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Time-Varying Mechanisms between Foreign Direct Investment and Tourism Development under the New Normal in China

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Abstract

This study is aimed at investigating what has happened to the dynamic linkages between foreign direct investment (FDI) and tourism development in China since the emergence of the so-called new normal economy. A time-varying parameter vector autoregressive model is used for the first time to analyze the equi-spaced and time-point impulse responses between FDI, Foreign exchange earnings from international tourism (FEE), and gross domestic product using annual data taken from 1983 to 2017. The results for the equi-spaced impulse response show that a difference in intensity for the interaction effect between FDI and FEE will change with different interval. In addition, impulse response diagrams for FDI and FEE based on changes in economic development at three significant points in time reveal that the effect FDI in the new normal period has had the greatest impact on FEE thus far in 2017, followed in decreasing impact by 2003 and then 1997.

Keywords: foreign direct investment; impulse response analysis; foreign exchange earnings from international tourism; new normal; TVP-VAR model

Introduction

In recent years, the Chinese economic environment has been characterized by a sluggish growth in productivity. Since the global financial crisis of 2007 and 2008, China has experienced a significant drop in gross domestic product (GDP) growth rates affecting many industries nationwide. Tourism is one of the most significant income-generating sectors for GDP growth in economies worldwide. Therefore, tourism is often treated as a promising source for economic growth and development in many countries (Tran Van et al., 2018). The development of a nation's tourism industry can not only bring about greater income and higher standards of living, but will in some countries' cases ultimately represent the nation's primary force for driving economic growth (Endo, 2006).

The development of tourism will oftentimes generate more employment opportunities in a country. Developing economic activities relevant to the tourism sector will also generate a new investment opportunities, further driving economic growth either directly or indirectly (Deng et al., 2014). For example, mega sport tourism events, The World Cup, have a lot of positive socio-economic influence (Nunkoo et al., 2018). The global GDP of the world's tourism sectors amounted to some US$7.2~8.3trillion, accounting for 9.8%~10.4% of total global GDP worldwide and generating 284~313 million jobs from 2015 to 2017, as per based on the World Travel and Tourism Council (Ribeiro et al., 2018; Wang and Liang, 2018).

The governments in many developing countries will consider tourism as a promising source of GDP growth and development, one that will improve their exports while at the same time promote employment as well as human development within their borders considerably.

In order to promote such economic development, tourism industries need to increase productivity, create employment opportunities, expand infrastructure, and develop domestic competitiveness. Notably, all these economic activities can be supported using foreign direct investment (FDI) since China’s economic reforms of the late-1970s. FDI inflows have increased from US$0.16 billion in 1979 to US$ 131.04 billion in 2017. In fact, FDI plays a key role in the development of tourism all around the world, just like any other service industry supporting economic development, in turn affecting trade, technology transfers, and employment. However, the mechanisms of a specific country’s economic growth will invariably affect this dynamic relationship between FDI and tourism. It is well known that China has experienced the world’s fastest economic growth over the past 35 years (Tung, 2016). However, this growth rate dropped to less than 7% per year since 2013 (Holbig, 2018). In this study, China’s GDP growth rate is parsed using a Markov switching autoregressive (MS(M)-AR(p)) model in order to investigate the specific impact the relationship between FDI and tourism will have under different regime of GDP growth. Furthermore, the research contributions of this paper include the following points. First, the research of this paper is mainly to explore the problems of China's tourism and economy under the new normal, and provide suggestions for the improvement of China's tourism economic problems. Secondly, when using the TVP-VAR model for time-point impulse response analysis, the Markov-Switching model can be used to analyze the relationship between FDI and tourism. Moreover, this method is used to detect the turning point, which avoids the randomness of the subjective selection of transition point in previous literature. Thirdly, this paper uses the TVP-VAR model for the first time to analyze the time-varying mechanism between FDI and tourism development. It not only analyzes the time variation between the two variables of one year, two years and three years, but also analyzes the time variation between the two variables at the three key transition points. The combination of dual analysis can not only analyze how the interaction between foreign direct investment and tourism development changes over time, but also investigate whether two variables have undergone major changes in China's economic development stage. This is a very important contribution to the analysis of the mechanism of China's foreign direct investment and tourism development under the new normal.

Literature Review

The important role that FDI plays in most of the world's economies is undeniable. More specifically, FDI promotes economic growth, which affects tourism, and in turn tourism will stimulate economic growth further (Bezuidenhout and Grater, 2016). Therefore, tourism is increasingly important to the development of the world economy (Tang et al., 2007; Gupta, 2015; Kaur and Sarin, 2016; Lee and Chang, 2016; Kostakis and Theodoropoulou, 2017). Moreover, there is an inseparable relationship between foreign direct investment and foreign exchange earnings from international tourism (Jayaraman et al., 2014; Gupta, 2015). The research literature on the relationship between FDI and tourism is extensive, and correspondingly, the number of studies undertaken on whether there is causal relationship between FDI and tourism is quite large. FDI and tourism is playing important role as it not only generate employment but also improve infrastructure of the economy. So, due to small share of tourism sector in an economy, non-existence of causality among growth tourism and FDI for some economies may occur. But for economies growth this does not imply the tourism sector had not been important. It has been empirical estimated by various researchers that tourism and FDI is either bidirectional or unidirectional related with economic growth. Therefore, it is a need to study the relationship of tourism and FDI (Kaur and Sarin, 2016).

To highlight a few, researchers Kaur and Sarin (2016) found that there is no significant causal relationship between FDI and GDP, tourism does impact FDI but latter does not impact former. However, Yazdi et al. (2017b) found that there is indeed a positive effect between tourism and economic growth, and that FDI inflows in the tourism sector will promote the growth of tourism. Fauzel et al. (2017) also found a positive correlation between tourism and FDI in stimulating economic growth.

More specifically, relevant research on the topic has indicated that FDI is indeed critical for the development of tourism (Yazdi et al., 2017a). For example, Barrowclough (2007) found that FDI in tourism exhibits a significant growth trend that will often sustain itself over time. Endo (2006) investigated the importance of FDI in the tourism industry's revenues on a global scale, finding that while the vast majority of FDI will be aimed at developed countries, the role of FDI in tourism for some developing countries is more important than its overall economic activity. Some studies have also shown that a significant Granger causality can be found between FDI and tourism development. Specifically, Bezic and Radic (2017) found that there a bidirectional causal relationship exists in the short-term between FDI and tourism, while a relationship of stable co-integration is exhibited in the long run when adopting econometric methods. However, it has also been found that the causal relationship running between FDI and tourism can be one-way (Peric and Radic, 2016).

Furthermore, scholars have analyzed this relationship through specific case studies. Fiji was used as an example to study the relationship between FDI and tourism income. Here it was found that the impact of FDI on tourism income is positive. In general, an increase of 10% in the ratio of FDI to GDP will lead to a tourism revenue increase of approximately 0.49% (Jayaraman et al., 2014). In studying the influence of FDI on tourism as well as other related control variables using the Cobb Douglas production function in the case of Croatia, it was found that further development of tourism in Croatia is dependent upon FDI, and that FDI has a significant impact on tourism development in general (Bezic and Radic, 2017). In a third case study using data taken on FDI and tourism in Africa from 2003 to 2012, it was found that there is a strong positive relationship between FDI and tourism development, although this is oftentimes variable in magnitude depending on the unique characteristics of specific countries, and the potential of tourism in Africa has not been fully exploited. (Bezuidenhout and Grater, 2016). For a final example, Tomohara (2016) used sample data from 29 regions in Japan to establish an empirical model for studying the interaction between FDI and tourism, discovering many positive spillover effects from the interaction between tourism-related industries and FDI.

As noted earlier however, other studies have found evidence that there in fact is no relationship between the FDI and tourism. For example, Yazdi et al. (2017a) found no relationship of causality between FDI and tourist receipts when using pooled mean group estimators in a panel data model. All in all, the empirical results of past studies on the relationship between tourism and FDI have been diversified because of their various methodologies and samples (Perić and Radić, 2015; Bezic and Radic, 2017; Yazdi et al., 2017a). Therefore, it is worth alternatively exploring the time-varying mechanisms between FDI and tourism development using a TVP-VAR model. Investigating these mechanisms in China, and under dramatic economic changes that have occurred since the emergence of the so-called new normal world economy, should present important findings.

The remainder of this paper is organized as follows. The study's methodology and data section will describe the primary indicators of Chinese tourism development, FDI, and economic growth, in addition to more general information on the study's methodology. The empirical results section will present the study's findings. The last section will offer conclusions and a discussion.

Methodology and Data

Data

In our paper, foreign exchange earnings from international tourism (FEE), which was used to represent the tourism development. GDP was employed to divide different regimes of economic growth of China. FDI is the abbreviation for "Foreign direct investment". The annual data of FDI, FEE, and GDP provided by the CEInet Statistics Database (http://db.cei.cn) was downloaded for the years 1983 to 2017. Thereafter, the first-order differences of the natural logarithm of the three aforementioned variables were computed, and the final series are abbreviated as DLFDI, DLFEE, and DLGDP, respectively.

[Insert Figure 1 here]

Figure 1 plays the trend of the growth rate of the natural logarithm of the three variables that are the DLFDI, DLFEE, and DLGDP in China, which shows that three series indeed have a strong correlation. Specifically, DLFDI is the most volatile amongst them, while DLGDP is relatively much more stable. The rationale behind this finding can be attributed to domestic and foreign factors. Regarding the foreign factors, the weakness in the economic growth abroad during the 1990s drew foreign investors to the Chinese market, resulting in a rapid increase in China's FDI at the time. Regarding the domestic factors, FDI has been the most important driver for China's economic growth since its economic reforms of the late-1970s. In fact, China has been the second largest country in the world for attracting FDI since 1993. Moreover, it is obvious that the 1997 Asian financial crisis, the 2002 severe acute respiratory syndrome (SARS) epidemic, as well as the emergence of the new normal economy since 2012 are the greatest source of volatility in the significant changes seen between the study's three variables through the sample time period.

[Insert Table 1 here]

Table 1 displays the descriptive statistical analysis results of DLFDI, DLFEE, and DLGDP in China. The statistical analysis was performed by six indicators including mean, standard deviation, kurtosis, skewness, J-B statistic, and ADF test value. It can be seen that the standard deviations of the three variables is generally small. Notably, the volatility of DLGDP will be especially diminished when compared with the other two variables. The variable DLFDI exhibits the highest degree of kurtosis, at 2.40, which indicates that the change exhibited in DLFDI is more sharpness than the other two variables. The skewness of the DLFDI, DLGDP, and DLFEE are 8.712, 3.003, and 5.984, respectively. This indicates that tailing for the distribution of the three variables is obvious. Under an assumption of normal distribution, the Jarque-Bera statistic (J-B statistic) progressively obeys the chi-square distribution, with a degree of freedom of 2. The J-B statistic for DLFDI and DLFEE is 78.886 and 18.370, respectively. This means the null hypothesis is rejected at a significance level of 10%, indicating that DLFDI and DLFEE is not a normal variable. The augmented Dickey–Fuller test for DLFDI, DLGDP, and DLFEE reveals the variables are significantly stable at the 1%, 5%, and 10% level. This tells us that DLFDI, DLGDP, and DLFEE are all stationary variables. Therefore, it can be concluded that each series meets an assumption of being stationary in the nonlinear MS(M)-AR(p) model.

In this study, a Markov-switching autoregression (MS(M)-AR(p)) model is compiled to detect changes in economic growth while avoiding the randomness of break point selection. Thereafter, a TVP-VAR model is used to analyze the time-varying relationship between FDI and tourism development under the different regime of China's recent GDP growth, providing a venue for detailed analysis. The TVP-VAR model has been developed since the early 1980's (Bekiros and Paccagnini, 2013), then it was used to analyze macroeconomic policy issues by Primiceri (2005), Koop et al. (2009), Nakajima et al. (2011) and Koop and Korobilis (2013). Nakajima et al. (2011) indicated that the TVP-VAR model is more powerful than traditional vector autoregression (VAR) models. In terms of empirical testing for this study, the variation that occurs between the two variables within one year, two years, and three years will be investigated. Subsequently, the time-point impulse responses found at these three important nodes will be used to analyze how the interaction between FDI and tourism development changes over time.

In this study, a TVP-VAR model is used to investigate the time-varying relationship between two variables through different periods, and these different time point is objectively detected by the Markov switching autoregressive model.

The TVP-VAR Model

The coefficients of the TVP-VAR model vary with the variation of the impact size and the variation of the propagation mechanism. The model coefficients can well capture the time-varying and nonlinear characteristics of the model's lag structure, and can effectively characterize the relationship between variables from a dynamic perspective. Therefore, the empirical analysis has better explanatory power. The TVP-VAR model can fully describe parameters as well as persistent changes, while at the same time avoiding the deviations in estimates caused by volatility fluctuation.

A typical VAR model can be expressed as:

$$\mathrm{A}y_t = F_1 y_{t-1} + F_2 y_{t-2} + \cdots + F_s y_{t-s} + \mu_t, t = s+1, \cdots n \tag{1}$$

where, y_t is a $k \times 1$ dimensional observable vector, $\mathrm{A}, F_1, F_2, \cdots, F_s$ are the $k \times k$ dimension coefficient matrices, the disturbance term μ_t is a $k \times 1$ structural shock assumption, and $\mu_t \sim N(0, \sum\sum')$, A, as well as $\sum$ make up the $k \times k$ diagonal matrix for lower triangular matrix presented below:

$$\sum = \begin{bmatrix} \delta_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \delta_k \end{bmatrix}, \quad A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{bmatrix}$$

if $B_i = A^{-1}F, i = 1, \ldots, s$, Formula (1) can be rewritten as:

$$y_t = B_t y_{t-1} + B_2 y_{t-2} + \cdots + B_s y_{t-s} + A^{-1} \sum \varepsilon_t, \quad \varepsilon_t \sim N(0, \ I_k) \tag{2}$$

where each row element in B_i is straightened, and can be rewritten into column vector β of $k^2 s \times 1$, and $X_t = I_k \otimes (y'_{t-1}, \ \cdots, \ y'_{t-s})$ is defined where $\otimes$ denetes the Kronecker product. The model can be expressed as:

$$y_t = X_t \beta + A^{-1} \sum \varepsilon_t \tag{3}$$

This last formula is a classic structural VAR model, in which each coefficient is constant. The formula can be generalized and extended to the TVP-VAR model as long as the coefficient is time-varying, as shown below:

$$y_t = X_t\beta_t + A_t^{-1}\sum_t \varepsilon_t, \quad t = s+1, \cdots, n, \tag{4}$$

where in matrix β_t, A_t represents the time-varying parameters of the model, y_t represents the growth value of FDI, Foreign exchange earnings from international tourism (FEE) and GDP combined, and the structural impacts are independent of each other, as in $\sum_t = \text{diag}(\sigma_{1t}, \ldots, \sigma_{kt})$.

Generally speaking, in order to reduce the number of parameters for the model to estimate, non-zero elements in the matrix A_t can be stacked into one row vector. That is, $a_t = (a_{1t}, \ldots, a_{kt}), a_{jt} = log\sigma_{jt}^2, j = 1, \ldots k, t = s+1, \ldots, n.$

Assuming that the time-varying parameters in the equation noted above obey the following random walks:

$$\begin{bmatrix} \varepsilon_t \\ \mu_{\beta t} \\ \mu_{\alpha t} \\ \mu_{ht} \end{bmatrix} \sim N\left[0, \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & \sum_\beta & 0 & 0 \\ 0 & 0 & \sum_\alpha & 0 \\ 0 & 0 & 0 & \sum_h \end{bmatrix}\right]$$

$$\beta_{t+1} = \beta_t + \mu_{\beta_t}, \ \alpha_{t+1} = \alpha_t + \mu_{\alpha_t}, \ h_{t+1} = h_t + \mu_{h_t}, t = s+1, \ldots, n.$$

where $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0})$, $\alpha_{s+1} \sim N(\mu_{\alpha_0}, \Sigma_{\alpha_0})$, $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$

The MS(*M*)-AR(*p*) model

The Markov-Switching model (Krolzig, 1997) is an analytical model for studying the structural dynamic changes of time series structures. This model is suitable for the analysis of structural changes of time series variables, and often used to modelling and analyzing the interior of an unobservable system (Niu et al., 2013).

$$\Delta y_t = \mu_{S_t} + \sum_{i=1}^{p} \theta_i \Delta y_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_{S_t}^2) \tag{5}$$

where y_t is the target variable to be explored, θ_i represents the parameter coefficients, ε_t is a random disturbance item, and σ represents the standard deviation. The intercept term μ_{S_t} and variance term $\sigma^2_{S_t}$ will depend on the state variable S_t, which is specifically the regime of GDP growth variable for the system. Note that μ_{S_t} will switch between the two regime of GDP growth. For example μ_{S_t} will be positive if S_t= 1, and negative otherwise. The transition between the two regime of GDP growth will also depends on the Markov chain process. OxMetrics (Krolzig, 1997) were used here to estimate the model parameters by maximizing the likelihood of observations (Arora et al., 2013).

Empirical Results

Parameter estimation

Before compiling the study's TVP-VAR model, it is necessary to select an optimal lag order for the model, due to the time delay of the variables will affect the mechanism (Zhang et al., 2018).

[Insert Table 2 here]

Table 2 displays the optimal lag order, which can be achieved by the software of EViews. For this study, five information criteria were used to select an optimal lag order from different maximum orders. It can be seen that the optimal lag order varies with the maximum order. The information criteria for LR (Likelihood Ratio), SC (Schwarz), and HQ (Hannan-Quinn) information criterion are relatively stable when the maximum lag is less than 6. Therefore, 1 was ultimately chosen as the optimal lag order for this study's model (Liu and Song, 2018).

The model parameter results showed in Table 3 and Figure 2 are estimated by the

Markov chain Monte Carlo (MCMC) algorithm with 1,000 times simulation in OxMetrics (Zhang et al., 2018).

[Insert Table 3 here]

Table 3 presents the estimation results using the MCMC algorithm, which include posterior means, standard deviations, 95% credible intervals, Geweke convergence diagnostics statistics and inefficiency. Table 3 illustrates that the posterior mean of the parameters are within the 95% confidence interval, and the Geweke convergence diagnostic (CD) values are also within the 5% critical range. This indicates that the posterior distribution converges to zero. Thus, the null hypothesis cannot be rejected (He and Zhou, 2018). The results for the inefficient factors indicate that each factor is within a reasonable range, meaning the model's estimated parameters are both stable and effective (Liu et al., 2018).

[Insert Figure 2 here.]

The sample autocorrelation coefficient, convergence trajectory, and posterior distribution density function for the corresponding parameters are presented in Figure 2. Note that the sample paths look stable and that the sample autocorrelations drop smoothly after discarding the initial (1,000) samples after burn-in. This indicates that the sampling method will efficiently produce samples with low levels of autocorrelation (Nakajima et al., 2011).

The first row in Figure 2 presents how the sample autocorrelation varies after the pre-burn-in sample is removed. This means that the directional volatility spillovers from one of the variables to the others will vary greatly over time. The second row presents the dynamic simulation paths (1,000) for the six parameters. It can be seen from the convergence trajectory that most of the parameter sequences basically approximate a white noise process, which indicates that the parameters obtained by sampling are in fact independent of each other.

In order to further describe the dynamic mechanisms between DLFDI and DLFEE, the study utilizes a TVP-VAR model to carry out equi-spaced and time-point impulse response testing. An equi-spaced impulse response refers to the shock the dependent variable receives from the independent variable after a one period lag, after a two period lag, and after a three period lag. A time-point impulse response is the unit impact for the dependent variable shock to the independent variable at a given time point.

Equi-spaced impulse response

Equi-spaced impulse response analyses are used here to analyze the time-varying mechanisms in the relationship between the growth of FDI and tourism devlopment, as well as to explore whether there is a difference between a one period lag (one year), a two period lag (two years), or a three period lag (three years) in impulse response.

[Insert Figure 3 here]

Figure 3 presents the Equal interval impulse response of the DLFDI and DLFEE after one year, two years, and three years each. Note that therein, the greater the volatility in the graph, the greater the impact of the impulse response. Specifically, the left column of Figure 3 presents the impact that DLFEE has on DLFDI, while the right column present the impact that DLFDI has on DLFEE.

First of all, it can be seen from the left column of Figure 3 that a positive shock impact from DLFEE directed at DLFDI indicates that influence decreased gradually after 1997. The impact reaches a maximum of 0.003 during the United Kingdom's return of Hong Kong to China in 1997, while the impact declines slowly and falls to a local minimum consistent with the SARS epidemic of 2003. Thereafter, it has improved around 2007, while the impact continues to decline and hits an absolute minimum (0.0003) corresponding with the year of 2010. The impact that DLFEE has on DLFDI reaches a larger point during the emergence of the new normal economy, indicating that the effect of information diffusion from inbound tourists in China played one of the most important roles in the international tourism industry for China since its economic reforms of the late-1970s. This phenomenon will affect the willingness of investors to inject FDI into a market during different periods.

From the equi-spaced impulse response results presented in Figure 3, it can be seen that the effect is largest at the one year lag. Furthermore, the fluctuation intensity as well as frequency changes are obvious. The impact intensity is found to be weaker at the two years lag. On the whole, however, the intensity is generally similar and the impact can be seen as stable. Subsequently, the positive shocks that DLFDI have on DLFEE will gradually increase, reaching their maximum (0.018) in 1993. Thereafter, the impact from positive shock gradually decreases due to the impact of the 1997 Asian financial crisis. The impact then gradually stabilizes around 2003, while overall impact response gradually weakens correspondingly. These finding indicate that the impact of FDI growth on the development of inbound tourism will be unstable within one year. However, after two or three years, the impact volatility of DLFDI on

DLFEE will become stable. In this study's case, this was found to accurately reflect the stabilizing impact that China's FDI growth had on its inbound tourism after two year and three years periods.

On the whole, it can be seen that the one-year impact exhibits the greatest difference between the study's different time periods. This conclusion can be observed best from the graphs for the two different situations, that DLFDI has an impact on DLFEE and DLFEE has an impact on DLFDI presented in Figure 3. Note however that the impact is in fact more obvious in the left panel. As the impact between DLFDI and DLFEE for the two year and three years intervals is weaker than for the one year interval, it can be concluded that there are significant differences under different lag periods, and that the one-year impact is considerably stronger.

Time-points impulse response

From the results of the study's equi-spaced impulse response testing, a large difference in the positive shock between the two variables around 1997 and 2003 presents itself. Therefore, a MS (M)-AR(p) model is compiled and run in order to analyze whether there are any special points of note or different relationships of influence therein may better reveal specific regime of GDP growth.

Based on the AIC, HQ, and SC information criterion, the Akaike information criterion (AIC), Hannan-Quinn information criterion (HQ) and Schwarz information criterion (SC) values for the study's nonlinear MS(M)-AR(p) model are calculated and compared in different regime of GDP growth as well as different lag orders, respectively (Krolzig, 1997). The MSIH(2)-AR(0) is found to be the most reliable and effective model, where "I" and "H" represent the intercept and heteroscedasticity respectively, since the AIC, HQ, and SC information criterion were found to be the smaller than the values for the others model when we consider the parameters will be conditioned on the state of the Markov chain.

[Insert Table 4 here]

Table 4 lists specific time periods, corresponding smoothing probability, constant, standard deviation, T value, and variance of GDP growth rate in regime 1 (high growth and high volatility) and regime 2 (low growth and low volatility), which is divided by MSIH (2)-AR (0) model. The intercept term during GDP growth regime 1 is 0.092, while the intercept term during GDP growth regime 2 is 0.177, and the standard deviation for GDP growth regime 1 is smaller than the standard deviation for GDP growth regime 2 as well. However, note that the t- statistic for GDP growth regime 1 is much larger than its value for GDP growth regime 2. Table 4 also presents the result estimates for the study's MS(M)-AR(p) model. Here the study's sample series were divided into two regime of GDP growth using the MS(M)-AR(p) model, namely a high-growth high-fluctuation regime of GDP growth and a low-growth low-fluctuation regime of GDP growth. Therein, the magnitude of the value for smoothing probability in the regime of GDP growth variable will indicate which economic growth of regime will lead to GDP growth best. The larger the value for smoothing probability, the greater the likelihood of the given period being in a regime of GDP growth.

It can be seen in Table 4 that China's economic growth in the two periods from 1997 to 2002 and from 2012 to 2017 can be primarily characterized as high-growth high-fluctuation regime of GDP growth, with smoothing probabilities of 0.954 and 0.968, respectively. On the other hand, the low-growth low-fluctuation regime of GDP growth in China were found in the two periods from 1984 to 1996 and from 2003 to 2011, with smoothing probabilities of 0.972 and 0.929, respectively. In addition, although economic growth changes considerably therein, the probability of smoothing was around 1.0 all the way. This indicates that the trends in China's economic growth are constantly changing, characterized by different regime of high-growth high-fluctuation and low-growth low-fluctuation GDP growth.

[Insert Figure 4 here]

Figure 4 displays the tendency of the natural logarithm of GDP growth rate. The economic changes in China from 1983 to 2017 are split into high-growth and low-growth regime. It can be seen in Figure 4 that the average rate of economic growth is unsurprisingly large in the high-growth regime, and that the average rate of economic growth is correspondingly small in the low-growth regime. These dynamic changes between the two regimes of GDP growths are likewise very obvious. While studying different trends in DLFDI as well as DLFEE over different regime of GDP growth within general economic growth is a worthwhile pursuit, exploring the different characteristics of influence in these variables over different periods time is a more comprehensive aim that will help make up for the gaps in research that currently exist in the literature on the topic.

The shaded area in Figure 4 corresponds to the economic growth rate under low-growth low-fluctuation regime. As seen in Figure 4, the period of slower and more stable economic growth includes the period from 1997 to 2002. The remainder of the sample is characterized by a high-growth high-fluctuation regime of economic growth from 2012 to 2017. It can be seen from these two different regime of GDP growth that there are three significant transition points in China’s economic growth herein. When the Asian financial crisis broke out in 1997, China’s economic growth rate was between 7% and 8%. Domestic demand was insufficient, prices fell, unemployment rose, and it wasn’t until 2003 when China’s GDP growth rate reached 9.3% that the gloom of the financial crisis had dissipated. During this period, China’s economy was in a low-growth low-fluctuation regime.

In the context of external influences on the Chinese market, the follow-up impacts of the international financial crisis in 2007 continue to emerge to this day. The European debt crisis continues, the United States’ economy remains weak, the path to world economic recovery still seems long, and the international demand has remained in low. Moreover, the impact of the global economic recession as well as a continued downturn in external demand have also had a significant effect on the Chinese economy. In the context of China’s domestic factors, the impact of insufficient domestic demand as well as overcapacity in some industries led China’s economic growth into a new period of adjustment in 2012. Meanwhile, downward pressure on the economy has been relatively large, and economic growth continues to decline.

China’s economic growth peaked in 1985, 1988, and 1994. Initially, the economic growth hit its highest points in 1985 and 1988, but then plummeted in 1990. After national economic policy was adjusted accordingly, economic growth again peaked in 1994. Since 2003, when China joined the World Trade Organization, the country’s pace of economic integration and globalization has accelerated, gradually entering a period of new economic growth. With the initial onset of the subsequent financial crisis in 2007, economic growth reached its peak and then began to fall again by 2008.

[Insert Figure 5 here]

Figure 5 shows the results of the time-point impulse response in 1997, 2003 and 2012, respectively. The left part of the graph is the result of a unit of FEE shock on FDI, and the right part of the graph is the result of a unit of FDI shock on FEE. It can be seen from the study's time-point impulse response testing that the impulse response between DLFDI and DLFEE approaches zero gradually over the long term. This finding is consistent with the characteristics for equi-spaced impulse response. Firstly, note that the shock impact of DLFEE indicates that the shock DLFEE has on DLFDI is largest in 1997. Generally speaking, the impact of DLFEE will make DLFDI rise rapidly. This value peaks at 0.003. The impact of Hong Kong's return to China is the strongest factor for consideration here, as the return of Hong Kong promoted substantial development in inbound tourism for China around 1997. Concurrently, this investment boom instilled greater confidence for DLFDI investors as well. Moving on, the impact response was second-largest in 2003 peaked 0.0017, while the impact from these shocks was relatively weak in 2012. With an increase in the number of impact periods, shock response exhibited similar variable dynamic changes at the study's three specific focus points in time. The shock impact quickly declines from the beginning of the study's sample period, and approaches bottom in the seventh period. This indicates a characteristic increase and subsequent decrease in the shock DLFEE will have on DLFDI. For the study's three focal years, the impact that inbound tourism has on DLFDI is noticeably more significant, corresponding with the impact of Hong Kong's return to China. Additionally, it can be seen that the influence of the SARS epidemic is relatively large, and that the impact that DLFEE has on DLFDI is not as pronounced under the economic new normal.

Secondly, it can be seen from the shock impact of DLFDI that its self-sustainability will, on the whole, gradually decline as a result of extending impulse response periods. The impact of DLFDI on DLFEE is found to be weakest in 1997 and most influential during the new normal economy around 2012. Taken during the first stage, this impact is the largest in 2012. The impact response then levels out continuously through 2003 and 1997. After the first stage, the impact is changing. With the increase in impact period, impact response will gradually approach zero, and borders zero in the sixth period for the three study's three specific years. On the whole, the slope of the trend is largest in 2012, indicating that the impact that DLFDI has on DLFEE is greatest during the new normal economy. China's tourism industry expanded rapidly around this period, brought about by increasing DLFDI as well as he spread of tourism information owing to China's transition into the new normal economy in 2012.

In summary, in comparing the effects of the impact between the study's two variables at its three specific time points, it is found that the impact that DLFEE has on DLFDI is most significant in 1997, indicating that the return of Hong Kong worked to greatly promote the development of inbound tourism and increase DLFDI into China. It is likely that this economic phenomenon ultimately solved shortages in tourism funding and interruption of the industry's supply chain. Moving on, the impact of shock in 2012 is found to be the smallest here, indicating that the impact of DLFEE on DLFDI is not obvious in this case, which must be due to the economic and policy transformations occurring in China at the time under the economic new normal. In this vein, it comes as no surprise that the impact that DLFDI has on DLFEE is found to be the largest during the new normal period when the impact was smallest in 1997. Generally speaking, the impact of DLFDI on DLFEE is more obvious than impact of DLFEE on DLFDI. This study's analysis of these three points in time have shown that DLFDI had the greatest impact on DLFEE during the period of the new normal economy.

Impulse response analysis for transition points

[Insert Figure 6 here]

Figure 6 shows the impulse response analysis graphs four-year before and after the three special time points in 1997, 2003 and 2012, respectively. The first line in Figure 6 presents the impact that DLFDI has on DLFEE, indicating that DLFDI exerts a positive shock on DLFEE. The figure's second line shows the impact that DLFEE will have on DLFDI. The impulse response here indicates a positive shock from DLFEE on DLFDI. Note that each column in Figure 6 presents the impulse response for the four-year interval around 1997, 2003, and 2012. In taking a closer look at the impact that DLFDI has on DLFEE, it is shown that the impact is generally consistent, and that the positive impact gradually weakens. As far as the impact of DLFDI to DLFEE, four years thereafter (2001, 2007, and 2016), the impact becomes greater than the current (1997, 2003, and 2012) impact, indicating that the impact of DLFDI on DLFEE exhibits a lag during the period where Hong Kong was returned to China, the SARS outbreak period, as well as the emergence of the new normal economy. These findings indicate that these impacts will require a short period of adaptation (four years) before exhibiting their greatest impact efficiency. In terms of the impact that DLFEE has on DLFDI, the positive shock impact from DLFEE reaches its peak during the first period, demonstrating that the impact of DLFEE on DLFDI first rapidly increases, quickly reaching its maximum, and then gradually decreases over time, ultimately dipping toward zero. At all three break points, the impact of DLFEE on DLFDI will remain basically the same, indicating that the impact of DLFEE on DLFDI characteristically moves from strong to weak.

During the outbreak of SARS and the emergence of the new normal economy thereafter, it is found that the impact from four years ago (1993, 1999, and 2008) is significantly greater than currently (1997, 2003, and2012). Because of measures taken by governments to halt the spread of the SARS virus, inbound tourism was naturally affected during this period. The stagnation of economic development in China's tourism industry at the time consequently brought about a decline in investor confidence and goodwill, thereby affecting DLFDI inflows in turn. For the new normal economic period, all Chinese industries were forced to face new and deepening national reforms for innovation and development. As a result, the present day impact is still not obvious. Regardless, the overall impact intensity is considerable, implying that the economic efficiency of China's tourism industry for the growth of FDI is excellent, and that it can likewise generate substantial gains in the development of national FDI.

As can be seen from Figure 6, the positive shock from DLFDI causes significant fluctuations in DLFEE. From 1993, the impact that DLFDI has on DLFEE, originally 0.034, gradually rises to 0.041 in 1997. It subsequently falls back to 0.045 in 1999, rising thereafter to 0.046 in 2001, 0.055 in 2003, 0.058 in 2007, and then to 0.063 in 2008. This value remains basically unchanged at around 0.063 in 2012 and to 2016. This shows us that the impact that DLFEE has on DLFDI is in constant fluctuating, all the way from 1993 to 2016. It can be seen that the impact that DLFEE has on DLFDI hits its maximum after the study's first period. This impact increases from 0.003 in 1993 to 0.0033 in 1997, and then rises quickly to 0.045 in 1999, falling back to 0.0017 in 2001 thereafter, then continuing to rise toward 0.002 in 2003. Lastly, we see a decline from 0.011 in 2008 to 0.005 in 2012. However, the value reaches an overall minimum of 0.0002 in 2016. From the observations made above, it can be concluded that the impact between DLFDI and DLFEE fluctuates considerably from 1993 to 2016, which indicates that there is are long-term mechanisms of influence that continuously promote and continuously between FDI growth and Chinese tourism development.

Judging from the impact mechanisms found between the study's two variables for the four-years around (2008, 2012, and 2016) the period of emergence for the new normal economy, the positive shock that DLFDI has on DLFEE does not seem to be affected by the development of the new normal economy in China. However, the impact that DLFEE has on DLFDI does indeed bring about significant change in the four-year period around the new normal (2008, 2012, and 2016). The effect is the most obvious before the new normal (2008), but after the new normal (2016), the effect is weak. However, under the influence of the new normal, tourism development has undeniable positive effect on DLFDI. As such, it can be concluded for economic policymakers that it is critical that one seize the opportunity for making full use of the role that DLFDI plays in inbound tourism. With the help of modern technology, optimizing new development models for growing a nation's tourism industry under the new normal by building on the findings of this study is possible and desirable.

Conclusions and Discussion

The purpose of this study was to analyze the impact of growth rate for the natural logarithm of the foreign direct investment and tourism within the context of China's economic growth rate changing during the emergence of the so-called new normal economy. Using annual data on foreign direct investment, foreign exchange earnings from international tourism and gross domestic product taken from 1983 to 2017, the turning point in the stage of economic growth in China was determined using a MSIH(2)-AR(0) model for 1997 (the return of Hong Kong to China as well as the Asian financial crisis), for 2003 (the outbreak of SARS), and for 2012 (the new normal economy). For the first time in the field, a time-varying TVP-VAR model was utilized to analyze the impact of the growth rate for the natural logarithm of the foreign direct investment and the growth rate for the natural logarithm of the foreign exchange earnings from international tourism at each of these transition periods in time. The impact of the study's two variables between a one year lag, a two year lag, and a three year lag was analyzed in order to better understand whether the relationship between the two variables changes significantly. The time-point impulse responses for the study's three specific points in time were then analyzed changes of foreign direct investment and tourism development over time, in different shifts regime from economic development. Lastly, an analysis on the relationship between the two variables was provided to offer valuable reference materials for the development of modern tourism around the world as we move into the new normal economy.

Using the equi-spaced impulse responses observed from the study's TVP-VAR model, it was first found that the responses between growth rate for the natural logarithm of the foreign direct investment and growth rate for the natural logarithm of the foreign exchange earnings from international tourism in China indicate strong stability for two year and three year lags, but that in most of the sample intervals the impact that the growth rate for the natural logarithm of the foreign exchange earnings from international tourism had on the growth rate for the natural logarithm of the foreign direct investment were found to be significantly lower than that of the impact of the growth rate for the natural logarithm of the foreign direct investment on growth rate for the natural logarithm of the foreign exchange earnings from international tourism. This first finding indicates that there is significant difference in the interaction effect between the growth rate for the natural logarithm of the foreign exchange earnings from international tourism and the growth rate for the natural logarithm of the foreign direct investment. With the increase of Chinese international influence in recent years, foreign direct investment is playing an increasingly important role as the driving force for the development of China's tourism industry in new normal economic period. Nations around the world should take the initiative and utilize this opportunity to invest in tourism projects in China.

Secondly, in comparing the impulse responses between the study's two variables at three specific points in time, it was found that the impact that the growth rate for the natural logarithm of the foreign exchange earnings from international tourism has on the growth rate for the natural logarithm of the foreign direct investment in China was largest in 1997. This indicates that the United Kingdom's return of Hong Kong to China greatly promoted the development of inbound tourism and stimulated enthusiasm in foreign investors, thereby alleviating the problems in tourism fund shortages and supply chain disruption China was experiencing in the immediately preceding period. Thereafter however, the impact of the growth rate for the natural logarithm of the foreign exchange earnings from international tourism on the growth rate for the natural logarithm of the foreign direct investment was found to not be as significant in 2012, due to the economic transformations and upgrading occurring in

China as a result of the policy changes deemed necessary for the new normal economy. Overall, the impact of the growth rate for the natural logarithm of the foreign exchange earnings from international tourism on the growth rate for the natural logarithm of the foreign direct investment was found to be largest at the first period .The impact of the growth rate for the natural logarithm of the foreign direct investment on the growth rate for the natural logarithm of the foreign exchange earnings from international tourism was the smallest in 1997, there was no obvious difference between 2003 and 2012. Furthermore, it was found that the impact that the growth rate for the natural logarithm of the foreign direct investment has on growth rate for the natural logarithm of the foreign exchange earnings from international tourism is greater than the impact that growth rate for the natural logarithm of the foreign exchange earnings from international tourism will have on the growth rate for the natural logarithm of the foreign direct investment. From the study's three specific points in time for analysis, it was found that impact of the growth rate for the natural logarithm of the foreign direct investment on growth rate for the natural logarithm of the foreign exchange earnings from international tourism was largest in the new normal economic period. Thus, it can be concluded that investors should seize present opportunity to increasingly allow foreign direct investment to play a great role as the driving force for tourism in China.

Lastly, in utilizing interval impulse response testing in four-year interval periods of analysis over the study's three focal points in time, it was found that the impact of growth rate for the natural logarithm of the foreign exchange earnings from international tourism and the growth rate for the natural logarithm of the foreign direct investment fluctuated from 1993 to 2016. This indicates that there is a long-term and continuous growth as well as constant decline in the impact mechanisms that exist between growth rate for the natural logarithm of the foreign exchange earnings from international tourism and the growth rate for the natural logarithm of the foreign direct investment in China. Notably, the study's analysis concluded that the impact of the growth rate for the natural logarithm of the foreign direct investment on growth rate for the natural logarithm of the foreign exchange earnings from international tourism was not affected by the development of the new normal economy. That said, it must also be noted that the impact that growth rate for the natural logarithm of the foreign exchange earnings from international tourism has on the growth rate for the natural logarithm of the foreign direct investment was observed to present a significant change around the emergence of the new normal. It has become a point of major strategic choice for China's development in how it transforms the potential advantages that tourism resources present into realistic advantages in economic development. It is recommended here that relevant policy action be taken to capitalize on the already substantial investments made in China's Belt and Road Initiative, draw on the China's rich historical as well as cultural heritage, and promote the nation's unique human landscape to develop tourism further under the economic new normal.

This study's offers many contributions to the field. Specifically, this study represents one of the first times a TVP-VAR model has been used to analyze the time-varying mechanisms that exist between foreign direct investment growth and tourism development. Not only did this study analyze the time-varying impulse responses between the two variables in one year, two year, and three years lags, but also analyzed the time-point impulse responses at three critical points in time for its case study very carefully. This combination of a two-fold analysis not only offered insights into how the interaction between the growth rate for the natural logarithm of the foreign direct investment and tourism development will shift over time, but also garnered insight into whether any significant changes occurred in the transition points between different regime of GDP growth in China's economic development for the growth rate for the natural logarithm of the foreign direct investment and growth rate for the natural logarithm of the foreign exchange earnings from international tourism. Analyzing the interaction mechanisms between China's foreign direct investment and its tourism development under the new normal is currently a very important subject for consideration by researchers as well as policymakers. Moreover, when using its TVP-VAR model for time-point impulse response testing, this study also utilized a *MSIH*(2)-*AR*(0) model to select specific regime for observing transformations in economic development, thereby avoiding the randomness that past studies on the point selection from previous literature. All in all, this paper studies the development of China's tourism industry under the new normal. In the new normal period, China's tourism industry provides reference for China's economic development. At the same time, this paper compares the impact of foreign direct investment and tourism development on the time-point impulse response in 1997 (Hong Kong regression), 2003 (SARS) and 2012 (new normal period) in combination with the actual economic background.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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Table 1. Descriptive statistical analysis results

Variable	Mean	Standard Deviation	Kurtosis	Skewness	J-B statistic	ADF test
DLFDI	0.146	0.227	2.400	8.711	78.886***	-3.754***
DLFEE	0.143	0.160	1.008	5.984	18.370***	-6.020***
DLGDP	0.145	0.062	0.755	3.003	3.225	-3.119**

Note: This table displays the descriptive statistics for the time series of DLFDI, DLGDP, and DLFEE in China. All annual data cover the period from 1983 to 2017. The notes ***, **, and * represent findings at the 10%, 5%, and 1% level of significance, respectively.

Table 2. Optimal lag order

Maximum lag order	LR	FPE	AIC	SC	HQ
1	1	1	1	1	1
2	1	1	1	1	1
3	1	2	2	1	1
4	1	2	4	1	1
5	1	1	2	1	1
6	6	6	6	1	6
7	6	7	7	7	7

Table 3. Parameter estimation results of the TVP-VAR model

Parameter	Mean	Standard Deviation	95% Confidence	Geweke's CD Value	Inefficient factor
$\boldsymbol{S_{b1}}$	0.023	0.003	[0.018, 0.031]	0.095	0.870
$\boldsymbol{S_{b2}}$	0.023	0.002	[0.020, 0.028]	0.270	2.270
$\boldsymbol{S_{a1}}$	0.075	0.029	[0.044, 0.157]	0.038	6.720
$\boldsymbol{S_{a2}}$	0.064	0.016	[0.036, 0.095]	0.509	6.890
$\boldsymbol{S_{h1}}$	0.799	0.365	[0.169, 1.421]	0.000	19.820
$\boldsymbol{S_{h2}}$	0.789	0.509	[0.107, 1.619]	0.062	22.390

Note: Where S represents Sigma (diagonal) represents a diagonal matrix, subscript represents a diagonal label, and the overall representation is the result of the first two diagonal elements of the posterior distribution, and the remaining diagonal element results are similar.

Table 4. MSIH(2)-AR(0) model estimation for China GDP Growth

Regime	Regime 1 (High growth and high volatility)		Regime 2 (Low growth and low volatility)	
	Time division	Smooth probability	Time division	Smooth probability
	1997-2002	0.954	1984-1996	0.972
	2012-2017	0.968	2003-2011	0.929
Intercept	0.092		0.177	
S.D	0.004		0.013	
T value	20.464		13.594	
variance	0.017		0.052	

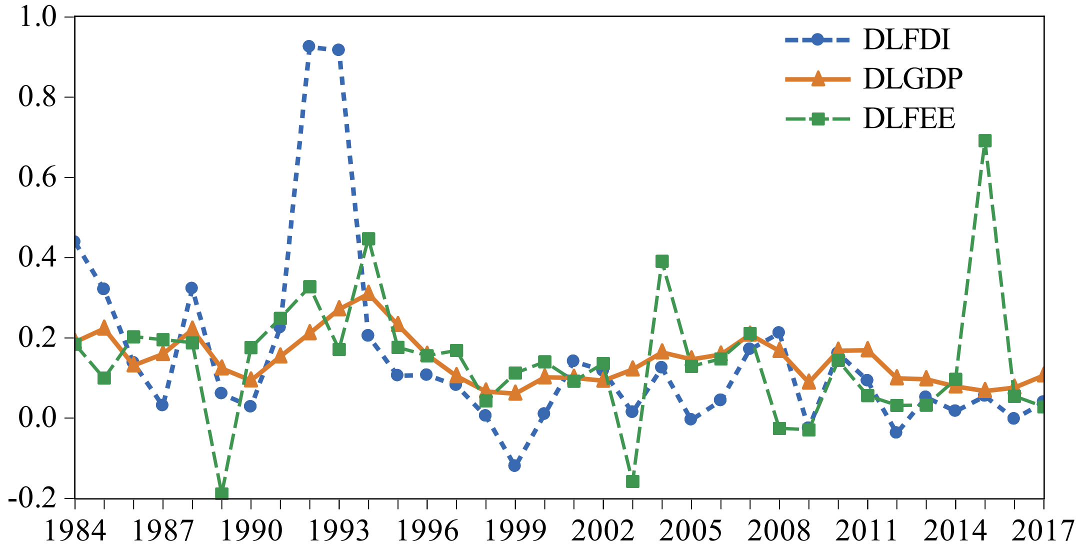

Figure1. Growth trend of FDI, tourism development, and GDP in China

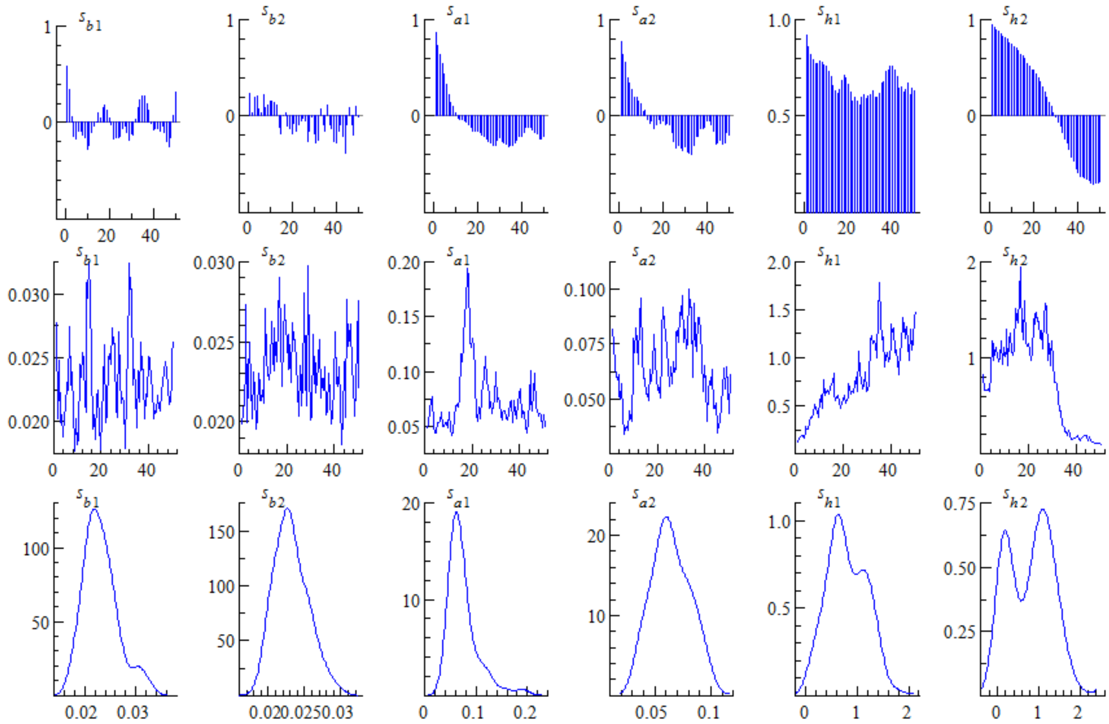

Figure 2. Markov chain Monte Carlo estimation results for TVP-VAR model

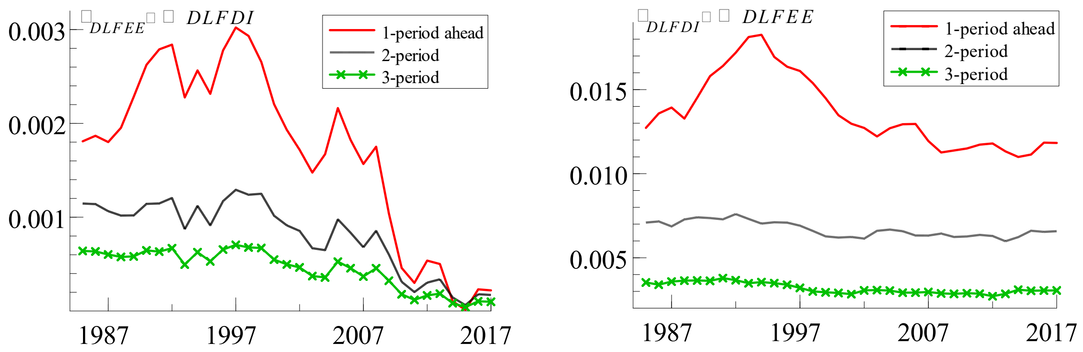

Figure 3. Impulse responses between DLFDI and DLFEE for one, two, and three years

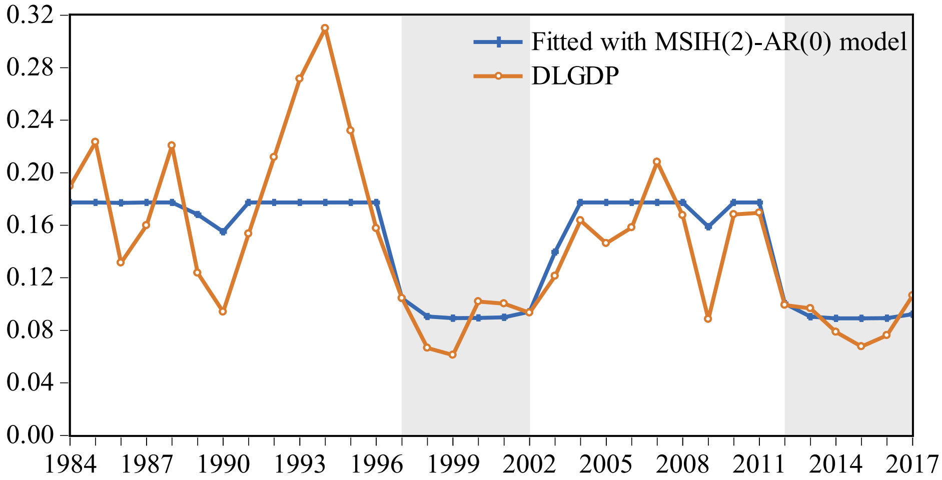

Figure4. Modelling China's economic growth with MSIH(2)-AR(0) model

Shaded areas: 1997-2002, 2012-2017 economic change regime of GDP growth with low growth and low fluctuation

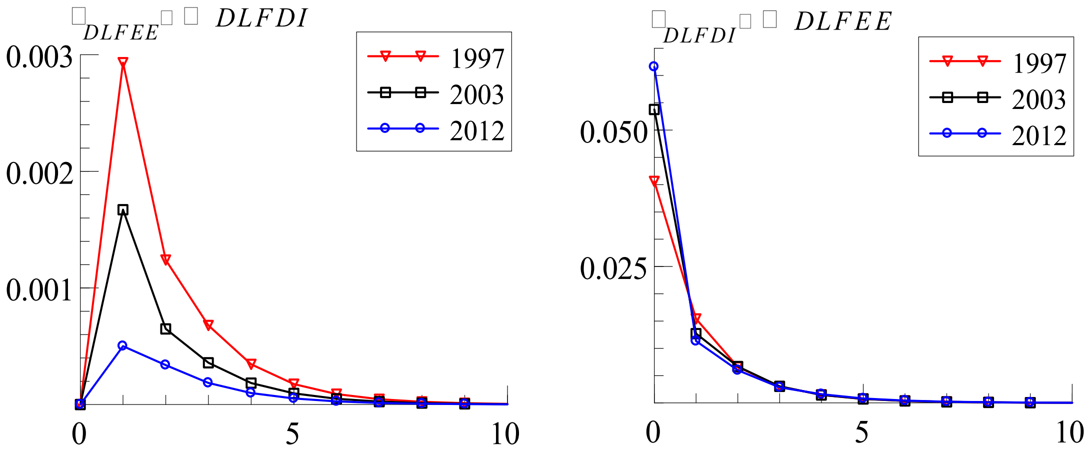

Figure 5. The time-point impulse responses between FDI and FEE in China for 1997, 2003, and 2012

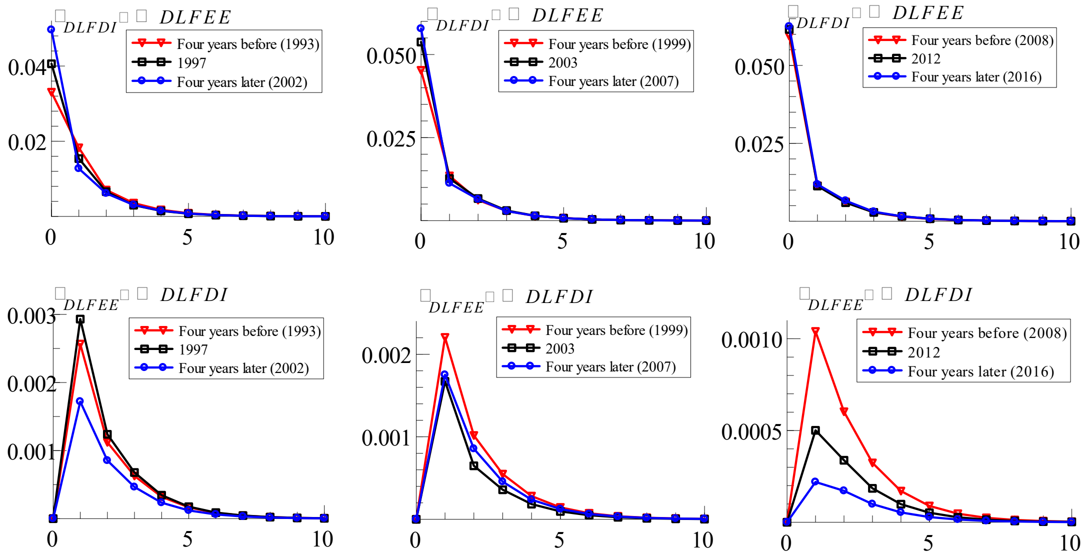

Figure 6. The impulse response analysis for the four-year intervals around 1997, 2003, and 2012