong and Taiwan) have attracted considerable attention over recent years (Cheng and Glascock, 2005; Johansson and Ljungwall, 2009). In some cases, Taiwan can be a starting point for studying the linkage of economic growth and financial market development of China. For example, researchers have been interested to the unique credit, financing and governance channels in supporting fast growth of the private sector in China. Based on evidence from Taiwan, we can compare whether the Chinese experience of stock market development was unique during early stages of economic growth (Allen *et al.*, 2005)[2]. Third, the natural experiment of Taiwan Strait Crisis is preferable in its exogeneity. Political uncertainty and financial markets have been well known for their endogenous correlations (Karolyi, 2003), for example, the Mexican peso crisis in 1994 and the 1992 European Exchange Rate Mechanism (ERM) crisis and the devaluation of pound sterling in the UK. In this study, the crisis was politics-based and exogenous. It was triggered by the "One China Principle" and Taiwan's first direct "presidential" election in 1996. In addition, this crisis was unaffected by other confounding events, like Taiwan's 1990 stock market crash and the 1997 Asian Financial Crisis. Thus, we can obtain a convincing causal estimate to the price of political uncertainty.

Before the 1990s, Taiwan largely kept a political regime which was created by the ruling party, Kuomintang (KMT, Nationlist Party of China). After three decades of authoritarian leadership under KMT, Lee Teng-hui was sworn in as the "president" in 1988. Later, he won his another six-year term in the 1990 parliamentary election. Taiwan's first direct presidential election was scheduled on March 23, 1996. As the incumbent, Lee was looking ahead for re-election. The crisis started when Lee planned a visit to his alma mater, Cornell University, for his alumni reunion in June 1995. Although the US had not granted Taiwan's leaders a visitor's visa since 1979, the congress passed resolutions to push the Clinton administration to grant Lee a visa. Finally, the US Government approved Lee's "private visit" in May. Lee visited Cornell in early June and in the eyes of Beijing made a "provocative" speech. From the very beginning in April, Beijing strongly opposed Lee's visit. Beijing also worried this election would become a structural break in cross-strait relations. In the early 1990s, Taiwan's local Democratic Progressive Party (DPP) pushed forward an "independent" Taiwan. After Lee's visit, the first spike in military tensions occurred. From July to August of 1995, Mainland China launched two sets of missile tests and military assault exercises. With military and political tensions escalating, Lee got KMT's nomination for the next election that August. Running against Lee was the DPP and the other two groups of candidates. The second peak of the crisis came in early 1996. Beijing declared Taiwan could be taken over by force if the coming election lead to Taiwan's independence. In February, Beijing announced the third round of missile tests and large scale military drills before the election. The USA deployed two aircraft carrier battle groups to the Taiwan Strait in March. On March 23, Lee won by a landslide. The cross-strait status quo did not alternate. The crisis was over.

Major findings in this study are consistent with existing research on the price of political risk, e.g. political uncertainty commands a risk premium. According to the time line in Figure 1, I set up intervention at March 1995 (1995M3) for SCM estimation. The actual-counterfactual gap from the SCM process highlighted a substantial decline of stock prices in Taiwan. Next, various cross-validation tests confirmed that Taiwan's stock prices dramatically underperformed its newly industrialized peers and the developed markets during the 12-month crisis. No other potential confounding event could generate a similar effect on Taiwan's stock market as this political crisis did. To summarize, this study reminds us that political risks could generate enormous impacts on asset pricing, especially in emerging markets. In particular, political uncertainty following new geopolitical dynamics requires proper identification and assessment in future work.

Besides the introduction, Section 2 provides an overview of data used in this study and makes a preliminary descriptive analysis. Section 3 discusses how to apply natural experiment and non-traditional causal inferential techniques for country-specific risk analysis. Next, Section 4 focuses on SCM applications, including counterfactual benchmark, model robustness, statistical inferences and result discussions. Finally, major findings are wrapped up in Section 5.



Notes: This figure depicts some key events and stock prices in Taiwan during the 1995-96 political crisis. For example, in March-April 1995, the US Congress started an agenda to grant Lee a visa for his coming visit to the USA. In May 1995, the US Government approved a private visa for Lee, which was strongly opposed by Mainland China. In June, Lee attended his graduate school alumni reunion and spoke at Cornell University. In July-August 1995, Mainland China conducted the two rounds of missile tests and air-naval drills in waters close to Taiwan. In March 1996, Lee won the election. The status quo across the Taiwan Strait was not changed. The crisis was over. Data: monthly stock price index (1988M1 as 100) and MSCI

Figure 1.
Timeline of the 1995-96 political crisis and stock prices in Taiwan

2. Data

To implement the SCM approach, I use aggregate monthly price index from Morgan Stanley Capital International (MSCI). Pre-crisis observations are from July 1992 (1992M7) to March 1995 (1995M3)[3]. Crisis observations are from 1995M4 to 1996M3. The rationale of applying aggregate monthly price series are three-fold. First, the validity of SCM estimation largely relies on in-sample fitting of the actual trajectory and its synthetic counterpart. Applying high-frequency data may affect the quality of counterfactual. Previous studies noticed that daily data or weekly data may be too noisy to properly reflect financial markets' responses toward political shocks (Knight, 2007; Imai and Shelton, 2011). For this study, it is appropriate to use lower-frequency (monthly) observations. Second, monthly data are enough to satisfy the dimension issue. Compared with regular regression models, the non-parametric SCM is more permissive to the number of observations. Last but not least, besides data availability, the choice of aggregate market data emphasizes "average investor hold the market" (Ang, 2014), even individual investors may have heterogeneous preferences. Thus, using aggregate market data would provide a more intuitive explanation toward how the market becomes inefficient under certain circumstances. For example, the 1995-1996 political shock had noticeable impacts on asset prices in Taiwan.

To build up the synthetic counterfactual, I start from selecting appropriate peer units for Taiwan. For a convincing comparison, I concentrate on the units which had high-level of economic development or stable economic growth from the 1980s to the early 1990s. Moreover, these peer units should not experience similar (confounding) interventions in that period. Combining the two standards, my peer group includes 20 developed and newly-industrial markets, including Australia (AU), Belgium (BE), Switzerland (CH), Chile (CL), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), Greece (GK), Hong Kong (HK), Ireland (IE), Italy (IT), Japan (JP), Korea (KR), The Netherlands (NL), Portugal (PT), Sweden (SE), Singapore (SG) and the USA (US). All monthly series are derived from MSCI historical stock price data.

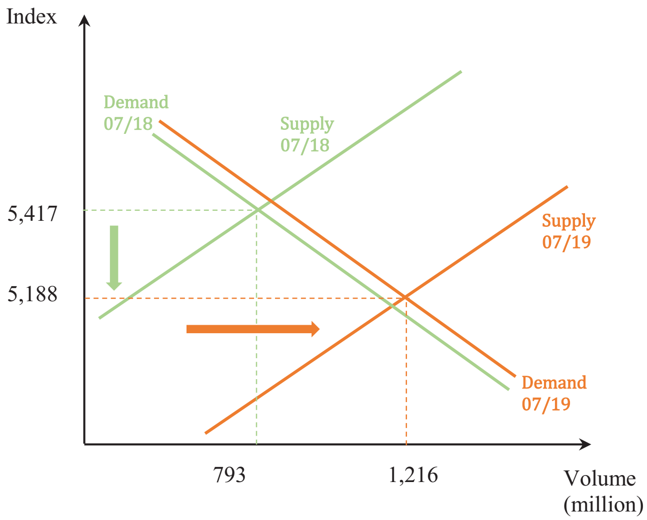
Table I presents distribution statistics of daily returns of Taiwan, Hong Kong, Singapore and S&P500 during the crisis, five years before the crisis and five years after the crisis.

Statistics	Taiwan 1990M4-1995M3	Taiwan 1995M4-1996M3	Taiwan 1996M4-2001M3	Hong Kong 1990M4-1995M3	Hong Kong 1995M4-1996M3	Hong Kong 1996M4-2001M3
Observation	1,203	236	1,215	1,241	240	1,228
Mean%	−0.036	−0.094	0.007	0.112	0.108	0.026
SD	0.024	0.016	0.018	0.015	0.011	0.022
Skewness	−0.07	−0.195	−0.034	−0.438	−1.064	0.339
Kurtosis	4.409	5.210	4.809	7.064	11.094	10.046
		Singapore			S&P500	
Observation	1,250	244	1,251	1,265	252	1,262
Mean%	0.041	0.079	−0.021	0.045	0.113	0.06
SD	0.012	0.009	0.017	0.007	0.006	0.012
Skewness	−0.151	0.314	0.623	−0.009	−0.625	−0.22
Kurtosis	7.939	6.235	9.367	5.495	5.925	6.027

Notes: Data: daily returns (local currency). Mean%: average returns by percentage. Crisis: April 1995-March 1996; Pre-crisis: 5-year observations; Post-crisis: 5-year observations
Source: Compustat Global – Security Daily, provided by Wharton Research Data Services

Table I.
Daily returns distribution statistics

From April 1995 to March 1996, average daily return of Taiwan was negative, at −0.094 per cent. In contrast, five-year average daily return before the crisis was higher. Similarly, we can observe a robust recovery after the crisis. In short, we can observe a clear "U" shape return movement around the crisis. Here is an example of a single day experience. As Figure 2 shows, on the July 18, after mainland China announced the first round of missile firing, Taiwan's stock market plummeted. On the next day, the political turbulence caused the Taiwan Capitalization Weighted Stock Index (TAIEX) fell 4.4 per cent. TAIEX dropped from 5,417 points on July 18 to 5,188 points on July 19, 1995. Panic market sentiment created the largest single-day decline in that month. At the same time, trading volume that inflated from 793.3 million shares on July 18 to 1,216.5 million shares on July 19. The index decline was largely caused by the substantial out-shift of the supply curve and the loss of investors' confidence. Unlike an obvious downward trend in the first moment, the second moment of returns kept largely stable in Taiwan (no volatility surprise). Table I illustrates distribution of daily return over the same subperiods. Deviations from normality were observed over all subperiods. As Table I indicates, negatively skewed returns and negative average indicated that extreme negative returns dominated during the crisis. Thus, standard deviation would underestimate market risk in Taiwan. Also, kurtosis suggested fat tails or a higher probability of extreme values persist in the crisis. The unusual return behaviors shed light on that the crisis had noticeable impact on Taiwan's stock market. Moreover, the



Notes: This figure illustrates one shock to Taiwan's stock market on July 19. TAIEX declined from 5,417 to 5,188 (4.42 per cent) after Beijing announced an unexpected missile tests from July 21 to July 28, 1995. At the same time, trading volume inflated from 793.3 million shares to 1,216.5 million shares. For individual stock prices, as Gordon model suggested, the drops were caused by the higher required returns and the lower expected growth rates

Figure 2.
A daily example of Taiwan's stock market shock on July 19, 1995

pattern of return distribution in Taiwan differed from other markets across the subperiods in Table I.

Besides pre-intervention stock prices, predictors for the SCM counterfactual may include other observed covariates. These indicators could make sure there is a good fit between the real and counterfactual trajectories. In this study, it is reasonable to consider some macroeconomic variables for the counterfactual. These characteristics of the treated unit (Taiwan) should be properly matched with its peer units. As for the macroeconomic indicators, I include Gross Domestic Product (GDP) change (per cent), gross national saving of GDP (per cent), inflation rate (average consumer price per cent), total investment of GDP (per cent), unemployment rate (of total labor per cent), total export change (per cent), and current account balance of GDP(per cent). These variables are obtained from the International Monetary Fund (IMF) and World Economic Outlook (WEO) database. Their values are available on annual basis.

3. Specifications

3.1 Causal inference and natural experiment

As discussed, causal inference has important implications for country risk analysis. In practice, exogeneity is one major concern for causal inference via conventional regression models. Without proper randomization in a controlled experiment setting, exogenous treatment and causality cannot be guaranteed[4]. Structural equation model (SEM) and potential outcome (POM) approaches have been the two mainstream instruments for estimating causal relationship. Compared with SEM, POM can set up a direct causality link if analysts have a clearly defined counterfactual for the unobserved outcomes[5]. Data from natural experiments are ideal applications for counterfactual models. Through a natural experiment, causal parameters can be estimated independently after controlling other covariates. In practice, validity of causal inference from natural experiment largely depends on the counterfactual or comparison units. Because of recent econometric advances, counterfactual models are increasingly popular for estimating treatment effect and policy evaluations. Empirically, researchers have developed several treatment estimators for causal identification, such as the DD model, the propensity score matching (PSM) estimator, the regression discontinuity design and the SCMs. These estimators have been widely applied for natural experiment studies. However, these models require certain econometric assumptions, such as conditional independence assumption (CIA), stable unit treatment value assumption (SUTVA) and unconfounderness.

3.2 Synthetic control methods

This study concentrates on the non-parametric SCM. In essence, SCM combines the features of panel data DD models and matching estimators. Both DD and SCM use a proper counterfactual for causal inference. However, the power of SCM lies in its ability to create appropriate benchmarking peer groups for analysis. In the DD framework, the treatment effect can be measured in three steps. First, we separate all units into two groups, i.e. a group of units exposed to intervention (the treatment group) and a group without intervention (control group) as a counterfactual. Second, we split the longitude observations into two sections, i.e. a pre-intervention period and a post-intervention period. Then, we can calculate the difference between the treated units and the counterfactual units in the two periods. Third, conditional on other covariates (or not) the intervention effect can be measured as the regression parameter of the binary intervention variable:

$$\begin{array}{ll} Y_{it} = \mathbf{b}_i^{'}\mathbf{f}_t + \alpha_i + \delta_{it}D_{it} + \varepsilon_{it}; & \forall i = 1, \ldots, M \\ Y_{jt} = \mathbf{b}_j^{'}\mathbf{f}_t + \alpha_j + \epsilon_{jt}; & \forall j = 1, \ldots, N \end{array} \tag{1}$$

$$\text{Intervention } D_t = \begin{cases} 0 & \forall \mathrm{t} = 1, \ldots, \mathrm{T}_0 \\ 1 & \forall \mathrm{t} = \mathrm{T}_0 + 1, \ldots, \mathrm{T}_0 + \mathrm{h} \end{cases}$$

In a panel format, equation (1) denotes Y_{it} as outcomes of units i exposed to the intervention (D_{it}) and Y_{jt} as outcomes of control units. Besides the binary D_{it}, Y_{it} and Y_{jt} can be driven by a set of common factors $\mathbf{f}_t$ in the pre-intervention period ($t = 1, \ldots, T_0$). However, in the post-intervention period ($t = T_0 + 1, \ldots, T_0 + h$), Y_{it} are driven by $\mathbf{f}_t$ and the intervention of D_{it}, while Y_{jt} is still a function of $\mathbf{f}_t$. Treatment effect is $\boldsymbol{\delta}_{it}$. DD model estimates $\boldsymbol{\delta}_{it}$ as equation (2):

$$\begin{aligned} \boldsymbol{\delta}^{DD} &= \{\mathbb{E}(Y_{it}|D_t = 1) - \mathbb{E}(Y_{it}|D_t = 0)\} - \{\mathbb{E}(Y_{jt}|D_t = 1) - \mathbb{E}(Y_{jt}|D_t = 0)\} \\ &= \{\mathbb{E}(Y_{it}) - \mathbb{E}(Y_{jt})|D_t = 1\} - \{\mathbb{E}(Y_{it}) - \mathbb{E}(Y_{jt})|D_t = 0\} \end{aligned} \tag{2}$$

The simple specification is one major benefit of DD model. However, besides regular assumptions needed for causal inference (CIA, SUTVA and unconfounderness), the validity of DD for multiple-period data requires that outcomes of the treatment and control groups have common underlying trends before the intervention. In practice, using the averaged outcome, the control group sometime may not be a good counterfactual for the treated unit. SCM, on the other hand, provides a promising solution to the "common trends" concern. Instead of assigning equal weight, SCM uses an optimally weighted control group to proxy the underlying trend of the treated units in the pre-intervention period. After minimizing the difference between the treated and counterfactual trajectories before the intervention, intervention effect can be measured as the treated-counterfactual gap in the post-intervention period.

For each treated unit Y_{it}, using pre-intervention outcomes, SCM can find an optimal combination of Y_{jt} to satisfy the common underlying trend assumption. Specifically, if $\sum_{j=1}^{N} w_j^* \cdot Y_{jt} \to Y_{it}$ in $t = 1, \ldots, T_0$, then the causal impact of the intervention can be measured as the gap between the treated unit and its synthetic counterfactual in the post-intervention period as equation (3)[6]:

$$\begin{aligned} \boldsymbol{\delta}^{SCM} &= \{Y_{it} - \sum_{j=1}^{N} w_j^* \cdot Y_{jt}|D_t = 1\} - \{Y_{it} - \sum_{j=1}^{N} w_j^* \cdot Y_{jt}|D_t = 0\} \\ \hat{\boldsymbol{\delta}}^{SCM} &\approx Y_{it} - \sum_{j=1}^{N} w_j^* \cdot Y_{jt} \quad \forall t = T_0, \ldots, T_0 + h \end{aligned} \tag{3}$$

One critical step in SCM is generating the optimal weight of control units (w_j^*). In an ideal situation, the optimally weighted peer group should be a good unit-specific counterfactual. Thus, the optimal weights are generated by minimizing the discrepancy between a predictor vector of the treated unit ($\mathbf{Z}_i$) and a weighted predictor vector of comparison units ($\mathbf{Z}_j \mathbf{W}$) as following:

$$\begin{aligned} ||\mathbf{Z}_i - \mathbf{Z}_j\mathbf{W}||_V &= \min_{w_j \in \mathbf{W}} \left[(\mathbf{Z}_i - \mathbf{Z}_j\mathbf{W})'\mathbf{V}(\mathbf{Z}_i - \mathbf{Z}_j\mathbf{W})\right]^{1/2} \\ \text{s.t.} \sum_{j=1}^{N} w_j^* &= 1 \text{ and } w_j^* \geq 0; \ \forall t = 1, \ldots, T_0 \end{aligned} \tag{4}$$

For vector **Z**, it can be pre-intervention outcomes (Y) and other predictors (**X**). In the process of minimization, w_j is constrained to be positive and the sum of weights equals one ($\sum_{j=1}^{N} w_j^* = 1$ and $w_j^* \geq 0$). And **V** is a symmetric and semi-definite matrix. In practice, SCM users could have different combinations of predictors. In the original SCM specification of Abadie *et al.* (2010), the vector of predictors includes some selected pre-intervention outcomes and their covariates. These covariates can be added to SCM as an averaged value over years. The performance of SCM predictors is measured by their in-sample fitting. In other words, good SCM predictors should have low real-counterfactual gap or prediction error before the intervention. For inferential techniques, analysts can choose non-parametric ranking methods or boot-strapping for standard errors.

As previous literature suggested, the SCM estimator is an extension of the traditional linear panel data model, for example, the DD estimator (Abadie *et al.*, 2010). Also, the algorithm of SCM is similar to the commonly used matching methods in controlling imbalance of pre-intervention confounders between the treated and control groups (Iacus *et al.*, 2011). However, compared with conventional matching estimators, SCM provides a solution for balancing tests in comparative case studies. It is not rare, in comparative case studies, that researchers may have a small sample of the treated units and comparison units [7]. The SCM algorithm ensures that the observed characteristics (covariates) of the treated units are close to its synthetic conterfactual.

For the context of this study, SCM has some unique benefits. First, as above, the SCM model could relax the "common trends" assumption for the DD specifications. Using an optimally weighted control group, SCM ensures the treated unit (Taiwan) and its counterfactual could have similar pre-intervention trends. In other words, via the SCM approach, we can still estimate the intervention effect even the pre-crisis outcomes of Taiwan and comparison units have different trends. Second, the SCM approach can avoid the concern of cross-sectional dependence in "macro-panels". Compared with micro panels, the long time series in macro-panels may lead to correlation between units. If the residuals are correlated cross-units, test results of regression models can be biased. Third, unlike conventional DD models, SCM can better account for the impact of time-invariant covariates. For example, in this study, the outcome variable is monthly stock prices. Due to data availability, some covariates are only available at yearly levels. But the SCM algorithm can use pre-crisis outcomes and pre-crisis covariates, at different frequencies, to generate an optimal counterfactual. Last but not least, SCM reports the intervention effect at every time interval during the crisis. In contrast, the regression-based DD coefficient can only represent the average intervention effect. Thus, SCM could showcase non-constant intervention effect over time.

To illustrate the difference between SCM and regression approaches, this study implements several DD estimations (Appendix). These estimations are conducted via various specifications. In practice, researchers can use the fixed-effects model or the least square dummy variable approaches to control unobserved heterogeneity among the treated and control units. Besides conventional DD model, this study also considers the "common trends" assumption. Robustness tests are conducted to test possible bias caused by different pre-crisis trends of Taiwan and comparison units. The results are presented in Table AI. In the next section, We will come back and compare the two sets results of SCM and DD models.

4. Applications

4.1 Counterfactual Taiwan

As mentioned, SCM can be an innovative peer-group option for country-risk analysis. SCM utilizes the features of cross-sectional and time series data. It also bridges both quantitative and qualitative elements in practical risk analysis. This methodology allows analysts to conduct persuasive ("apple-to-apple") comparisons for causal inference. The 1995-96 political crisis over the Taiwan Strait provided us a unique natural experiment to apply SCM for causal inference and examine how political shocks would affect financial market. For the purpose of illustration, I will first construct counterfactuals for Taiwan through various predictor combinations. Next, I will show how to implement validity tests and statistical inference to confirm the causal effects of the political crisis.

Following equation (4), my first step is to select SCM predictors. In essence, this paper aims to estimate causal effect of external political shocks to aggregate market index after controlling macroeconomic variables and stock markets' past performance. Considering data availability, my predictors include yearly macroeconomic variables (**X**) and stock price index (scaled aggregate prices, **R**) in the pre-intervention period of Taiwan and its comparison units (peers). As in Table II, the macroeconomic variables are from publicly available World Economic Outlook database (WOE, IMF). Stock prices, as mentioned, are indexed MSCI monthly prices from 1992M7 to 1995M3 with the scaled value of 1992M6 as 100. Second, the SCM algorithm is implemented as Abadie *et al.* (2010). And I will compare various combinations of predictors and pick up the one with the lower real-counterfactual discrepancy. Here I use the criterion of root of mean squared error (RMSE) to measure the fitness of a counterfactual trajectory to actual stock price series before the political crisis (1995M4). The

Unit	GDP%	Saving%	Inflat.%	Invest.%	Unemp.%	Export%	CA/GDP%
TW	7.53	31.55	3.84	28.28	1.51	6.58	3.12
SE	0.39	19.36	2.99	20.30	9.68	2.03	−0.95
PT	1.31	22.75	6.59	25.29	5.11	5.74	−0.71
IT	0.68	19.12	4.55	19.87	9.76	8.63	−0.10
FI	−0.04	18.22	2.73	19.79	15.00	13.44	−1.57
ES	0.62	19.12	5.48	21.79	21.70	10.67	−2.36
KR	7.41	37.78	5.76	38.17	2.63	13.00	−0.38
HK	6.16	34.01	9.06	28.94	1.95	13.12	2.31
AU	3.79	20.55	1.56	24.21	10.43	7.55	−3.62
SG	9.85	46.26	2.54	35.18	1.74	14.34	11.09
JP	0.44	31.79	1.23	30.93	2.51	2.30	2.83
CH	0.34	32.12	2.73	26.10	3.93	1.44	6.03
BE	1.27	24.33	2.38	23.03	8.49	4.09	4.42
CL	7.64	20.80	13.22	27.40	7.00	9.65	−3.34
FR	1.11	21.01	2.12	20.50	10.13	4.79	0.51
DE	2.43	22.89	4.08	24.13	7.60	0.51	−1.24
GK	0.37	20.49	13.70	21.37	9.33	4.94	−0.88
IE	3.93	18.25	2.31	16.81	16.03	12.92	2.41
NL	1.97	25.62	2.20	22.79	5.53	4.67	3.44
DK	2.43	18.35	1.78	18.35	8.62	3.25	2.72
US	3.45	17.46	2.87	20.52	6.83	6.35	−1.23

Notes: This table reports macroeconomic predictors for the counterfactual Taiwan. In SCM specification, the counterfactual is constructed by an optimally weighted comparison group. The optimal weighted are calculated via a convex combination of predictors. In this study, the set of predictors include pre-intervention outcomes and selected macroeconomic indicators. GDP%: GDP growth rate (%); Saving%: gross national saving of GDP (%); Inflat.%: inflation rate or average consumer price (%); Invest.%: total investment of GDP (%); Unemp.%: unemployment rate (of total labor %); Export%: total export change (%); and CA/GDP%: current account balance of GDP(%)
Source: International Monetary Fund and World Economic Outlook database

Table II. Macroeconomic predictors for SCM counterfactual ideal predictor vector is the one which has the lowest RMSE among my candidate models. For simplicity, I choose five specifications (S1-S5) with various combinations of (**R** and **X**) to illustrate the process of SCM[8]. Specifically, S1 includes 33 (all) monthly pre-intervention outcomes from 1992M7 to 1995M3 and have no macroeconomic variables. S2 is a specification which has all 33 outcomes and a full set of macroeconomic variables as in Table II, including GDP growth rate (percentage), saving rate (percentage), inflation rate (percentage), investment rate(per cent), unemployment rate (percentage), export in GDP (percentage) and current account in GDP (percentage). The values of macroeconomic variables are the average yearly values frm1990 to 1992. Also, S3 covers all macroeconomic variables but only includes every five-month outcomes from 1992M7. Unlike S3, S4 includes all 33 monthly pre-intervention stock prices. However, S4 only uses a subset of macroeconomic variables, i.e. GDP growth rate (per cent), saving rate (per cent), inflation rate (per cent), investment rate(per cent), and current account in GDP(per cent). In other words, unemployment rate (per cent) and export in GDP (per cent) are used in S2 and S3 but not in S4. Instead, S5 applies on every five-month stock prices as in S3 and the subset of predictors as in S4. Overall, this step illustrates how analysts can mix and match predictors to derive an optimal counterfactual. In practice, if researchers may have a lot of candidate models if they use multiple predictors.

The optimal SCM weights of peer units from S1-S5 are presented in Table III. For example, S1 suggests that the counterfactual Taiwan is built up by the combination of five units, including Finland (0.483), Korea (0.17), Hong Kong (0.114), Belgium (0.13) and Chile

Unit	S-1	S-2	S-3	S-4	S-5
SE	0	0	0	0	0
PT	0	0.124	0.081	0.366	0
IT	0	0	0	0	0
FI	0.483	0.122	0.321	0.154	0.377
ES	0	0	0	0	0
KR	0.170	0.175	0.237	0.015	0.284
HK	0.114	0.002	0	0	0
AU	0	0	0	0	0
SG	0	0.306	0.255	0.373	0.232
JP	0	0	0	0	0
CH	0	0	0	0	0
BE	0.130	0.073	0	0.016	0
CL	0.103	0.052	0.091	0.075	0.090
FR	0	0	0	0	0
DE	0	0	0	0	0
GK	0	0	0	0	0
IE	0	0.146	0.015	0	0.016
NL	0	0	0	0	0
DK	0	0	0	0	0
US	0	0	0	0	0
RMSE	17.88	19.36	17.62	19.20	17.56

Notes: This table reports the optimal weights (w_j^*) of peer units from five different SCM specifications. For example, in S-1, the weight of Finland was 0.483, and the weight of Korea and Hong Kong are 0.170 and 0.114, respectively. In each specification, the weights are greater or equal to zero ($w_j^* \geq 0$) and summed to one ($\sum_{j=1}^{N} w_j^* = 1$). As discussed in Section 4.1, S1-S5 have various combinations of pre-intervention outcomes and macroeconomic predictors. Performance of these five predictor sets are evaluated by in-sample fittings, e.g. RMSE. Here, RMSE values are calculated via pre-intervention observations from 1992M7 to 1995M3. The best specification should have the lowest in-sample RMSE

Table III.
SCM Weights via different predictor sets

(0.103). Under SCM constraints, the optimal weights of S1 are greater than zero and are summed up to one. In a similar fashion, S2 to S5 report their optimal weights of peer units. As mentioned, the performance of in-sample fitting of S1 to S5 is measured by their RMSE values, which are reported at the bottom row of Table III. The lower RMSE value indicate better in-sample fitting between actual trajectory and its counterfactual trajectory. Here, we can see S5 has the lowest RMSE in the five candidate models. Thus, I will use variables in S5, i.e. every five-month prices from 1992M7 and a subset of selected macroeconomic indicators, as the vector of predictors for SCM.

Next, using pre-intervention outcomes, counterfactual Taiwan is constructed with the optimally weights peer units as in S5. Table IV reported actual and synthetic values of selected predictors in S5. For example, actual stock prices in 1995M1 was 238.1 (1992M7 as 100) and the SCM value was 240.5 in that month. Similarly, Taiwan's actual GDP growth rate (average of 1990-1992) was 7.53 per cent and the synthetic value was 5.13 per cent. Graphically, Figure 3 illustrates Taiwan's actual price index (blue solid line) and counterfactual (red dash line) trajectories. The two vertical dash lines indicate the beginning and the end of the political crisis. We can see the SCM counterfactual largely follows the trend of actual prices of Taiwan in the pre-crisis period. During the crisis, however, we can see a noticeable gap (blue shade) between the two trajectories. Actual stock prices in Taiwan was noticeably lower than the optimal weighted peer group. In other words, without the crisis, Taiwan should follow a similar trend of its counterfactual. The 1995-96 crisis, however, dragged down stock prices. Table V, for example, suggests that actual price index was 31 lower than its counterfactual in April 1995. Then the gap kept increasing and peaked in August 1995 (the second missile drill). When the crisis was getting close to the end, actual index started to converging its counterfactual.

Even we can observe a substantial actual-counterfactual gap of Taiwan during the crisis, it is still possible that the treatment effect came by chance. As a placebo test, I will use other peer units to repeat the natural experiment for robustness check. For illustration, I choose Korea, Hong Kong, Singapore and Ireland to introduce a hypothetical political crisis at the same time as in Taiwan. Similar SCM processes are implemented as above. Their results are graphically represented in Figure 4. Among the four units, Korea, Hong Kong and Singapore, including Taiwan, were often cited as the "Little Asian Dragons", because of their high economic growth in the 1980s to the 1990s. Ireland, was known as the "Celtic Tiger", also experienced fast economic growth in the 1990s. Figure 4 indicates that the hypothetic political shock did not introduce similar stock market downturns in other markets as in Taiwan. Price index in Korea and Singapore outperformed their counterfatuals during the crisis. There was no obvious difference between actual prices in Ireland and its counterfactual. For Hong Kong,

Predictor	Taiwan	Synthetic	Predictor	Taiwan	Synthetic
Prices 1993M5	151.8	148.8	GDP growth %	7.53	5.13
Prices 1993M10	142.1	174.1	Saving rate %	31.55	30.49
Prices 1994M3	194.5	199.4	Inflation rate %	3.84	4.48
Prices 1994M8	260.5	240.2	Investment %	28.28	29.20
Prices 1995M1	238.1	240.5	Current account %	3.12	1.61

Notes: This table reports values of predictors of actual Taiwan and its SCM benchmark (Synthetic). The predictors shown in this Table includes selected pre-intervention outcomes (monthly stock prices) and macroeconomic indicators. The set of predictors are obtained from S-5 as in Table II. For a good counterfactual, predictor values of the synthetic unit should be very close to the actual values

Table IV. Predictors values of Taiwan and the SCM counterfactual

Notes: This figure plots the trajectories of Taiwan monthly price index (blue solid line) and the SCM benchmarking counterfactual (red dash line). Graphically, magnitude of the crisis can be measured as real-counterfactual spread (shaded area) between the two series during the crisis. The crisis was from 1995M4 to 1996M3 (two vertical dash lines). The scaled index is calculated by setting the baseline index of 1988M1 as 100. Data: MSCI monthly country index (USD)

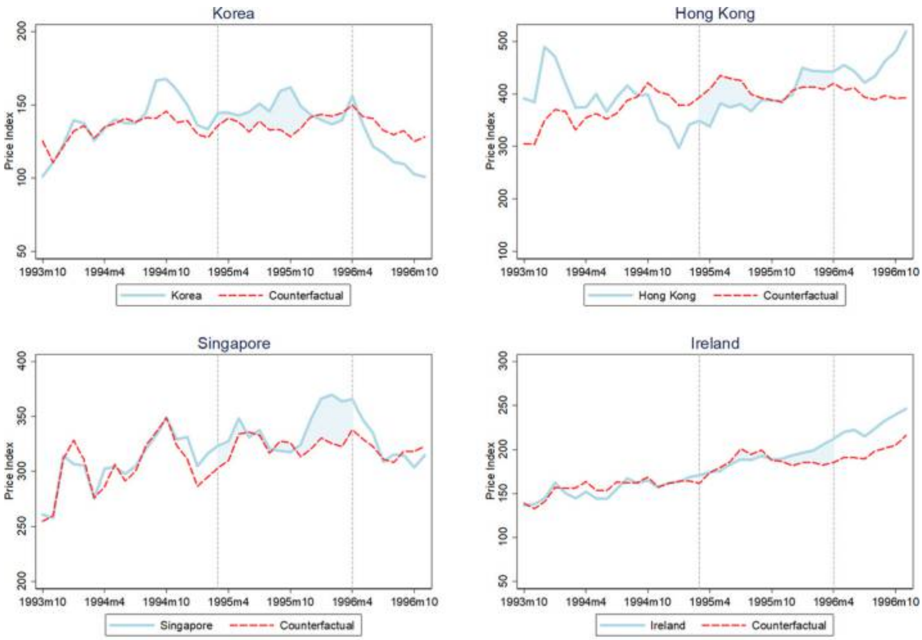
Figure 3.
Taiwan and the synthetic benchmark: price index

Table V.
SCM Estimated impact of the political crisis for Taiwan

Month	Taiwan	Synthetic	Difference	Month	Taiwan	Synthetic	Difference
1995M4	225.8	256.8	−31.0	1995M10	179.4	261.4	−81.9
1995M5	219.6	270.9	−51.3	1995M11	175.4	254.3	−78.9
1995M6	208.2	277.7	−69.5	1995M12	189.3	253.2	−63.9
1995M7	197.0	282.2	−85.2	1996M1	175.8	252.7	−76.9
1995M8	178.0	269.2	−91.3	1996M2	179.0	250.6	−71.5
1995M9	186.9	273.4	−86.5	1996M3	188.8	247.4	−58.6

Notes: This table reports outcomes (monthly prices) of Taiwan, the SCM counterfactual (Synthetic) and their gap (Difference) in the post-crisis period (12 months). If the crisis had a noticeable effect on Taiwan's stock market, there should be a substantial difference (gap) between the actual and the synthetic series. The SCM results suggested a large negative gap between the two series, namely Taiwan's stock prices noticeably underperformed its peers during the crisis. Alternatively, without the political crisis, stock prices in Taiwan should have been much higher

the counterfactual was consistently higher than the actual price index series before and after the hypotheric crisis. Similar process can be extended to all peer units. I will come back to this point in the next section. In sum, unlike Taiwan, there was no evidence that the crisis had similar negative impact in Taiwan's peer group.



Notes: The four panels plot actual and SCM counterfactual price indexes of Korea (top left), Hong Kong (top right), Singapore (bottom left) and Ireland (bottom right). Similar to Taiwan, the hypothetical intervention was introduced during 1995M4-1996M3 (vertical dash lines). Data: MSCI monthly country index (USD)

Figure 4.
Actual-counterfactual spreads of Taiwan's peer units: Hong Kong, Ireland, Korea and Singapore

4.2 Robustness and statistical inferences

There are two empirical issues toward robustness of my SCM results. First, confounding factors may blur the unusual stock market behaviors. Thus, I should clarify whether the substantial drop in stock prices came from other events happened around that time. Second, I need to make sure that proper peer units have been used in building up the counterfactual. Otherwise, the observed intervention impact may merely due to a wrong benchmark. Because of the two issues, I will implement various robustness tests to confirm causality link between the political crisis and the stock market's reaction. Here, I choose cross-time validation for the first issue and cross-unit validation for the second issue.

For cross-time validations, I switch the intervention date to other times when confounding events could occur. In a fairly efficient market, price revisions toward the events should be quick. One potential event was the Taiwan's initiative for Asia-Pacific Regional Operations Center (APROC) in January 1995. APROC aimed to improve Taiwan's economic influence in Asia-Pacific region, as a new center of operations and shipment in the Asia-Pacific region. Figure 5 illustrate the SCM result when the intervention occurred in 1995M1 (vertical dash line). Unlike Figure 3, we cannot observe a difference between the actual index and its counterfactual after this event. There was no noticeable divergence between them before 1995M4. A similar case was the establishment of Taipei Exchange in November 1994. Taipei Exchange was created for over-the-counter and debt-security trading in Taiwan. Again, Figure 6 repeated a similar process with intervention in 1994M11. We cannot observe a similar substantial drop in price index as the

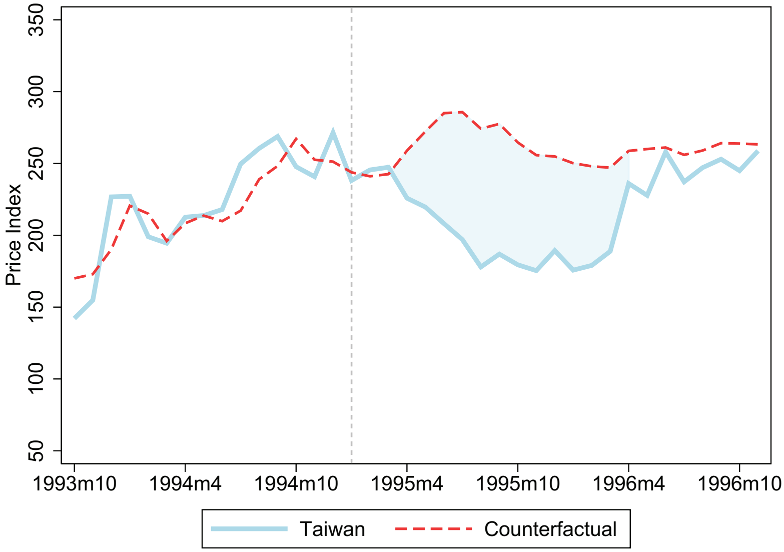


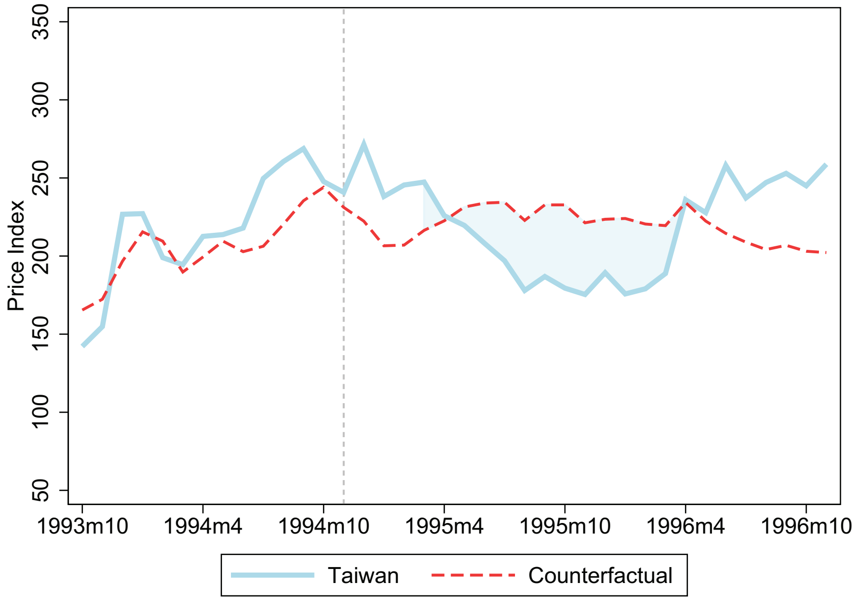
Figure 5.
Cross-time validation: APROC in January 1995

Notes: This figure plots a cross-time validation with the hypothetic intervention of APROC in January 1995 (1995M1). The two trajectories are Taiwan's monthly price index (blue solid line) and the SCM counterfactual (red dash line). Graphically, magnitude of the hypothetical intervention can be measured as real-counterfactual spread (shaded area) between the two series during the crisis. In this test, the hypothetical intervention was introduced in 1995M1 (the vertical dash line). The scale index is calculated by setting the baseline index of 1988M1 as 100. Data: MSCI monthly country index (USD)

intervention in 1995M4. Moreover, if the new exchange in Taipei would have any effect on stock market, its net effect should be positive on stock price (due to the higher confidence).

As for peer units, I choose leave-one-out cross-validation (LOOCV) to measure out-of-sample prediction error. In each round of LOOCV, I will drop one peer unit ($i = 1 \ldots 20$) and use the remaining units to build up a new counterfactual (CV_i). Then, I use two criteria to evaluate the performance of the twenty counterfactuals, e.g. in-sample (pre-intervention) RMSE of Taiwan and averaged out-of-sample (post-intervention) treatment effect on the treated (ATET). If my SCM counterfactuals did not heavily rely on one particular peer unit, RMSE and ATET should be consistent during LOOCV. In other words, if there is noticeable fluctuation in RMSE or ATET, we should doubt SCM results may be too sensitive to some peer unit. So the SCM findings are less robust toward the choice of peer-group. The definitions of RMSE and ATET are as following:

$$\begin{aligned} RMSE_i &= \left\{ \frac{1}{t_1} \left(Y_{it} - \hat{Y}_{it} \right)^2 \right\}^{1/2} \quad \forall t_1 = 1, \ldots, T_0 \\ &= \left\{ \frac{1}{t_1} \left(Y_{it} - \sum_{j=1}^{N} w_j^* \cdot Y_{jt} \right)^2 \right\}^{1/2} \end{aligned} \tag{5}$$



Notes: This figure plots a cross-time validation with the hypothetic intervention of Taipei Exchange in November 1994 (1994M11). The two trajectories are Taiwan's monthly price index (blue solid line) and the SCM counterfactual (red dash line). Magnitude of the hypothetical intervention can be measured as real-counterfactual spread (shaded area) between the two series during the crisis. In this test, the hypothetical intervention was introduced in 1994 M11 (vertical dash line). The scaled index is calculated by setting the baseline index of 1988M1 as 100. Data: MSCI monthly country index (USD)

Figure 6.
Cross-time validation: Taipei Exchange, November 1994

RMSE measures goodness-of-fit between the actual and synthetic trajectories before the intervention (t_1). Aiming at treatment effect, ATET also considers the direction of actual-synthetic gap (positive or negative) in selected post-intervention periods (t_2). Here, ATET values are calculated as the average treatment effect in the 12 months after the crisis (1995M4 to 1996M3):

$$\begin{aligned} ATET_i &= \left\{ \frac{1}{t_2} \left(Y_{it} - \hat{Y}_{it} \right) \right\} \quad \forall t_2 = T_0 + 1, \ldots, T_0 + h \\ &= \left\{ \frac{1}{t_2} \left(Y_{it} - \sum_{j=1}^{N} w_j^* \cdot Y_{jt} \right) \right\} \end{aligned} \tag{6}$$

Table VI reports SCM weights, RMSE and ATET in the LOOCV tests. For example, Sweden (SE) is dropped in the first cross-validation test (CV-1). The remaining 19 peer units will be used for SCM process. Results in Table VI suggests that RMSE are largely consistent across all tests (CV-1 to CV-20). Similarly, ATET values also remained stable over 20 cross-validation tests. Thus, we are confident that SCM results are robust to different

Table VI. Cross-unit validations: LOOCV results

Unit	CV-1	CV-2	CV-3	CV-4	CV-5	CV-6	CV-7	CV-8	CV-9	CV-10
SE	N/A	0	0	0	0	0	0	0	0	0
PT	0	N/A	0	0	0	0.051	0	0	0	0
IT	0	0	N/A	0	0	0	0	0	0	0
FI	0.334	0.382	0.370	N/A	0.369	0.370	0.359	0.370	0.168	0.401
ES	0	0	0	0	N/A	0	0	0	0	0
KR	0.291	0.258	0.291	0.466	0.278	N/A	0.249	0.280	0.538	0.263
HK	0	0	0	0	0	0	N/A	0	0	0
AU	0	0	0	0	0	0	0	N/A	0	0
SG	0.231	0.257	0.224	0.102	0.238	0.335	0.27	0.235	N/A	0.247
JP	0	0	0	0	0	0.167	0	0	0	N/A
CH	0	0	0	0	0	0	0	0	0.006	0
BE	0	0	0	0	0	0	0	0	0	0
CL	0.089	0.084	0.092	0.094	0.088	0.077	0.078	0.089	0.132	0.088
FR	0	0	0	0	0	0	0	0	0	0
DE	0	0	0	0	0	0	0	0	0	0
GK	0	0	0	0	0	0	0	0	0	0
IE	0.056	0.019	0.024	0.338	0.027	0	0.044	0.025	0.156	0.001
NL	0	0	0	0	0	0	0	0	0	0
DK	0	0	0	0	0	0	0	0	0	0
US	0	0	0	0	0	0	0	0	0	0
RMSE-1	17.54	17.64	17.53	18.18	17.55	18.59	17.63	17.55	17.29	17.66
RMSE-2	8.81	8.89	8.96	9.94	8.94	8.94	8.92	8.96	9.94	8.94
ATET	−71.24	−71.19	−71.07	−59.17	−70.75	−68.46	−70.09	−70.7	−62.63	−71.65

Notes: This table presents the results of cross-unit validations. As mentioned in Section 4.2, this study chooses leave-one-out cross-validation (LOOCV) to detect extreme comparison units. Empirically, extreme comparison units could invalidate SCM estimations, as the SCM results would be very different without using them as comparison units. To verify my SCM results, I use LOOCV tests. In each round, the LOOCV algorithm will drop out one comparison unit (N/A) and implements SCM estimation with the remaining units. Thus, we can compare how the SCM results from various groups of comparison units. The LOOCV tests can be viewed as external validity tests. N/A: The unit left out in each round of LOOCV. RMSE-1: calculated from 1992M7 to 1995M3. RMSE-2: calculated from 1994M4 to 1995M3. ATET: average treatment effect on the treated

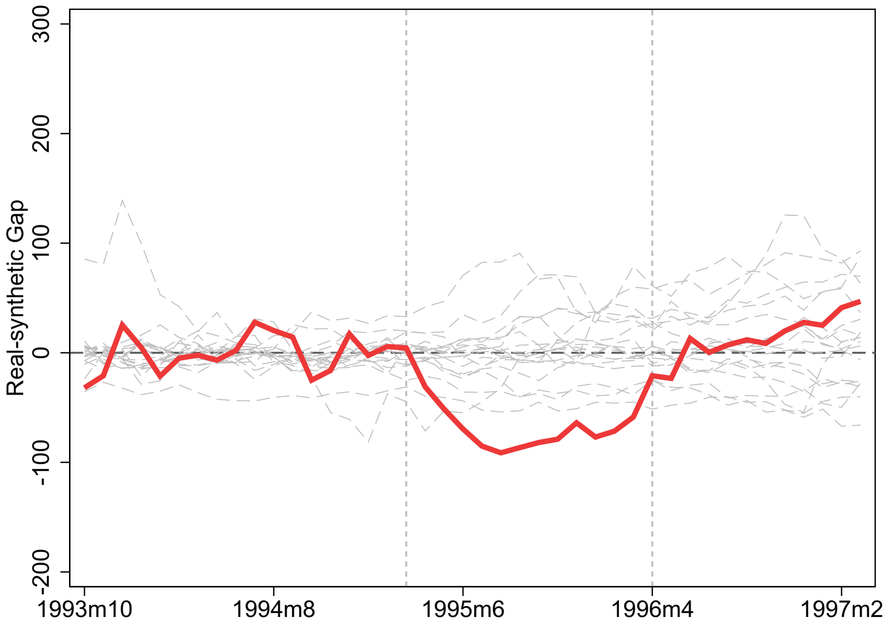
(*continued*)

Table VI.

Unit	CV-11	CV-12	CV-13	CV-14	CV-15	CV-16	CV-17	CV-18	CV-19	CV-20
SE	0	0	0	0	0	0	0	0	0	0
PT	0	0	0	0	0	0	0	0	0	0
IT	0	0	0	0	0	0	0	0	0	0
FI	0.366	0.378	0.390	0.380	0.390	0.378	0.394	0.384	0.402	0.353
ES	0	0	0	0	0	0	0	0	0	0
KR	0.303	0.27	0	0.269	0.290	0.286	0.277	0.285	0.258	0.274
HK	0	0	0	0	0	0	0	0	0	0
AU	0	0	0	0	0	0	0	0	0	0
SG	0.214	0.245	0.502	0.246	0.226	0.229	0.238	0.230	0.252	0.245
JP	0	0	0	0	0	0	0	0	0	0
CH	N/A	0	0	0	0	0	0	0	0	0
BE	0	N/A	0	0	0	0	0	0	0	0
CL	0.094	0.087	N/A	0.086	0.092	0.091	0.091	0.091	0.088	0.086
FR	0	0	0	N/A	0	0	0	0	0	0
DE	0	0	0.068	0	N/A	0	0	0	0	0
GK	0	0	0.040	0	0	N/A	0	0	0	0
IE	0.024	0.02	0	0.019	0.002	0.015	N/A	0.009	0	0.041
NL	0	0	0	0	0	0	0	N/A	0	0
DK	0	0	0	0	0	0	0	0	N/A	0
US	0	0	0	0	0	0	0	0	0	N/A
RMSE-1	17.49	17.59	20.01	17.60	17.59	17.55	17.64	17.57	17.69	17.56
RMSE-2	9.02	8.92	10.58	8.98	9.08	9.01	8.93	9.03	8.87	8.86
ATET	−70.61	−71.13	−67.48	−70.55	−70.54	−70.68	−72.06	−70.67	−72.58	−70.92

combinations derived from the peer group. Missing or replacing a single peer unit would not invalidate our major findings. In sum, cross-time validation suggests the 1995-1996 stock market downfall was directly related to the political crisis. Next, in a counterfactual study, cross-unit validation tests indicate that my SCM findings are robust toward peer unit selection.

Because SCM generally uses small samples, non-parametric ranking methods are recommended for statistical inference in SCM applications. For example, Abadie *et al.* (2010) applied placebo studies and ranking tests. In practice, analysts could apply alternative small-sample inferential techniques and bootstrapping. For the purpose of illustration, I will use placebo tests and ranking method for statistical inference. The principle of placebo tests is mentioned in the previous section, namely applying a hypothetical intervention to the treated unit and all peer units and comparing their treatment effects. Akin to the cases of Korea, Hong Kong, Singapore and Ireland, we implemented similar SCM processes to all 20 units in the peer group. Figure 7 showcases placebo tests of treatment effects of Taiwan (red solid line) and other 20 peer units (gray dash lines). During the treatment periods (two vertical dash lines), the treatment effect of the political crisis was more noticeable in Taiwan with respect to comparison units. Taiwan had a higher stock price decline most of the crisis. After



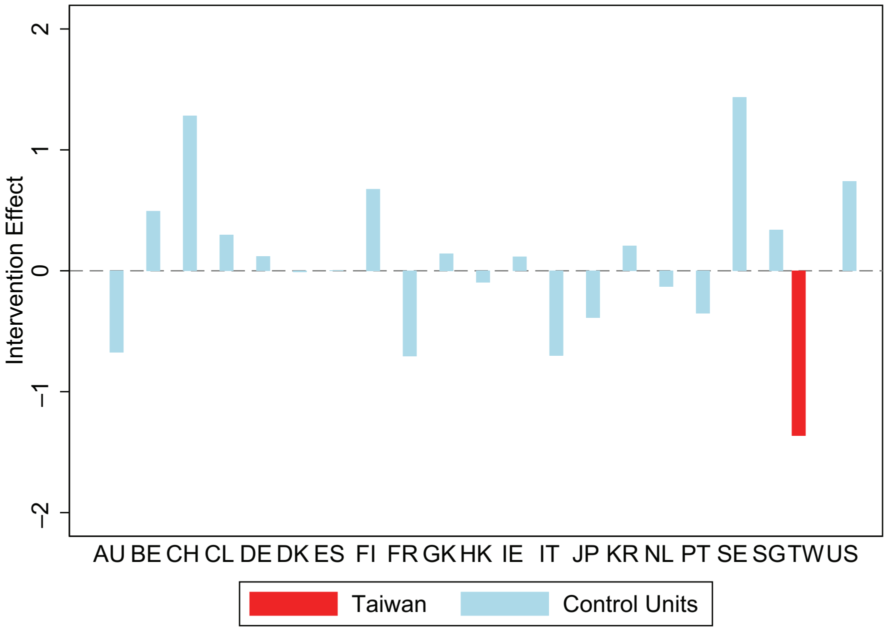
Notes: This figure plots placebo tests of Taiwan and its comparison units. The hypothetical intervention of 1995-1996 political crisis was assigned to all units. Then, we can obtain the real-counterfactual gaps of Taiwan (red solid line) and peer units (gray dash lines). Graphically, magnitude of the crisis can be measured as real-counterfactual gap in post-crisis, given proper pre-intervention fitting. In this test, the hypothetical intervention was introduced in 1995M3 (the vertical dash line). The scaled index is calculated by setting the baseline index of 1988M1 as 100. Data: MSCI monthly country index (USD)

Figure 7.
Placebo tests of hypothetical intervention: Taiwan and peer units

controlling pre-intervention RMSE, Figure 8 plots the intervention effects (standardized) of Taiwan and the peer group, which is a ratio of post-crisis (12 months) ATET to pre-crisis RMSE (12 months). Figure 8 highlights that Taiwan had the highest drop of stock prices over the crisis. Thus, we are confident that there is only a small probability (of 1/20 or $p = 0.05$) that Taiwan cannot stood out in the peer group.

4.3 Discussions

Major findings in this study are consistent with previous research on the asset pricing implications of political uncertainty, e.g. the existence of priced political risk (Pastor and Veronesi, 2012, 2013; Liu *et al.*, 2017). Researchers have pointed out several channels through which political dynamics could influence financial markets. On one side, in an efficient capital market, political costs will be reflected in the firm's market value in an unbiased manner (Schwert, 1981). Price reactions are stronger if the markets are caught by a



Notes: This figure presents net (standardized) intervention effect for inferential ranking test. The ratio is calculated as the ratio of post-intervention average treatment effect (ATET) to pre-intervention RMSE. A negative ratio indicate the hypothetical crisis caused a price decline and vice versa. Here, both ATET and RMSE are based on 12 months before and after the crisis (1995M3), respectively. In this test, Taiwan (red bar) had the largest negative net intervention effect compared with its peer units (blue bars). AU: Australia; BE: Belgium; CH: Switzerland; CL: Chile; DE: Germany, DK: Denmark; ES: Spain; FI: Finland; FR: France; GK: Greece; HK: Hong Kong; IE: Ireland; IT: Italy; JP: Japan; KR: Korea; NL: The Netherlands; PT: Portugal; SE: Sweden; SG: Singapore; TW: Taiwan; and US: USA

Figure 8.
Statistical inference of intervention: a ranking test

surprise, i.e. unexpected political events or policy changes (Pastor and Veronesi, 2012). On the other side, prior studies also well stressed the connection between political uncertainty and investment decisions. For example, political instability could increase "the value of waiting for new information" and depress current investment (Bernanke, 1983; Pindyck, 1991). At industry level, researchers have found that even a temporary increase of political uncertainty would lead to immediate decline of investment expenditure, especially for industries being sensitive to political outcomes (Julio and Yook, 2012).

A convincing historical example was the "Great Disorder" of Germany during the transition from Imperial to Weimar Germany in the early 1920s (Bittlingmayer, 1998). After the WWI, political uncertainties in Germany, such as revolution, struggle over reparations, and an unstable government, caused noticeable decline of output and a volatile financial market. Real monthly real stock returns declined from 0.45 per cent during the period 1880-1913 to −1.14 per cent for 1914-1923 in Germany. At the same time, volatility spiked. Similar stories has repeated again and again up to contemporary markets. For example, after Mitterrand was elected President of France in May 1981, the unanticipated result immediately caused substantial downward price revisions in French and the US stock markets (Phillips-Patrick, 1989). For investors, Mitterrand's election could lead to radical changes in French government policies (nationalization). The response of the capital markets suggested that foreign ownership increases political risk after the 1981 election. But its impact was partially offset by a firms' future growth options. Focusing on US gubernatorial elections, one recent study of Jens (2017) added more empirical evidence to link how political uncertainty alternates firms' investment behavior in the USA. This study found that an incoming a gubernatorial election would depress (delay) the investment of firms.

For emerging markets, researchers have obtained similar evidence as well. Using the Hang Seng Index of Hong Kong, Chan and Wei (1996) have shown that political uncertainty had noticeable and immediate impact on stock returns and volatility. They found that favorable political news is correlated to positive returns and negative news is correlated to negative returns. The study of Kim and Mei (2001) also confirmed the substantial and asymmetric impact of political events on stock price and volatility in Hong Kong. They pointed out that political news could trigger return jumps and large return movement in the markets. Based on one political scandal in 2012 of China, Liu *et al.* (2017) studied the impact of this political event on asset prices in Chinese stock markets. After controlling endogeneity, the authors found significant decline in stock prices during the political shock. For policy-sensitive firms, their return volatility largely climbed.

Effectiveness of the identification strategy is another important concern in this study[9]. To compare the performance of SCM with other conventional estimators, this study implements several alternative specifications, e.g. linear regression-based DD models. As in Table AI, the baseline model is the conventional two-period and two-group (treated and control) design. In other words, we have one group variable to indicate the status of treatment (Taiwan or not) and one time variable to indicate the timing of intervention (during crisis or not). The actual effect of the intervention is then estimated by coefficients of the interaction term (*Diff-Diff*) of the time-group variable. In addition, several robustness estimations are conducted for testing the "common trends" assumption, namely whether there was a "slope-change" of the dependent variable before the crisis. These models use various leads of the treatment, i.e. the lead of one-month (Column II), two-month (III), three-month (IV) and six-month (V). In Table AI, Panel A presents results of two time period DD models, e.g. during the crisis (Time-Crisis = 1) and no crisis (Time-Crisis = 0). Panel B represents results of three-level time variables DD models. Here, observations are grouped into three time periods, namely pre-crisis (Time-Crisis = 0), during crisis (Time-Crisis = 1) and post-crisis (Time-Crisis = 2).

First of all, we can see the different magnitude of intervention effects estimated by DD and SCM models. For example, using conventional DD models (Column I in Table AI), the average treatment effects of the crisis is –49.5 (two-time) and –50.8 (three-time). On the other side, the average impact of crisis is –70.5 in SCM estimation (the mean of *Difference* in Table V). Second, the noticeable and statistically significant coefficients of pre-crisis trend (*Pre-trend*) suggest that we cannot ignore the different pre-crisis trends between Taiwan and the control group. Figure A1 shows the price series of Taiwan (light blue line) and the average prices of the control group (red dash line) before the crisis. Obviously, the two series did not follow a common trend through the time. Without satisfying the "common trends" assumption, the validity of DD models will be weakened. Being a supplement to DD models, SCM can relax the "common trends" constraint. The optimally weighted counterfactual ensures the actual Taiwan and its synthetic counterpart have similar pre-intervention trends. Third, compared with DD, SCM could reveal time-variant intervention effect. For example, in Table V, the effect of crisis was much higher in July, August and September 1995 (–85.2, –91.3 and –86.5) when mainland China launched missile tests and assault drills. Overall, this study suggests SCM can be an alternative in empirical financial studies. SCM provides a simple and robust estimation toward time-variant intervention effects.

Although this study centers on Taiwan, the SCM approach can be applied to estimate the causal impact of exogenous shocks in other markets. For external validity or generalizability of the SCM findings, as mentioned, this study conducted various cross-validation tests[10]. Due to endogeneity and reverse causality, this study chooses "out-of-sample" testing of the 1995-1995 Taiwan Strait Crisis on other markets, instead of "out-of-sample" testing other political crisis which may suffer from the two concerns. Here we are particularly interested to the emerging markets which were similar and to Taiwan in economic and financial development around the 1990s, for example Hong Kong, Korea, Singapore and Ireland. Especially, as one of little dragons, Korea is often viewed as one economic rival of Taiwan, as they had similar industries and rapid economic growth after the Second World War (Easterly, 1995). For example, Korea and Taiwan both followed the "Japanese model" for their catch-up growth (Albala-Bertrand, 1999). In the 1960s to the 1980s, they both transformed from import substitution models to export-oriented models (Funke and Ruhwedel, 2001). Moreover, both governments played critical roles for industrial coordination (Rodrik, 1995). For robustness, using the same comparison group and intervention, this study implements SCM estimation to Korea. Monthly real-synthetic gap of Korea and its counterfactual are reported in Table AII. The results suggest that the 1995-1996 Taiwan Strait Crisis had no clear-cut impact on Korea's stock market. We cannot observe an immediate decline of stock prices as in Taiwan. On the other side, the synthetic index fairly fit the real monthly price index during the majority of time. And there were a few of months in which the actual prices outperformed its counterfactual, for example 1995M9 and 1995M10. The real-synthetic gap during the crisis may come from lack of fit of the two trajectories before the crisis. For future work, further evidence could help to interpret the transient but noticeable real-synthetic deviations in Korea.

Based on the POM framework, this study estimated causal impact of the 1995-1996 political crisis on Taiwan's stock market. First, my SCM results indicate a noticeable decline of stock prices during the crisis, while similar drop was not observed in the peer group. The results reflect the price of political uncertainty. Next, this section illustrates how analysts can make statistical inference via non-parametric techniques, such as the ranking tests of placebo studies. Moreover, for robustness of my SCM findings, this section implements both cross-time and cross-unit validations. My cross-time validation tests suggest that the political shock was the only event which was directly related to Taiwan's stock market turmoil in that period. Other exogenous events cannot derive similar market impacts. My cross-unit validation tests, on the other hand, indicate that my SCM findings are robust to the various optimal combination of the peer group. My LOOCV tests cannot detect any individual peer unit which would invalidate major SCM findings. In other words, dropping any one of the 20 peer unit would not lead to different benchmarking counterfactuals.

In summary, this study provides new evidence to the theory of political uncertainty and stock markets via an alternative approach. The substantial gap between Taiwan and its synthetic counterparts is consistent with the expected price decline as predicted in the general equilibrium model of Pastor and Veronesi (2012, 2013). More specifically, the drop in stock prices reflects the lower expected cash flows and an increase in discount rate. Similar findings have been documented in other studies, for example Brogaard and Detzel (2015), Kelly *et al.* (2016) and Liu *et al.* (2017).

5. Conclusion

Using one counterfactual study in an emerging market, this paper illustrates how to establish a causality link between political shocks and financial markets' responses. The inextricable linkage between political risk and asset pricing has become one critical component in international investment. In particular, there is a growing demand for data-centric approaches and causality estimation in country risk assessment. On one hand, besides diversifying assets portfolios, investors also need a better understanding to dynamic risk scenarios. On the other hand, analysts have noticed that financial markets could overlook some risks or underestimate their potential impacts. Therefore, accurate risk identification, measurement and forecasting have become the most desirable instruments for effective country risk management. Focusing on the Taiwan Strait Crisis in 1995-1996, this study applies an innovative models to combine qualitative and quantitative elements for estimating impact of political risk on stock prices.

This paper highlights the SCMs. SCM is distinct from conventional estimators by its optimally weighted counterfactual. This methodology could implement convincing comparisons among the unit exposed to political risk and its synthetic benchmarking peer group. In addition, SCM combines the features of learning from others (cross-sectional evidence) and learning from the past (time series evidence). In particular, this study stresses two empirical issues of SCM. First, SCM can help analysts to avoid mis-matching the characteristics of peer units. SCM automatically generates the best combination of predictors which has the lowest in-sample prediction error. Second, as a supplement for regression-based methods, the SCM model can provide alternative validation tests and inferential techniques.

In sum, the SCM results suggest that Taiwan's stock prices dramatically underperformed its newly industrialized peers and other developed markets during the crisis. After minimizing the difference between actual stock prices of Taiwan and its' benchmarking index before the crisis, we can observe a substantial difference (gap) between the two series in the post-crisis period. And the two series started to converge when the crisis went away. Placebo tests suggest that the actual-counterfactual differences are statistically significant. For robustness, this study tests the effect of potential confounding events. No other individual event could lead to a similar drop of Taiwan's stock prices during that period. In addition, the SCM results are robust to the selection of peer units in various cross-validation tests. Findings from this study are consistent with existing literature of the price of political risk. The noticeable decline of Taiwan's stock prices reflects that the political crisis commands a risk premium.

Notes

1. A recent case was China's economic boycott toward South Korea's tourism and retailing industry in 2017 at the deployment of Terminal High Altitude Area Defense (THAAD) missile system in South Korea.
2. As Allen *et al.* (2005) suggested, in terms of financing channels, Taiwan and China were had similar experience in equity market development, the growth of corporate bond market and the size of equity issuance.
3. Monthly price series are scaled by the MSCI benchmark with the price in January 1988 (1988M1) as 100.
4. More exactly, we are talking about random assignment (internal validity) here. Like most natural experiment studies, non-random sampling would be a concern for the external validity of the results. For context of this study, the major concern is how to choose proper peer units for the counterfactual.
5. Most counterfactual models are based on the seminal work of Rubin (1974, 1978) causal model.
6. Here is the SCM estimator for a particular treated unit. We can also use notations of average causal effect, if there are multiple units exposed to interventions.
7. Two critical assumptions are required for applying matching methods, in particular the popular propensity score matching estimator (PSM). More than the conditional independence assumption (CIA), the validity of PSM also depends on the common support assumption, namely matching should be implemented over the common support region. The second assumption ensures that there is enough overlap of observed covariates between the treated and control groups. This assumption may be hard to test when researchers have a small sample of the treated and control units. With limited observations, we cannot make sure the treated group and the control group have similar distributions in observed attributes.
8. The methods for choosing the best SCM predictor combination via comprehensive selections have been discussed in some studies. Details of this topic is beyond the scope of this paper.
9. Special thanks to the anonymous referee pointed out this issue.
10. There are two caveats when researchers apply the SCM model for political crisis in other markets. First, we need to make sure there is no confounding shocks (omitted variable). Second, more importantly, researchers should pay attention to reverse causality (simultaneous bias), namely the outcome variable and the explanatory variables could be determined simultaneously. In emerging markets, it is not rare that political shocks (i.e. coups) could be triggered by corruption, economic slowdown and financial crisis. For example, in the 1991 Coup of Thailand, the Royal Thai Army claimed that they overthrew a "corrupted government". The elected prime minister was accused of abusing power and corruption. Similarly, the 2006 Thai Coup caused non-constitutional overturn of government. However, the origins of this political crisis were more complicated. And political instability started long before the coup. In particular, Thailand government's policy toward rural and urban income disparity largely contributed to this political crisis.

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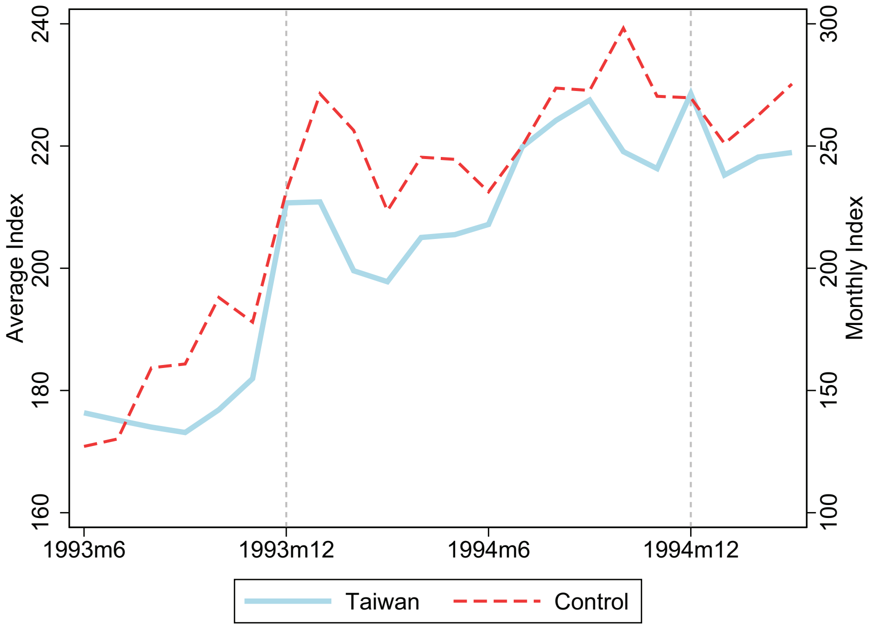
Appendix



Notes: This figure illustrates testing for the "common trends" assumption for DD models. The figure plots the monthly price series of Taiwan (light blue line) and the average monthly prices of the control groups (red dash line) before the 1995-96 Taiwan Strait Crisis. We can observe noticeable "slope changes" in the two trends. Thus, we cannot assume the "common trends" assumption is satisfied. Considering the treated unit and control units followed different trends before the intervention, the validity and robustness of DD models will be weakened

Figure A1. Testing the common trends assumption: Taiwan and control group

	I	II	III	IV	V
Panel A: 2-level time					
Time-Crisis	32.74**	23.73**	26.29**	28.68**	25.39**
	3.14	6.78	5.18	4.94	4.61
Diff-Diff	−49.49**	−75.74**	−77.37**	−77.00**	−78.54**
	10.66	8.76	7.61	7.78	8.479
Pre-trend		26.83*	29.13**	29.39**	33.30**
		10.99	10.25	10.53	11.46
Panel B: 3-level time					
Time-Crisis (During)	58.48**	23.73**	26.29**	28.68**	25.39**
	3.10	6.79	5.18	4.94	4.61
Time-Crisis (Post)	86.42**	87.51**	88.50**	89.40**	93.78**
	3.34	3.37	3.39	3.42	3.44
Diff-Diff	−50.79**	−75.74**	−77.37**	−77.00**	−78.54**
	10.79	8.77	7.62	7.79	8.49
Pre-trend		25.74*	28.30**	28.84**	33.92**
		11.05	10.23	10.45	10.73

Notes: Significance levels: ** 1%, * 5%. Robust standard errors are reported under the coefficients. Data: The sample includes monthly stock prices of Taiwan and twenty control units from July 1992 to June 1997 (Number of observations = 1,260). Source: MSCI monthly country index (USD). Note: This table reports estimated impact of the 1995-1996 political crisis by DD models. The actual effect of the intervention is estimated by coefficients of Diff-Diff (the interaction term). Panel A presents results of two-level time variables of DD estimators. In other words, observations are split into two time periods, namely during the crisis (Time-Crisis = 1) and no crisis (Time-Crisis = 0). Panel B represents results of three-level time variables DD models. Here observations are grouped into three time periods, namely pre-crisis (Time-Crisis = 0), during crisis (Time-Crisis = 1) and post-crisis (Time-Crisis = 2). In addition, Column I reports results of the basic DD models by holding the common trend assumption. Results in Columns II-V are used for testing pre-intervention trends, namely whether there was a "slope-change" of the dependent variable before the crisis. Specifically, the models use various leads of the treatment, i.e. the lead of 1-month (Column II), 2-month (III), 3-month (IV) and 6-month (V)

Table AI.
Specification test: DD estimations

Month	Korea	Synthetic	Difference	Month	Korea	Synthetic	Difference
1995M4	144.7	140.9	3.8	1995M10	162.0	128.3	33.7
1995M5	142.8	138.4	4.4	1995M11	149.1	134.0	15.1
1995M6	145.1	131.6	13.5	1995M12	143.1	141.9	1.2
1995M7	150.8	139.0	11.8	1996M1	139.7	143.5	−3.8
1995M8	145.6	132.9	12.7	1996M2	136.7	142.4	−5.7
1995M9	159.3	133.2	26.0	1996M3	139.6	144.5	−4.8

Notes: This table reports monthly prices of Korea, the SCM counterfactual (Synthetic) and their gap (Difference) in 12 months after the 1995-1996 Taiwan Straight Crisis. Unlike the case of Taiwan, this crisis did not cause any decline of Korea's stock prices. On the other side, monthly price index of Korea largely outperformed its synthetic counterfactual during the crisis. For the case Korea, real-synthetic gap during the crisis could be from lack of fit of the two trajectories in the pre-crisis period

Table AII.
External validity test: SCM estimation for Korea