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**Article**

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## GENERAL & APPLIED ECONOMICS | RESEARCH ARTICLE

# Spatial productivity and efficiency spillovers in the presence of transient and persistent efficiency: Evidence from China's provinces

Hazwan Haini<sup>1\*</sup>

**Abstract:** This study examines the spatial productivity and efficiency spillovers of Chinese provinces using a spatial Durbin production frontier model that accounts for persistent and transient efficiency using a panel dataset of Chinese provinces from 1985 to 2017. The role of spatial effects is often overlooked in the literature, yet technological progress can spillover and diffuse from provinces and promote regional growth. The spatial Durbin production frontier model allows for the decomposition of direct and indirect (spillover) total factor productivity (TFP) growth, as well as the gross direct and indirect efficiency of the respective provinces. The estimated results show that spatial productivity and efficiency spillovers are positive and lead to higher productivity growth. On average, indirect effects provide an additional TFP growth of 3.1% and an additional efficiency spillover of 18.98%. However, the estimated results also show that TFP growth is declining over time and there is room for efficiency gains if persistent efficiency is increased. These should be addressed through further reforms and policies that promote sustainable growth.

**Subjects:** Economics; Econometrics; Development Economics



Hazwan Haini

### ABOUT THE AUTHOR

Hazwan Haini has recently been awarded a PhD in Economics from Loughborough University. His research interests include economic growth, applied economics and spatial econometrics, with focus on ASEAN economies and China. He has published in several peer-reviewed journals and has presented in numerous international conferences. His recent work was published in *Economic Change and Restructuring*, and *Applied Economic Letters* and his most recent conference was the Chinese Economic Association Annual Conference in Edinburgh.

Hazwan has supported teaching at Loughborough University as a Graduate Teaching Assistant, delivering tutorials and lectures for the Economics Department. His teaching skills have been recognised and has been awarded an Associate Fellow of the Higher Education Academy.

### PUBLIC INTEREST STATEMENT

This paper investigates the spatial productivity and efficiency of Chinese provinces from 1985 to 2017, using a spatial Durbin translog production function model. The role of spatial effects in economic models have often been overlooked yet the literature highlights that technological progress can diffuse across regions. The model employed allows for the estimation of total factor productivity (TFP) growth and gross efficiency change, which can be decomposed into direct and indirect spillovers. On average, the estimated indirect effects provide an additional TFP growth of 3.1% and an additional efficiency spillover of 18.98%. Furthermore, the provinces that benefit most from overall TFP growth are the coastal provinces. This benefits the inland provinces due to the positive spillover effects. However, TFP growth is declining over time and there is room for additional efficiency gains which can be addressed through further reforms and growth-oriented policies.

**Keywords:** China; productivity; efficiency; spatial regression; spillovers; TFP  
**JEL:** C23; O49; R11; O47

## 1. Introduction

China has experienced strong economic growth over the last 40 years, being one of the weakest economies in the world to becoming the second-largest economy after the United States. China began its reforms in 1978, opening its economy for trade and foreign investment, gradually liberalising prices, diversified ownership of its enterprises, strengthened property rights and kept inflation under control (Chow, 2004). However, the long-run prospects of maintaining its rapid growth is of concern as economic growth in China is slowing down over time. Empirical researches claim that the rapid growth of China, particularly in the early stages of reforms, was due to a high and stable level of capital input (Ezaki & Sun, 1999). Yet, capital-intensive growth can lead to diminishing improvements in productivity over time (Krugman, 1994). As China's growth slows down and levels out, sustainable development through productivity and efficiency growth becomes increasingly important for China's future, as maintaining a high level of investment and savings rate is unsustainable.

This study examines the productivity and efficiency growth of China's provinces from 1985 to 2017 employing a spatial Durbin production frontier model that allows for the decomposition of spatial productivity and efficiency<sup>1</sup> growth of provinces, in the presence of persistent and transient efficiency. The spatial Durbin production frontier can be decomposed to provide estimates of spatial technological progress and efficiency spillovers while taking into account long-run and short-run efficiency (Glass & Kenjegalieva, 2019). This is important as a number of studies have suggested that technological progress and efficiency gains can spillover into neighbouring provinces, increasing the total factor productivity and efficiency gains that an individual province may obtain. The spatial spillovers arising from efficiency performance multipliers from Chinese provinces are important to consider as provinces are part of a larger collective system and network that is relatively larger than an individual provinces' performance. Furthermore, examining the technological progress in provincial-level China can provide a deeper understanding of the respective provinces over time and provide further implications for policymakers. Productivity studies examining China has suggested that China has grown through an influx of capital inputs (Ezaki & Sun, 1999; Krugman, 1994) as well as through consistent total factor productivity (TFP) growth over time that is attributed with convergence to other countries (Laurenceson & O'Donnell, 2014). Furthermore, it is suggested that TFP growth in China may be a result of one-off events, such as its entry into the World Trade Organisation (Wu, 2000). Finally, considering transient and persistent efficiency can provide policymakers with information to identify short-term solutions or long-term structural policy changes to improve its productivity and efficiency. This study, to the best of the author's knowledge, is the first examination on the productivity and efficiency of Chinese provinces that provide evidence of spatial productivity and efficiency spillovers, while taking into account transient and persistent efficiency.

There are few studies that account for spatial effects on China's productivity and efficiency growth (Scherngell, Borowiecki, & Hu, 2014; Zhu, Lai, & Fu, 2008). The role of spatial spillovers is generally overlooked in the productivity and efficiency literature. Yet, it is essential to consider spatial spillovers especially for economies like China, which has a diverse physical and topographical features, potentially affecting production costs. Furthermore, studies have highlighted the regional disparity of growth in China, which have arisen from the regional preferential policies that favoured certain provinces in China (Démurger et al., 2002). Although these preferential policies were extended to all provinces in China, regional disparity is still observed, suggesting that other factors may be at play. Geography has played an important role for regional development in China, both economically and historically, where its Eastern provinces have more natural favourable conditions as opposed to its mountainous and hilly interior provinces (Bao, Chang, Sachs, & Woo, 2002). As a result, building transportation and infrastructure network links between provinces

incurs higher costs for its interior regions. In addition, other studies provide empirical evidence of spatial spillover effects of public health and education expenditures on economic growth in China's provinces (Haini, 2020). Geographical factors can impact the role of human capital formation and labour mobility in an economy. Consequently, it is crucial to consider spatial elements when examining a vast country like China. The methodology employed accounts for spatial distances between provinces providing new empirical evidence to the literature.

The estimated results provide evidence of spatial spillover effects for productivity and efficiency. On average, the indirect technological progress provides an additional average spillover of 3.1% TFP growth, while the indirect gross time-varying efficiency provides an additional average spillover of 18.98%. Furthermore, the estimated results suggest that there still exist areas for continued development in China, as the average gross efficiency is at 93.55%, suggesting that GDP can be increased by another 6.45%. This result contrasts with previous claims that efficiency improvements in China has been exhausted in the 1990 s (Wu, 2000). On the other hand, in terms of productivity growth, the estimated results show that technological progress is declining over time, which reiterates the arguments on China's slowing growth. More importantly, the Eastern coastal provinces in China benefited from higher technological progress, which highlights concerns over increasing inequality in China due to rapid technological change (Xu & Ouyang, 2015). Nonetheless, in aggregate, China has grown considerably and have benefited from productivity and efficiency gains during its economic reform. There is strong evidence of spatial spillover effects from productivity and efficiency, which may have arisen through the influx in capital and disembodied technological progress leading to knowledge spillover effects. In general, these estimations support previous empirical researches on productivity in China (Laurenceson & O'Donnell, 2014; Scherngell et al., 2014). Policy implications are discussed in the results sub-section.

The rest of the paper is organised as follows. Section 2 provides a brief literature review on productivity and growth in China. Section 3 provides a background on the physical and topographical conditions focusing on the provincial economic structures in China. Explanation on data sources and methodology are discussed in Section 4. Section 5 discusses the obtained empirical results while Section 6 concludes the study.

## 2. Productivity and economic growth in China

Productivity growth is a major determinant of future standard of living, and a permanent decline would be a source of serious concern (Munnell, 1990). However, the measurement of productivity can be misleading, as labour productivity can be increased by employing more capital. For this reason, an influx of capital into an economy can increase productivity growth. On the other hand, productivity growth through an increase in capital flows is unsustainable, as economies will converge to its steady-state (Romer, 1986). Although it is suggested that an increase in physical capital and human capital formation can improve productivity growth (Haini, 2019a), increasing investment rate will only temporarily increase growth due to marginal returns and thus, will not be permanent. Therefore, understanding the productivity and efficiency of an economy is essential as it provides valuable information to policymakers to promote sustainable long-term economic growth.

Examining China's productivity is interesting due to the structural changes it experience, transitioning from a centrally planned economy to a market economy. During pre-reform China, Mao Zedong forced various industries to move their operations to under-developed interior provinces, and this re-allocation of resources have influenced China's modern development (Bao et al., 2002). In addition, certain labour policies affected the market such as China's *Hukou* policy that restricted the movement of labour between rural and urban areas. The *Hukou* system identifies a person to be an urban or rural residency status, thus limiting labour to either agricultural or non-agricultural. It is well established that centrally planned economies produce well-below their best practice output due to systemic reasons and have low levels of technological progress when compared to other economies (Wu, 2000). As a result, many previous researches have been made to examine

the role of productivity and efficiency in post-reform China. Meanwhile, advances in the productivity and efficiency literature have allowed researchers to determine whether efficiency issues are attributable to long-term structural changes (persistent efficiency) or non-systematic difficulties that can be solved in the short term (transient efficiency) (Colombi, Kumbhakar, Martini, & Vittadini, 2014). The distinction between short- and long-run efficiency allows policymakers with more information for policy implications. The long-run matters because policies designed for the short-run are likely to backfire (Baumol, 1986). Thus, it is important to consider both efficiency and productivity issues in the case of China.

The source of productivity growth in China has been debated. Differences in results usually depend on methodological approaches in productivity and efficiency. Some researches employ the growth accounting methodology and provide evidence that productivity growth in China was mainly due to the high and stable level of capital input alongside TFP growth or technological progress of around 4% (Ezaki & Sun, 1999). Similarly, Wu (2000) concluded that technological progress should be encouraged if China wants to sustain its growth as the potential for efficiency improvement has almost been exhausted. Furthermore, it is criticised that technological progress was slow in cities with dominant state sectors such as Beijing, Shanghai and Tianjin when compared to other provinces. In addition, reforms in the agriculture industry played an important role in productivity growth. Agriculture productivity was high in the early 1970s and 80s due to the introduction of the household responsibility system and the dual price track system for agricultural goods (Zheng & Hu, 2006). However, they also find that TFP growth has been slowing down during the late 1990s and claim that technological progress in China was mainly achieved through the transfer of foreign technology.

On the contrary, Wu (2011) re-examined China's productivity and find that one-third of its growth is attributable to TFP growth, which is sustainable, yet not as high as other advanced economies. Similarly, Chen, Huang, and Yang (2009) find that growth in China has been propelled by technical progress, while efficiency change and adjustment in production scale may have an adverse effect on growth. They also find that growth is stronger in coastal regions than non-coastal regions, which suggests that production units face different production opportunities. Likewise, Tian and Yu (2012) find similar results, where TFP growth in Eastern China is significantly higher than the other regions. These differences in regional growth can be attributed to the capital stock, human capital, and economic infrastructure, as well as geographical conditions which are discussed further in the following section. Therefore, examining China using provincial-level data also avoids the assumption that all provinces have access to similar production technologies.

In addition to efficiency improvements and technological progress, there are other factors that may affect productivity and efficiency. Trade liberalisation is a factor that can affect productivity growth. There are arguments for both sides. On the one hand, there are critics who argue that the effect of openness on growth is overstated and may be doubtful, as there may be endogeneity and measurement problems (Krugman, 1994). However, on the other hand, other theories of growth have provided support for the positive effects of trade openness (Romer, 1986), alongside a number of recent empirical researches that highlight the role of trade openness in economic growth (Haini, 2019b). Since reforms, China has gradually liberalised its economy with continuous commitment, especially after it entered the World Trade Organisation in 2001. It is well established that China has benefited from disembodied technological progress from foreign investment (Wu, 2000), which supports the theory that open countries have a greater ability to absorb technological advances generated in leading nations (Edwards, 1998). Furthermore, it is suggested that foreign direct investment can provide positive productivity spillover effects through direct knowledge transfer, capital, and new skills into the economy (Javorcik, 2004). More importantly, there are several empirical researches that provide evidence of the positive effects of openness on China's regional productivity growth, suggesting that openness can promote economic development (Jiang, 2011). Consequently, it may be interesting to examine the effects of openness in Chinese provinces using spatial productivity models and whether spillover effects are present.



### 3. China's regional economic structures

The role of geography in economic growth has often been overlooked, as many economic models are dimensionless in space. Yet, observations have shown that productivity growth in many tropical countries are lagging, while temperate zone countries continue to benefit from growth and technological progress (Bloom & Sachs, 1998). In addition, many tropical countries have disadvantageous geography, particularly landlocked countries, as they lack access to the coast. Furthermore, agricultural productivity is very low in many tropical countries as yields are low, and health issues with regards to disease burdens are common. China is a vast country that covers over nine million square kilometres, and its provinces vary in climate. Most provinces are sub-tropical alongside the more temperate northern provinces. China's eastern provinces have excellent access to coastal seaports and benefit from having flat land in contrast to its landlocked regions which are mountainous and poor. Hence, the economy focused on its eastern provinces for development (Bao et al., 2002). Historically, the southeast coastal region was sparsely populated and uncultivated; however, after the outbreak of the Opium War in 1840, Western powers forced China to open coastal ports.

Although economic policy is a dominant factor in directing growth, understanding the topographical conditions between regions is important as it can have significant effects on income levels and growth through its impact on network links (Gallup, Sachs, & Mellinger, 1999). It is well established that coastal countries generally have higher incomes compared to landlocked countries, which are disadvantaged by their lack of access to the sea, which increases their transport costs in international trade. This makes investments in landlocked areas to be unfavourable. Furthermore, when China began reforming and opening up, the government implemented the Open-Door Policy creating Special Economic Zones (SEZs), which are preferential policies for foreign firms in specific provinces. These preferential policies are mainly deregulation policies as prior to the reforms, many provinces were over-regulated as a result of China's centrally planned economy (Démurger et al., 2002).

This is important for China's development as deregulation is a source of productivity growth as well, as firms in the SEZs can import inputs duty-free, collaborate with foreign companies in investment and manufacturing providing productivity spillovers through knowledge transfer and capital inflows (Ortega-Argilés, 2012). Guangdong and Fujian were the first SEZs that was established in the early 1980s, two coastal provinces that blossomed into important export platforms, and soon after many deregulation policies were extended to other coastal provinces. After Deng's Southern tour of China in 1992, the government extended this preferential policy to all interior and inland provinces, yet foreign investment continued to flow into the coastal regions, implying the disadvantages that interior provinces have. Similarly, Banerjee, Duflo, and Qian (2012), find evidence suggesting that transportation networks have a moderate and positive causal effect on per capita GDP in China, and its infrastructure is key to promoting growth and development as it allows access to the markets.

Therefore, if distances between provinces can affect growth or productivity through incurring transport costs, spatially closer provinces can potentially benefit from having lower transportation costs and provide spillover effects through agglomeration, factor mobility and technological diffusion (Wu, Dang, Zhao, & Zhang, 2019). As a result, examining the productivity and efficiency in provincial-level China provides an excellent case-study to investigate the effects of spatial spillovers in the context of productivity and efficiency.

### 4. Empirical methodology

This section discusses the econometric model and spatial weights matrix employed in the study followed by a brief discussion on the data and variables used.

#### 4.1. Spatial Durbin production frontier model

Consider Equation (1) which presents the stochastic frontier model introduced by Aigner, Lovell, and Schmidt (1977). This consists of the outcome variable  $y_{it}$ , a row of vector input variables  $x_{it}$  and

other control variables that may be included. The idiosyncratic error  $v_{it}$  and the time-varying technical efficiency  $\mu_{it}$ , is included as well.

$$y_{it} = x_{it}\beta + v_{it} - \mu_{it} = x_{it}\beta + \varepsilon_{it} \tag{1}$$

Several models were developed over time to include additional components of persistent efficiency, in addition to time-varying technical efficiency  $\mu_{it}$ , and idiosyncratic error  $v_{it}$ , and the most recent development of persistent efficiency was proposed and simulated by Colombi et al. (2014), and Tsionas and Kumbhakar (2014). The model is written as Equation (2), which presents the separation of the error term into four components. The first component  $v_{0i}$ , captures random noise and as the study explores the productivity of Chinese provinces. Thus,  $v_{0i}$  can be interpreted as province-specific effects. The second component  $\mu_{0i}$  captures long-run (persistent) efficiency. Both  $v_{0i}$  and  $\mu_{0i}$  are time-invariant. The third component  $\mu_{it}$  captures short-run time-varying (transient) efficiency while  $v_{it}$  captures random noise or idiosyncratic error.

$$y_{it} = x_{it}\beta + v_{0i} - \mu_{0i} + v_{it} - \mu_{it} = x_{it}\beta + \varepsilon_{0i} + \varepsilon_{it} \tag{2}$$

These four-component error structures can be defined as two composed error term as shown in Equation (5),  $\varepsilon_{0i} = v_{0i} - \mu_{0i}$  and  $\varepsilon_{it} = v_{it} - \mu_{it}$ , which has an efficiency term and a noise term, which is use useful for the estimation of the model. Identifying persistent efficiency is important especially in the case of China where the reforms have allowed provinces to operate with more autonomy and incentives.

Meanwhile, this study also considers spatial dependence, which refers to the location of samples in space, and spatial heterogeneity, which refers to the fact that spatial econometric relationships may vary systematically over space (LeSage & Pace, 2009). Spatial econometric regression requires a spatial weights matrix ( $W_N$ ) within an estimation, where a basic regression Equation (3) can be augmented with a spatial weights' matrix such as Equation (4). Equation (4) is known as the Spatial Durbin Model and assumes dependence between outcome  $y_{it}$  and the spatial lags of both the outcome ( $\rho W_{it}y$ ) and explanatory variables ( $W_{ij}x_{jt}$ ). As such, the Spatial Durbin nests both the spatial lag and spatial error models.

$$y_{it} = x_{it}\beta + \mu_{it} \tag{3}$$

$$y_{it} = \rho W_{ij}y_{it} + x_{it}\beta + W_{ij}x_{jt}\beta + \mu_{it} \tag{4}$$

Traditionally the issue of spatial dependence is seldomly discussed in stochastic frontier modelling and have only been developed in recent years (Glass, Kenjegalieva, & Sickles, 2016). An essential feature of spatial stochastic frontier is the estimation of efficiency spillovers which complements the literature on estimating productivity spillovers. Estimating the spatial Durbin stochastic frontier with a four-component error structure was first introduced by Glass and Kenjegalieva (2019) using a cost frontier.

$$y_{it} = \alpha + \eta_1 t + \eta_2 t^2 + g_{it}\varpi + z_{it}\psi + \sum_{j=1}^N w_{ij}g_{jt}\zeta + \sum_{j=1}^N w_{ij}z_{jt}\theta + \delta \sum_{j=1}^N w_{ij}y_{jt} + v_{0i} + v_{it} - u_{0i} - u_{it} \tag{5}$$

$i = 1, \dots, N; t = 1, \dots, T$

As a result, this study employs a spatial Durbin production frontier with a four-component error structure using random effects as shown by Equation (5), where variables are in log form and mean-differenced. The model is estimated using random effects and maximum likelihood, as it is assumed that all errors are independently distributed. Using fixed effects will not be suitable as the time-varying idiosyncratic error  $v_{it}$  will be correlated with the fixed effects (Badunenko & Kumbhakar, 2016). The efficiency error terms  $\mu_{it}$  and  $\mu_{0i}$  are also assumed to have half-normal distributions (Greene, 2004). Finally, the production frontier is estimated using a one-step simulated maximum likelihood method as the Bayesian approach may involve a loss of information (Filippini & Greene, 2016). In this case, the study estimates the spatial production frontier in the first stage, splits the time-varying error components in the second stage and finally the time-invariant errors in the final stage.



In each cross-section, there are  $N$  provinces indexed  $i = 1, \dots, N$  that operates over time  $T$  indexed  $t = 1, \dots, T$ .  $y_{it}$  is the observation for the output variable, real GDP, for the  $i$ th province at time  $t$ .  $g_{it}$  is a vector of exogenous independent input variables, real capital stock and labour employed.  $t$  is a time trend, where both  $t$  and  $t^2$  are included to account for Hick-neutral technological change.  $\sum_{j=1}^N w_{ij}g_{jt}$  is a vector of spatial lags of the inputs, real capital stock and labour employed.  $z_{it}$  is a vector of control variables and  $\sum_{j=1}^N w_{ij}z_{jt}$  is a vector of spatial lags of the control variables.  $\sum_{j=1}^N w_{ij}y_{jt}$  is a vector of spatial lags of the outcome as spatial Durbin specification requires spatial lags of both dependent and independent variables. However,  $W_N t$  and  $W_N t^2$  are dropped when estimating for the local spatial parameters as  $t$  and  $t^2$  are perfectly collinear with  $W_N$ , when  $W_N$  is row-normalised (Glass & Kenjegalieva, 2019).  $\alpha$  is the intercept and  $\eta_1, \eta_2, \varpi, \psi, \zeta, \theta$ , and  $\delta$  are vectors of parameters. These variables shift the frontier technology. In addition, the four-component error structure is as follows:  $v_{0i}$  captures random province-specific effects,  $v_{it}$  is the random noise or idiosyncratic error,  $u_{0i}$  captures persistent inefficiency while  $u_{it}$  captures transient inefficiency.

In addition, a spatial weight matrix ( $W_N$ ) is constructed to account for spatial lags. There are various methods of constructing a spatial weight matrix, as such the use of a contiguity or distance matrix. The specification of  $W_N$  may be suitable with elements that reflects the geographical nature of China as it considers the reallocation of resources, such as transportation links between provinces. Thus, the spatial weight matrix employed for this model is based on great circle distance, which is the shortest geographical distance, between provinces. The assumption here is that the shorter the distance between provinces, the greater the degree of spatial interaction between the provinces, which leads to lower transportation cost due to closer network links. Furthermore, geographical distance is appropriate for this case, as the transportation links between provinces ensure provinces are not isolated from each other. The data for China's provincial distances are calculated using great circle distances between the major city of the respective province. The matrix is also row normalised so that the weights in each row are normalised to have the unit sum  $\sum_{j=1}^n w_{ij} = 1, i = 1, \dots, n$ . The row normalisation of  $W_N$  allows straightforward interpretation as the fraction of all spatial influence on province  $i$  attributable to province  $j$  and preserves the spatial scaling of the data (Anselin, 2003).

Once the parameters of the spatial Durbin frontier have been established, the second part of the estimation is to calculate the direct, indirect and total marginal effects to account for productivity spillovers (Glass et al., 2016). In addition, the absolute direct, indirect and total time-invariant and time-varying costs efficiencies are calculated. Moreover, the absolute direct, indirect and total technological progress are obtained from the parameters of the spatial Durbin frontier. This is done by transforming the estimates to identify the own net time-invariant, own net time-varying and gross time-varying efficiency (GVE), while the technological progress is based on a generalised Malmquist TFP index that accounts for a spatial production frontier (Glass & Kenjegalieva, 2019). In effect, the GVE estimates can be interpreted as a different collective measure of a province's internal and external efficiency as part of a larger system and network. The intuition suggests that the spillover impacts as an efficiency performance multiplier that allows a unit (province in this case) to increase their efficiency due to a large efficiency spillover through the economy's system or network efficiency (Glass & Kenjegalieva, 2019). Further details on the assumptions of the frontier, simulation, efficiency and technological progress spillovers is discussed in Glass and Kenjegalieva (2019).

Finally, the persistent and transient efficiency scores estimated are bounded from in the interval  $[0, 1]$  as standard efficiencies in the literature of stochastic frontier modelling, with 0 being the lower-bound. The persistent and transient efficiency estimates differ from the estimates of the GVE scores  $(1 - \mu_{0i})$  scores and  $(1 - \exp(\mu_{it}))$  scores, as GVE direct ( $GVE^{Dir}$ ), GVE indirect ( $GVE^{Ind}$ ), and GVE total ( $GVE^{Tot}$ ) scores are unbounded. This allows for the simple interpretation of where scores greater than 1, suggest that efficiency spillover is sufficiently large and has pushed the province beyond the best practice frontier. It is suggested that the spillover acts as an efficiency

performance multiplier and that the network's collective performance is relatively better than its own efficiency (Glass & Kenjegalieva, 2019). Similarly, the technological progress scores are interpreted similarly, where scores greater than 1, suggests a positive technical progress. The next subsection provides a more detailed discussion of the data and variables.

#### 4.2. Data and variables

The data is compiled from the National Bureau of Statistics of China, which provides issues of the China Statistical Yearbook, an official publication that includes aggregate, provincial, and town-level data. Provincial-level data for 30 Chinese provinces from 1985 to 2017 are compiled for all variables apart from capital stock. Hainan is dropped from the sample as it is not contiguous or landlocked with the other provinces. Furthermore, the sample time-period is chosen as there are missing data before 1985. The spatial Durbin simulation requires no missing data to run and thus the sample time-period is not motivated by reasons other than missing data. All variables are logged-transformed and mean-differenced prior to estimating the model, which can be easily interpreted as elasticities.

The construction of the spatial Durbin frontier model uses the traditional variables of frontier modelling. The output  $y_{it}$  is real GDP and is standard for analysing productivity. This is measured annually and in provincial-level. The inputs  $g_{it}$  is a  $(1 \times 2)$  vector, where the first vector is real capital stock, denoted by  $k$ , and the second input is the labour employed per 10,000 persons, denoted by  $l$ . Data for real capital stock is estimated using the methodology described in Wu (2015), who provides an alternative approach to estimating China's provincial-level capital stock series. The Chinese Statistical Yearbook does not provide provincial-level capital stock data and the lack of data has been a major problem. Researchers have attempted to calculate their own provincial-level capital stock as there are problems of double-accounting in previous methods of calculating provincial-level capital stock in China. As such, the capital stock calculated follows the conventional perpetual inventory method and overcomes the problems of assuming ad hoc rates of depreciation for sectors and regions (Wu, 2015).

Meanwhile, the control inputs  $z_{it}$  is a  $(1 \times 3)$  vector of variables; where *gov* measures government spending as a share of GDP, *opn* is traditional measure of openness and is the ratio of imports and exports to GDP, and *coast* is a dummy variable for provinces that are coastal and are not landlocked. The coastal provinces are Fujian, Guangdong, Guangxi, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin and Zhejiang.

Table 1 presents the summary statistics of the level variables employed. There is considerable variation across the provinces and over time, suggesting heterogeneity from the sample size. The sample time-period covers 1985 to 2017 where China has undergone many structural changes throughout its reforms. As such, the statistics are expected to vary, in particular, output GDP and the inputs, capital stock and labour employed. The control variables exhibit less variation compared to the output and inputs, especially government spending as a share of GDP which has a low variation.

#### 5. Results and discussion

This section begins with the production frontier coefficients and parameters followed by efficiency scores. The spatial technological progress scores are then presented. Table 2 reports the coefficients and parameters elasticities (log-transformed and mean-differenced) of the spatial Durbin production frontier. The estimated results also capture the spillover effects of the independent variables through the direct, indirect and total parameters. The direct impact is the change of observation of a provinces' own independent variable on its own GDP, while the indirect effect is the change of a provinces' own independent variable on all neighbouring provinces' GDP. An important characteristic here is that the spillovers specified by the spatial Durbin model is global and transmit to all provinces in the spatial weight matrix (Anselin, 2003). It also provides estimates of the local spatial spillovers, captured by  $W_N$  variables, which interact with their immediate neighbours that share a common border, thus does not consider the full spatial weight matrix.

**Table 1. Summary statistics**

Variable	Description	Mean	SD	Min.	Max
<i>y</i>	Real GDP (100 mil. Yuan)	7151.22	11288.95	15.39	83446.73
<i>k</i>	Real capital stock(100 mil. Yuan)	288.46	389.14	1.16	2794.64
<i>l</i>	Labour employed (per 10,000 people)	2216.66	1508.27	105.72	6963.00
<i>gov</i>	Ratio of government spending to GDP	0.14	0.05	0.05	0.52
<i>opn</i>	Ratio of imports and exports to GDP	0.25	0.35	0.02	3.69

*N* = 990 and is the number of observations from 30 provinces during the period 1985–2017. Real GDP, real capital stock and labour employed are reported in levels. The dummy variable *Coast* includes Fujian, Guangdong, Guangxi, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin and Zhejiang

Glass and Kenjegalieva (2019) specify that the direct parameters of the spatial production frontier can be interpreted in the same way as the parameters from a non-spatial frontier. Thus, the monotonicity properties apply to the direct parameters. Monotonicity is a condition where any additional units of an input can never decrease the level of output and is important in the theoretical consistency in frontier analysis (Sauer, Frohberg, & Hockmann, 2006). In frontier modelling, theory states that production functions should monotonically increase all outputs. If a production frontier is not monotonically increasing, the efficiency of estimates cannot be reasonably interpreted (Henningsen & Henning, 2009). The first order direct output and input parameters, *k* and *l*, are both positive, which satisfies the monotonicity property of the production function at the sample mean. In addition, the specification of a spatial Durbin model is supported through the significant coefficient of the local spatial variables of  $W_N$  except for  $Wk$ ,  $Wl^2$  and  $Wkl$ . As the specified model is supported and satisfied through the monotonicity conditions and positive parameters, the four error terms are modelled to estimate a frontier and identify efficiency scores.

Spatial lag coefficient or  $W\rho$  reflects the spatial dependence, measuring average influence on observations by their neighbouring observations (LeSage & Pace, 2009).  $W\rho$  is positive at 0.587 and significant at the 1% level which is a good indicator of fit for spatial econometric models. In addition, a higher and positively significant value of  $W\rho$  improves the fit of the model and loglikelihood (LL). Furthermore,  $W\rho$ , captures the global spillover effects of dependent variable *y*, which incorporates the feedback effects that arises because of impacts passing through all neighbouring provinces and back to the respective province (LeSage & Pace, 2009). The positive and significant  $W\rho$ , suggests that growth in provinces can promote regional growth through feedback effects.

The model coefficient and direct elasticities of *k* are positive and significant at the 1% level which is in line with the production theory. The theory on spatial production frontier does not specify whether the indirect and total elasticity should be positive or negative (Glass & Kenjegalieva, 2019). Table 2 shows that the indirect and total elasticity of *k* is positive and significant at the 10% level suggesting that an increase in capital inputs across provinces have a beneficial effect on own province's *y*. On the other hand, the local spatial elasticity of capital,  $Wk$ , is negative but insignificant and will not be discussed. The flow of capital in China may result from foreign direct investment with foreign technologies (Javorcik, 2004), where lagging provinces may benefit from the possibility of rapid growth through technological diffusion (Gallup et al., 1999). Again, this may have arisen due to the advantages that coastal provinces have. It

**Table 2. Spatial Durbin production frontier coefficients and associated parameters**

Variable	Model Coeff.	Direct Parameter	Indirect Parameter	Total Parameter	Variable	Model Coeff.
k	0.393***	0.405***	0.491*	0.896*	Wk	-0.063
	(0.024)	(0.027)	(0.267)	(0.281)		(0.116)
l	0.331***	0.315***	0.618	0.933*	Wl	-0.043**
	(0.037)	(0.036)	(0.351)	(0.361)		(0.148)
k <sup>2</sup>	-0.161***	-0.181***	-0.927**	-1.108*	Wk <sup>2</sup>	-0.224*
	(0.018)	(0.024)	(0.358)	(0.376)		(0.135)
l <sup>2</sup>	0.027	0.041	-0.572*	-0.531	Wl <sup>2</sup>	-0.139
	(0.025)	(0.029)	(0.368)	(0.386)		(0.148)
kl	0.090	0.132**	0.868***	1.000*	Wkl	0.040**
	(0.034)	(0.042)	(0.561)	(0.591)		(0.218)
t	0.021*	0.022**	0.026*	0.048*	Wkt	0.027*
	(0.014)	(0.014)	(0.020)	(0.033)		(0.029)
t <sup>2</sup>	-0.005**	-0.005**	-0.006**	-0.011**	Wlt	-0.041*
	(0.002)	(0.002)	(0.003)	(0.005)		(0.023)
kt	0.045***	0.048***	0.156*	0.204**	Wgov	-0.087***
	(0.004)	(0.005)	(0.076)	(0.080)		(0.090)
lt	-0.018***	-0.022***	-0.182**	-0.204**	Wopn	0.052**
	(0.003)	(0.004)	(0.057)	(0.060)		(0.027)
gov	-0.052***	-0.072***	-0.091***	-0.163***	constant	-0.203***
	(0.017)	(0.017)	(0.174)	(0.180)		(0.029)
opn	0.005**	0.002**	0.125**	0.127**		
	(0.010)	(0.010)	(0.059)	(0.060)		
coast	0.427***	0.510***	0.308**	0.818***		
	(0.097)	(0.105)	(1.353)	(1.378)		
v <sub>0i</sub>	0.89				LL	809.71
	(0.016)					
v <sub>it</sub>	0.246				Wp	0.549***
	(0.002)					
u <sub>0i</sub>	0.079				u <sub>it</sub>	0.006
	(0.030)					(0.062)

Definition of variables is in Table 1. \*, \*\*, \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parenthesis. The dummy variable Coast includes Fujian, Guangdong, Guangxi, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin and Zhejiang. Standard errors are in parenthesis. Variables are log-transformed prior to estimation.  $v_{0i}$  captures country-specific effects.  $\mu_{0i}$  captures long-run (persistent) efficiency.  $v_{it}$  captures random noise or idiosyncratic error while  $\mu_{it}$  captures short-run time-varying (transient) efficiency.

was observed that when interior regions implemented the preferential policies, the inflow of foreign capital into these provinces was limited compared to its coastal provinces (Démurger et al., 2002). The interior provinces may have benefited from the indirect effects of capital through diffusion from its more advanced provinces. These estimated results are similar to Scherngell et al. (2014), as they find that knowledge capital can provide an inter-regional spillover in China.

Moreover, the model coefficient and direct elasticities of  $l$  are positive and significant at the 1% level, which supports the production theory. However, the indirect elasticity is insignificant, and the local spatial effect  $Wl$ , is negative and significant at the 5% level, which does not fit expectations. There may be reasons why indirect elasticity is insignificant and local spillover is negative and

significant. Firstly, the landlocked interior regions of China are mountainous and isolated from the advance coastal provinces. The distance and the poor infrastructure links make cross-border migration more difficult than internal migration (Démurger et al., 2002). Furthermore, internal migration itself is restricted in China due to the policy of the household registration system (*Hukou*). This restriction of labour movement leads to constrained factor mobility and may have resulted in the negative local spillover as there may be less labour force to slow the process of capital deepening. Similar results were found by Ezaki and Sun (1999), who found that the contribution of labour is small and has been declining steadily. Furthermore, previous empirical researches on China's productivity has shed light suggesting that the economy needs to take full advantage of the underutilised demographic dividend (Yao, Kinugasa, & Hamori, 2013). China has slowly taken steps to address this as they have recently relaxed its controversial one-child policy, which was implemented in 1979. Thus, China needs to actively increase the participation and quality of labour to benefit from its vast demographic.

The elasticities of the control variables also present an interesting picture. The model coefficient, the direct, indirect and total elasticity of *gov*, which is the share of government spending over GDP, are all negative and significant at the 1% level. This is consistent with some studies that observe the significant negative relationship between government size and economic growth (Fölster & Henrekson, 2001). Meanwhile, some studies find that openness to trade may reduce government size (Ferris, Park, & Winer, 2008). This is interesting as Table 2 reports the total elasticity of *opn* to be positive and significant at the 10% level. This may shed some light on why the estimates of *gov* affect growth negatively while *opn* is positive as openness to trade may serve as a function to promote a leaner government.

Finally, the control variable *coast* reports expected results, as the coefficient, direct, indirect and total elasticity is positive and significant at the 1% level supporting the view that coastal provinces may have advantages over its interior provinces. This is unsurprising, as historically the Open-Door Policy began with the establishment of SEZs in Guangdong and Fujian, followed by the Coastal Open Cities policy in the 1980 s, the Coastal Open Economic Zones in 1985 and finally the Coastal Open Belt in 1988 before extending the Open Door Policy to the interior provinces (Démurger et al., 2002). This may provide reasons on why China's coastal provinces grew rapidly post-reform era, as pre-reform China saw Mao restricting investment in the coastal provinces. Consequently, geography factors here play an important role as the coastal provinces have access to the international markets and lower costs of transportation that rapid economic growth.

Table 3 presents the averaged efficiency scores of provinces from the fitted structural form of the spatial Durbin frontier model. Gross efficiency is the interaction between persistent efficiency ( $1 - \exp(-\mu_{0i})$ ) and transient efficiency ( $1 - \exp(-\mu_{it})$ ) and these efficiency scores are bounded between 0 and 1. On the other hand,  $GVE^{Dir}$ ,  $GVE^{Ind}$ , and  $GVE^{Tot}$  efficiency scores, are unbounded, where scores above 1 suggests that provinces perform beyond the best practice frontier, thus providing a more complete picture of economic performance (Glass & Kenjegalieva, 2019).

To the best of the author's knowledge, as this is the first application of a spatial Durbin production frontier model applied to China's provinces, some caution must be made when comparing efficiency estimations to previous productivity and efficiency studies on China. The average

**Table 3. Average efficiencies of provinces**

	Gross Efficiency	Persistent Efficiency	Transient Efficiency	$GVE^{Dir}$	$GVE^{Ind}$	$GVE^{Tot}$
Total average	93.55%	94.08%	99.51%	93.71%	18.98%	112.69%

Persistent efficiency scores are derived from  $(1 - \exp(-\mu_{0i}))$  and transient efficiency scores are derived from  $(1 - \exp(-\mu_{it}))$ . Gross efficiency is the interaction between persistent and transient efficiency.

gross efficiency scores are at 93.55% suggesting that if China improves its persistent efficiency, it can increase GDP by a further 6.45%. Moreover, in closer examination of the transient and persistent efficiency scores, it can be suggested that efficiency can be improved by increasing persistent efficiency through long-term structural changes. Finally, when taking into account spatial spillovers, it can be observed that indirect effects lead to spatial efficiency gains.

Tables 4 and 5 provide an in-depth decomposition of the gross time-varying efficiency scores across the provinces and over time. The efficiency scores are unbounded as Tables 4 and 5 take into account a province's own net time-invariant, own net time-varying and gross varying efficiency (GVE), whereby a province can benefit from a higher level of performance as the spillover from neighbouring provinces can act as an efficiency performance multiplier as part of a system (Glass & Kenjegaliev, 2019). As a result, the efficiency scores are unbounded and go beyond 100%.

Focusing on the gross time-varying efficiency, it can be observed that the efficiency scores of the coastal provinces are distributed throughout the sample, with Sichuan as the most efficient province and Heilongjiang as the most inefficient province. The expectation is that the initial reforms in the coastal provinces provided the coastal regions with first-mover advantages and from geographical advantages. However, the estimations in Table 4 show that this is not the case as efficiency scores of the provinces are similar to one another. On the one hand, these provide support for previous studies that suggests that efficiency gains are exhausted in China (Wu, 2000). Yet, others conclude that allocative efficiency varies considerably across areas that can influence the distribution of resources (Bin, Chen, Fracasso, & Tomasi, 2018). This might arise due to the methodology employed when estimating and defining efficiency as this study examines the technical efficiency of the provinces, which is relative to a frontier. More importantly, Table 4 provides evidence of spatial efficiency spillovers suggesting that individual provinces benefit from spillover effects through being part of a collective network and system that provide efficiency performance multiplier throughout the region (Glass & Kenjegaliev, 2019). Thus, the spatial efficiency spillover effects can improve efficiency gains, that are suggested to be exhausted, and lead to further productivity growth.

Furthermore, when examining the gross time-varying efficiency over time in Table 5, it can be observed that efficiency scores have not varied much in both its total, direct and indirect impact. This can provide some form of explanation as to why transient efficiency is at its capacity while persistent efficiency has room for improvement. The policy implication here is to correct for these inefficiencies and identify sources of structural problems that can improve persistent efficiency. The results provide support on previous researches that suggests that China needs to sustain growth through technological progress as efficiency gains have nearly been exhausted (Wu, 2000). Nonetheless, it provides support that spatial efficiency gains are present and any further improvements in efficiency can have a spillover effect on neighbouring provinces.

Equally important, the spatial Durbin model can be decomposed to provide estimates for productivity growth over time and across the provinces. Table 6 reports the technological progress of the respective provinces while Table 7 presents the productivity growth of the provinces over time. The average total technological progress for the sample is at 5.7%, where 3.1% of technological progress can be attributed to indirect spatial spillover effects. The estimated technological progress of the provinces in Table 6 supports the literature that highlights the advantages that coastal provinces obtain in terms of attracting foreign direct investment, which potentially leads to technological progress through foreign technology transfer (Javorcik, 2004).

These estimations suggest that productivity growth in China may arise from disembodied technological progress, which is supported by a number of empirical researches on China (Laureson & O'Donnell, 2014; Luckstead, Choi, Devadoss, & Mittelhammer, 2014; Scherngell et al., 2014; Tian & Yu, 2012; Wu, 2011). However, there are empirical researches that raise concerns of regional disparity between the coastal and non-coastal provinces. In Figure 1, this can be visually observed as the total



**Table 4. Gross time-varying efficiency of provinces**

Province	Total gross time-varying efficiency	Indirect gross time-varying efficiency	Direct gross varying efficiency
Sichuan	112.99%	18.93%	94.06%
Xinjiang	112.98%	19.07%	93.90%
Hunan	112.94%	18.99%	93.96%
Henan	112.94%	18.99%	93.96%
Guangdong*	112.94%	19.02%	93.92%
Jiangxi	112.91%	18.97%	93.94%
Qinghai	112.91%	19.04%	93.87%
Gansu	112.91%	19.01%	93.89%
Shandong*	112.87%	18.99%	93.88%
Hebei*	112.87%	18.94%	93.93%
Tianjin*	112.82%	18.87%	93.95%
Beijing	112.79%	18.88%	93.91%
Chongqing	112.76%	18.92%	93.84%
Guizhou	112.76%	18.98%	93.78%
Jilin	112.76%	18.99%	93.77%
Hubei	112.75%	18.99%	93.76%
Shanxi	112.75%	18.96%	93.79%
Anhui	112.74%	18.90%	93.84%
Shanghai*	112.71%	18.88%	93.84%
Shaanxi	112.69%	18.99%	93.71%
Guangxi*	112.68%	19.01%	93.67%
Yunnan	112.68%	19.05%	93.63%
Jiangsu*	112.60%	18.85%	93.76%
Ningxia	112.52%	19.00%	93.53%
Zhejiang*	112.52%	18.96%	93.56%
Tibet	112.40%	19.07%	93.33%
Fujian*	112.32%	19.00%	93.31%
Liaoning*	112.20%	19.01%	93.18%
Inner Mongolia	112.07%	19.01%	93.06%
Heilongjiang	111.91%	19.04%	92.87%
<b>Total average</b>	<b>112.69%</b>	<b>18.98%</b>	<b>93.71%</b>

Gross time-varying scores are unbounded as it takes into account the own net time-invariant, own net time-varying and gross time-varying efficiency. This is calculated using the spatial multiplier matrix which passes through a provinces' first order and neighbouring provinces and rebounds back to the unit. The scores above 1 suggests that the efficiency spillover is sufficiently large and has pushed the province beyond the best practice frontier.

technological progress of the provinces are concentrated in the coastal south and coastal east provinces while the inland provinces, such as Qinghai and Xinjiang do not benefit from technological progress as much as the coastal ones. On a positive note, the spatial spillover effects suggest that the inland provinces can still benefit from technological diffusion despite achieving less technological progress. However, policymakers must identify policies to ensure that the inland provinces can attain higher levels of productivity growth through developments in infrastructure links that can lead to further regional growth for China. This also raises concerns on the increasing wage inequality, which may have been the result of rapid technological progress in the coastal provinces (Xu & Ouyang, 2015). As China benefits from foreign technology and transitions from an agrarian industry to a manufacturing and service-intensive one, wage inequality may persist due to the *Hukou* system that restricts movement of labour.

**Table 5. Gross time-varying efficiency over time**

Year	Total gross time-varying efficiency	Indirect gross time-varying efficiency	Direct gross time-varying efficiency
1985	112.82%	18.99%	93.83%
1986	112.75%	18.98%	93.77%
1987	110.77%	18.64%	92.13%
1988	111.39%	18.74%	92.65%
1989	113.53%	19.11%	94.42%
1990	113.30%	19.05%	94.25%
1991	112.86%	18.97%	93.89%
1992	110.72%	18.59%	92.13%
1993	111.46%	18.74%	92.71%
1994	112.66%	18.96%	93.70%
1995	112.89%	19.01%	93.88%
1996	113.60%	19.14%	94.46%
1997	113.55%	19.12%	94.43%
1998	113.28%	19.08%	94.20%
1999	113.45%	19.10%	94.35%
2000	113.14%	19.04%	94.09%
2001	113.73%	19.14%	94.59%
2002	112.81%	18.98%	93.83%
2003	111.76%	18.80%	92.96%
2004	111.75%	18.80%	92.94%
2005	112.24%	18.89%	93.34%
2006	112.47%	18.93%	93.53%
2007	112.85%	19.00%	93.85%
2008	113.43%	19.10%	94.33%
2009	112.78%	19.00%	93.78%
2010	112.56%	18.97%	93.59%
2011	113.01%	19.05%	93.96%
2012	113.24%	19.09%	94.15%
2013	112.86%	19.04%	93.83%
2014	111.96%	18.89%	93.07%
2015	112.87%	19.05%	93.83%
2016	113.06%	19.09%	93.97%
2017	113.23%	19.13%	94.10%
<b>Total average</b>	<b>112.69%</b>	<b>18.98%</b>	<b>93.71%</b>

Gross time-varying scores are unbounded as it takes into account the own net time-invariant, own net time-varying and gross time-varying efficiency. This is calculated using the spatial multiplier matrix which passes through a provinces' first order and neighbouring provinces and rebounds back to the unit. The scores above 1 suggests that the efficiency spillover is sufficiently large and has pushed the province beyond the best practice frontier.

Furthermore, Table 7 highlights the concerns for China's slowing growth, as it shows technological progress declining over time, from 14.2% technological change in 1986 to 0.8% in 2017. In Figure 2, this can be observed visually, where total and direct technological progress is declining over time and interestingly, indirect technological progress is gradually increasing albeit at a slower rate. On the one hand, the indirect spillover effects suggest that technological diffusion is occurring. This supports recent studies that suggest Chinese provinces have benefited from technological diffusion (Wu et al., 2019). An interesting observation here is that there seems to be an inverse relationship between direct

**Table 6. Technological progress of provinces**

Province	Total technological progress	Indirect technological progress	Direct technological progress
Beijing	1.341	1.256	1.066
Shanghai*	1.315	1.237	1.062
Tianjin*	1.286	1.234	1.044
Guangdong*	1.260	1.183	1.077
Zhejiang*	1.228	1.174	1.054
Jiangsu*	1.198	1.138	1.060
Shandong*	1.156	1.099	1.056
Fujian*	1.152	1.121	1.031
Liaoning*	1.141	1.105	1.036
Ningxia	1.105	1.102	1.002
Shanxi	1.066	1.040	1.026
Inner Mongolia	1.059	1.045	1.015
Heilongjiang	1.050	1.026	1.025
Shaanxi	1.049	1.024	1.027
Jilin	1.025	1.017	1.010
Guangxi*	1.024	1.012	1.012
Hebei*	1.023	0.987	1.038
Hubei	1.001	0.977	1.027
Yunnan	0.959	0.947	1.012
Gansu	0.957	0.961	0.997
Jiangxi	0.956	0.949	1.008
Henan	0.954	0.927	1.032
Tibet	0.949	1.012	0.938
Chongqing	0.946	0.949	0.999
Sichuan	0.946	0.923	1.026
Hunan	0.939	0.924	1.018
Guizhou	0.923	0.927	0.997
Anhui	0.906	0.901	1.008
Xinjiang	0.904	0.891	1.013
Qinghai	0.901	0.895	1.006
<b>Total average</b>	<b>1.057</b>	<b>1.031</b>	<b>1.024</b>

Total factor productivity growth index is decomposed using a Malmquist index. The direct and indirect effect is calculated using the spatial multiplier matrix which passes through a provinces' first order and neighbouring provinces and rebounds back to the unit.

and indirect technological progress. As the methodology proposed by Glass and Kenjegaliev (2019) is relatively new, this inverse relationship is difficult to interpret. Intuitively, it may be a result of China's gradual implementation of labour reforms (*Hukou* policy) and its deregulation of foreign investment in provinces across China (Chow, 2004). These structural changes promotes increased labour mobility and the freer flow of capital across the provinces. Furthermore, this allows an individual province to benefit from a larger collective and network system from the region as a whole, increasing its technological progress from spillover effects.

However, the total technological progress is slowing down over time. More interestingly, it is surprising to see that China's technological progress has been declining rapidly despite entering

**Table 7. Technological progress over time**

Year	Total technological progress	Indirect technological progress	Direct technological progress
1986	1.142	1.015	1.123
1987	1.134	1.014	1.116
1988	1.127	1.014	1.109
1989	1.119	1.013	1.102
1990	1.108	1.011	1.095
1991	1.095	1.006	1.087
1992	1.084	1.003	1.079
1993	1.078	1.004	1.072
1994	1.075	1.006	1.066
1995	1.074	1.010	1.061
1996	1.072	1.015	1.055
1997	1.068	1.017	1.049
1998	1.069	1.023	1.043
1999	1.072	1.030	1.038
2000	1.068	1.033	1.031
2001	1.063	1.035	1.025
2002	1.055	1.034	1.018
2003	1.046	1.033	1.012
2004	1.037	1.031	1.005
2005	1.028	1.029	0.998
2006	1.017	1.025	0.992
2007	1.013	1.026	0.986
2008	1.016	1.034	0.982
2009	1.016	1.039	0.977
2010	1.018	1.046	0.973
2011	1.018	1.050	0.969
2012	1.017	1.054	0.964
2013	1.020	1.062	0.961
2014	1.022	1.068	0.956
2015	1.020	1.072	0.951
2016	1.015	1.073	0.946
2017	1.008	1.073	0.939
<b>Total average</b>	<b>1.057</b>	<b>1.031</b>	<b>1.024</b>

Total factor productivity growth index is decomposed using a Malmquist index. The direct and indirect effect is calculated using the spatial multiplier matrix which passes through a provinces' first order and neighbouring provinces and rebounds back to the unit.

the WTO in 2001. This implies that China's rapid growth and earlier gains in technological progress has been mainly achieved through the transfer of disembodied foreign technology, which is unsustainable in the long-run (Wu, 2000). This emphasises the need for China to re-focus its domestic economy and formulate policies to reduce inequality through policies that can improve the skills of its labour force, through education policies that can result in human capital formation.

In general, the estimated results supports the view that China has grown through both increases in input and technological progress (Chen et al., 2009; Laurenceson & O'Donnell, 2014), and has allowed

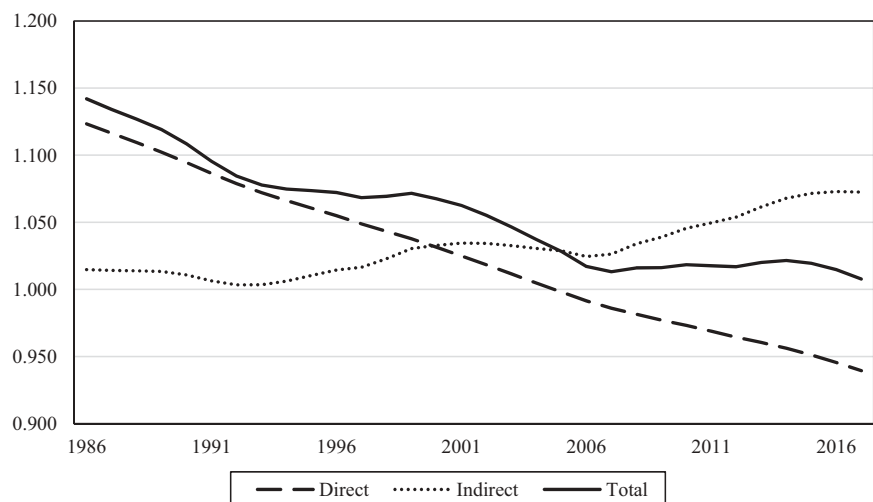
**Figure 1. Spatial distribution of total technological progress.**

Source: Author's compilation from Table 6 using total technological progress.



**Figure 2. Technological progress over time.**

Source: Author's compilation from Table 5 using total technological progress.



China to improve its position and benefit from productivity growth over time and across provinces. Furthermore, the findings also support the argument put forth by Zhu et al. (2008), where they find spatial dependence in provincial-level TFP across regions. However, China should re-focus its efforts on sustainable economic growth and push productivity growth through its domestic economy by developing its labour force and innovation. Growth through technological progress is important as it is a major driving force of structural change that can promote sustainable long-run growth (Baumol, 1986). This can potentially push China out of the middle-income group, by re-focusing its efforts on developing high-value exports and pushing for consumption growth. Finally, China needs to identify policies that can encourage further innovation and promote human capital formation through investments in education and health in order to sustain growth through technological progress.

## 6. Concluding remarks

This study examines the productivity and efficiency of China's provinces from 1985 to 2017 using a spatial Durbin production frontier model. Previous research suggests that China has grown by benefiting from large inflows of capital and its vast demographic labour supply. More importantly, some empirical findings suggest that China's productivity growth is slowing down and efficiency gains have been exhausted. However, many of these previous studies overlook the role of spatial spillovers. Yet China is a large country and its provinces vary considerably in terms of its geography and topography. There is a strand of literature that highlights the uneven growth path that its provinces experience, as its coastal provinces grew faster than its interior provinces. These differences in productivity and efficiency can potentially have spillover effects on neighbouring regions.

China's regional disparity is a result of its geographic and topographic conditions and its history. The western provinces are mountainous and hilly with poor infrastructure links, while the eastern coastal provinces have flatlands and excellent access to coastal waters and the international market. Although coastal provinces were subjected to preferential policies, these policies were extended to all provinces, yet, many foreign investments still flowed into the coastal provinces. As a result, the importance of geography cannot be overlooked. This study considers the geography in China by employing a row-normalised spatial weight matrix constructed based on great circle distance between the provinces. Furthermore, in addition to the traditional production frontier variables, such as capital stock and labour, this study employs three additional variables: government spending to GDP, openness to trade, and a coastal dummy. The study employs the spatial Durbin production frontier using random effects to control for endogeneity.

The estimated results are positive and significant for capital stock and labour, which is expected. More interestingly, capital stock and labour estimates have positive and significant spillover effects, supporting previous findings that technological progress may have diffusion effects and that transportation links between provinces may promote factor mobility. In addition, government size has a negative and significant effect on growth, which may be expected for post-reform China, and that openness to trade has a positive and significant effect on growth, which is expected as foreign direct investment flowed into the country. The coastal dummy is significant and positive supporting the views that coastal provinces may have benefited more from its interior provinces. Furthermore, the spatial Durbin production frontier is decomposed to provide estimates for productivity and efficiency for the respective provinces. The average gross efficiency in China is at 93.55% suggesting that GDP can increase by another 6.45%. Taking into account spatial spillovers, the average gross time-varying efficiency increases to 112.69% with 18.87% attributable to indirect effects. Furthermore, the estimated results show evidence of productivity growth as the average technological progress over the sample period is at 5.7%. The average indirect effects for technological progress is at 3.1%, providing evidence of technological diffusion. However, productivity growth is concentrated in the coastal provinces and is slowing down over time. Thus, China has grown rapidly through large capital inflows that allowed them to converge to the frontier and have benefited from disembodied technological progress.

However, economic and productivity growth has been slowing down, and there are doubts whether China's traditionally high savings rate can still be maintained raising concerns of sustainable growth. Policymakers should promote further technological progress through deregulation, research and development and education which affects human capital formation. There are several possible avenues for future research. It may be possible to examine the productivity of China's provinces on a provincial sector-level nested within the provincial-level data. Employing a spatial multi-level production function model may provide further inferences, particularly with regards to the economic sectors. It may provide further insight into China's agriculture productivity and China's transition towards a modern economy and how the restrictive *Hukou* policy may have affect labour productivity in the respective sectors.



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#### Note

1. Productivity is measured by the total factor productivity index decomposed using the parametric Malmquist index while efficiency is measured by technical efficiency.

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