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Measuring the Benefits of the Development Strategy of the "21st Century Maritime Silk Road" via an Intervention Analysis Approach: Evidence from China and Neighbouring Countries in Southeast Asia

Summary: The present study adopts a new political intervention analysis approach to evaluate the impact of the "21st Century Maritime Silk Road" (MSR) policy. The basic concept is to investigate dependence amongst cross-sectional units to construct counterfactuals without intervention. Thus, the effect of policy intervention is simply the difference between the outcomes with and without intervention. The panel data of 14 countries along MSR are used to illustrate the methodology. Real data analysis shows that the MSR policy exerts a positive effect on the trade of China and Southeast Asian countries. Furthermore, policy implications are provided based on the analysis.

Key words: Political intervention analysis, Panel data, Time series, Factor analysis model.

JEL: C13, C33, E65, F17.

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In September and October 2013, China's President Xi Jinping proposed the "New Silk Road Economic Belt" and the "21st Century Maritime Silk Road" (MSR) strategies, which were abbreviated as the "One Belt and One Road" (OBOR) Initiative, during his visits to Kazakhstan and Indonesia. This initiative is currently China's national strategy and has become a major component of its foreign policy.

As an important component of OBOR, MSR aims to strengthen linkage amongst countries along the route by liberalising trade, enhancing financial cooperation, promoting trade and investment facilitation and broadening mutual recognition and understanding. Although this concept has been discussed extensively by numerous domestic and foreign media, we intended to measure the economic impact of the MSR policy on trade in this study. However, answering this question using traditional econometric modelling is difficult. Therefore, we need to determine how and why trade in these countries has changed over time and the role played by the China factor in the region. Moreover, the modelling strategy changes once external conditions are modified. That is, credible post-change observations that can provide reliable inference for post-change outcomes may be insufficient.

As pointed out by Allen George and Allen Head (1999), if the reactions of units towards policy changes are similar or even if their responses are different, then information on other units that are not subjected to policy intervention can help construct the missing outcomes of those under policy intervention as long as they are driven by several common factors. Motivated by this idea, we focused on modelling the intervention effect of the MSR policy by using the trading data of China and other countries along the route. We intend to predict the possible outcome if MSR does not exist in these countries. Notably, if we know the outcomes of a unit with and without policy intervention, then the effect of the policy intervention is simply the difference between the two. However, we cannot simultaneously obtain the outcomes of a unit with and without intervention; thus, we need to construct the counterfactuals of the unit subjected to intervention. Then, we use the other units that are not subjected to intervention to predict what would have happened to the former if it had not been subjected to policy intervention. We may further evaluate the evolution of the policy effect over time using time series techniques based on the estimated intervention effect.

This paper is organised as follows. Section 1 summarises the content of MSR. Section 2 reviews related works on policy intervention analysis. Section 3 introduces the empirical methodology, including model notation and estimation issues. Section 4 provides the empirical analysis results. Section 5 concludes the study.

1. Implication and Background of MSR

As an important component of OBOR, MSR was announced before the Indonesian Parliament on October 03, 2013 during Xi Jinping's visit to Indonesia. MSR is projected to go from China's coast to Europe through the South China Sea and the Indian Ocean in one route, and from China's coast through the South China Sea to the South Pacific in the other route. As described by some commentators, this plan can be regarded as the "most significant and far-reaching initiative that China has ever put forward".

At this stage, MSR mainly includes three geographical routes: (1) China *via* Russian Central Asia to Europe; (2) China *via* the Persian Gulf and Central Asia to the Mediterranean and (3) China *via* Southeast Asia to the Southern Indian Ocean. Supported by centre cities along the route, China encourages cooperation platforms and the development of promising international economic cooperation systems, such as New Eurasian Land Bridge (connect Western China to Western Russia), China-Mongolia-Russia Corridor (North China to Eastern Russia *via* Mongolia), China-Indochina Peninsula Corridor (Southern China to Singapore *via* Indo-China), and China-Pakistan Corridor (South Western China to and through Pakistan).

The Chinese government states that MSR includes five basic areas of connectivity: policy, infrastructure, trade, currency and people. In particular, the implementation of this initiative will involve trade and investment facilitation measures; infrastructure construction (e.g. railways, highways, airports, ports, telecommunications, energy pipelines and logistic hubs); industrial and subregional economic cooperation (primarily overseas industrial parks and economic corridors); financial cooperation and the promotion of mutual understanding and trust amongst people.

The following facts demonstrate how seriously China is treating this initiative. The MSR proposal is included in the Resolution of the Third Plenum of the 18th Central Committee of the Chinese Communist Party. The National Development and Reform Commission (NDRC), China's top economic planner, is responsible for releasing the guidelines for the implementation of this grand plan. This initiative will doubtlessly become a major foreign and economic policy hallmark by the end of President Xi's tenure.

MSR appears to be an unprecedented proposal in the history of contemporary Chinese diplomatic relations. Many Chinese researchers consider it a response to the strategic realignments that have been occurring in China's neighbourhoods in the past years, particularly the US "rebalancing to Asia". However, this initiative is more than just a reaction to the US strategic rebalance in the region. It is also a reflection of Beijing's attempt to shift from a "low-profile" international strategy to a more active stance in striving for further accomplishments.

China is currently facing a series of domestic problems, such as overproduction and overcapacity, high debt levels in key sectors and huge foreign exchange reserves. MSR is expected to solve these dilemmas by opening foreign markets to domestic companies, transferring labour-intensive and low value-added manufacturing facilities to overseas markets and finding investment opportunities abroad. With China's entry into a new pattern of economic growth, the Chinese government realises that it should maintain a friendly international environment through win-win cooperation amongst countries to achieve its own prosperity, whilst maintaining domestic stability and securing access to external resources, which is also the purpose of MSR. Several mechanisms have been designed to promote this purpose, including the Silk Road Fund and the Asia Infrastructure Investment Bank (AIIB). The MSR proposal was presented to foreign dignitaries during the Beijing APEC meetings in 2014.

MSR is a part of China's new round of "opening-up" to the world. It reflects China's strong desire to improve and promote cooperation with developing countries and to revitalise global economic growth by helping developing countries narrow their economic gaps. Although this plan exhibits uncertainties and has elicited concerns from other countries to a certain extent, it can offer considerable potential for promoting the economic, diplomatic, political and cultural aspects of countries along MSR. Ultimately, regional countries will achieve balance between the economic benefits of MSR and their own domestic interests.

2. Literature Review on Intervention Analysis

Intervention analysis, which was introduced by George E. P. Box and George C. Tiao (1975), provides a framework for assessing the effect of an intervention on a time series. An intervention, whether natural or man-made, is assumed to affect a process by changing the mean function or trend of a time series. We also intend to estimate how much an intervention can change a series. For example, suppose that a region has instituted a new maximum speed limit on its highways, and we want to determine the extent of the effect of the new limit on accident rates. Thereafter, intervention analysis techniques for time series have been extensively applied in various fields to solve practical problems, such as government policy making, financial stress tests, economic policy evaluation and environmental problem assessment.

Intervention analysis in a time series examines how the mean level of a series changes after an intervention when the same autoregression integrated moving average (ARIMA) structure for the series is assumed to hold before and after the intervention. Early works can be found in Robert G. Orwin (1997) for fitting the impact of economic events or strategies with ARIMA models. With the development of research, structural time series methods have become attractive alternatives to ARIMA methods because they can easily accommodate stochastic explanatory variables and multivariate data, regardless of whether a time series is stationary (Andrew Harvey 1996; Harvey and Jared Bernstein 2003). For example, Alvaro Angeriz and Philip Arestis (2008) applied intervention analysis to multivariate structural time series models to deal with the empirical aspects of a "new" monetary policy known as inflation targeting. They pointed out that the proposed method can avoid certain biases caused by traditional regression estimators and can provide new empirical evidence in the case of some countries belonging to the Organisation for Economic Co-operation and Development. Afterward, an increasing number of models and methods have been developed to describe the specific dynamic properties of a time series. For example, Esteban-Pretel Julen and Yasuyuki Sawada (2014) studied the structural changes that occurred in Japan's post-World War II era of rapid economic growth. They adopted a two-sector (agricultural and non-agricultural) neoclassic growth model to analyse the evolution of the Japanese economy and provided empirical evidence for the proposed model. Other related works can be found in Jin-Hong Park, Dipankar Bandyopadhyay, and Elizabeth Letourneau (2014) and James J. Heckman, John Eric Humphries, and Gregory Veramendi (2016).

In summary, all the aforementioned literature seeks to simulate or replicate the behaviour of a specific time series and to further evaluate the evolution of interventions or incidents. In the context of policy intervention analysis, researchers are frequently interested in assessing or estimating the effects of events or interventions. Comparative case studies are developed for this purpose. The key concept of this method is to estimate the evolution of the outcomes for a unit under intervention and compare it with the evolution of the concurrent outcomes estimated for a control group without intervention. On this basis, the control group reproduces the counterfactual outcome trajectory that the units with intervention would have experienced without intervention (Alberto Abadie, Alexis Diamond, and Jens Hainmueller 2010). Numerous examples in applied economics fit into this framework. For example, Ornella Ricci (2015) studied the impact of the monetary policy announcements of the European Central Bank on the stock price of large European banks from June 2007 to June 2013 by performing an intervention analysis to estimate the cumulated abnormal returns for the stock prices of banks during announcement days. This study found that banks are more sensitive to nonconventional measures than to interest rate decisions. In addition, banks with weak balance sheets and operating under high risks are more sensitive to monetary policy interventions. Cheng Hsiao, Steve H. Ching, and Shui Ki Wan (2010) proposed a simple panel data approach for assessing the impact of Hong Kong's political and economic integration into Mainland China based on Hong Kong's real gross domestic product (GDP) growth rate. Hong Kong's real GDP growth rates were compared with what would have happened if sovereignty transfer did not occur in 1997 or no Closer Economic Partnership Arrangement was made with Mainland China in 2003. Motivated by this work, Zaichao Du and Lin Zhang (2015) evaluated the effects of home-purchase restrictions and trial property taxes on housing prices in China *via* the counterfactual construction method. They found that purchase restrictions reduced the annual growth rate of housing prices in Beijing, and the trial property tax of Shanghai had no substantial effect on housing prices. Erich Battistin and Andrew Chesher (2014) investigated treatment effect estimation with covariate measurement errors and applied the measurement error correction procedure to estimate the returns of educational qualifications to be employed in the UK. They pointed out that the proposed method can be used in the case of contaminated error data, which are common in economics research, and achieves better performance than conventional treatment effect analysis. Typical examples can also be found in the studies of Heckman and Edward J. Vytlacil (2005), Pedro Carneiro, Heckman, and Vytlacil (2010) and Matias D. Cattaneo (2010).

Quantitative studies on the evaluation of the actual effectiveness of implementing the MSR proposal remain scant. In this regard, we use intervention analysis to estimate the effect of this policy. We also need to model how and why the economies of countries along MSR have changed over time, and then identify the factors that have led to the changes. Political elements cannot be observed or measured directly, and thus, they are frequently regarded as latent variables; accordingly, latent or factor analysis models are a reasonable choice for modelling structural change in a policy strategy (Abadie, Diamond, and Hainmueller 2007). The use of factor models exhibits several advantages. Firstly, these models can accommodate correlation amongst cross-sectional units because some common factors exist amongst them, whereas their impacts on each unit are allowed to vary. Secondly, these models generalise the traditional linear panel data framework, thereby allowing for the effects of unobserved variables varying over time, which is precisely how we design factor models in the current study.

For factor modelling, the number of unknown factors should be identified and common factors and factor loadings should be estimated (Jushan Bai 2003; Alexei Onatski 2009). This process may lead to biased or invalid results when sample size is small. Moreover, as mentioned earlier, a model assumption changes once external conditions are modified, which indicates that credible post-change observations that can provide reliable inference for post-change outcomes may be insufficient. Similar to the work of Hsiao, Ching, and Wan (2010), we overcome the aforementioned issues by constructing counterfactuals of the missing outcome to estimate the policy intervention effect. We recommend the use of other units without policy intervention to predict what would have happened to the unit with intervention. A simple data-driven procedure, referred to as a conditional path estimation approach, is developed to predict counterfactual trajectory.

3. Research Method

3.1 Model Notation and Estimation of the Political Intervention Effect

Model notation and estimation of the political intervention effect are introduced briefly in this subsection. Notably, political elements cannot be observed or measured directly, and thus, are frequently regarded as latent variables. In practical applications, the factor model is commonly adopted for modelling policy changes because it can examine the relationship between manifest variables (economic indicators) and latent variables (policy factors). Once the unit with intervention is identified, the effect of a policy intervention is simply the difference between the outcomes with and without intervention. Consequently, we need to initially construct the counterfactuals of the unit with policy intervention.

Similar to the work of Hsiao, Ching, and Wan (2010), we use y_{it}^0 to denote the outcome of the i^{th} unit at time t without policy intervention, and y_{it}^0 can be modelled using the following factor model:

$$y_{it}^0 = b_i^T f_t + \alpha_i + \varepsilon_{it}; \quad i = 1,2, \dots, N, t = 1,2, \dots, T, \tag{1}$$

wheref_t denotes the $K \times 1$ (unobserved) common factors that vary over time; b_i denotes the $k \times 1$ vector of the coefficient that may vary across i; α_i denotes the fixed individual-specific effects, which reflect heterogeneity amongst units and ε_{it} is the error term of the i^{th} unit at time t with $E(\varepsilon_{it}) = 0$. Equation (1) is rewritten in matrix form as follows:

$$y_t^0 = Bf_t + \alpha + \varepsilon_t, \tag{2}$$

where $y_t^0 = (y_{1t}^0, \cdots, y_{Nt}^0)^T, \alpha = (\alpha_1, \cdots, \alpha_N)^T, \varepsilon_t = (\varepsilon_{1t}, \cdots, \varepsilon_{Nt})^T$ and the $N \times K$ factor loading matrix $B = (b_1, \cdots, b_N)^T$.

Model (1) assumes that the individual outcome is composed of two parts. The first part is a function of some common time-varying factors f_t, which drive all cross-sectional units. The second part consists of an individual specific effect α_i and a random component ε_{it}. We emphasise that the random error ε_{it} is uncorrelated across individuals and the correlation across units are mainly caused by the common factors f_t. In practical applications, the impact of common factors on individuals can be heterogeneous by allowing $b_i \neq b_j$. Furthermore, the time series properties of f_t can be stationary or nonstationary.

Let y_{it}^1 denote the outcome of the i^{th} unit of time t with intervention and y_{it}^0 denote the outcome of the i^{th} unit without intervention at time t. Thus, the intervention effect for the i^{th} unit at time t is:

$$\Delta_{it} = y_{it}^1 - y_{it}^0. \tag{3}$$

However, we frequently cannot simultaneously observe y_{it}^0 and y_{it}^T. Suppose intervention occurs at time T_1. Then, the outcome $y_t = (y_{1t}, \cdots, y_{Nt})^T$ takes the following form:

$$y_t = y_t^0 \text{ for } t = 1,2, \cdots, T_1. \tag{4}$$

From time $T_1 + 1$ to T, a policy change for the i^{th} unit occurs. Without losing generality, we assume that the first unit receives the intervention effect since the time position $T_1 + 1$, which yields:

$$y_{1t} = y_{1t}^1 \text{ for } t = T_1 + 1, \cdots, T, \tag{5}$$

and other units are unaffected by the policy intervention with:

$$y_{1t} = y_{it}^0 \text{ for } i = 1,2, \cdots, N, \text{ for } t = 1,2, \cdots, \mathrm{T}. \tag{6}$$

Under the preceding assumptions, we may predict y_{1t}^0 by $\hat{y}_{1t}^0 = \hat{\alpha}_1 + \hat{b}_1^T \hat{f}_t$ for $t = T_1 + 1, \cdots, T$. If both N and T are large, we may use the maximum likelihood procedure to identify the number of common factors, K, and to estimate α_1, $b_1$and f_t (Bai and Serena Ng 2002). In practical problems, however, neither N nor T is large. In this case, we adopt the approach of Hsiao, Ching, and Wan (2010) to predict y_{1t}^0 using $y_t^* = (y_{2t}, \cdots, y_{Nt})^T$.

The basic concept of this approach can be summarised as follows. Let c be a normalised vector lying in the null space of B, with the first element of c being 1, such that $c^T B = 0$. Denote $c = (1, -\tilde{c}^T)^T, \bar{c} = c^T \alpha, \varepsilon_t^* = (\varepsilon_{2t}, \cdots, \varepsilon_{Nt})^T$. Multiplying c^T on both sides of (2) yields $y_{1t}^0 = \bar{c} + \tilde{c}^T y_t^* + \varepsilon_{1t} - \tilde{c}^T \varepsilon_t^*$. This result implies that we can predict y_{1t}^0 with y_t^* in lieu of f_t. Considering the conditional expectation of y_{1t}^0 with respect to y_t^* leads to $y_{1t}^0 = \mathrm{E}(y_{1t}^0 | y_t^*) + \bar{\varepsilon}_{1t} = \bar{c} + \tilde{c}^{*T} y_t^* + \bar{\varepsilon}_{1t}$ where $\tilde{c}^{*T} = \tilde{c}^T (I_{N-1} - cov(\varepsilon_t^*, y_t^*) var(y_t^*)^{-1}), \bar{\varepsilon}_{1t} = c^T \varepsilon_t + \tilde{c}[cov(\varepsilon_t^*, y_t^*) var(y_t^*)^{-1}] y_t^*$. The regression coefficients $\bar{c}$ and $\tilde{c}^*$ are called conditional paths. To obtain the estimates of $\bar{c}$ and $\tilde{c}^*$, Hsiao, Ching, and Wan (2010) proposed choosing $\bar{c}$ and $\tilde{c}^*$ by minimising the following weighted residual sum of squares:

$$\frac{1}{T_1} (y_1^0 - e\bar{c} - Y\tilde{c}^*)^T A (y_1^0 - e\bar{c} - Y\tilde{c}^*), \tag{7}$$

where $y_1^0 = \left(y_{11}, \cdots, y_{1T_1}\right)^T, e$ is a $T_1 \times 1$ vector of $1'S$; $Y = \left(y_1^*, y_2^*, \cdots, y_{T_1}^*\right)^T$ is a $T_1 \times (N-1)$ matrix of T_1 time series observations of y_t^* and A is a $T_1 \times T_1$ positive definite matrix.

The counterfactuals $y_{1t}^0, t = T_1 + 1, \cdots, T$ depend on the individual specific effect α_1, the common factors f_t and the random error ε_{1t}. However, based on $y_{1t}^0 = \bar{c} + \tilde{c}^{*T} y_t^* + \bar{\varepsilon}_{1t}$ and $E(\bar{\varepsilon}_{1t} | y_t^*) = 0$, we may predict y_{1t}^0 with $\hat{y}_{1t}^0 = \hat{\bar{c}} + \hat{\tilde{c}}^{*T} y_t^*$ and further evaluate the intervention effect Δ_{1t} by $\hat{\Delta}_{1t} = y_{1t} - \hat{y}_{1t}^0$ for $t = T_1 + 1, \cdots, T$. This new approach for estimating Δ_{1t} allows us to evaluate the policy intervention without identifying f_t or B, such as that in Bai and Ng (2002), which is highly convenient in small sample sizes.

3.2 Evaluating the Evolution of the Policy Intervention Effect over Time

For the estimated Δ_{1t}, we may evaluate the evolution of the policy effect over time by using time series techniques. In particular, we assume that the intervention effect Δ_{1t} follows an autoregressive-moving-average model with the following backshift operator expression:

$$\phi(B)\Delta_{1t}= \mu + \theta(B)e_t, \tag{8}$$

where B is the backshift operator, $\phi(B)$ is the autoregressive (AR) operator, $\theta(B)$ is the moving average (MA) operator and e_t is an independent and identically distributed (i.i.d) process with zero mean and constant variance. If all the roots of the AR characteristic equation $\theta(B) = 0$ lie outside the unit circle, then the treatment effect Δ_{1t} in (8) is stationary. As pointed out by Hsiao, Ching, and Wan (2010), Equation (8) can be estimated according to the following cases:

(i) If all the roots of $\phi(B) = 0$ lie outside the unit circle, then the intervention effect is stationary and the long-term effect is:

$$\Delta_1= \theta^{-1}(B)\mu = \mu^*, \tag{9}$$

where $\theta^{-1}(B)$ is the inverse operator of $\theta(B)$, such that $\theta^{-1}(B)\theta(B) = I$, and I is the identity operator;

(ii) If one of the roots of $\phi(B) = 0$ lies on the unit circle, then the intervention effect is integrated at order 1. On the basis of the estimated $\hat{\Delta}_{1t}$, we can use the procedure of Box and Gwilym M. Jenkins (1970) to construct a time series model as follows:

$$\tilde{\phi}(B)\hat{\Delta}_{1t}= \tilde{\mu} + \tilde{\theta}(B)v_t, \tag{10}$$

where v_t is i.i.d. with mean zero and variance σ_v^2;

(iii) Suppose that the roots of $\phi(B) = 0$ lie outside the unit circle. When T_1 and $T - T_1 \to \infty$, we have:

$$\phi(B)\hat{\Delta}_{1t}= \mu + \theta(B)e_t + \phi(B)\delta_{1t} + o(1),$$

where δ_{1t} is a mean zero $I(0)$ process. We can approximate $\theta(B)e_t + \phi(B)\delta_{1t}$ using a q^{th} order moving-average process $\theta^*(B)v_t$. Moreover, if all the roots of the MA characteristic equation $\theta^*(B) = 0$ lie outside the unit circle, then $\hat{\Delta}_{1t}$ can also be approximated using the AR process as:

$$\tilde{\phi}(B)\hat{\Delta}_{1t}= \tilde{\mu} + v_t, \tag{11}$$

with $\tilde{\phi}(B) = \theta^{*-1}(B)\phi(B)$ and $\mu = \theta^{*-1}(B)\mu$.

(iv) Suppose all the roots of $\phi(B) = 0$ lie outside the unit circle. When T_1 and $T - T_1 \to \infty$, we have:

$$\underset{(T-T_1)\to\infty}{\text{plim}} \frac{1}{T-T_1}\sum_{t=T_1+1}^{T} \hat{\Delta}_{1t} = \Delta_1. \tag{12}$$

This expression guarantees that the sample mean of $\hat{\Delta}_{1t}$ is a consistent estimation of the long-term effects Δ_1.

Subsequently, we conducted real data analysis to illustrate the applications of the aforementioned intervention analysis approach.

4. Empirical Findings

4.1 Data and Sample

In this subsection, we evaluated the intervention effects of MSR on China and relevant adjacent countries. We further assessed the economic impact of this initiative, particularly on foreign trade in these countries. For this purpose, we first found an appropriate control group and experimental period, and then selected some countries to construct counterfactuals to investigate the policy intervention effect.

The policy evaluation period was set from October 2013 to December 2016. Our sampling period began in October 2013 because it was the start time of MSR and ended in December 2016 because the initiative has been widely practiced by this time. In addition, a 3-year period after the launch of MSR appeared to be a reasonable time limit for predicting the effect of this intervention.

Data from 14 countries and regions, namely, China, Indonesia, Bangladesh, Hong Kong, India, Kuwait, Malaysia, Pakistan, the Philippines, Singapore, Sri Lanka, Thailand, Vietnam and Taiwan, were included. When China was considered, the remaining 13 countries/regions were used as the control group because they either share common factors with China or belong to neighbouring countries that are geographically located at forts along MSR.

We also used the monthly import and export growth rates of these countries to construct the counterfactuals in the absence of policy intervention. All the data were obtained from the National Database (2017)[1].

Monthly growth rates can be evaluated using two alternative approaches. The first approach measures change compared with the corresponding month in the previous year; the second approach measures change since the previous month. In this study, we adopted the former approach because the sequential growth rates of some countries exhibit strong periodicity even after seasonal adjustments. Moreover, monthly import and export growth rates, i.e. our outcome variables of interest, may be the most widely used indicators for assessing foreign trading. A disadvantage of these two indicators is that they can fluctuate considerably over a short period in response to several factors. However, considering the availability of macroeconomic variables at the country level (many policy interventions and events of interest occur at an aggregate level) and a data length of 3 years that may reflect the rough trend and direction of the empirics, the two indicators are still preferable.

4.2 Results of China

Firstly, we constructed the counterfactuals for the monthly import and export growth rates of China without policy intervention from October 2013 to December 2016. The estimated policy intervention effects are simply the difference between the actual rates and the predicted counterfactuals. For import, the estimated average treatment effect during this period is 0.1293 percent, and the average actual monthly growth rate is 1.0182 percent, which indicates that the average predicted monthly growth rate without

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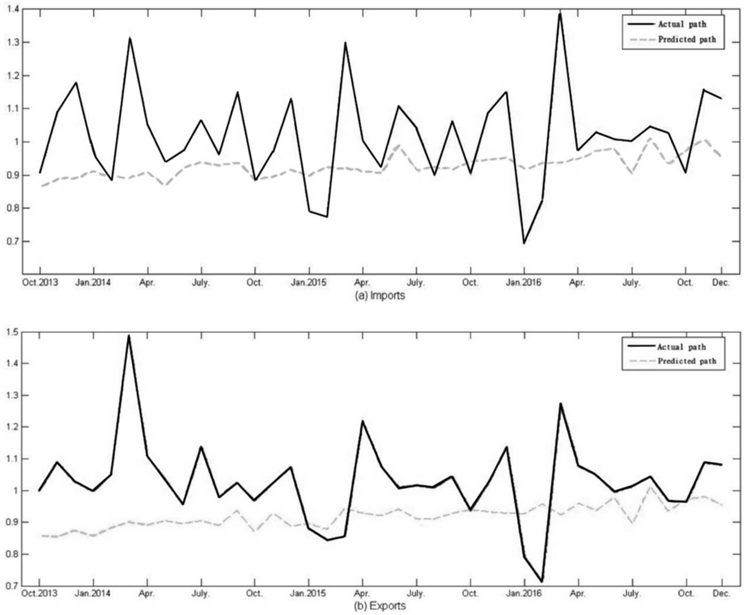
[1] **National Data - National Bureau of Statistics of China.** 2017. Database. http://data.stats.gov.cn/easyquery.htm?cn=B01&zb=A0101&sj=2014D (accessed July 20, 2017).

MSR is 0.8889 percent. That is, the monthly growth rate of import has increased by over 0.1293 percent compared with the rate without MSR. For export, a similar result can be obtained, i.e. the monthly growth rate for export will increase by over 0.1314 percent without MSR. The corresponding T statistics of the intervention effects for the two preceding cases are 2.7732 and 2.9345, respectively, which arehighly significant.

The actual and hypothetical growth paths are plotted in Figure 1. From the figure, we can see that: (a) the actual growth rates for import and export exhibit comparatively large fluctuations, whereas the predicted paths appear to be relatively stable; (b) most of the intervention effects are positive, thereby indicating that MSR plays an active role in promoting trade with China and (c) the predicted paths for import and export increase gradually and both reach a maximum value in August 2016.



Source: Data were collected from the National Bureau of Statistics of China (2017)[2].

Figure 1 Predicted Counterfactual of the Monthly Growth Rate of China for (a) Imports and (b) Exports

To evaluate the intervention effects over time, we measure the estimated intervention effects using an AR(2) model, which is given by $\hat{\Delta}_{1t} = 0.0741 + 0.7325\hat{\Delta}_{1t-1} - 0.541\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for imports and $\hat{\Delta}_{1t} = 0.0481 - 0.486\hat{\Delta}_{1t-1} - 0.364\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for exports. The implied long-run effect is 0.1305 for imports and 0.1356 for exports.

In 2015, NDRC, the Chinese Foreign Ministry and the Chinese Commerce Ministry jointly issued a guide, entitled "Promote to build the silk road economic belt and

[2] **National Bureau of Statistics of China.** 2017. http://data.stats.gov.cn/easyquery.htm?cn=B01&zb=A0101&sj=2014D (accessed July 20, 2017).

the vision and action of the maritime silk road in the 21st century" to further promote the implementation of MSR in relevant countries and areas. In the same year, these countries and regions received a direct investment from China with an annual growth rate of 18.2 percent. Until 2016, China envisioned operating 1881 Sino-EU long-distance trains, including 502 return trains. All the preceding events indicate that MSR exerts an active positive impact on China's foreign trade.

4.3 Results of Countries in Southeast Asia

We present the results of major countries in Southeast Asia in this subsection. For illustration, the results of five countries, namely, Singapore, Malaysia, India, the Philippines and Indonesia, are provided. China is the sponsor of MSR, and thus, it cannot be included in the control group. Consequently, data from China are deleted and data from the remaining 13 countries was used instead to conduct analysis in the subsequent context. The corresponding results are presented in Figures 2-6.

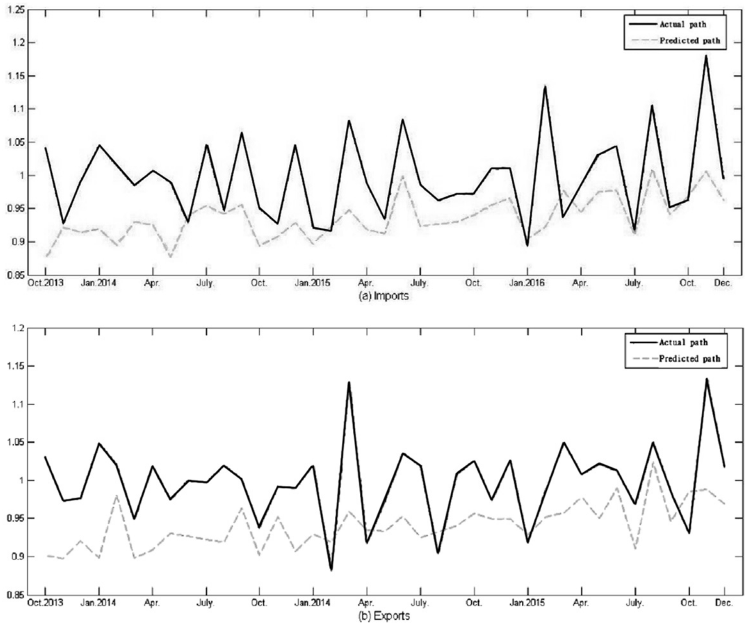
Singapore is a developed country with high social stability. It has a well-developed infrastructure, a free-enterprise economy and a friendly investment environment. Moreover, with its ideal geographical location, Singapore has served as a vital transportation hub in the course of promoting MSR. Similarly, the counterfactuals for the monthly import and export growth rates of Singapore without policy intervention from October 2013 to December 2016 were constructed. The estimated average treatment effects are 0.0608 percent and 0.0571 percent for import and export, respectively. These results indicate that the monthly import and export growth rates of Singapore have increased by over 0.0608 percent and 0.0571 percent, respectively, compared with the rates without MSR. The corresponding T statistics are 2.5804 and 2.4762, respectively, which are highly significant.

Figure 2 plots the actual and constructed growth paths for the import and export of Singapore during this period. From Figure 2, we can see that: (1) most of the intervention effects are positive for import and export, thereby indicating that Singapore's trade has benefited from the MSR initiative and (2) the intervention effect for import is slightly larger than that for export.

To evaluate the intervention effects over time, we fit the estimated intervention effects using an AR(2) model, which is given by $\hat{\Delta}_{1t} = 0.0689 - 0.6522\hat{\Delta}_{1t-1} - 0.3237\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for imports and $\hat{\Delta}_{1t} = 0.0564 - 0.4834\hat{\Delta}_{1t-1} - 0.1491\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for exports. The implied long-run effect is 0.0632 for imports and 0.0587 for exports.

Meanwhile, the Logistics Performance Index (LPI), a major global transport and logistics hub, is an important indicator in assessing the trade activity of nations. We present the LPI ranking results of the aforementioned five countries in Table 1. As shown in the table, Singapore has a high LPI score and is ranked at first level in the world. Without doubt, a high LPI ranking obtains good performance in MSR, and this result is consistent with those in Figure 2.

India and Malaysia have experienced a long privatisation reform of state-owned enterprises. India focuses on the "soft environment", which includes enterprise systems, talent markets, policies and laws, to attract investments. By contrast, Malaysia tends to attract high-tech investments. Both countries seek to conduct active cooperation with China in the fields of infrastructure and energy. As shown in Table 1, India and Malaysia have medium global LPI rankings, with Malaysia performing slightly better than India.



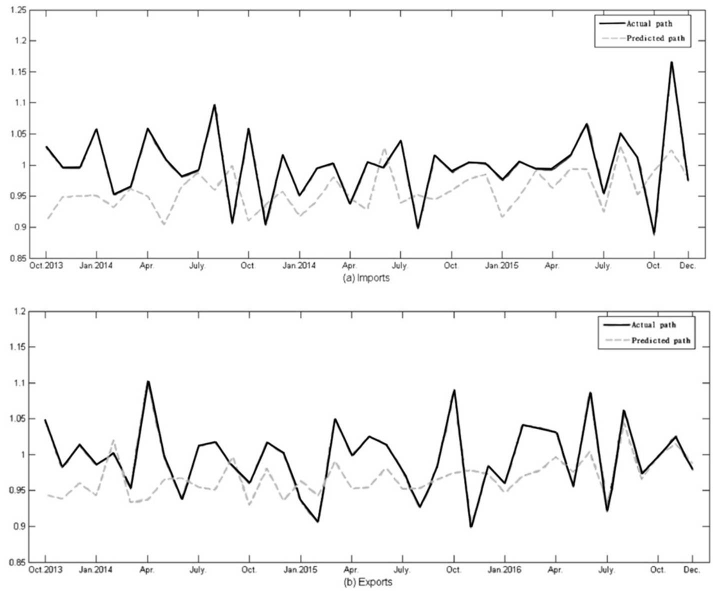
Source: National Bureau of Statistics of China (2017).

Figure 2 Predicted Counterfactual of the Monthly Growth Rate of Singapore for (a) Imports and (b) Exports

The predicted paths for the monthly import and export growth rates of the two countries without policy intervention are drawn. For Malaysia, the estimated average treatment effect is 0.0386 percent for import and 0.0285 percent for export. The corresponding T statistics are 1.7954 and 1.8049, respectively, which are moderately significant. For India, the estimated average treatment effect is 0.0405 percent for import and 0.0263 percent for export. The T statistics are 1.7918 and 1.7713, respectively, which are also moderately significant.

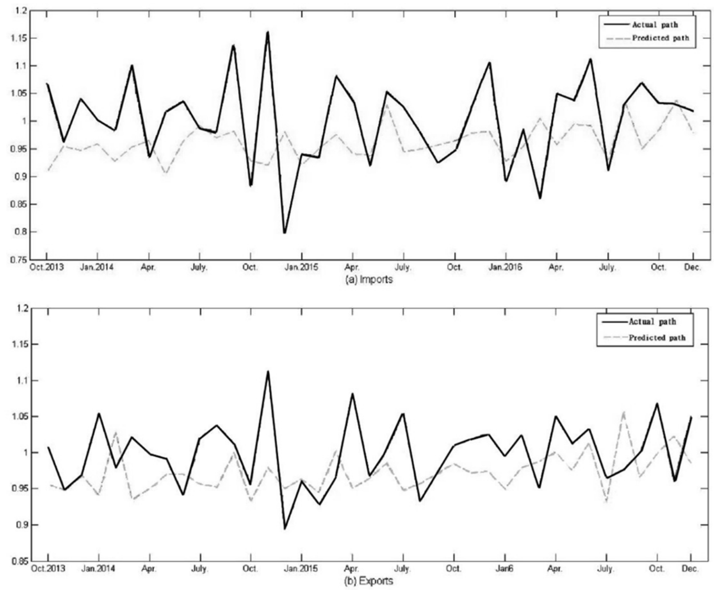
By examining Figures 3 and 4, the results of India and Malaysia appear to be similar, i.e. relatively large fluctuations of the predicted paths can be detected for import and export, and most of the intervention effects are positive. However, the effects are lower in significance compared with those in China and Singapore. For Malaysia, the fitted intervention effect model is given by $\hat{\Delta}_{1t}= 0.0386 - 0.7281\hat{\Delta}_{1t-1} - 0.1463\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for imports, and $\hat{\Delta}_{1t}= 0.0287 - 0.1825\hat{\Delta}_{1t-1} - 0.3184\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for exports. The implied long-run effect is 0.0395 for imports and 0.0322 for exports.

For India, the fitted intervention effect model is given by $\hat{\Delta}_{1t}= 0.0392 - 0.5066\hat{\Delta}_{1t-1} - 0.4913\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for imports and $\hat{\Delta}_{1t}= 0.0264 - 0.4581\hat{\Delta}_{1t-1} - 0.2923\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for exports. The implied long-run effect is 0.0411 for imports and 0.286 for exports.



Source: National Bureau of Statistics of China (2017).

Figure 3 Predicted Counterfactual of the Monthly Growth Rate of Malaysia for (a) Imports and (b) Exports

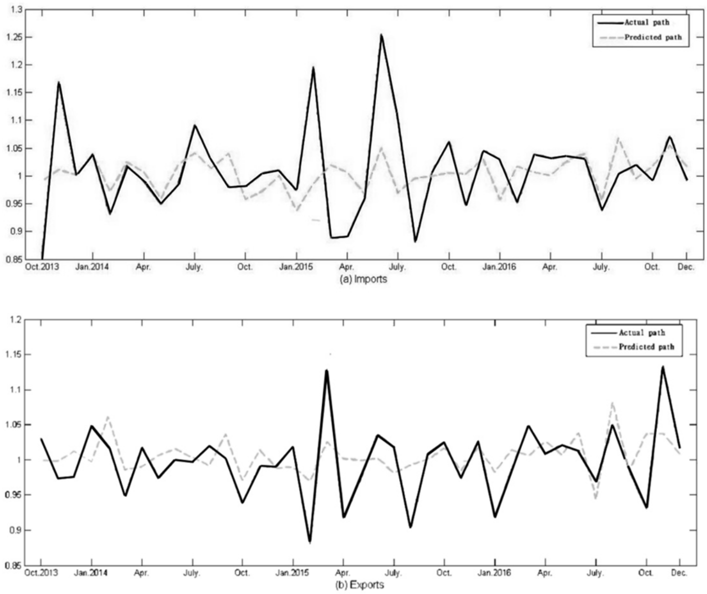


Source: National Bureau of Statistics of China (2017).

Figure 4 Predicted Counterfactual of the Monthly Growth Rate of India for (a) Imports and (b) Exports

We calculated the predicted paths for the monthly import and export growth rates of the Philippines and Indonesia without policy intervention. For the Philippines, the estimated average treatment effect is 0.0051 percent for import and −0.0079 percent for export. For Indonesia, the estimated average treatment effect is 0.0091 percent for import and 0.0094 percent for export. All the results are statistically insignificant.

From Figures 5 and 6, we can see that: (i) the predicted paths for import and export fluctuate strongly for both countries and (ii) the intervention effects are weak, particularly for export in the Philippines, in which most of the effects are negative.

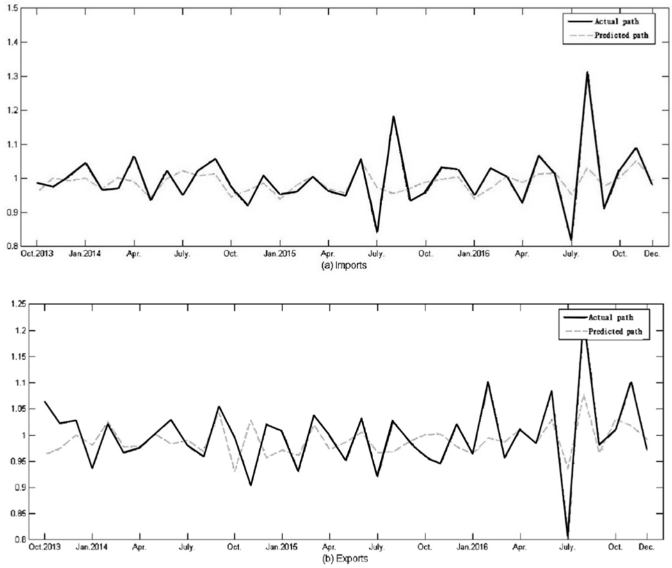


Source: National Bureau of Statistics of China (2017).

Figure 5 Predicted Counterfactual of the Monthly Growth Rate of the Philippines for (a) Imports and (b) Exports

For the Philippines, the fitted intervention effect model is given by $\hat{\Delta}_{1t} = 0.0062 - 0.1513\hat{\Delta}_{1t-1} - 0.2435\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for imports and $\hat{\Delta}_{1t} = 0.0091 - 0.7753\hat{\Delta}_{1t-1} - 0.5137\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for exports. The implied long-run effect is 0.0043 for imports and −0.0065 for exports.

For Indonesia, the fitted intervention effect model is given by $\hat{\Delta}_{1t} = 0.0092 - 0.738\hat{\Delta}_{1t-1} - 0.411\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for imports and $\hat{\Delta}_{1t} = 0.0084 - 0.5651\hat{\Delta}_{1t-1} - 0.247\hat{\Delta}_{1t-2} + \hat{\eta}_t$ for exports. The implied long-run effect is 0.0078 for imports and 0.0099 for exports.



Source: National Bureau of Statistics of China (2017).

Figure 6 Predicted Counterfactual of the Monthly Growth Rate of Indonesia for (a) Imports and (b) Exports

The Philippines and Indonesia are two developing countries in Southeast Asia. Over the past few years, the deteriorating trade relations between China and the Philippines have been rooted in the South China Sea dispute and the competition for oil and gas resources. These conflicts do, to a large extent, affect the trade relations between the two countries. For Indonesia, the unstable regulatory environment and poor infrastructure strongly hinder its economic development. Recently, Indonesian President Joko Widodo proposed the strategy of "Global Maritime Protection", which coincides with China's MSR. It aims to establish a comprehensive strategic cooperative partnership with neighbouring countries. The results correspond to the observations in Table 1, where the LPI of the Philippines is ranked at the lowest level, whilst Indonesia has second worst ranking.

Table 1 LPI and the Corresponding World Ranking of Different Countries

County	2007		2010		2012		2014	
	LPI	World ranking	LPI	World ranking	LPI	World ranking	LPI	World ranking
Indonesia	3.01	43	2.76	75	2.94	59	3.08	53
Malaysia	3.48	27	3.44	29	3.49	29	3.59	25
Philippines	2.69	65	3.14	44	3.02	52	3	57
Singapore	4.19	1	4.09	2	4.13	1	4	5
India	3.31	31	3.29	35	3.18	38	3.43	35

Source: Data were collected from the World Bank (2015)[3].

[3] **World Bank.** 2015. World Bank Open Data. https://data.worldbank.org/ (accessed July 22, 2015).

5. Conclusion

In this study, the intervention effect of the MSR policy is examined and the evolution of the policy effect over time is evaluated. Our results can be summarised as follows.

Firstly, we modelled the policy change *via* factor models. Once the unit with intervention is identified, the effect of the policy intervention is simply the difference between the outcomes with and without intervention. However, we cannot simultaneously obtain the outcomes of a unit with and without intervention. We constructed the counterfactual outcome trajectory of the unit with intervention and used the other units without intervention to predict what would have happened to this unit if it had not been subjected to policy intervention. Secondly, we evaluated the evolution of the policy effect over time using time series techniques for the estimated intervention effects.

In light of the empirical findings, we may draw the conclusion that MSR has a significant impact on promoting trade for China and Singapore, whereas the results vary considerably for other Southeast Asian countries. In particular, India and Malaysia have benefited from this initiative in terms of trade to a certain extent. However, for the Philippines and Indonesia, the effect is weak and ignorable. For these Southeast Asian countries, a huge difference exists in the aspects of natural resources, social and economic development levels, investment environment and policies. Such difference leads to the varying performance of implementation and promotion of MSR. To further advance economic and trade cooperation amongst countries along the route, the environment for overseas investment should be assessed beforehand, and the strategies for overseas investment and cooperation should vary case-by-case. The key areas for cooperation are not only limited to infrastructure construction, which requires a long investment recovery cycles. Collaboration in various areas, such as energy, technology, agriculture and telecommunications, should be encouraged and explored.

In this study, we adopt the term “unit” to denote the object of interest that is subject to policy intervention. In practice, the terms “city”, “sector” or “region” can be substituted as necessary. That is, our method can be generalised to different cases. However, specific model assumptions and cross-sectional dependence should be calibrated to match the empirical behaviour of the data. This study also has potential shortcomings because the impact of policy intervention in terms of trade diversion is not considered in the analysis. This factor can have significant welfare implications. In our future research, we will focus on this problem and extend our method to more complicated data, such as nonlinear and unstable time series in the economy.

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