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Technological factors and total factor productivity in China: evidence based on a panel threshold model

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Abstract: This study investigates the effects of technological factors, including indigenous research and development (R&D) investments, technology spillovers coming from foreign direct investments, export, and import, on China's total factor productivity (TFP). Using provincial panel data of China, covering 30 provinces over the period 2000–2014, our results confirm that indigenous R&D investments play a leading role in promoting TFP. Linear analysis suggests that, except for export, the technology spillovers through openness are beneficial for TFP growth. However, a further discussion based on a panel threshold model suggests that the different behaviours of these technology spillovers are dependent on the technological absorptive capacity affecting factors, such as human capital and indigenous R&D investments. The human capital will strengthen the spillover effects of each technology spillover. However, R&D intensity initially tends to hamper their spillover effects. Once the R&D intensity exceeds a certain level, the negative spillover effect of export on TFP tends to be alleviated, and the positive spillover effect of foreign direct investment and import on TFP will increase.

Keywords: Technology spillovers; Technological factors; Total factor productivity; Panel threshold model.

1. Introduction

Since the Reform and Opening up initiated in 1978, the Chinese economy has boosted, reflected by an average annual economic growth in Gross Domestic Product (GDP) on an unprecedented scale of almost 9.8%, and more than 10% during the period after 1992, reaffirming China's continuous economic opening (Liu et al., 2018). For a long time, the engine of China's rapid GDP growth has been the input of capital and labour. However, in recent years, as external demand has continued to decline and domestic overcapacity has become increasingly serious, China's GDP growth has been slowing down. The constantly evolving macroeconomic situation of China in recent years implies that China's economic growth should be dependent on the growth of total factor productivity (TFP). The TFP growth, which means more output of an economy is produced from a given amount of inputs, plays a central role in the sustained economic growth of any economy. Therefore, it is quite important to investigate the driving forces of changes in TFP fluctuations and formulate effective policy implications and measures for China's policy makers to make long-term and sustainable development.

The trend of TFP growth is considered to be infulenced by a wide range of economic variables, such as technological factors, including indigenous research and development (R&D) and technology spillovers, market regulations, and financial developments. Many scholars agree that developing countries can possibly promote TFP by maximising the use of technology spillovers that are embodied in foreign direct investment (FDI) and trade and are transferred from developed countries. Considerable research corroborates that international openness influences the growth and productivity of host countries through technology spillovers. However, the current knowledge of their spillover effects is limited; hence, drawing general conclusions as to how these openness channels affect China's TFP is fairly difficult. This problem results from the following specific reasons. Initially, the proxy variables for their spillover effect on TFP are rather different in the existing empirical literature. For instance, at either provincial or city level in China, several different proxy variables in the case of FDI are available. Tuan et al. (2009) chose the actual use of FDI to reflect its spillover effect on TFP. Qi et al. (2009) defined the effect of FDI on TFP as the ratio of investment in fixed assets by foreign-funded enterprises to gross investment in fixed assets. Xie and Wu (2014) took the ratio of FDI to GDP to denote its spillover effect on Chinese provincial TFP. Inconsistent with these studies, Cai and Chen (2010) and Xiao and Lin (2011) borrowed the framework of Coe and Helpman (1995) and Van Pottelsberghe de la Potterie and Lichtenberg (1998) (hereafter CH-LP) to investigate the influence of FDI on China's TFP. The same problems can also be found in studies exploring the effects of trade on TFP. Accordingly, the different proxy variables for either FDI or trade may result in biased or mixed regression results. In addition, a few papers have presented the concomitant impacts of indigenous R&D, FDI, export, and import on TFP in the case of China. Analysis and comparison of different technological factors that influence TFP must be conducted under one united framework.

Second, technology spillovers from FDI, export and import on TFP could be heavily influenced by a host country's specific characteristics, such as the stock of human capital, financial development, technological gaps, and indigenous innovation efforts (Zhao and Zhang, 2010; Fuchs-Schündeln and Izem, 2012; Su and Liu, 2016; Burda and Severgnini, 2018). Given that China is a large country with substantial variations in its economic development level across provinces, there is an enormous regional imbalance in terms of technological absorptive capacity, which may lead to different spillover effects (Curtis, 2016; Huang et al., 2018). Only a few of the previous empirical studies based on China's sub-province data examine this issue. In these extant empirical studies, the conventional linear regression method may suffer multicollinearity problems and fail to solve the problem of a structural break in the impact of technology spillovers on TFP. Consequently, this method only presents an average effect of technological factors on TFP, which is not an objective depiction of reality.

Third, the economic reform will also exert a strong effect on TFP. Countries with judicial and effective economic systems have high incomes and have an abundance of skilled labourers (Nunn, 2007; Curtis, 2016; Jin et al., 2018). They may have great incentives to develop and maintain a good contracting environment. In these countries, the resources are allocated rationally and the technological innovation factors flow reasonably. Furthermore, enterprises will have a highly appropriate business structure in terms of organisation and work specialisation, thereby encouraging them to specialise in adopting new technologies and management skills, which, in turn, promotes TFP. The effect of the economic reform on TFP has been captured by Pattnayak and Thangavelu (2002), Bartelsman et al. (2013), Curtis (2016), and Papaioannou (2017). The scenario that China's continual economic reform will influence provincial TFP in the long run is expected. However, only a few studies consider the impact of the economic reform on TFP.

To address these aforementioned problems, this study employs the CH-LP framework to examine the technological factors of China's TFP, using both linear and nonlinear analyses. The major contributions are threefold. First, this study considers technological factors, including indigenous R&D and technology spillovers through FDI, export, and import in a comprehensive and united framework, which enables us to compare their relative strengths in influencing TFP concurrently. Second, the roles that the domestic factors affecting absorptive capacity have played in TFP fluctuations are considered, which helps in accounting for regional heterogeneity and understanding how these technological factors affect TFP. Third, this study explores the role of the economic reform in improving TFP, which is seldom discussed in previous literature.

Our paper progresses as follows. Section 2 reviews the existing studies. Section 3 presents the empirical model, the data, and the estimation methods. Section 4 discusses the results based on conventional regression methods and the nonlinear analysis. Section 5 concludes the paper and provides policies related to improvements in TFP.

2. Literature review

The increasing desire for sustainable development has inspired an extensive amount of studies. Literature that addresses TFP can be roughly classified into two categories based on their different research purposes. The first strand aims to measure the TFP, and the other investigates the drivers of TFP growth.

2.1 Measuring total factor productivity

Due to the great importance of TFP in the production process, the measurement of TFP has received great attentions in empirical studies (Färe et al., 1994; Tone, 2001; Chen and Golley, 2014; Li and Lin, 2015; Chu and Cozzi, 2016). Up to now, two popular approaches, i.e., the parametric approach (e.g., Madsen, 2007; Cai, 2012; Yang et al., 2014; Curtis, 2016; Papaioannou, 2017; Edquist and Henrekson, 2017; Huang, 2018) and the non-parametric approach (e.g., Färe et al., 1994; Emrouznejad and Yang, 2016; Huang et al., 2017a; Jin et al., 2018), have been widely employed to measure TFP. For the parametric approach, TFP can be obtained as the Solow residual from the Cobb-Douglas production function in which the capital (K) and labor (L) are inputs to produce output (Y). The output elasticity of capital or labor can be estimated econometrically (Yang et al., 2014; Curtis, 2016) or using growth accounting framework (Madsen, 2007; Jorgenson et al., 2008; Cai, 2012; Papaioannou, 2017; Huang, 2018). Both econometrics analysis and growth accounting framework assess the contribution of inputs to output assuming constant returns to scale. However, the estimated elasticities on labor or capital coming from regression analysis are constant during the sample period. Inconsistent with the econometrics analysis, the output elasticity of capital or labor varies across place and period based on the growth accounting framework.

Non-parametric approach is another popular method concerning the measurement of TFP surrounding the Data Envelopment Analysis (DEA) and et al (Sahoo and Acharya, 2007; Ngo and Nguyen, 2012; Huang et al., 2017a). Superior to the parametric approach; it does not have to assume a specific production function in advance. For instance, the Malmquist TFP index is defined as the ratio of efficiency changes between two separate observations either in the same period or in the same production unit in two different time periods. The distance function is then employed to measure the TFP evolution directly. Besides, in recent studies, there has been a growing trend whereby many researchers have been motivated to measure the green TFP using the nonparametric approach including DEA-based method (Li and Lin, 2015; Emrouznejad and Yang, 2016).

2.2 The drivers of TFP

Apart from the measurement of TFP, the second strand of research that the current study relates to is a large body of empirical literature investigating the nexus between openness, R&D activities, human capital, economic reform and TFP. To motivate our paper, we briefly mention a few of them, but particularly emphasise the technological factors including indigenous R&D and technology spillovers coming from FDI and trade.

2.2.1 Indigenous R&D and TFP

R&D activities exert direct and indirect effects on TFP and constitute as a major engine for promoting overall economic development. Direct effect refers to technology innovations, whereas indirect effect means to facilitate the understanding and imitation of efficient technology transfer. Most of the existing literature has already highlighted how indigenous R&D activities contribute to explaining the growth of TFP at both macro and micro-level (Frantzen, 1998; Lai et al., 2006; Coe et al., 2009; Madsen et al., 2010; Tientao et al., 2016; Bengoa et al., 2017). At the macro-level, through a panel cointegration analysis of a sample of 21 Organization for Economic Co-operation and Development (OECD) countries over the period 1965–1991, Frantzen (1998) confirmed that indigenous R&D activities exert a positive and significant influence on TFP growth. Moreover, Griffith et al. (2004) found that R&D had been important for the convergence of TFP levels within industries across twelve OECD countries. By employing a panel dataset of China's 29 provincial agricultural sectors over the period 1990-2003, Chen et al. (2008) found evidence supporting that the public investment in R&D is associated with TFP growth. Coe et al. (2009) investigated the impact of R&D capital stock on TFP in the long run using a panel dataset covering 24 countries from 1971 to 1990 and panel cointegration technique. They asserted that the positive impact of R&D capital stock on G7 (Group oof seven) countries' TFP is larger than that on other countries' TFP. By employing a panel dataset covering 12 OECD countries and 15 manufacturing industries between 1995 and 2005, Badinger and Egger (2016) found sizeable R&D effects on productivity primarily within or among similar industries. Tientao et al. (2016) estimated indigenous R&D and its spatial spillovers on TFP based on a sample of 107 countries for the period 2000–2011. They found that both indigenous R&D and its spillovers play a positive and significant role in increasing TFP. Bengoa et al. (2017) applied the panel cointegration approach and a panel dataset covering Spanish regions during 1980-2007 to estimate the long-run effects of R&D activities on TFP. The empirical results show a significant direct effect of public R&D investment on TFP. At the micro-level, similar evidence for the roles of R&D played in TFP growth is also found. On the basis of considerable firm-level data over the period 2003–2006, Qi et al. (2009) explored the role of indigenous R&D in TFP for Chinese enterprises. They concluded that R&D plays a positive role in TFP growth and that domestic firms with great absorptive capacity benefit from positive productivity spillovers from FDI. Based on a large panel dataset covering Swiss 50 industries between 1993 and 2013, Edquist and Henrekson (2017) compared the roles of Information and Communication Technology (ICT) investments and R&D investments on TFP growth. They found that only R&D invesments alone is significantly associated with contemporaneous TFP growth, suggesting that R&D affects TFP much faster than ICT-investments. Apart from the considerable direct effects from R&D, Lai et al. (2006), Hu and Tan (2016), and Edquist and Henrekson (2017) also showed that indigenous R&D exerts an indirect effect on TFP growth.

2.2.2 Technology spillovers and TFP

Although indigenous R&D has been assumed to be a key factor in TFP growth, there is no doubt that technology spillovers through openness in the form of FDI and trade are also regarded as one of the most important factors that influence TFP against the background of an open economy. First, the opening up to the rest of the world was accompanied by an extensive increase of FDI inflows. As early as in 2002, China overtook the United States as the world's largest recipient of FDI. As FDI has been dominated by capital- and technology-intensive varieties, they can transfer advanced technologies and managerial experience to local firms through technology spillover effects. Accordingly, technology spillover coming from FDI is expected to promote productivity and efficiency (Saggi, 2002; Hübler and Keller, 2010; Madsen et al., 2010; Ahmed, 2010; Fujimori and Sato, 2015; Liu et al., 2016; Huang et al., 2018). However, in empirical studies, the corresponding benefits of FDI accruing to the host country are not obvious, and they turn out to be either negligible or even negative. For instance, Wang and Liu (2008) borrowed the CH-LP framework to analyse time series from 1985 to 2005 for China. They confirmed that technology spillovers that come from FDI promote China's TFP at a highly significant level. Using DEA-Malmquist method and the CH-LP framework, Xiao and Lin (2011) explored the effect of technology spillovers through FDI and import on China's provincial TFP. They confirmed that FDI plays a positive and significant role in increasing TFP and its components. However, there is also a large volume of empirical literature failing to find positive evidence for FDI on TFP growth. Qi et al. (2009) corroborated that the effect of FDI's technology spillover on TFP can be either positive or negative, depending on the absorptive capacity of China's local firms. Cai and Chen (2010) investigated the impact of FDI and import on TFP by employing the CH-LP framework and China's provincial dataset from 1990 to 2008. They showed that a great difference in the spillover effects emerges across China's regions. In Eastern China, technology spillovers through import play a more important role than does FDI, whereas the impact of FDI on TFP is more evident in Central China than is that of import. However, no significant spillover effect exists in Western China. Javorcik and Spatareanu (2011) employed firm-level panel data from Romania to investigate whether the origin of FDI influences TFP. The evidence suggests that there is significant indication that FDI comes from the European investors and American investors exert different effects on TFP. Fujimori and Sato (2015) explored the effect of FDI on TFP in both the long- and the short-run using Indian macro aggregated panel data over the period 1995–2004. They confirmed that FDI stock increases TFP mainly through backward linkage effects in the long-run, although it decreases TFP in the short-run. By relying on a specially designed survey of over 4000 manufacturing firms in Vietnam, Newman et al. (2015) explored the nexus between FDI and the productivity of host country domestic firms. The results confirm that positive spillovers from downstream FDI firms, in particular joint venture FDI firms, to domestic input suppliers, and negative spillovers from upstream FDI firms to downstream domestic producers. The two controversial viewpoints in the above literature indicate that the benefits from FDI are not automatically formed and stable.

Second, open trade, including export and import, is conducive to the free flow of technologies across borders and helps enhance competitive pressure and the opening up of new markets. It provides a way for global firms to exploit innovations and is generally shown as being one of the important channels that facilitates the spillovers of knowledge and technology among trade partner countries (Miller and Upadhyay, 2000; Lucas, 2009; Cai and Chen, 2010; Huang et al., 2017b). Unfortunately, the empirical evidence provided in many of previous studies is still controversial and inclusive across either countries or regions. By employing a panel dataset covering 83 countries between 1960 and 1989, Miller and Upadhyay (2000) concluded that large amounts of trade result in great openness, which facilitates an economy's adoption of highly efficient techniques of production and leads to fast TFP growth. Using a dataset of 16 OECD countries over the period of 1870–2004, Madsen (2007) tested whether knowledge has been transmitted internationally through the channel of trade. He affirmed a robust relationship between TFP and imports of technology. In addition, the imports of technology should be responsible for 93% of the increase in TFP over the past century. At the micro-level, Parameswaran (2009) also provided detailed evidence on supporting that trade openness promotes technological progress in Indian Manufacturing Industry. Using a large firm-level dataset from China's manufacturing industries, Hu and Tan (2016) found that the degree of export participation is positively correlated with TFP improvements. However, some previous literature has also provided reverse evidence. For instance, Xiao and Lin (2011) discovered that only the imports of capital products play a positive role in increasing China's TFP and that, conversely, the imports of consumption products decrease TFP. By employing a panel dataset comes from annual surveys of manufacturing firms conducted by the National Bureau of Statistics of China between 1998 and 2005, Du et al. (2017) found that domestic firms displayed significant productivity gains upon export entry, whereas foreign affiliates showed no evident TFP changes.

2.2.3 Other factors and TFP

Other factors including human capital, indigenous R&D, economic reform, technological gap, and social capital are occasionally discussed in TFP literature. Curtis (2016) explored the effect of economic reform on China's TFP in non-agricultural economy from 1992 to 2007. He found that TFP growth could be gained by expanding the private sector and closing the least productive state enterprises. Using 1,328 items of firm-level data between 2003 and 2008, Liu et al. (2016) confirmed that the effect of FDI spillovers on TFP depends on the productivity gap and the share of foreign equity participation. Based on a panel dataset of Chinese cities over the period 1991–2010, Su and Liu (2016) argued that the effect of FDI on productivity growth could be intensified by the human capital endowment of the city. Bengoa et al. (2017) investigated the impacts of human capital and social capital on TFP by taking a spatial approach for Spanish regions during 1980–2007. They verified that human capital and social capital exert direct positive impacts on TFP growth. Moreover, their effects are geographically bounded, and negative spatial spillovers offset direct outcomes.

Based on the above literature reviews, we find that the knowledge of understanding the effects of different technological factors on TFP has not come to a consensus. Apart from the use of different proxy variables, the possible presence of threshold effects may be another major cause. However, the traditional linear regression method cannot solve the problem of structural break in the impact of independent variables on TFP, and cannot find additional details about the roles of the factors affecting absorptive capacity played on TFP.

3 Methodology and data management

3.1 Model specifications

3.1.1 General model

Under the background of an open economy, China's technological progress is not only determined by domestic R&D inputs but is also influenced by international knowledge spillovers, either directly or indirectly. Hereby, we define TFP for China as follows:

$$TFP = AS^{\gamma} \tag{1}$$

where *TFP* denotes the total factor productivity; *A* is the constant, representing the exogenous factors of an economic environment; and *S* represents R&D stock, an excellent measure of knowledge depending on indigenous R&D activities and technology spillovers coming from foreign countries.

$$S = (S^{D})^{\alpha}(S^{F})^{\beta} \tag{2}$$

where S^{D} and S^{F} stand for the domestic R&D capital stock and the technology spillovers coming from foreign countries, respectively. We assume that three major openness channels, namely, FDI, export, and import, are available in the case of China.[1] Accordingly, the total R&D capital stock for China can be shown as follows:

$$S = (SRD)^{\alpha}(SFDI)^{\beta_1}(SEX)^{\beta_2}(SIM)^{\beta_3} \tag{3}$$

where *SRD* denotes the indigenous R&D capital stock, and *SFDI*, *SEX*, and *SIM* refer to the technology spillovers through FDI, export, and import, respectively. Substituting Eq. (3) with Eq. (1) and making natural logs of both sides, we have:

$$\ln TFP_t = \beta_0 + \beta_1 \ln SRD_t + \beta_2 \ln SFDI_t + \beta_3 \ln SEX_t + \beta_4 \ln SIM_t + \varepsilon_t \tag{4}$$

where t represents the time term, ε_t represents the stochastic error term, and $\beta_i (i = 1, 2, 3, 4)$ stand for the elasticity coefficients of indigenous R&D capital stock and technology spillovers from FDI, export, and import respectively.

3.1.2 Technology spillovers based on the CH-LP framework

Given that we cannot obtain the data between China's provinces and China's

In fact, outward direct investment (ODI) is also an important technology spillover channel in international academia (Coe and Helpman, 1995; Van Pottelsberghe de la Potterie and Lichtenberg, 1998). However, China's "Going Out" strategy was carried out late, and the official data collection at the provincial level began in 2004. In addition, the size of ODI is much smaller than that of FDI. Consequently, we did not consider the impact of ODI on TFP.

cooperative partner countries or regions from officially published statistics, we hypothesise that China's provinces have experienced technology spillovers in the proportion of their FDI, export, and import to the total FDI, export, and import between China and its trade partner country (region), respectively. The spillovers received by province m (m=1, 2 ,…, K, N) can be achieved by timing the technology spillovers received by China and the share of province m's FDI, import, and trade to the total. On the basis of the CH-LP framework, the technology spillovers transferred through FDI, import, and export for China's provinces can be presented as:

$$SFDI_{mt} = \frac{FDI_{mt}}{FDI_t} \sum_{n=1}^{N} \frac{FDI_{nt}}{K_{nt}} S_{nt}^{d} \tag{5}$$

$$SIM_{mt} = \frac{IM_{mt}}{IM_t} \sum_{n=1}^{N} \frac{IM_{nt}}{Y_{nt}} S_{nt}^{d} \tag{6}$$

$$SEX_{mt} = \frac{EX_{mt}}{EX_t} \sum_{n=1}^{N} \frac{EX_{nt}}{Y_{nt}} S_{nt}^{d} \tag{7}$$

where the subscripts m and t denote China's province and year, respectively. N is the number of partner countries (or regions). $SFDI_{m,t}$, $SIM_{m,t}$, and $SEX_{m,t}$ refer to the technology spillovers received by province m coming from FDI, import, and export, respectively. $FDI_{n,t}$ stands for the partner country (or region) n directly invested in China at time t. $IM_{n,t}$ stands for China's exports to its trade partner country n. $EX_{n,t}$ denotes China's exports from its partner country (or region) n. $\frac{FDI_{mt}}{FDI_t}$, $\frac{IM_{mt}}{IM_t}$, and $\frac{EX_{mt}}{EX_t}$ can be recognized as the share of province m's FDI, import, and export to China's total FDI, import, and export, respectively. K, S, and Y represent the gross fixed capital formation, R&D capital stock, and GDP of the partner country (region), respectively.

3.1.3 Control variable

China has made many economic reforms since 1978. Among them, the continual stated owned enterprise (SOE) reform that includes a gradual clarification and decentralisation of property rights has received considerable attention. Since the latter half of the 1990s, many of China's SOEs have been converted to shareholding enterprises. Given that SOEs are poorly managed compared with non-state enterprises (Sinton and Fridley, 2000; Scherngell et al., 2014; Curtis, 2016), the efficiency of SOEs may be lower than is that of non-state enterprises, such as private enterprises and foreign-owned enterprises. As suggested by Herrerias et al. (2013), we introduce the share of output represented by state-owned industrial enterprises above designated size in all industrial enterprises above designated size[2] (hereafter the share of SOEs) to reflect the impact of the economic reform on TFP.

3.1.4 Empirical model

The model outlined above is estimated as a panel data model, which is shown as follows:

$$\ln TFP_{i,t} = \beta_0 + \beta_1 \ln SRD_{i,t} + \beta_2 \ln SFDI_{i,t} + \beta_3 \ln SEX_{i,t} + \beta_4 \ln SIM_{i,t} + \beta_5 \ln SE_{i,t} + \varepsilon_{it} \quad (8)$$

where subscripts i ($i = 1,2,3,\ldots K,N$) and t ($t = 1,2,3,\ldots K,T$) indicate provinces and years, respectively. ε_{it} is the error term. *SE* stands for the economic reform, which is represented by the share of SOEs. Other variables share the same meaning as equation (4). β_m ($m = 0,1,\ldots,5$) denote the coefficients to be estimated.

Due to the great inertia of TFP, the TFP for adjacent years will remain almost constant. Therefore, this dynamic factor should be considered. To explicitly introduce dynamic factors into the regression equation, we add the TFP in the previous year ($\ln TFP_{i,t-1}$) to the panel model, then the empirical model of TFP can be specified as a reduced form:

Before 2011, the enterprise above designated size means that the output of this enterprise is more than 5 million Yuan RMB in the current year.

$$\ln TFP_{i,t} = \alpha \ln TFP_{i,t-1} + \beta_1 \ln SRD_{i,t} + \beta_2 \ln SFDI_{i,t} + \beta_3 \ln SEX_{i,t} + \beta_4 \ln SIM_{i,t} + \beta_5 \ln SE_{i,t} + \varepsilon_{i,t} \quad (9)$$

Since the introduction of the first-order lag term of the dependent variable into the right-hand side, regression equation (9) becomes a standard dynamic equation. Dynamic models are advantageous over static models, because they easily capture more information on TFP evolution. However, the residual term $\varepsilon_{i,t}$ may be related to the first-order lag term of the dependent variable. For the estimation, the traditional ordinary least square method is inapplicable, because it will produce biased estimates. Arellano and Bond (1991) developed a generalised method of moments (GMM) estimator, which yields consistent parameter estimates for this model type. This approach is suitable when the number of cross sections is much larger than that of time periods. In addition, this approach is superior in eliminating the unobserved specific heterogeneity with a first differencing transformation. The current study uses the differencing GMM (Diff-GMM) approach to estimate the dynamic models.

3.2 Measuring TFP

In this section, we present the measures of TFP for China's provincial regions based on growth accounting introduced in Section 2.1. The technological innovations and improvements as well as more efficient use of existing inputs contribute to the TFP growth. To construct the TFP data for the current study, the growth accounting method which is a parametric approach is employed. The Cobb–Douglas production function, where factors' shares are allowed to change over time and across regions based on the Divisia–Tornqvist index (e.g., Madsen, 2007; Cai, 2012; Papaioannou, 2017; Burda and Severgnini, 2018; Huang, 2018) is shown as:

$$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha_{i,t}} L_{i,t}^{\beta_{i,t}} \quad (10)$$

where the subscripts i (i=1, 2, 3, …, K, N) and t (t=1, 2, 3, …, K, T) indicate provinces and years, respectively. $Y_{i,t}$ denotes the real GDP of each province in period t, K refers to the physical capital stock of each province, and L stands for the labour input measured as the number of employees in three industries. $\alpha_{i,t}$ and $\beta_{i,t}$ denote the shares of the capital's reward and labour's reward at period t for province i respectively, and they are subject to $\alpha_{i,t}+\beta_{i,t}=1$. A is a labor and capital neutral technology parameter, associated with TFP. Based on equation (10), direct measures of TFP for each province i and time t can be obtained by:

$$TFP_{i,t}=\frac{Y_{i,t}}{K_{i,t}^{\alpha_{i,t}}L_{i,t}^{1-\alpha_{i,t}}} \tag{11}$$

In the following, the most important step is to determine the income share of capital. Following Cai (2012) and Huang (2018), the income share of the capital can be obtained through $\alpha_{i,t}=\left(D_{i,t}+B_{i,t}+P_{i,t}\right)/GDP_{i,t}$, where the footnotes i and t stand for province and period, respectively. D, B, P, and GDP denote the aggregate capital depreciation of fixed assets, the operating surplus, net taxes on production, and the gross domestic product, respectively. All the corresponding data can be found in the *China Statistical Yearbook* (various years).

3.3 Data and estimation methods

3.3.1 Data source and management

Considering the availability of data, we choose China's 30 provinces over the period 2000–2014 in the study, encompassing 450 observations. The measurements and management of the variables used to perform the statistical estimations are summarised as follows:

(1) Output production

The values of output production (Y) are measured by real GDP at the provincial level in the unit of 100 million RMB (Yuan) and are converted to the 2000 constant price using the GDP deflator. The corresponding data can be obtained from the *China Statistical Yearbook*.

(2) Physical capital stock

The physical capital is denoted by the fixed asset investment. The variable should be initially deflated to the constant price in 2000 using the provincial-level price indexes of the investment in fixed assets. Thereafter, the perpetual inventory method is used to obtain the capital stock:

$$K_t = I_t + (1-\sigma)K_{t-1} \tag{12}$$

where K_{t-1} is the physical capital stock in the previous year, and K_t and I_t are the physical capital stock and the fixed investment for the current year, respectively. The capital depreciation rate i.e., σ is assigned to be 5%[3]. In accordance with Huang et al. (2018), Capital stock K for the base year (2000) can be obtained through $K_{2000}=I_{2000}/(g+\sigma)$, where g stands for the annual growth rate of the fixed asset investments between 2000 and 2014. I_{2000} and I_{2014} denote the fixed asset investments in 2000 and 2014, respectively.

(3) Labour inputs

The data on labour inputs for each province are denoted by the number of employees in three industries taken from the *China Provincial Statistical Yearbooks.*

(4) Indigenous R&D stock

The data on indigenous R&D for each province are denoted by intramural expenditures on R&D taken from the *China Statistical Yearbook on Science and Technology* (various years). The data on R&D are first converted into the constant price in 2000 using the GDP deflator index. The perpetual inventory method is then

[3] In the case of China's provincial dataset, authors applied different physical capital stock depreciation rates in their studies. For instance, Xiao and Lin (2011) took the capital depreciation rate as 5%. Deng and Wang (2016) constructed a capital stock series by the perpetual inventory method, with an annual depreciation rate of 6%. Huang (2018) suggested 9.6% for σ.Yang et al. (2014) assigned the capital depreciation rate to be 15%.

applied to calculate the R&D stock, as mentioned above. Since there is significant difference between the physical capital stock and R&D capital stock, a different depreciation rate for R&D capital stock is set to be 9.6% for each year[4] (Xiao and Lin 2011; Scherngell et al., 2014)..

(5) Technology spillovers

According to the published statistical data from the National Science Foundation, and UNESCO (United Nations Educational, Scientific and Cultural Organisation) et al., most global R&D expenditures are enjoyed by developed countries (region). By considering China's main partners, as characterised by investment and trade, G7 countries (i.e., the United States, Canada, Germany, England, France, Italy, and Japan) are considered as being the main sources of technology spillovers. In addition, as Hong Kong, South Korea, and Singapore have a big impact upon FDI and trade of the Chinese mainland, the G7 countries, Hong Kong, South Korea, and Singapore are selected as the main sample in the empirical study.

FDI is denoted by actual use of FDI. The data on China's imports form and exports to these countries (regions)[5] are, respectively, calculated as the customs of the countries (regions) of origin and destination. These data can be found in the *China Statistical Yearbook*. The data on export, import, and FDI for China's provinces come from the *China Provincial Yearbooks* (various years). The data on gross fixed capital formation and expenditures on R&D of these foreign countries (regions) can be found in the World Bank database. Finally, the perpetual inventory method (σ=9.6%) is employed to obtain the data on R&D capital stock for these foreign countries or

[4] To conduct a sensitivity analysis, we also respectively use 15% as the depreciation rate for indigenous R&D capital stock and 9.6% for physical capital stock. The coressponding results are presented in Appendix. In our estimation, effects of technological factors on TFP are not sensitive to different depreciation rates of the physical capital stock and indigenous R&D capital stock as used in this literature.

1: According to Huang et al. (2017b), a large proportion of China's commodities exported to Hong Kong are only en route, and only a small part is retained. Hereby, the data on China's exports to Hong Kong should be adjusted by subtracting the amount of re-exports. For simplicity, we assume that China's exports to Hong Kong are the same as are Hong Kong's exports to China.

regions.

(6) The share of SOEs

The data on the share of SOEs for China's provinces in each year can be obtained from the *China Industry Statistical Yearbook*. Table 1 shows the definition and description of the aforementioned variables in the regression model.

3.3.2 Estimation methods

On the basis of the above analysis, we initially investigate the effects of technological factors and the economic reform on TFP using a conventional linear regression technique. Fixed effects (FE) and random effects (RE) are popular estimators used to analyse panel data. The Hausman test (Hausman, 1978) is employed to determine whether either FE or RE would be suitable. When the presence of heteroskedasticity or serial correlation has been detected, the results coming from FE or RE estimations might be biased. Thereby, either the feasible generalised least squares (FGLS) method or the panel-corrected standard errors (PCSE) method would be a possible alternative. However, both FGLS and PCSE are poor if the cross-sectional dimension is larger than is the time dimension. Finally, we employ the Driscoll–Kraay (DK) estimation, by which the standard error estimates are robust to the general forms of cross-sectional and temporal dependence (Hoechle, 2007). Given that a province with low TFP tends to promote its TFP by increasing the indigenous R&D inputs, a mutual effect could occur between TFP and R&D activities, and the model may suffer from endogeneity. The instrumental regression technique is effective in controlling the possible endogeneity problem. To make the regression immune to potential endogeneity problems, we adopt the fixed effects instrumental variable (FE-IV) for estimation. In addition, to obtain additional hints on the evolution of the TFP, we also include the dynamic panel model based on the Diff-GMM estimator. Table 2 reports a series of results estimated by the DK, FE-IV, and Diff-GMM estimators, with σ=5%

and σ=9.6% for calculating physcial capital stock and indigenous R&D capital stock, respectively. For simplicity, we have not shown the results based on FGLS and PCSE estimations in Table 2.

Considering that the effects of the technology spillovers on TFP are affected by domestic factors affecting absorptive capacity (Miller and Upadhyay, 2000; Qi et al., 2009; Ahmed, 2012; Liu et al., 2016; Bengoa et al., 2017) and that the traditional linear regression method fails to tackle structural breaks, we re-examine their effects on TFP by applying Hansen's endogenous threshold approach (Hansen, 1999; 2000). The panel threshold analysis can investigate the changes in the impact that the independent variable has on TFP at different intervals. The threshold regression model with one threshold value can be described as follows:

$$\ln TFP_{i,t} = \begin{cases} \alpha_i + \beta_1 X_{i,t} + u_{i,t} & q_{i,t} < \gamma \\ \alpha_i + \beta_2 X_{i,t} + u_{i,t} & q_{i,t} \geq \gamma \end{cases} \quad (13)$$

where subscripts i and t refer to province and time, respectively. $\ln TFP$ is the natural logarithm of TFP. α_i denotes the level of province i fixed-effect. $u_{i,t}$ is a zero mean, finite variance, i.i.d. disturbance. X refers to the vector of independent variables, including indigenous R&D, technology spillovers, and the economic reform. β_1 and β_2 denote the vectors of coefficients of the independent variables on the two sides of the threshold. If the single threshold is confirmed, the question of whether there is a double threshold effect should be tested through:

$$\ln TFP_{i,t} = \begin{cases} \alpha_i + X_{i,t}^{'} \beta_1 + u_{i,t} & q_{i,t} \leq \gamma_1 \\ \alpha_i + X_{i,t}^{'} \beta_2 + u_{i,t} & \gamma_1 < q_{i,t} \leq \gamma_2 \\ \alpha_i + X_{i,t}^{'} \beta_3 + u_{i,t} & \gamma_2 < q_{i,t} \end{cases} \quad (14)$$

where β_1, β_2, and β_3 represent the vectors of coefficients of the independent variables on the three sides of the threshold. $\gamma_i\ (i = 1,\ 2)$ denotes the corresponding threshold value. $q_{i,t}$ are the threshold variables that we have chosen to reflect the technology absorptive ability. The human capital represented by the average years of schooling (unit: years) and R&D inputs (defined as the ratio of R&D inputs to GDP; unit: %) are selected as the reflectors of absorptive capability. The average years of schooling can be calculated as follows:

$$HC = \frac{6n_1 + 9n_2 + 12n_3 + 16n_4}{Total} \tag{15}$$

where n_i (i=1,2,3,4) denote the number of population who receives Primary schooling, Junior Secondary schooling, Senior Secondary schooling, and College and Higher level, respectively. Total stands for the number of population aged 6 and above. The corresponding data can be obtained from the *China Statistical Yearbook*.

4 Results and discussion

4.1 Linear analysis

Table 2 reports the estimated parameters of all four models. Columns (2), (3), and (4) present the results based on the static models, including the FE, DK, and FE-IV estimations. Column (5) shows the results based on the dynamic model by employing the difference GMM estimator. The Hausman test is significant at the 1% level, suggesting that the FE estimator should be fit for our model. With the modified Wald test for the group-wise heteroskedasticity, developed by Greene (2000), and the Wooldridge test, presented by Wooldridge (2002), for autocorrelation, serial correlation and heteroskedasticity are detected in the FE model. Therefore, Column (3) presents the results based on the DK estimator. To both check the robustness of our results against possible endogeneity among the regressors and obtain additional information on the TFP fluctuation, we further apply the FE-IV and Diff-GMM estimators. Columns (4) and (5) provide the results with the FE-IV and Diff-GMM estimators, respectively.

Table 2 shows that, for all the static models, the estimated results confirm the positive and highly significant impacts of the indigenous R&D on TFP. In addition, the coefficient of indigenous R&D (ln*SRD*) is quantitatively larger than are those of the technology spillovers coming from FDI, export, and import, thereby indicating that China's indigenous R&D inputs play a more important role in increasing TFP compared to the technology spillovers coming from openness. Regarding the technology spillovers, FDI (ln*SFDI*) and import (ln*SIM*) positively and consistently increase TFP, although a difference in the significance among the models occurs. FDI inflows are potentially important sources of China's productivity improvements, because foreign-invested firms are technologically superior. They can help the industries of the host country to catch up with the international technology frontier through their interactions. The developing countries are likely to be the major beneficiaries of the technology spillovers coming from import. First, imports expand varieties of inputs which reduce the cost of innovation and engender creation of more variety. Second, by imitating the imported goods and improved application methods adopted along with the imported goods, import is also conducive to TFP growth. Theoretically, to enhance the competitiveness of the products in the world market, local firms have initiated to adopt the advanced technology. In addition, the increasingly strict green trade barriers also oblige local firms to improve their production technology. Therefore, the technology spillover coming from export may facilitate the economy's adoption of more efficient techniques of production. However, an interesting finding is that the coefficient of the export ($\ln SEX$) is consistently negative in the four models, suggesting that the technology spillover from export has stunted China's TFP growth. The following two reasons may be responsible for this nexus in the case of China. First, Chinese policymakers have long taken exportation as one of the three main engines to sustain rapid economic growth by Chinese policymakers. To encourage the development of China's export-oriented industries, policymakers implement a wide range of policies, including either freedom from or reduction of duty/value added tax and exemptions of export tariff. To take advantage of these preferential economic policies, multinational enterprises have been transferring certain low-technology industries, such as pulp and paper, chemical products, and chemical feed stock, into China. Second, domestic firms are also lured into producing massive amounts of low added-value commodities with few production costs. Consequently, technology spillovers through exports have not had a positive impact in improving China's TFP.

Interestingly, the coefficient of economic reform (ln*SE*) is positive in all four models, indicating that an increase in the share of SOEs will promote TFP, which is not consistent with our assumption. Given China's special economic system, SOEs have controlled and monopolised certain industries, including the petroleum and petrochemical industry and the communication industry, et al., which are closely connected with the economic lifeline of a country. The monopoly of these industries has made great contributions to the steady development of China's economy. Therefore, the monopoly of some industries in China may contribute to the increase of TFP.

There may be potential problems with endogeneity in the models reported for the FE and DK estimators. To address this problem, the estimation results based on the FE-IV estimator and the GMM estimator are also illustrated in Table 2. In the FE-IV estimation, the one period lag of R&D capital stock (ln*SRD*) is selected as the IVs. As reported, the results from the FE-IV estimation are generally consistent with those from the FE and DK estimators. For the dynamic panel model, the estimated coefficient on the lagged TFP variable ($L\ln TFP$) is positive and statistically significant at the 1% level, suggesting that the evolution of TFP has strong inertia over time. Hence, the current TFP is heavily influenced by the TFP in the previous year. However, the major issue with the GMM approach is the choice of appropriate IVs, which leads to the problem of over-identification. To deal with this problem, the Hansen test is conducted. The IVs used in GMM and the corresponding autocorrelation tests are described in the notes to Table 2. AR(1) and AR(2) are Arellano and Bond (1991) tests for the first-and second-order autocorrelations, respectively. Because the *p*-values of the Hansen tests and the Arellano and Bond (1991) tests of AR(2) for GMM are both well above 0.1, the IVs utilised in the GMM estimations are both well-designed and valid. Besides, these post-estimation results verify that the dynamic panel model is an appropriate specification for China's TFP.

In order to check the robustness of the results, the estimated results shown in Appendix (Table 1) were repeated with a 9.6% depreciation rate for physical capital stock and a 15% for indigenous R&D capital stock employed to the stock of knowledge. As shown, the estimated results are, for the most part, highly significantly similar, reinforcing the results and the inference in the above-mentioned section. However, the capacity of a host country to absorb technology spillovers is likely to be dependent upon technological affecting factors, including human capital endowment, financial development, and initial technological level. In the following, we employ the panel threshold to further investigate how these factors determine the effects of different technology spillovers on TFP.

4.2 Nonlinear analysis

Before turning to nonlinear estimates, we first test whether the threshold effect exists between technology spillovers and TFP by using the R&D intensity and the human capital as the threshold variables. To determine whether the coefficient of the economic reform will change with the increase in the share of SOEs, we also test the threshold effect for the economic reform. Subsequently, we determine the number of thresholds and, finally, calculate the confidence intervals and the slope coefficients for the threshold parameters. For each of the bootstrap tests, 2000 bootstrap replications are used. Table 3 shows the tests of the threshold effects.

As shown in Table 3, a single threshold of *F*-statistics is significant at the 1% level, and a double threshold of *F*-statistics is also significant at the 5% level. In addition, the *F*-statistic is even significant at the 5% level for a triple threshold in some cases, which strongly rejects the linear structure of the model. The results that the economic reform and each technology spillover have at least two threshold values at the 5% significance level confirm that their impacts on TFP are fairly sensitive to changes in the share of either SOE, R&D intensity, or human capital. They experience structural breaks when they are at different intervals.

Table 4 presents the estimated coefficients for the technology spillovers and the economic reform when R&D intensity, human capital, and the share of SOE are at different levels, respectively. Table 4, specifically rows 2–4, shows that, when the human capital is lower than the first threshold (6.89 years), the coefficient of FDI (ln*SFDI*) exerts a negative and insignificant role in TFP, indicating that the technology spillover through FDI decreases TFP. Once the human capital exceeds the first threshold, but is below the second threshold (7.93 years), the effect of FDI's technology spillover on TFP is changed, from being negative to positive; suggesting that the technology spillover through FDI can promote the TFP after the human capital exceeds 7.93 years. When the human capital is above the second threshold, a highly significant and postive effect of the technology spillover from FDI on TFP could be seen, indicating that the FDI's technology spillover promotes China's provincial TFP, with increasing effect as the human capital increases.

The results demonstrated in rows 5–7 of Table 4 confirm that the negative effect of export's technology spillover on TFP is always present. When the human capital is lower than the first threshold (6.89 years), the technology spillover through export will decrease TFP at the 1% significance level. With the increase of the human capital, the negative effect of export on TFP will decline not only in size but also in significance. If the human capital lies between the first threshold and the second threshold (10.25 years), then export's technology spillover still exerts a statistically significant and negative effect on TFP, but its size decreases from 0.1064 to 0.0519, accompanied by the decline in significance. Once the human capital exceeds the second threshold, the impact of the technology spillover from export will change from significant to insignificant but will remain negative. This finding proves that the increase in human capital alleviates the negative spillover effect of the export on TFP.

Similar to the results shown in rows 2–4 of Table 4, the effect of the technology spillover through import on TFP (rows 8–10 in Table 4) will change not only from negative to positive but also from insignificant to significant, implying that the human capital enhances the positive spillover effect of import on TFP. When the human capital is below the first threshold (6.89 years), import's technology spillover plays a negative but insignificant role in increasing TFP. Once the human capital exceeds the first threshold but remains below the second threshold (10.25 years), the effect of import's technology spillover on TFP is changed not only from −0.0139 to 0.0413 but also from insignificant to significant at the 10% level. When human capital is above 10.25 years, the import's technology spillover effect on TFP will increase from 0.0413 at the 10% level to 0.0596 at the 5% level.

However, as shown in rows 11–13 and 17-19 of Table 4, when the R&D intensity is smaller than the first threshold value (0.29), the effects of the technology spillovers through FDI and import will increase TFP at a highly significant level. Once the R&D intensity exceeds 0.29 but remains below the second threshold value (0.87), the effects of the technology spillovers coming from FDI and import will decrease in both value and significance. This suggests that the positive effects of technology spillovers coming from FDI and import will decrease. Fortunately, if the R&D intensity continues to increase and bigger than 1.15, then the positive effects of these technology spillovers coming from FDI and import on TFP will always be enhanced, accompanied by the rise in R&D intensity. However, as shown in rows 14-16 of Table 4, export's technology spillover tends to decrease TFP with significance when R&D intensity lower than the first threshold (0.29). Accompanied with the increase in R&D intensity, the export's negative spillover effect on TFP will increase in both value and significance. However, once the R&D intensity exceeds the second threshold (0.87), the negative effect of export's technology spillover will decrease consistently.

The results shown in row 20 of Table 4 confirm that, when the share of SOEs is taken as the threshold variable and is smaller than is the first threshold value (0.4207), then the effect of the share of SOEs on TFP is both positive and highly significant. Once the share of SOEs exceeds the first threshold but remains below the second threshold (0.7174), the coefficient of ln*SE* will not only increase from 0.0766 to 0.1471 but also go from being positive at the 5% significant level to being positive the 1% significant level, indicating that the rise in the share of SOEs will appear as an important impetus for TFP growth. However, if the share of SOEs continues to increase, exceeding 0.7174, then a negative spillover effect will take place, suggesting that the high share of SOEs will decrease TFP. Given the special economic system in

China, some industries should operate under Chinese governments. The monopoly of some industries has made a great contribution to the steady development of China's economy, which is beneficial to TFP growth. Consequently, the TFP tends to increase as the share of SOEs rises. However, the efficiency of SOEs may be lower compared with non-SOEs in most cases; the increase of the share of SOEs may lead to a decline of TFP when the share of the SOEs has attained a certain level.

In addition, to test the sensitivity of the threshold effect in the empirical results, we repeat the test with σ=9.6% for physical capital stock and σ=15% for indigenous capital stock. The corresponding results are reported in the Appendix. A comparison between Table 4 and the Appendix suggests that the estimated results are, for the most part, robust, even when we slightly change the thresholds values and the coefficients.

5 Conclusions and policy implications

As China has entered the "new normal", the country is very concerned with sustainable economic growth, which should be mainly dependent on TFP growth. Employing China's provincial panel data, covering 30 provinces over the period of 2000–2014, the current study builds a comprehensive framework that combines indigenous R&D and technology spillovers through openness in the form of FDI, export, and import. Linear regression methods, including the FE, DK, FE-IV, and Diff-GMM estimators, are applied to explore the behaviours of these technological factors on TFP. Given that China's regions are heterogeneous in terms of the development stage and mitigation potential, the effects of technology spillovers upon TFP may be influenced. Nonlinear analysis is further employed to investigate and verify the threshold effect of the technology spillovers on TFP. The main conclusions are as follows.

5.1 Conclusions

On the basis of the linear regression methods, we confirm that indigenous investments in R&D play a more important role in promoting TFP than do technology spillovers. Technology spillovers through openness are beneficial to TFP growth, except for export, although FDI's technology spillover on TFP is not estimated to be significant in all models. The increase in the share of SOEs also exerts a positive role in increasing TFP. In addition, China's TFP in a given year is greatly influenced by the TFP in the previous year.

Panel threshold model analysis confirms that the effects of the different types of technology spillovers on TFP are highly connected to the different levels of factors affecting technological absorptive capacity. In addition, the effect of the economic reform on TFP will change as the share of SOEs changes. When the human capital is relatively low, evidence that the technology spillovers through FDI and import will decrease TFP because of poor technological absorptive capacity emerges. Furthermore, the negative effect of export's technology spillover on TFP is great. As the human capital increases, the positive effects of the technology spillovers through FDI and import on TFP will appear and tend to increase, whereas the negative effect of export's technology spillover on TFP will decrease, suggesting that the accumulation of human capital can strengthen the spillover effect of the technology spillovers on TFP.

When the local R&D intensity is low, evidence that the technology spillovers through FDI and import could play a positive and significant role in increasing China's TFP emerges. Additionally, the export's technology will decrease TFP. As the R&D intensity increases but remains below a certain level, the positive effects of these technology spillovers on TFP tend to decrease, whereas the negative spillover effect from export will increase, suggesting that indigenous R&D intensity hampers the spillover effect of the openness on TFP. With a further increase in R&D intensity, the positive effect of the technology spillovers through FDI and import on TFP will increase, whereas the negative effect of export's technology spillover on TFP will decrease, indicating that the R&D intensity can also strengthen the spillover effect on TFP.

Incorporating the share of SOEs as another threshold variable, we also find a nonlinear relationship between the economic reform and TFP with the rise of the share of SOEs. When the share is relatively low, increasing the share of SOEs will tend to increase TFP. However, if the share of SOEs has exceeded a certain level, the increase in the share of SOEs will decrease TFP.

5.2 Policy implications

Technology spillovers are an important sources of China's TFP and will play a central role in the 'new normal' times. Consequently, China should, as much as is possible, take advantage of the technology spillovers. First, the Chinese government should still recognise the indigenous R&D as the most important element for promoting TFP. Second, as confirmed by the empirical results, the technology spillovers on TFP are dependent on factors affecting technology absorption capacity, indicating that China must take full account of the differentiated influences of different opening policies in formulating policies on promoting TFP. Third, the accumulation of human capital exerts a constant role in promoting the positive spillover effect of the three technology spillovers on TFP, indicating that the investments in social human capital are beneficial to promote the positive spillover effects of the openness. Specifically, R&D intensity does not play a consistent role in increasing TFP. Only when the R&D intensity exceeds a certain level will the increase of R&D intensity strengthen the positive spillover effect of the openness on TFP. Consequently, the Chinese government should conduct differentiated policies for different regions. For the provinces with relatively low R&D investment and human capital, policies to increase the human capital will contribute significantly to the increase in TFP.

The nonlinear relationship between the share of SOEs and TFP also presents insightful suggestions for promoting TFP. In China, the share of SOEs can exert a considerable positive effect on TFP growth only when it is maintained at a suitable level. Otherwise, the share of SOEs will decrease China's TFP.

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Table 1. Definition and description of variables.

variables	Definition (unit)	Mean	Std	Min	Max
ln*TFP*	ln form of total factor productivity	-0.0358	0.3572	-0.6614	0.7662
ln*SRD*	ln form of R&D stock (unit:10^8Yuan RMB)	5.3395	1.5375	1.0099	8.5575
ln*SFDI*	ln form of technology spillover through FDI (unit:10^8Yuan RMB)	3.0942	1.6471	-1.1378	5.8764
ln*SEX*	ln form of technology spillover through export (unit:10^8Yuan RMB)	4.0309	1.6636	0.1573	8.156
ln*SIM*	ln form of technology spillover through import (unit:10^8Yuan RMB)	3.9451	1.6690	-0.3783	7.8411
ln*SE*	ln form of the ratio of output represented by SOEs in industry to all industrial enterprises above designated size	-0.9046	0.5372	-2.2631	-0.1153

Note: SOEs refers to the state owned enterprises above a designated size. For the variables, the capital depreciation rates for calculating physical capital stock and indigenous R&D capital stock are assigned to be 5% and 9.6%, respectively.

Table 2.The estimated results based on FE, DK, FE-IV and Diff-GMM.

No	1	2	3	4
Method	FE	DK	FE-IV	Diff-GMM
Constant	-2.7761***	-2.7761***	-2.8747***	
	(0.0578)	(0.0576)	(0.0821)	
ln*SRD*	0.4382***	0.4382***	0.4457***	0.1867***
	(0.0198)	(0.0206)	(0.0359)	(0.0233)
ln*SFDI*	0.0208	0.0203	0.0364***	0.0173*
	(0.0151)	(0.0197)	(0.0105)	(0.0082)
ln*SEX*	-0.0592**	-0.0592	-0.0688***	-0.0514*
	(0.0242)	(0.0505)	(0.0231)	(0.0327)
ln*SIM*	0.0416*	0.0416**	0.0612**	0.0264**
	(0.0246)	(0.0154)	(0.0251)	(0.0104)
ln*SE*	0.0456	0.0465	0.0316	0.0568
	(0.0424)	(0.0424)	(0.0315)	(0.0485)
L.ln*TFP*				0.5749***
				(0.0241)
Hausman(p)	133.28(0.00)			
HT	361.72***			
ACT	95.42***			
AR(1)				-3.53(0.00)
AR(2)				-0.83(0.26)
Hansen				29.72(1)
Within-R^2	0.8901	0.8901	0.9142	
Obeservations	450	450	420	390

Notes: For the results shown in Table 2, the capital depreciation rate σ for physcial capital stock is assigned as 5%, and the capital depreciation rate for indigenous R&D is set to be 9.6%. DK represents the Driscoll–Kraay estimator; FE-IV refers to the fixed effects instrumental variables estimator. Diff-GMM stands for the differencing generalised method of moments (GMM) estimator. HT and ACT represent autocorrelation test and heteroscedasticity test, respectively. The null hypothesis for the heteroscedasticity test is that there is no heteroscedasticity, and the null hypothesis for the autocorrelation test is that there is no first order autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Values in () denote the std.error for the coefficient. The one period lag of R&D capital stock (ln*SRD*) is chosen as the instrument variable in the FE-IV estimation. For the Diff-GMM estimation, AR (1) and AR (2) are Arellano and Bond (1991) tests for autocorrelation in differences. Considering that the Hansen test is a better fit for heteroscedasticity, we choose the Hansen test (a test for over identification) restrictions, rather than the Sargen test. p-values for these tests are shown in parentheses. Estimation is based on the xtabond2 command in Stata 12. ln$TFP_{i,t-1}$ is chosen as the predetermined variable. ln*SRD* is considered as the endogenous variable. The first and above lags of the predetermined variable and the second and above lags of the endogenous variable are used for GMM-type instruments.

Table 3. Test of threshold effects.

Threshold variable	Independent variable	Hypothesis test	*F*-statistics	Critical values 90%	95%	99%
HC[b]	ln*SFDI*	Test for single threshold	9.2545***[a]	2.6691	3.7149	6.3097
		Test for double threshold	6.2193***	2.5571	3.5363	6.1466
		Test for triple threshold	3.4659*	2.8625	3.8902	6.2645
	ln*SEX*	Test for single threshold	15.4940***	2.8766	3.8955	6.3709
		Test for double threshold	6.5079**	2.5212	3.7740	6.5885
		Test for triple threshold	3.3136*	2.8069	4.1295	7.4621
	ln*SIM*	Test for single threshold	18.8436***	2.7511	3.8134	6.3195
		Test for double threshold	6.4785***	2.5400	3.6502	6.0476
		Test for triple threshold	3.3661*	2.7149	3.7220	6.0351
R&D intensity	ln*SFDI*	Test for single threshold	6.1946**	2.7561	3.7226	6.3483
		Test for double threshold	6.1145**	2.7757	3.8454	8.1155
		Test for triple threshold	5.7427**	2.5178	3.6890	7.4354
	ln*SEX*	Test for single threshold	5.2930**	2.7136	3.7832	7.4528
		Test for double threshold	5.6297**	1.1562	2.7249	7.7862
		Test for triple threshold	4.6341**	2.5356	3.9582	6.3676
	ln*SIM*	Test for single threshold	5.7482***	2.6721	3.6138	5.5242
		Test for double threshold	4.1525**	2.9087	3.4955	4.6979
		Test for triple threshold	6.0182**	2.7259	3.7871	6.5991
The share of SOEs	ln*SE*	Test for single threshold	13.6525***	2.3219	3.5240	6.2364
		Test for double threshold	6.3919**	3.5215	5.5409	7.8792
		Test for triple threshold	2.2852*	2.8248	3.9590	7.0341

Notes: the capital depreciation rate σ for physcial capital stock is assigned as 5%, and the capital depreciation rate for indigenous R&D is set to be 9.6%..

a***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

b: HC stands for the human capital.

Table 4. The estimated results based on panel threshold analysis.

Threshold variable	Independent variable	Threshold values	Variables	Coefficients	Threshold values	Variables	Coefficients	Threshold values	Variables	Coefficients
HC[a]	$\ln SFDI$	$\gamma < 6.89$	$\ln SFDI$	-0.0316	$6.89 \le \gamma < 7.93$	$\ln SFDI$	0.0028	$7.93 \le \gamma$	$\ln SFDI$	0.0319**[f]
			$\ln SEX$	-0.0592**[b]		$\ln SEX$	-0.0592**		$\ln SEX$	-0.0592**
			$\ln SIM$	0.0417*		$\ln SIM$	0.0417**		$\ln SIM$	0.0417**
	$\ln SEX$	$\gamma < 6.89$	$\ln SFDI$	0.0089	$6.89 \le \gamma < 10.25$	$\ln SFDI$	0.0089	$10.25 \le \gamma$	$\ln SFDI$	0.0089
			$\ln SEX$	-0.1064***		$\ln SEX$	-0.0519**		$\ln SEX$	-0.0328
			$\ln SIM$	0.0371*		$\ln SIM$	0.0371*		$\ln SIM$	0.0371*
	$\ln SIM$	$\gamma < 6.89$	$\ln SFDI$	0.0079	$6.89 \le \gamma < 10.25$	$\ln SFDI$	0.0079	$10.25 \le \gamma$	$\ln SFDI$	0.0079
			$\ln SEX$	-0.0542**		$\ln SEX$	-0.0542**		$\ln SEX$	-0.0542**
			$\ln SIM$	-0.0139		$\ln SIM$	0.0413*		$\ln SIM$	0.0596**
R&D	$\ln SFDI$ [c]	$\gamma < 0.29$	$\ln SFDI$	0.0926***	$0.29 \le \gamma < 0.87$	$\ln SFDI$	0.0254*	$0.87 \le \gamma < 1.15$	$\ln SFDI$	0.0367**
			$\ln SEX$	-0.0721***		$\ln SEX$	-0.0721***		$\ln SEX$	-0.0721***
			$\ln SIM$	0.0408*		$\ln SIM$	0.0408*		$\ln SIM$	0.0408*
	$\ln SEX$ [d]	$\gamma < 0.29$	$\ln SFDI$	0.0237*	$0.29 \le \gamma < 0.87$	$\ln SFDI$	0.0237*	$0.87 \le \gamma < 1.15$	$\ln SFDI$	0.0237*
			$\ln SEX$	-0.0438***		$\ln SEX$	-0.0588***		$\ln SEX$	-0.0322**
			$\ln SIM$	0.0395*		$\ln SIM$	0.0395*		$\ln SIM$	0.0395*
	$\ln SIM$ [e]	$\gamma < 0.87$	$\ln SFDI$	0.0292*	$0.87 \le \gamma < 1.15$	$\ln SFDI$	0.0292*	$1.15 \le \gamma < 2.99$	$\ln SFDI$	0.0292*
			$\ln SEX$	-0.0701***		$\ln SEX$	-0.0701***		$\ln SEX$	-0.0701***
			$\ln SIM$	0.0612***		$\ln SIM$	0.0464**		$\ln SIM$	0.0593**
The share of	$\ln SE$		$\ln SE$	0.0766**	$0.4207 \le \gamma < 0.7174$	$\ln SE$	0.1471***	$0.7174 \le \gamma$	$\ln SE$	-0.0696*

SOEs	$\gamma < 0.4207$								

Notes: (a) ***, **, and *denote significance at the 1%, 5%, and 10% levels, respectively. (b) HC denotes human capital stock. (c-f) When $1.15 \leq \gamma$, the coefficients for $\ln SFDI$ and $\ln SEX$ are 0.0455 (significant at the 1% level) and 0.0161 (significant at the 5% level), respectively. When $2.99 \leq \gamma$, the coefficient on $\ln SIM$ for is 0.0871 (significant at 1%).

Appendix.

Table 1. Robustness test for the linear analysis.

No	1	2	3	4
Method	FE	DK	FE-IV	Diff-GMM
Constant	-2.7064***	-2.7064***	-2.5662***	
	(0.0561)	(0.0517)	(0.0582)	
ln*SRD*	0.4404***	0.4404***	0.4351***	0.2447***
ln*SFDI*				
	(0.0179)	(0.0281)	(0.0238)	(0.0136)
ln*SEX*				
	0.0143	0.0143	0.0228*	0.0368**
ln*SIM*				
	(0.0143)	(0.0186)	(0.0132)	(0.0117)
ln*SE*				
	-0.0653***	-0.0653	-0.0797**	-0.1275
L.ln*TFP*	(0.0227)	(0.0434)	(0.0355)	(0.0966)
Hausman(p)	0.0442*	0.0442*	0.0468*	0.0328**
HT	(0.0235)	(0.0255)	(0.0315)	(0.0107)
ACT	0.0837*	0.0837*	0.0566	0.0173
AR(1)	(0.0576)	(0.0433)	(0.0484)	(0.0246)
AR(2)				0.5218***
Hansen	109.58(0.00)			(0.0363)
Within-R^2	233.82***			
Obeservations	93.71***			
				-3.41(0.00)
				-1.53(0.34)
				31.56(1)
	0.8977	0.8977	0.9013	
	450	450	420	390

Note: As a robustness test, the capital depreciation rates for calculating physical capital stock and indigenous R&D capital stock are assigned to be as 9.6% and 15%, respectively. All the variables and symbols share the same meanings as shown in Table 2.

Table 2. Robustness test for the nonlinear analysis.

Independent variable	Threshold variable	Threshold value	Coefficient
	HC[b]	$\gamma < 6.89$ $6.89 \leq \gamma < 7.93$ $7.93 \leq \gamma$	-0.0012 0.0169 0.0231
ln*SFDI*	RD intensity	$\gamma < 0.87$ $0.87 \leq \gamma < 2.99$ $2.99 \leq \gamma$	0.0626**[a] 0.0164 0.0557***
ln*SEX* ln*SIM*	HC RD intensity HC	$\gamma < 6.89$ $6.89 \leq \gamma < 9.76$ $9.76 \leq \gamma$ $\gamma < 0.28$ $0.28 \leq \gamma < 0.79$ $0.79 \leq \gamma < 2.99$ $2.99 \leq \gamma$ $\gamma < 6.89$ $6.89 \leq \gamma < 10.25$ $10.25 \leq \gamma$	-0.1176*** -0.0557** -0.0339 -0.0348 -0.0498* -0.0671** -0.0244* -0.0195 0.0438* 0.0646***
	RD intensity	$\gamma < 0.57$ $0.57 \leq \gamma < 0.79$ $0.79 \leq \gamma < 2.99$ $2.99 \leq \gamma$	0.0424** 0.0371* 0.0551** 0.0714***

Notes: As a robustness test, the capital depreciation rates for calculating physical capital stock and indigenous R&D capital stock are assigned to be as 9.6% and 15%, respectively. All the variables and symbols share the same meanings as shown in Table 4. (a) ***, **, and *denote significance at the 1%, 5%, and 10% levels, respectively. (b) HC denotes human capital stock.

Highlights

- We analyse the relationship between technological factors and TFP for China.
- Indigenous R&D plays a dominant role in promoting China's TFP.
- All the technology spill overs coming from openness are beneficial to TFP growth, except for the export.
- The effects of the technology spillovers on TFP are related to the domestic factors affecting absorptive capacity.