The Impact of Transportation Infrastructure on Regional Innovation Capability: A Dynamic Durbin Panel Data Approach

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Abstract. Using data from 30 provinces in China over the period 1995–2015, by applying a dynamic spatial panel data model, it is shown that per capita number of patent applications is stable. Then we use bias corrected QML estimator method to explore the spatial spillover effects of transportation infrastructure on regional innovation capability. Results show: (1) China’s regional innovation capability has a cumulative effect on time and space, and still has time lag effect in space: (2) effect of transport infrastructure on regional innovation capability is not limited to local, the transportation infrastructure will also affect the neighboring areas’ innovation, namely traffic infrastructure has a spatial spillover effect.

Introduction

With the rapid growth of China’s economy, China’s transportation infrastructure has been greatly developed, and has become one of the most important factors in China’s regional economic growth. By the end of 2010, China’s transportation infrastructure have been ranked in the world, the railway mileage and road mileage reached 9.1 Million km and 400.82 million km, ranking third and second in the world. Transportation infrastructure are traditionally seen as innovation capacity catalysts for the region they serve, there is a broad consensus among economists (Barro\textsuperscript{1}, Lucas\textsuperscript{2}). With the rise of new economic geography, many scholars have discussed the spatial spillover mechanism of regional infrastructure to regional innovation capability: the network characteristics of transportation infrastructure will reduce transportation costs and transaction costs, improve regional accessibility, thus have a spatial spillover effect on regional innovation capability: When the decline of the transport cost and the transaction cost leads to regions with strong innovation capacity promote areas with weak innovation capability, transportation infrastructure play diffusion effect on regional innovation capacity, transportation infrastructure has positive spillover effect on regional innovation ability; When the transportation costs and transaction costs decrease, the areas with strong innovation capability attract the innovation capability in the weak regions, transportation infrastructure play agglomeration effect on regional innovation capacity(Krugman\textsuperscript{3}, Boarnet\textsuperscript{4}).

Therefore, the important position of transportation infrastructure indicates
that China has made substantial capital investment in transportation facilities in recent years. What is actually less known is to what extent the transportation infrastructure contributes to neighboring areas’ regional innovation capacity, including the direct, indirect and total effects.

The new growth theories developed in the early 1990s suggest that the major source of economic growth is innovation. In recent years, with the generation and development of the new economic geography theory, scholars gradually began to incorporate the spatial effect into the study of transportation infrastructure and regional innovation capability. And, the method of spatial econometrics has been gradually used in the study of the spatial spillover effect of transportation infrastructure. Liu Bing-Lian, Wu Peng, Liu Yu-hai[5](2010) analyzed the TFP growth in China, using the spatial panel data approach, found that transportation infrastructure had obvious positive impact on TFP in China. Zhang Qiang and Zhang Ying-qin[6](2017), Li Jing and He Yi-li[7](2017), Liang Shuang-lu and Liang Qiao-ling[8](2017) believe that transportation infrastructure has a significant spillover effect on regional innovation capability.

Since 2000, the spatial econometrics literature began to absorb the time into space panel model, that is, dynamic spatial durbin panels model, many scholars had explored the setting and estimation methods of the dynamic spatial panel model. Elhorst[9](2012), compared with the traditional measurement model, the dynamic spatial panel model has four advantages: (1) can solve the serial dependence in the time and space; (2) can solve the spatial dependence in each time point; (3) can explore the spatial and temporal effects cannot be observed; (4) can solve the problem caused by the spatial lag or time lag dependent variable. Therefore, it is more effective and accurate to estimate the spatial spillover effect of transportation infrastructure on regional innovation capability by using the dynamic spatial Durbin panel model. However, so far, there is no literature to accurately grasp the impact of infrastructure on regional innovation capability under the comprehensive consideration of the time cumulative effect of regional innovation capacity and its current and lag space effect using the dynamic space durbin panel model.

Against this background, this paper takes a broader network-related look at the effects of traffic infrastructure on the regional innovation capability in China using the dynamic space Durbin model. Accordingly, one question is addressed: does the traffic infrastructure have a spatial spillover effect on regional innovation capability, after considering the time effect of the regional innovation capacity and the cumulative effect of space? If yes, what is the elasticity?

Empirical Methodology

On the influence of transportation infrastructure on regional innovation, the empirical studies are based on the knowledge production function that D. Romer[10](1996) put forward. Therefore, knowledge production function as:

$$
\begin{align*}
\text{PAT}_i &= \tau \text{PAT}_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} \text{PAT}_j + \eta \sum_{j=1}^{N} w_{ij} \text{PAT}_{j,t-1} + \delta_i \text{TRAN}_i + \\
&+ \delta_{ij} \text{WTRAN}_i + \lambda Z_i + \mu + \delta_{ij} I_N + \varepsilon_i
\end{align*}
$$

Where the parameter $\tau$, is the response parameter of the lagged dependent variable $\text{PAT}_i$, t-1. The coefficient $\rho$ and $\eta$, represent the effect from neighboring regions’ innovation capability on region i at time t and t-1. $W_{ij}$ is an N×N weight matrix describing the spatial arrangements of regions. Its diagonal elements are set to zero by assumption, since no region can be viewed as its own
neighbour. $\varepsilon_t=(\varepsilon_{1t}, \ldots, \varepsilon_{Nt})$ is a vector of i. i. d. disturbance terms, whose elements have zero mean and finite variance $\sigma^2$. $\mu=(\mu_1, \ldots, \mu_N)$ is a vector with country fixed effects, $\partial_t$ is the coefficient of a time period fixed effect, and $\mathbf{1}_N$ is an $N \times 1$ vector of ones. The $\text{TRAN}$ represent the logarithmic form of transportation infrastructure, $\text{WTRAN}$ represent the logarithmic form of transportation infrastructure in neighboring area) from the explanatory variables. $Z$ denotes the logarithmic form of explanatory variables other than the transportation infrastructure.

According to Yu et al.\cite{11} (2008), when the number of spatial units ($N$) and the number of time points ($T$) in the sample go to infinity, such that the limit of the ratio of $N$ and $T$ exists and is bounded between $0$ and $\infty$, use a rigorous asymptotic theory, this QML estimator is biased. But when $\tau+\rho+\eta<1$, the QML can be proved to be stable. When $N/T\to\infty$, their QML and bias corrected QML estimators will $T$ consistent. when $T/N^{1/3}\to\infty$, the bias corrected QML estimator is improved on the $T$ consistency of the QML estimator. If $\tau+\rho+\eta=1$, spatial cointegration problem and the explosive roots will appear in the model, the QML and bias corrected QML estimator needs further adjustment. Since $N$ and $T$ in our empirical analysis are equal to $30$ and $21$, respectively. $N/T=1.43$, means that $N$ greater than $T$. $N^{1/3}=10$, $T/N^{1/3}=2.1$, means that $T$ greater than $N^{1/3}$. Therefore, the bias corrected QML estimator is the best choice. Therefore, we will use be the estimation method which is based on Elhorst et al.\cite{12} (2013) to estimate Eq. (1).

**Data and Variables**

The database covers 30 provinces (municipalities and autonomous regions) in China excluding Tibet, Taiwan, Hong Kong, and Macao over the period 1995–2015. Data obtained from the State Bureau of Statistic, the China Statistical Year book. Tibet is excluded in our analysis because most of the relevant data for it is either not available or zero during the time period examined.

The region innovation capability (PAT) is expressed per capita number of patent applications. The explanatory variable is transportation infrastructure ($\text{TRAN}$). The transportation infrastructure consists of three categories, namely, rail mileage, highway mileage and inland waterway mileage. In order to make the transportation infrastructure comparable in different years, we have calculated the density of traffic infrastructure in each province in 1995-2015.

This paper contain three control variables: (1) Foreign capital dependence, use the FDI amount accounting for the proportion of GDP lagged one period to analyze foreign capital dependence; (2) R&D activity, we use technical development (R&T) as a representative; (3) Human capital stock (HC) measured by the average duration of education per person older than six years old. Table 1 provides summary statistics of all the variables.

As Nannan Yuet al.\cite{13} (2013), we assume only neighboring provinces can influence each other, we use the ‘provincial borders’ to construct the ‘spatial geographic unit’. The adjacent space matrix is showed in Equation (2).

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1 The data is calculated by the following formula: $\text{HC}_t=(\text{HC}_{p1}t \times 6+ \text{HC}_{j2}t \times 9 + \text{HC}_{s3}t \times 12 + \text{HC}_{h4}t \times 16)/\text{total education population}$, where $\text{HC}_{p1}$, $\text{HC}_{j2}$, $\text{HC}_{s3}$, $\text{HC}_{h4}$ are the percentages of primary education, junior secondary education, senior secondary education, and higher education, respectively.
\( W_{ij} = \begin{cases} 1 & \text{if the province } i \text{ has a border with province } j \\ 0 & \text{otherwise} \end{cases} \) \tag{2} \\

\[ \sum_{j=1}^{N} W_{ij} = 1 \]

and

### Table 1. Summary Statistics of Control Variables.

<table>
<thead>
<tr>
<th>variable</th>
<th>Describe</th>
<th>Mean</th>
<th>std. Dev</th>
<th>Min</th>
<th>Max</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(logarithmic form)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PAT</td>
<td>per capita number of patent applications</td>
<td>4.4735</td>
<td>1.3694</td>
<td>1.9459</td>
<td>8.2108</td>
<td>660</td>
</tr>
<tr>
<td>TRAN</td>
<td>density of traffic infrastructure</td>
<td>3.7633</td>
<td>0.9556</td>
<td>0.6451</td>
<td>5.512</td>
<td>630</td>
</tr>
<tr>
<td>FDI</td>
<td>FDI actual use of the amount per year accounting for the proportion of GDP</td>
<td>9.9255</td>
<td>1.044</td>
<td>6.5259</td>
<td>12.3989</td>
<td>630</td>
</tr>
<tr>
<td>R&amp;T</td>
<td>per capita the number of personnel for science and technical development</td>
<td>6.7314</td>
<td>0.9824</td>
<td>4.5809</td>
<td>9.3774</td>
<td>630</td>
</tr>
<tr>
<td>TIA</td>
<td>the tertiary industry added value accounted for GDP</td>
<td>-0.9307</td>
<td>0.1639</td>
<td>-1.285</td>
<td>-0.2491</td>
<td>630</td>
</tr>
<tr>
<td>HC</td>
<td>Human capital stock</td>
<td>2.1712</td>
<td>0.0942</td>
<td>1.9332</td>
<td>2.5041</td>
<td>630</td>
</tr>
</tbody>
</table>

### Results

Table 2 showed the results of the bias corrected QML estimator, and column (1) showed the results without time effect, and the column (2) showed the results with time effect, these results based on the model (4). As test whether the model contain the time-period fixed effects, we calculated the F-test, the P value of F-test is less than 0.01, therefore the model which contained the time-period fixed effects is more efficient. Then, we calculated the value of \( \tau + \rho + \eta \), and applied the Wald-test to test the hypothesis \( \tau + \rho + \eta = 1 \). If the \( \tau + \rho + \eta \) is proved to be significantly less than 1, that means the model is stable, if the \( \tau + \rho + \eta \) is proved to be significantly greater than 1; that means the model has explosive root problem; if the \( \tau + \rho + \eta \) is significantly equal to 1, it means that the model is spatially cointegrated. When the model is non-stable, we must reformulate the model into spatial first-differences, and the coefficients should be re-estimated. Since the Wald test reported in column (2) shows that the dynamic spatial durbin panel is stable, therefore we don’t consider spatial first-differences, use bias corrected QML estimator to test the dynamic spatial durbin pane model. At the same time, we use the parameter estimates of the dynamic spatial durbin panel data model to compute direct and indirect effects of the different explanatory variables on region innovation capability. These direct and indirect effects, as well as the total effects, are reported in columns (3), (4) and (5) of Table 2, respectively.

The coefficients of \( \text{PAT}_{t-1}, W * \text{PAT}_t \) are both positive and significant as shown in column (2). The coefficient of \( W * \text{PAT}_t \), which represent the impact of the regional diffusion effect on region innovation capability, is 0.5556, shows that the innovation capability in neighboring region increase by 1%, the region
innovation capability grows 55.56%, it means that the region innovation capability has space accumulation effect; the coefficient of PAT_{t-1}, which represent the impact of the time diffusion effect on region innovation capability, is 0.8985, shows that the region innovation capability in previous year increase by 1%, the region innovation capability grows 89.85%; it means that region innovation has time accumulation effect. While, W*PAT_{t-1}, which represent the impact of the time and space diffusion effect, is negative and significant. the coefficient of W*PAT_{t-1} is -0.5294, shows that the innovation of neighboring region in last year has a negative effect on the region innovation this year, it means that region innovation has time and space effect at the same time.

The direct effect of the variable PAT_{t-1} is -0.9085 (t-value -16.4886). This is mainly due to the stronger ability to innovate, and its innovation level, management level and innovative production factors are in the lead, leading to the introduction of new technologies and new management methods to reduce. At the same time, the innovation of new technology and new management methods will take a long time, thus slowing down the innovation ability of innovation area. It also shows that the promotion of regional innovation capability is convergent. While its indirect effect is 0.9085(t-value 16.4886); it means the higher the regional innovation capacity in the region itself, or the lower the regional innovation capacity in the neighboring areas, the lower the extent of regional innovation capacity reform (the change of region innovation capacity in Eq.6), and vice versa. The total effect is 0.0000, but insignificant (t-value 0.4524).

The coefficient of transportation infrastructure (TRAN) has a positive and significant effect on the regional innovation capacity (0.0052, t-value1.7755), it shows that the higher traffic infrastructure stock, the higher the extent of regional innovation capacity, and vice versa. The direct, indirect and total effect of transportation infrastructure are not significant. It means that the transportation has no obvious impact on the regional innovation capacity reform.

The coefficient of transportation infrastructure’ spatial spillover (WTRAN) has positive and significant effect on the regional innovation capacity (0.1130, t-value 1.8757). It shows that the transportation infrastructure in neighboring region increase by 1%, the region innovation capability grows 18.76%. Therefore, the impact of transportation infrastructure on region innovation is not limited to local, also affect the neighboring areas’ innovation, the transportation infrastructure has a spatial spillover effect. More general, the transportation infrastructure play an diffusion effect on the region innovation capability. The direct, indirect and total effect of transportation infrastructure in neighboring areas are not significant. It means that the neighboring areas’ transportation infrastructure has no obvious impact on the regional innovation capacity reform.

The coefficient estimates of the control variables show that the human capital (HC), R&T activity impact the regional innovation capacity significantly. The foreign capital dependence (FDI) has positive effect, but are insignificant. The direct and indirect effect of control variables are shown in column (3). The direct, indirect and total effects of human capital stock (HC), R&T and foreign capital dependence (FDI) are positive but insignificant. It means human capital (HC), R&T and foreign capital dependence (FDI) have no obvious impact on the regional innovation capacity reform.
Table 2. Bias Corrected QML Estimator with Adjacent Space Weight Matrix.

<table>
<thead>
<tr>
<th>Determinants</th>
<th>No time dummies (1)</th>
<th>Time dummies (2)</th>
<th>Direct (3)</th>
<th>Indirect (4)</th>
<th>Total (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAT_{t-1}</td>
<td>0.8136 (33.7419)</td>
<td>0.8985 (34.6154)</td>
<td>-0.9085 (-16.4886)</td>
<td>0.9085 (16.4886)</td>
<td>0.0000 (0.4524)</td>
</tr>
<tr>
<td>WPAT_{t}</td>
<td>0.5500 (14.0827)</td>
<td>0.5556 (14.0473)</td>
<td>NR</td>
<td>NR</td>
<td>NR</td>
</tr>
<tr>
<td>WPAT_{t-1}</td>
<td>-0.4640 (-10.9440)</td>
<td>-0.5294 (-11.0338)</td>
<td>NR</td>
<td>NR</td>
<td>NR</td>
</tr>
<tr>
<td>TRAN_{t}</td>
<td>0.0329 (1.7559)</td>
<td>0.0052 (1.7755)</td>
<td>0.0060 (-0.0303)</td>
<td>0.0005 (0.0815)</td>
<td>0.0065 (-0.0119)</td>
</tr>
<tr>
<td>WTRAN_{t}</td>
<td>0.0905 (1.8349)</td>
<td>0.1130 (1.8757)</td>
<td>NR</td>
<td>NR</td>
<td>NR</td>
</tr>
<tr>
<td>HC_{t}</td>
<td>0.3576 (1.7836)</td>
<td>0.2942 (1.8286)</td>
<td>0.1628 (1.2411)</td>
<td>0.0136 (0.9753)</td>
<td>0.1764 (1.2268)</td>
</tr>
<tr>
<td>FDI</td>
<td>0.0061 (0.5205)</td>
<td>0.0074 (0.5340)</td>
<td>-0.5706 (-1.1242)</td>
<td>-0.0476 (-0.8985)</td>
<td>-0.6183 (-1.1174)</td>
</tr>
<tr>
<td>R&amp;T</td>
<td>0.0624 (2.3917)</td>
<td>0.0307 (2.4535)</td>
<td>0.0249 (0.1438)</td>
<td>0.0021 (0.2999)</td>
<td>0.0270 (0.1729)</td>
</tr>
<tr>
<td>observations</td>
<td>630</td>
<td>630</td>
<td>0.0777 (0.2678)</td>
<td>0.0065 (0.3648)</td>
<td>0.0841 (0.2898)</td>
</tr>
<tr>
<td>sigma^2</td>
<td>0.0216</td>
<td>0.0215</td>
<td>NR</td>
<td>NR</td>
<td>NR</td>
</tr>
<tr>
<td>log-likelihood</td>
<td>288.7732</td>
<td>-336.265</td>
<td>NR</td>
<td>NR</td>
<td>NR</td>
</tr>
<tr>
<td>(\tau + \rho + \eta)</td>
<td>NR</td>
<td>0.9248</td>
<td>NR</td>
<td>NR</td>
<td>NR</td>
</tr>
<tr>
<td>Wald-test (\tau + \rho + \eta = 1)</td>
<td>NR</td>
<td>14.8674</td>
<td>NR</td>
<td>NR</td>
<td>NR</td>
</tr>
<tr>
<td>P value</td>
<td>NR</td>
<td>0.0001</td>
<td>NR</td>
<td>NR</td>
<td>NR</td>
</tr>
</tbody>
</table>

Notes: In parentheses is t-value. NR=not relevant.

Conclusions

Using data from 30 provinces in China over the period 1995–2015, by applying a dynamic spatial Durbin panel data model, it is shown that per capita number of patent applications is stable. Then we use bias corrected QML estimator method to explore the spatial spillover effects of transportation infrastructure on regional innovation capability.

By using the dynamic spatial Durbin panel data model, it is shown that the China's region innovation capability, depends on the neighboring areas’ innovation capability, last year's regional innovation capability in the region, and also depends on the last year's regional innovation capability in the neighboring areas. This means that the innovation capability of China's region has a cumulative effect on time and space, and still has time lag effect in space. At the same time, as mentioned above, effect of transport infrastructure on region innovation capability is not limited to local, more important, the transportation infrastructure will affect the neighboring areas’ innovation, namely traffic.
infrastructure has a spatial spillover effect. Therefore, in the context of ignoring the time and space effects, it is certainly not accurate to study the influence of infrastructure on regional innovation capability.

Acknowledgements

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References