Applied Economics Letters

ISSN: 1350-4851 (Print) 1466-4291 (Online) Journal homepage: https://www.tandfonline.com/loi/rael20

A driving force for sustainable economic growth in China from the wave-like effects of technological diffusion

Chenxi Wu, Kangni Dang, Chen Zhao & Hao Zhang

To cite this article: Chenxi Wu, Kangni Dang, Chen Zhao & Hao Zhang (2019) A driving force for sustainable economic growth in China from the wave-like effects of technological diffusion, Applied Economics Letters, 26:15, 1228-1233, DOI: 10.1080/13504851.2018.1543936

To link to this article: https://doi.org/10.1080/13504851.2018.1543936

Published online: 11 Nov 2018.

APPLIED ECONOMICS LETTERS
2019, VOL. 26, NO. 15, 1228–1233
https://doi.org/10.1080/13504851.2018.1543936

ARTICLE

A driving force for sustainable economic growth in China from the wave-like effects of technological diffusion

Chenxi Wu[a], Kangni Dang[a], Chen Zhao[b] and Hao Zhang[a,c]

[a]School of Finance, Guangdong University of Foreign Studies, Guangzhou, PR China; [b]School of Economics & Trade, Guangdong University of Foreign Studies, Guangzhou, PR China; [c]South China Institute of Fortune Management Research, Guangdong University of Foreign Studies, Guangzhou, PR China

ABSTRACT

This paper analyses the influence of the spatial association of different provinces on technological diffusion and economic growth, using panel data from 30 Chinese provinces from 2005 to 2016. The results show that firstly, there is a strong spatial correlation in economic growth between the provinces from Moran's I index and Geary's C index. Secondly, the decomposition of the direct and indirect effects in the spatial Durbin model reveals that foreign direct investment is a crucial factor for sustained economic growth. Last but not least, technological diffusion, exhibited in wave-like characteristics in China.

KEYWORDS
Economic growth; technological diffusion; spatial model; FDI spillover

JEL CLASSIFICATION
C33; O32; O41

I. Introduction

China's economy has experienced exceptional growth for more than three decades since the Chinese economic reforms of the late 1970s. The average gross domestic product (GDP) growth rate over this period was as high as 9.66%, leading many to refer to the phenomenon as the 'Chinese economic miracle'. Nevertheless, China's GDP growth rate in recent years has witnessed a downward trend, moving from 10.6% in 2010 to 6.7% in 2016. Correspondingly, the debate over the reasons for the slowdown in China's economic growth has become increasingly fierce. The Moody even lowered its sovereign credit rating for China and forecast that China's economy will experience an L-shaped recession. The current economic decline seems as the result of China's economy entering the 'new normal' phase of a transition economy, and the well-supported foundation and conditions for sustained economic growth have not changed.

The controversy over the slowdown is essentially a dispute over the source of China's economic growth. Regarding the source of economic growth, Romer (1990) endogenized technical variables and established an economic growth model, Ljungwall and Tingval (2015) use R&D to explain the economic growth. Then the role of technological progress in promoting economic growth is reflected primarily in two central aspects, technological diffusion and technological innovation (Scott 1988). In China, obtaining technical knowledge from more advanced economies via technological diffusion functions as a critical source of technological progress (Shang, Poon, and Yue 2012). Technological development will radiate from a source region to its surrounding areas, first affecting its neighbouring regions. Although technological diffusion is not a fundamental driving force for economic growth in the long run, it is regardless a critical driving force for sustained economic growth through regional spillover. Technological diffusion promotes technological progress and effectively improves technological efficiency where technological innovation was earlier insufficient. To garner greater insight on these phenomena, we will establish a spatial econometric model and utilize the panel data from 30 Chinese provinces, taken from 2005 to 2016, to conduct an empirical investigation.

CONTACT Chen Zhao chenzhao2002@126.com; Hao Zhang haozhang@gdufs.edu.cn

II. Model and date

Model

Formula (1) shows the neo-classical Cobb–Douglas production function for the various regions and provinces of China.

$$Y_{it} = AL_{it}^{\alpha}K_{it}^{\beta} \tag{1}$$

where Y_{it} represents the total output of region i - in year t. L_{it} and K_{it} are the input of the labour factors and capital stock, respectively. The variables α, βdenote the corresponding elastic coefficients. A is a constant that indicates whether the comprehensive technical level is an exogenous variable.

From Fagerberg (1994), we treat technology endogenously, breaking it down into the categories of technological diffusion from foreign technology, domestic innovation from technological knowledge, and domestic absorption from technological knowledge. These aforementioned three factors are expressed as FDI_{it}, $R\&D_{it}$, T_{it}, , respectively:

$$Y_{it} = f(L_{it},\ K_{it},\ FDI_{it},\ R\&D_{it},\ T_{it}) \tag{2}$$

It is assumed that the scale of return for the labour and capital elements remains unchanged (namely $\alpha + \beta = 1$). Assuming that $y_{it} = Y_{it}/L_{it}$ and $k_{it} = K_{it}/L_{it}$, then the general econometric model established in order to more easily obtain a stable sequence for the non-spatial panel data is:

$$\begin{aligned} lnY_{it} = \lambda + \beta lnK_{it} + \gamma_1 lnFDI_{it} + \gamma_2 lnR\&D_{it} \\ + \gamma_3 lnT_{it} + \mu_i + \varepsilon_{it} \end{aligned} \tag{3}$$

Geographical distance will likely also affect the diffusion of technology between regions. Therefore, in order to better explain the relationship between technological diffusion and economic growth, according to LeSage and Pace (2008) we introduce a spatial panel econometric model expressed as:

$$\begin{aligned} lny_{it} = \rho \sum\nolimits_{j=1}^{N} W_{ij} lny_{it} + \alpha + X_{it}\beta \\ + \sum\nolimits_{j=1}^{N} W_{ij} X_{ijt}\theta + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \tag{4}$$

where X represents different independent variable, and W represents spatial weight matrix. As such, $W \cdot lny$ denotes the endogenous interaction effect of the dependent variable, while $W \cdot X$ denotes the exogenous interaction effect of the independent variable. ρ, α, β, θ are the corresponding regression coefficient, and θ, ρ are collectively referred to as spatial correlation coefficients.

Variables

For the y_{it}, the model's interpreted variable. $y_{it} = Y_{it}/L_{it}$. We chose y_{it} = regional GDP/number of employees in the region.

Given that $k_{it} = K_{it}/L_{it}$, the variable k_{it} is determined by both capital investment as well as labour input. We adopt the same estimation methodology used by Young (2003). We use the *FDI* as the measurement of transportation of technology from international sources, and use internal *R&D* expenditures (per 100 million RMB) as Regional technological innovation (*R&D*). The technical transaction volume was selected as the measurement for the Ability to absorb technical knowledge (T).

The geographical distance is measured through spherical Euclidean distance. Because the economic centre of a given province is typically the province's capital city, the geographic location parameters for the given province's capital city are used to estimate the geographical location parameters for the province in the calculation of the weight matrix. The W is expressed as:

$$w_{-ij} = \begin{cases} o & , i = j \\ \frac{1}{d_{-ij}} & , i \neq j \end{cases} \tag{5}$$

Data

The data used are from *Statistical Yearbook of China*. The descriptive statistics of data are presented in Table 1.

III. Empirical analysis

Spatial correlation test

The Moran's I Index and Geary's C Index are commonly used for global spatial autocorrelation. Moran's I index is between [−1,1]. $I>0$ indicates that there is a positive spatial correlation, while $I<0$ indicates a negative spatial correlation. The equation $I = 0$ indicates that there is no

Table 1. Descriptive statistics of relevant variables.

Variables	Obs.	Mean	s.d.	Max	Min
lny	360	9.2112	0.7378	11.3222	7.4736
lnk	360	10.1736	0.9598	12.2298	6.8699
lnFDI	360	3.2966	1.5741	5.7702	2.0482
lnR&D	360	3.1064	1.4973	6.0390	1.2459
lnT	360	2.0034	1.8651	6.5928	2.5834

Table 2. The Spatial correlation test of lny.

Year	Moran's I	Geary's C	Year	Moran's I	Geary's C
2005	0.137***	0.866***	2011	0.124***	0.872***
2006	0.134***	0.867***	2012	0.119***	0.877***
2007	0.125***	0.874***	2013	0.116***	0.881***
2008	0.130***	0.868***	2014	0.118***	0.88***
2009	0.127***	0.87***	2015	0.114***	0.883***
2010	0.132***	0.869***	2016	0.113***	0.886***

Note: ***, **, and * in the table indicate levels of significance at 1%, 5%, and 10%, respectively.

correlation between the sample regions. Geary's C is between [0, 2], a value that is greater than 1 indicates a negative correlation, a value up to 1 indicates irrelevance, and a value less than 1 indicates a positive correlation.A combination of Moran's I index and Geary's C index can well determine the spatial correlation. The result of Moran's I index and Geary's C index under the weight matrix W are shown in Table 2

The lny has significant spatial correlations as well as significant spatial agglomeration effects. Here we can see that the data strongly support the idea that utilizing spatial econometric models to measure the impact of technological diffusion on China's economic development is particularly important.

The model and empirical results

The Moran's I index and Geary's C index have shown the spatial correlation. However, we will use the LM test from Anselin et al. (1996) and the Robust-LM test from Elhorst (2001) to test whether spatial effects should be included in the empirical framework, and SLM or SEM we should use.

From Table 3, the R-LMlag and R-LMErr are both significance at 1%, which means that we can choose the SEM or SLM for empirical framework. So we use the SDM as the empirical model (6):

$$\begin{aligned} lny_{it} = {} & \rho \sum_{j=1}^{N} W_{ij} lny_{it} + \beta_1 lnk_{it} + \beta_2 lnFDI_{it} \\ & + \beta_3 \ln(R\&D)_{it} + \beta_4 lnT_{it} \\ & + \theta_1 \sum_{j=1}^{N} w_{ij} lnk_{ijt} + \theta_2 \sum_{j=1}^{N} w_{ij} lnFDI_{ijt} \\ & + \theta_3 \sum_{j=1}^{N} w_{ij} \ln(R\&D)_{ijt} + \theta_4 \sum_{j=1}^{N} w_{ij} lnT_{ijt} \\ & + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \tag{6}$$

Whether the SDM can be simplified to SEM or SLM depended on the Wald Test and LR Test (Elhorst 2014). We use the Wald Test and LR Test for the (5), and the p-value of Wald_spatial_lag, LR_spatial_lag, Wald_spatial_error, LR _spatial_ error are all 0.000. So the SDM cannot be simplified to SEM or SLM. The empirical results are shown in Table 4.

The Hausman test indicates that we should elect the FE model. Under the two-way FE model, the spatial correlation coefficient $\rho$is greater than 0 and very significant, indicating that labour-average GDP of each province will influence one another via spatial overflow. That indicates the economic output between provinces in China has a certain demonstration effect or spillover effect. The pursuit of GDP among provinces will promote each other and thus contribute to a long-term rapid development of China's economy as a whole.

Table 3. Model Test and LM, LR Test.

Variables	Panel OLS	Spatial fixed effects	Time period fixed effects	Spatial and time period fixed effects
lnk	0.481*** (4.67)	0.452*** (16.95)	0.413*** (18.75)	0.426*** (19.59)
lnFDI	0.0221 (0.34)	0.0173 (0.82)	0.0213*** (3.67)	0.0167*** (2.87)
lnR&D	0.055 (0.69)	0.0336 (0.95)	0.00948 (0.52)	0.0145 (0.77)
lnT	0.085* (1.85)	0.0901*** (4.19)	0.0220*** (4.56)	0.0270*** (5.57)
C	3.905*** (3.95)	–	–	–
R^2	0.7361	0.707	0.710	0.707
p-value of LMlag	0.000	0.000	0.000	0.000
p-value of R-LMlag	0.000	0.000	0.000	0.000
p-value of LMErr	0.000	0.000	0.000	0.000
p-value of R-LMErr	0.000	0.000	0.000	0.000

Note: The t-statistics of the parameter estimation are presented in parentheses. ***, **, and * in the table indicate levels of significance at 1%, 5%, and 10%, respectively.

Table 4. Empirical results.

Variables	SDM period fixed effects	SDM individual fixed effects	SDM Two way fixed effects	SDM random effect
lnk	0.462*** (16.29)	0.433*** (19.98)	0.428*** (19.64)	0.434*** (19.67)
lnFDI	0.00175 (0.07)	0.0160*** (2.87)	0.0184*** (3.27)	0.0165*** (2.84)
lnR&D	0.0571 (1.39)	−0.00288 (−0.15)	−0.00767 (−0.41)	0.00833 (0.45)
lnT	0.0621*** (2.75)	0.0247*** (5.32)	0.0254*** (5.18)	0.0263*** (5.47)
W*lnk	1.176*** (4.41)	−0.290*** (−2.86)	−0.238* (−1.84)	−0.274*** (−2.64)
W*lnFDI	−0.124 (−0.73)	0.0945*** (3.59)	0.198*** (4.16)	0.0954*** (3.48)
W*lnR&D	0.598* (1.82)	0.0937* (1.70)	0.117 (1.04)	0.0827 (1.45)
W*lnT	−0.385* (−1.95)	0.00451 (0.24)	0.0350 (0.95)	0.00233 (0.12)
Spatial rho	−0.308 (−1.43)	0.472*** (3.92)	0.442*** (3.25)	0.448*** (3.59)
Variance sigma2	0.121*** (13.38)	0.00192*** (13.31)	0.00186*** (13.28)	0.00210*** (12.72)
N	360	360	360	360
r2	0.670	0.707	0.677	0.714
HausmanTest			31.92*** (0.0002)	

Note: ***, **, and * in the table indicate levels of significance at 1%, 5%, and 10%, respectively.

Judging from the factors affecting output, China is still relying on investment to stimulate the economy, with the largest impact on capital, and a 1% increase in per capita capital investment will boost output per capita by 0.43%; however, capital investment has a clear negative spatial spillover effect, which will result in a 0.24% drop in per capita output in other provinces. The result demonstrates that there is a lack of coordinated large-scale capital input among the provinces in China which has a 'beggar-thy-neighbor'-like effect – the development of the economy of one province is likely to bring about negative effect to nearby regions and in turn leads to a reduction in the efficiency of capital investment as a whole.

For the technology diffusion brought about by foreign technology import (FDI), its elasticity for per capita output is 0.02%, but it has a high positive spillover effect whose elasticity reaches 0.2%. This shows that the technological development will not only promote the economic development of the province but also promote the development of other provinces, thus bringing continuous power to China's economic development. On the contrary, independent research and development in China's provinces have no obvious role in promoting economic development. This also reflects that the role of R&D in promoting the Chinese economy needs to be further strengthened. The regional absorption of technological knowledge has a significant effect on the economic growth of the province (0.025%), but the spillover effect on other provinces is not obvious.

IV. Decomposition of total effects

LeSage and Pace (2014) decomposed the average total effect (ATE) of their explanatory variables into the sum of the average direct effect (ADE) as well as the average indirect effect (AIE). Similarly applying such methodology, we get the results in Table 5.

As a result of the decomposition effect, the capital factor is found to have a significant effect on regional output, with a coefficient of 0.43. The FDI indicator is used to measure the degree of technological diffusion that comes from abroad. The empirical results show that FDI has a significant positive effect on the economic development of a given region as well as the given region's neighbours. FDI works to increase infrastructure and supports developing the services in a region, thereby improving its levels of technological development. FDI can also have a strong spillover due to its transmission mechanisms. As a result, the neighbouring regions of an FDI client can also benefit from the distant influx of FDI, in turn

Table 5. Decomposition of direct and Indirect effect.

Variables	lnk Coefficient	lnk t	lnFDI Coefficient	lnFDI t	lnR&D Coefficient	lnR&D t	lnT Coefficient	lnT t
ADE	0.430***	19.27	0.0202***	3.65	0.00261	0.15	0.0256***	5.30
AIE	−0.171	−1.09	0.200***	3.06	0.171*	1.65	0.0334	0.77
ATE	0.259	1.62	0.220***	3.28	0.174*	1.69	0.0590	1.32

Note: ***, **, and * in the table indicate levels of significance at 1%, 5%, and 10%, respectively.

raising their own level of technological development and thereby promoting economic growth in a sustained way.

Likewise, technological innovation (Represented by R&D) has a positive impact on neighbouring regions. There is a strong spillover effect in the production processes behind such knowledge, which constitutes the path for technological diffusion. Comparatively speaking, R&D tends to have a smaller coefficient which reflects the inadequacy in the given region for transforming innovation into truly productive forces or the extent to which research inputs have yet to be improved.

Technical transaction volume has a significant and positive effect in increasing the level technological development in the given region while at the same time promoting economic growth. The coefficient is 0.0256. It is found that technical transaction volume has a role in promoting technological development in neighbouring regions as well. In recent years, the increase in the total volume of China's technological transactions also reflects the importance that each region places on raising its level of technological development and increasing its technological exchanges.

V. Conclusion

In the new normal of China's economy as well as the unbalanced economic development of China's multiple and far-flung regions, it is extremely urgent to study the phenomena of spatial spillover in terms of economic activity in all of the country's regions so as to find better ways to promote sustainable and efficient economic development. This study used spatial measurement methodologies to investigate the relationship between the spillover effects of multiple technological elements and economic growth in China's 30 provinces from 2005 to 2016. The findings are as follows. First, significant spatial spillovers in the input of production factors are observed in China's regions. Economic activities in the different regions of China are found to have a high degree of spatial correlation. Traditional considerations typically made for each region as being independent of one another, and applying non-spatial econometric analysis to study their economy therein, is inapplicable. Second, among the three aforementioned sources of technology, FDI affects local and neighbouring regions most prominently. Foreign investment work to enable the positive externalities of technological diffusion, promote the learning of new technologies. The other two sources, namely regional technological innovation and technological transaction volume, are found to also have a significant effect on promoting regional economic growth regardless.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This research is supported by the National Natural Science Foundation of China [71603061], the 2018 'Thirteen-Five' Plan Project Sponsored by the Philosophy andSocial Science of Guangzhou [2018GZYB56], the Project of South China Institute of Fortune Management Research [The general project No.4] and the Project of Guangdong University of Foreign Studies [18SS09]

References

Anselin, L., A. K. Bera, R. Florax, M. J. Yoon. 1996. "Simple Diagnostic Tests for Spatial Dependence[J]." *Regional Science and Urban Economics* 26 (1): 77–104. doi:10.1016/0166-0462(95)02111-6.

Elhorst, J. P. 2001. "Dynamic Models in Space and Time[J]." *Geographical Analysis* 33 (2): 119–140. doi:10.1111/j.1538-4632.2001.tb00440.x.

Elhorst, J. P. 2014. *Spatial Panel Data Models[M]. Spatial Econometrics*, 37–93. Berlin, Heidelberg: Springer.

Fagerberg, J. 1994. "Technology and International Differences in Growth Rates[J]." *Journal of Economic Literature* 32 (3): 1147–1175.

LeSage, J. P., and R. K. Pace. 2008. "Spatial Econometric Modeling of Origin Destination Flows[J]." *Journal of Regional Science* 48 (5): 941–967. doi:10.1111/jors.2008.48.issue-5.

LeSage, J. P., and R. K. Pace. 2014. *Interpreting Spatial Econometric Models[M]//Handbook of Regional Science*, 1535–1552. Berlin, Heidelberg: Springer.

Ljungwall, C., and P. G. Tingvall. 2015. "Is China Different? A Meta-Analysis of the Growth-Enhancing Effect from R&D Spending in China[J]." *China Economic Review* 36: 272–278. doi:10.1016/j.chieco.2015.10.001.

Romer, P. M. 1990. "Endogenous Technological Change[J]." *Journal of Political Economy* 98 (5, Part 2): S71–S102. doi:10.1086/261725.

Scott, A. J. 1988. "Flexible Production Systems and Regional Development: The Rise of New Industrial Spaces in North America and Western Europe[J]." *International Journal of Urban and Regional Research* 12 (2): 171–186. doi:10.1111/ijur.1988.12.issue-2.

Shang, Q., J. P. H. Poon, and Q. Yue. 2012. "The Role of Regional Knowledge Spillovers on China's innovation[J]." *China Economic Review* 23 (4): 1164–1175. doi:10.1016/j.chieco.2012.08.004.

Young, A. 2003. "Gold into Base Metals: Productivity Growth in the People's Republic of China during the Reform Period[J]." *Journal of Political Economy* 111 (6): 1220–1261. doi:10.1086/378532.