The Effectiveness of International Knowledge Spillover Channels

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ABSTRACT

Using panel data from thirteen OECD countries for the period 1981–1999, we examine the significance of international knowledge spillovers via four different channels: inflow and outflow FDI, flows of intermediate goods imports and a disembodied direct channel. Using dynamic OLS models, we show that international knowledge spillovers via the inflow FDI and the disembodied direct channels are significant. In contrast, neither the outflow FDI nor import flows were effective knowledge spillover channels. We also show that size of country does not affect direct spillover effects, although the effect of inflow FDI is greater in small countries.

Key Words: Spillovers, Investment, Imports, Technology Proximity, Panel Cointegration.

JEL classification: O30, O47, O57, C23, F01

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1. Introduction

Previous studies have provided evidence that knowledge originating in a country transcends its national boundaries and contributes to the productivity growth of other countries. According to growth theories, the presence of strong international knowledge spillovers plays a key role in the convergence of per capita income among countries\(^1\). These studies usually presume that technology is embodied in a particular channel of knowledge transmission. The main channels considered by these studies are import flows, cross border investments and a direct channel.

Of these channels, import flows have been frequently used owing to data availability and the pioneering work of Coe and Helpman (1995) (henceforth CH). CH use panel data from 23 countries from 1971 to 1990 to estimate the magnitude of international R&D spillovers through import flows between these countries. By applying the conventional Ordinary Least Squares (OLS) estimation method to pooled cointegration models, they show significant spillover of the results of R&D investment through import flows. Lichtenberg and van Pottelsberghe (1998) use the alternative formulation of foreign R&D capital stock, which corrects the potential aggregation bias buried in the formulation suggested by CH. Despite this change, their estimation results do not substantially differ from the results of CH. In contrast to them, Kao, Chiang and Chen (1999), criticizing the shaky basis of the estimation strategy adopted by CH, conclude that the presence of international R&D spillover effects through import flows should be rejected, according to the results obtained from their dynamic OLS (DOLS) estimation. Kao and Chiang (2000) have claimed that DOLS has superior small sample properties with panel cointegration models, compared with conventional OLS and fully

\(^1\) Grossman and Helpman (1991) provide a good summarization of these theories. Recently Lee (2004) shows that the globalization of knowledge spillovers affects terms of trade as well as productivity growth among countries.
modified OLS (FMOLS).

Foreign direct investments (FDI) are also likely to be a substantial channel of international knowledge transfer. Hanel (1994) approximates the foreign R&D pool of knowledge for nineteen Canadian industries as being proportional to the share of sales accounted for by foreign subsidiaries, both in the intra- and extra-industry dimension. Foreign R&D seems to contribute to Canadian productivity growth, but to a much lesser extent than domestic R&D. But the significance of these estimates is fragile. Branstetter (2000), using data on patent citations between Japanese investing firms and American indigenous firms, shows that FDI is a significant channel of knowledge spillovers, both from investing firms to indigenous firms and from indigenous firms to investing firms. van Pottelsberghe and Lichtenberg (2001) (henceforth PL), using panel data from 13 OECD (The Organization for Economic Cooperation and Development) countries during the period 1971–1990, investigate whether inward and outward FDI, as well as imports, are effective in the international diffusion of technology in the context of CH’s framework. The results show that significant R&D spillovers take place through both imports and outward FDI. However, according to their study, the stock of foreign knowledge embodied in inward FDI has no significant effect.

Knowledge also circulates directly with no need for exchange of goods or investments. Therefore, knowledge spillovers that are not embodied in specific transactions should be considered in measuring international technology spillovers. Such disembodied direct knowledge spillovers are usually approximated using the measure of technology proximity suggested by Jaffe (1986, 1988). Guellec and van Pottelsberghe (2001), using this proximity measure as a weight in formulating foreign R&D capital stock, find that such disembodied cross-border spillovers are robustly significant.

Despite these studies of the various channels of international knowledge spillovers,
little empirical evidence has been produced about the relative effectiveness of such channels. The purpose of this paper is to examine the significance of international R&D spillovers through four different channels: inflow and outflow FDI, flows of intermediate goods imports and a disembodied direct channel. PL have also investigated the relative effectiveness of inflow and outflow FDI and imports. Their results, however, have limited implications due to the omission of disembodied direct spillovers and the adoption of an inadequate estimation method. An estimation model that fails to control for disembodied spillover effects lacks an important explanatory variable. This implies a misspecification of their model that could produce misleading results. In addition, according to Kao and Chang (2000), their OLS estimation results should have non-negligible biases since their estimation models are cointegrated.

This paper attempts to evaluate the effectiveness of channels of international knowledge spillovers using newly constructed panel data from 13 OECD countries, including all the G7 countries, for the period 1981–1999. These panel data are tested using panel cointegration test statistics proposed by Kao (1999), indicating that the estimation model is panel-cointegrated. The DOLS estimation method suggested by Kao and Chiang (2000) will be applied to the model, as it is claimed to have better small sample properties than OLS or FMOLS estimations. From the estimation results, this paper will demonstrate which of intermediate goods imports, inflow and outflow FDI, and disembodied direct, international knowledge spillover channels are significant and effective. In addition, this study compares the magnitudes of these effects between large G7 countries and small non-G7 countries. The results of the paper will have additional significance because it covers periods during which the processes of globalization and liberalization in trade and investment have advanced rapidly, as symbolized by the establishment of the World Trade Organization.

The paper is organized as follows: section 2 explains data sources and their basic
statistical features. The results of panel unit root tests and panel cointegration tests on the data are provided in section 3. Based on these tests, a panel cointegration model is proposed and the results of DOLS estimations are also provided in section 3. Section 4 summarizes the main results.

2. Data and Variables

2-1. Total factor productivity (TFP) and domestic R&D stocks

We use estimates of value-added, physical capital stock, labor service employed and labor income share in the manufacturing sector based on the STAN database compiled by the OECD. These estimates are used to measure TFP in the manufacturing sector under the assumption that the production technology is Cobb-Douglas and that output elasticities of production factors are time-invariant over the sample period. Accordingly, the output elasticity of labor services is calculated using the average share of labor income over the sample period. We base our estimates of domestic R&D capital stocks on R&D investment data from the OECD’s Science and Technology database. R&D investments influencing TFP include not only business sector R&D expenditures but also the R&D expenditures of research institutes and universities.

Missing values in these data are supplied, where possible, using data from other complementary sources. For instance, the Korean Statistical Bureau database has been used to supplement missing data on Korea, whilst the OECD’s Main Economic Indicators and the Laborsta database from the International Labor Organization (ILO) have been used to complete the data set for other countries. In a few cases, where no alternative sources are available to supply missing values, appropriate regression models have been used to predict them.

Physical capital and domestic R&D capital stocks are calculated according to a perpetual inventory model. A depreciation rate of 10% is used to estimate physical capital
stocks, while a 15% rate is applied to calculate R&D capital stocks, because the economic life cycle of a technology is shorter than that of physical capital. However, this setting is not a crucial one, as the use of various alternative combinations of depreciation rates does not substantially change the main results of the paper.

2-2. Foreign R&D stocks that directly spill over

Disembodied knowledge spillovers are estimated by foreign R&D capital stocks that directly spill over. Foreign R&D capital stock of a country is constructed as the weighted sum of the R&D capital stocks of 12 other countries, where the weight corresponds to bilateral technological proximity times patent citations share between countries.

\[ S^d_{ij,t} = \sum_{j \neq i} \left( w^p_{ij,t} \cdot S^d_{j,t} \right), \quad w^p_{ij,t} = \text{prox}_{ij,t} \times \text{cite}_{ij,t} \]  

The bilateral technological proximity between countries is computed following Jaffe (1986, 1988), using US patent data compiled and arranged by Hall, et al. (2001).

\[ \text{prox}_{ij,t} = \frac{F_{i,t} F'_{j,t}}{\left[ (F_{i,t} F'_{j,t}) (F'_{j,t} F_{i,t}) \right]^{1/2}}, \quad F_{i,t} = \frac{P_{i,t \downarrow}}{\sum_{z=1}^{Z} P_{i,t \downarrow}} \ldots \frac{P_{i,t \uparrow}}{\sum_{z=1}^{Z} P_{i,t \uparrow}} \] 

where \( P_{i,t \downarrow} \) is a patent granted and classified into a technology field \( z \) that is applied by country \( i \) in year \( t \). \( Z \) is the total number of technology fields classified by Hall, et al. (2001). Thus, \( F_{i,t} \) is the frequency distribution across \( Z \) technological classes of patents granted by the United States Patent and Trademark Office (USPTO) to country \( i \) in year \( t \). Guellec and van Pottelsberghe (2001) use \( \text{prox}_{ij,t} \) as weights in formulating such foreign R&D stocks. However, this formulation has a caveat due to the symmetry of this proximity measure. For instance, where only two countries are considered, disembodied spillovers between these two countries are of the same magnitude when they have the same domestic R&D stocks, since \( \text{prox}_{ij,t} = \text{prox}_{ji,t} \).
To be more realistic, the direction of knowledge flows indicated in patent citations data should be considered. For this purpose, the share of patent citations of country \( i \) from the patents of country \( j \) is calculated as follows:

\[
cite_{ij,t} = \frac{C_{ij,t}}{\sum_{h=1}^{n} C_{ih,t}},
\]

where \( C_{ij,t} \) is the number of citations of the patents of country \( j \) by the patent applications of country \( i \) in year \( t \).

2-3. Foreign R&D stocks embodied in import flows

Foreign R&D capital stocks embodied in the flows of intermediate goods imports are constructed using the method suggested by Lichtenberg and van Pottelsberghe (1998) as follows:

\[
S_{ij,t}^m = \sum_{j=1}^n \left( m_{ij,t} \frac{S_{j,t}^d}{V_{j,t}} \right) = \sum_{j=1}^n \left( w_{ij,t}^m \cdot S_{j,t}^d \right), \quad w_{ij,t}^m = \frac{m_{ij,t}}{V_{j,t}},
\]

where \( S_{ij,t}^m \) is the estimate of foreign R&D capital stock, embodied in the flow of intermediate goods imports, of country \( i \) accumulated at the end of year \( t \), and \( S_{j,t}^d \) and \( V_{j,t} \) are the estimates of domestic R&D capital stock and total value added in the manufacturing sector of country \( j \) in year \( t \). Further, \( m_{ij,t} \) is the total flow of intermediate goods imports from country \( j \) to country \( i \) in year \( t \). Data on the import flows of intermediate goods are extracted from the international trade data compiled by Nicita and Olarreaga (2001). To obtain data on the import flows of intermediate goods, we exclude trade flows in those industries classifiable as producing final goods at the three-digit industry level. Equation (4) shows that the stock of R&D that country \( i \) receives from country \( j \) through intermediate goods imports is estimated by country \( j \)'s R&D stock times the fraction of country \( j \)'s output exported to country \( i \).
2-4. Foreign R&D stocks embodied in FDI

Foreign R&D stocks embodied in inflow and outflow FDI are constructed according to the method suggested by PL as follows.

\[
S_{\textit{i},t}^n = \sum_{j \neq i} \left( n_{\textit{j},t} \cdot \frac{S_{\textit{j},t}^d}{K_{\textit{j},t}} \right) = \sum_{j \neq i} \left( W_{\textit{i},\textit{j},t}^n \cdot S_{\textit{j},t}^d \right), \quad w_{\textit{i},\textit{j},t}^n = \frac{n_{\textit{j},t}}{K_{\textit{j},t}}, \tag{5}
\]

\[
S_{\textit{i},t}^o = \sum_{j \neq i} \left( o_{\textit{j},t} \cdot \frac{S_{\textit{j},t}^d}{K_{\textit{j},t}} \right) = \sum_{j \neq i} \left( W_{\textit{i},\textit{j},t}^o \cdot S_{\textit{j},t}^d \right), \quad w_{\textit{i},\textit{j},t}^o = \frac{o_{\textit{j},t}}{K_{\textit{j},t}}, \tag{6}
\]

where \( S_{\textit{i},t}^n \) and \( S_{\textit{i},t}^o \) are the estimates of foreign R&D capital stocks, embodied in the inflow and outflow FDI respectively, of country \( i \) accumulated at the end of year \( t \). The term \( n_{\textit{j},t} \) is the flow of FDI from country \( i \) to country \( j \) while \( o_{\textit{j},t} \) is the flow of FDI from country \( j \) to country \( i \).

Data on inflow and outflow FDI are also based on OECD’s International Direct Investment database. \( K_{\textit{j},t} \) is the gross fixed capital formation of country \( j \) in year \( t \). We would prefer to specify FDI stocks rather than flows, but missing data and the heterogeneous methodologies adopted in different countries make the construction of FDI stocks difficult. To avoid problems of volatility and incompleteness in flow data, four-year moving averages are used, as in PL.

2-5. Basic statistical features of variables

<Table 1> shows averages and compounded average growth rates (CAGR) of domestic R&D capital stocks, foreign R&D capital stocks that are embodied in intermediate goods imports, inflow and outflow FDI, and foreign R&D capital stocks that directly spill over.

< Table 1 is about here >

It is noteworthy that South Korea has been outstanding in terms of the growth of domestic R&D stocks, while Spain is the only country that has a two-digit growth rate of foreign R&D stocks embodied in import flows over the sample period. Canada, Finland, Korea and Sweden show
outstanding growth rates in foreign R&D stocks embodied in inward FDI while Finland and Korea are also strong in the growth of foreign R&D stocks embodied in outward FDI. Note also that, on average, the magnitude of foreign R&D stocks that directly spill over is about 15 to 25 times smaller for the United States than for other countries. It reflects the fact that the United States dominates the other countries absolutely in the number of patents granted by the USPTO.

It is interesting to note that, on average, the magnitude of foreign R&D stocks embodied in inward FDI in Japan is only 7% of that in the United States, while the magnitude of foreign R&D stocks embodied in outward FDI in Japan is about 104% of that in the United States.

3. Estimation Model and Results

3-1. Estimation model

A basic estimation equation is developed by extending the estimation models of CH, and is given as follows:

$$\log \frac{A_{i,t}}{A_{i,95}} = \alpha_i + \beta_1 \log \frac{S_{d,i,t}}{S_{d,95,i}} + \beta_2 G \log \frac{S_{d,i,t}}{S_{d,95,i}} + \beta_3 \log \frac{S_{p,i,t}}{S_{p,95,i}} + \beta_4 G \log \frac{S_{p,i,t}}{S_{p,95,i}} + \beta_5 \log \frac{S_{m,i,t}}{S_{m,95,i}} + \beta_6 G \log \frac{S_{m,i,t}}{S_{m,95,i}} + \beta_7 \log \frac{S_{m,i,t}}{S_{m,95,i}}$$

$$+ \beta_8 G \log \frac{S_{m,i,t}}{S_{m,95,i}} + \beta_9 \log \frac{S_{m,i,t}}{S_{m,95,i}} + \beta_{10} G \log \frac{S_{m,i,t}}{S_{m,95,i}} + \varepsilon_{i,t},$$

$$i = 1, \ldots, 13, \ t = 81, \ldots, 99. \quad (7)$$

The term $G$ is a dummy variable equal to one for the G7 countries, and zero for non-G7 countries. Consequently, $\beta_2, \beta_4, \beta_6, \beta_8$ and $\beta_{10}$ measure the magnitude of the differences in the effects of corresponding variables between G7 and non-G7 countries. The term $A_{i,t}$ is the manufacturing TFP of country $i$ in year $t$.

Equation (7) estimates the effects of domestic and various foreign R&D capital stocks on manufacturing TFP. It transforms all variables into index values ($1995 = 1$) to free them from
the units of measurement. Denoting the indexed variables by corresponding small letters, equation (7) can be presented as follows:

$$
\log a_{i,t} = \alpha_i + \beta_1 \log s_{i,t}^d + \beta_2 G \log s_{i,t}^d + \beta_3 \log s_{i,t}^p + \beta_4 G \log s_{i,t}^p + \beta_5 \log s_{i,t}^m
$$

$$
+ \beta_6 G \log s_{i,t}^m + \beta_7 \log s_{i,t}^m + \beta_8 G \log s_{i,t}^m + \beta_9 \log s_{i,t}^m + \beta_{10} \log s_{i,t}^m + \epsilon_{i,t}
$$

$$
i = 1, \ldots, 13, t = 81, \ldots, 99.
$$

(8)

In this case, each estimated coefficient represents the elasticity of the manufacturing TFP index (1995 = 1) with respect to the index of each independent variable (1995 = 1). As Lichtenberg and van Pottelsberghe (1998) indicate, coefficients estimated using index numbers as against level values do not coincide, in general, because foreign R&D variables have time-variant components that cannot be incorporated into country specific constants when those variables are transformed into indexes. It is therefore true to say that CH misuse their estimated coefficients, as if they were estimated using level values, in the calculation of productivity elasticities of R&D stocks between countries. However, as long as the estimated coefficients are correctly interpreted, the transformation of variables into unit-free index values facilitates clearer analyses. This is because all countries’ data should be pooled for a single estimation equation even though these data have country specific elements in their measurement and compilation.

<Table 2> shows the results of several panel unit root tests suggested by Im, et al. (2003), and Hadri (2000). In Im, et al. (2003), the unit root is the null hypothesis to be tested, whereas Hadri (2000) tests the null hypothesis of stationarity. The results of panel unit root tests following Hadri (2000) indicate that the null hypotheses of stationarity for both dependent and explanatory variables are rejected at the 1% significance level, while the test results following Im, et al. (2003) show that the null hypotheses of non-stationarity for both dependent and explanatory variables cannot be rejected at the 10% significance level.
Accordingly, to ascertain that the regression of the model is not spurious, the results of panel cointegration tests need to be checked. Table 3 provides the results of five panel cointegration tests suggested by Kao (1999). They consistently confirm that there is panel cointegration among variables and that the regression of our proposed model is therefore not spurious. Consequently, the estimated coefficients can be viewed as representing the long-term relationships between the variables.

3-2. Estimation results

Table 4 summarizes the estimation results for equation (8). It shows the results of DOLS estimation suggested by Kao and Chiang (2000) and applied by Kao, Chiang and Chen (1999). According to Kao and Chiang (2000), conventional OLS estimation under panel cointegration exhibits substantial biases. The bias-corrected OLS estimator simply adjusts this bias, but in general does not improve on the conventional OLS, according to Chen, McCoskey and Kao (1999). Both FMOLS and DOLS are unbiased, but their small sample performances are differentiated using Monte Carlo experiments. Kao and Chiang (2000) show that the DOLS estimator exhibits better small sample properties than the FMOLS estimator. However, the DOLS estimation is required to establish the appropriate values of leads and lags prior to the estimation. In Table 4, the results of DOLS estimations correspond to various values of leads and lags. We also verify that for a wider range of leads and lags, the signs, significance and relative magnitudes of estimated coefficients do not change substantially.

From the first two rows of Table 4, we see that the effect of domestic R&D capital stocks on productivity is significantly positive but this effect does not seem to differ.
significantly between the (large) G7 countries and the (small) non-G7 countries. CH, PL and Lichtenberg and van Pottelsberghe (1998), using a common data set over the period 1971–1990, but with different model specifications, also show that domestic R&D stocks have significant effects on productivity. But in contrast to the findings in this paper, they find this effect to be larger in the G7 countries. In one of PL’s specifications, the effect of domestic R&D is insignificant for the small, non-G7, countries. The results of CH, PL and Lichtenberg and van Pottelsberghe (1998) have limited implications due to their ignoring disembodied direct spillovers in their model specifications, and the inadequacy of the conventional OLS estimation method applied to their models.

From the next two rows, the positive effect of direct knowledge spillovers is also shown to be consistently significant. Furthermore, the magnitude of this direct effect does not appear to differ between G7 and non-G7 countries. Guellec and van Pottelsberghe (2001), using data from 16 OECD countries from 1980 to 1998, also show that disembodied spillovers are strongly significant, but they do not investigate differences between the small and the large countries. Their research focus is, however, on comparing the effects between business R&D and public R&D, rather than on comparing effects of international knowledge spillovers via various channels.

The subsequent two rows show that the effect of indirect R&D spillovers via imports seems flimsy. The sign of the effect is even negative for some values of leads and lags, but the significance level is fragile. Kao, Chiang and Chen (1999), using the data set and the model specification used by CH, also show that the effect of international knowledge spillovers via imports is insignificant by applying the DOLS estimation method. This contradicts the results of CH, PL, and Lichtenberg and van Pottelsberghe (1998). Accordingly, the results in <Table 4> reinstate the claim made by Kao, Chiang and Chen (1999) with a richer estimation model and
new data.

As can be seen from the last four rows of Table 4, the effects of knowledge spillovers via inward and outward FDI show a clear contrast. On the one hand, knowledge spillovers through inward FDI are strongly significant but the effect is much bigger in the non-G7 than in the G7 countries. On the other hand, the effect of knowledge spillovers through outward FDI is consistently negative in the non-G7, but is consistently positive in the G7 countries. However, the magnitude of this positive effect of outward FDI is much smaller than that of inward FDI in the G7 countries. These results are in striking contrast to PL’s analysis of the data for 13 OECD countries (including all the G7 countries) during the period 1970–1990. They conclude that outward FDI is a significant channel of international knowledge spillovers, while inward FDI seems to be insignificant. Although the data span and the covered countries coincide only in part, this disparity between results of these two studies is quite surprising.

In particular, they show a clear contrast in the significance of inward FDI as a channel of international knowledge spillovers. As Blomstöm and Kokko (1998) point out in their review of productivity spillovers of inward FDI to host countries, there is no strong micro or macro level evidence on their exact nature and magnitude. However, judging from model specification, estimation strategy, and data reliability, we can claim that the results in this paper are closer to reality than the previous results. As for the effect of outward FDI, both studies agree that the positive effect is significant in the G7 countries, and the magnitude of the effect is larger in the G7 countries than in the (small) non-G7 countries. However, our results, shown in Table 4, indicate that the effect of outward FDI in these small non-G7 countries is significantly negative. This suggests that investments of these small countries into the large G7 countries have negative effects on the productivity of the (small) investing countries. On the contrary, in PL, the effect is significantly positive even though it is smaller than that for the G7 countries. It is also very hard
to find convincing evidence for either result since this is a sparsely researched area both at the micro and macro levels.

4. Conclusion

Using newly constructed panel data from 13 OECD countries, for the period 1981–1999, this paper carried out empirical studies to evaluate the effectiveness of various channels of international knowledge spillovers. We examined the significance of international knowledge spillovers via four different channels, including inflow and outflow FDI, flows of intermediate goods imports, and a disembodied direct channel. Although previous studies have investigated these channels separately and, even, occasionally as channels for international knowledge spillovers, our model specification has allowed us to establish more precisely the nature of such spillovers. Moreover, the estimation strategy applied to the model in this paper reflects recent advances in panel data econometrics that indicate the inadequacy of estimation strategies adopted in many previous studies.

The panel data in this paper were tested using appropriate panel cointegration test statistics, which indicates that the estimation model is panel-cointegrated. Thus, we applied the DOLS estimation method to the model, as it is claimed to have better small sample properties than OLS or FMOLS estimations. From the estimation results, we have demonstrated that the effects of international knowledge spillovers via the inflow FDI and the disembodied direct channel were significantly positive. In contrast, both the outflow FDI and flows of imports were shown to be ineffective as an international transmission channel for knowledge. We also find that size of the country does not affect the magnitude of direct spillover effects, but that the effects of inflow FDI are greater in small countries.

The processes of globalization and liberalization in trade and investment have advanced rapidly. The importance of cross-border knowledge spillovers in raising the economic
productivity of a nation has increased. Our results shed light on the relative importance of various channels through which knowledge spills over internationally. To support these results more convincingly, further studies with micro level data should be pursued in the future when appropriate data become available.
Reference


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<table>
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<th>Foreign R&amp;D stocks embodied in imports flow</th>
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*a When calculating averages and compound average growth rates, periods with missing data are excluded.

To clear comparison, the values of averages are presented by their relative values compared to the value of average for USA that is set as unity.
In Im, Pesaran and Shin (2003), the unit root is the null hypothesis to be tested whereas Hadri(2000) tests the null hypothesis of stationarity. Both tests are based on fixed effect model. *, **, *** indicate the parameters that are significant at 10%, 5%, 1% probability level respectively. In parenthesis, critical probabilities are given. Tests are based on STATA procedures that can be found in the Statistical Software Components(SSC) archive.

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<th>$\log s^d_{i,t}$</th>
<th>$\log s^p_{i,t}$</th>
<th>$\log s^l_{i,t}$</th>
<th>$\log s^k_{i,t}$</th>
<th>$\log s^{ik}_{i,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hadri(2000)</td>
<td>5.58</td>
<td>5.651</td>
<td>3.956</td>
<td>5.482</td>
<td>5.083</td>
<td>5.242</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Im, Pesaran and Shin(2002)</td>
<td>1.436</td>
<td>1.074</td>
<td>0.095</td>
<td>-1.169</td>
<td>2.926</td>
<td>0.179</td>
</tr>
<tr>
<td></td>
<td>(0.9245)</td>
<td>(0.8586)</td>
<td>(0.5378)</td>
<td>(0.1210)</td>
<td>(0.9983)</td>
<td>(0.5710)</td>
</tr>
</tbody>
</table>
### Panel Cointegration Test

<table>
<thead>
<tr>
<th>Test</th>
<th>Statistics</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$DF_{\rho}$</td>
<td>1.4203 *</td>
<td>(0.0778)</td>
</tr>
<tr>
<td>$DF_{i}^*$</td>
<td>-2.9744 ***</td>
<td>(0.0015)</td>
</tr>
<tr>
<td>$DF_{\rho}^*$</td>
<td>-1.5996 *</td>
<td>(0.0548)</td>
</tr>
<tr>
<td>$DF_{i}^*$</td>
<td>1.3922 *</td>
<td>(0.0819)</td>
</tr>
<tr>
<td>ADF</td>
<td>1.3819 *</td>
<td>(0.0835)</td>
</tr>
</tbody>
</table>

* Tests are based on GAUSS procedures provided in NPT version 1.3 that is retrieved from [http://web.syr.edu/~cdkao](http://web.syr.edu/~cdkao).
<table>
<thead>
<tr>
<th></th>
<th>(1) 1 lead, 1 lag</th>
<th>(2) 1 lead, 2 lags</th>
<th>(3) 2 leads, 1 lag</th>
<th>(4) 2 leads, 2 lags</th>
</tr>
</thead>
<tbody>
<tr>
<td>log $s_{i,t}^d$</td>
<td>0.1132*** (0.0396)</td>
<td>0.1288** (0.0283)</td>
<td>0.1872*** (0.0015)</td>
<td>0.1704*** (0.0069)</td>
</tr>
<tr>
<td>$G\log s_{i,t}^d$</td>
<td>-0.0097 (0.9528)</td>
<td>-0.1065 (0.5447)</td>
<td>-0.1415 (0.4210)</td>
<td>-0.2447 (0.1944)</td>
</tr>
<tr>
<td>log $s_{i,t}^d$</td>
<td>0.1063** (0.0213)</td>
<td>0.1158** (0.0187)</td>
<td>0.2343*** (0.0000)</td>
<td>0.2601*** (0.0000)</td>
</tr>
<tr>
<td>$G\log s_{i,t}^d$</td>
<td>0.1889 (0.1351)</td>
<td>0.0924 (0.4921)</td>
<td>0.1075 (0.4245)</td>
<td>0.0006 (0.9966)</td>
</tr>
<tr>
<td>log $s_{i,t}$</td>
<td>0.0425 (0.5204)</td>
<td>-0.0112 (0.8738)</td>
<td>-0.1211* (0.0869)</td>
<td>-0.1262* (0.0960)</td>
</tr>
<tr>
<td>$G\log s_{i,t}$</td>
<td>-0.0751 (0.4516)</td>
<td>-0.0214 (0.8403)</td>
<td>0.0906 (0.3946)</td>
<td>0.1342 (0.2397)</td>
</tr>
<tr>
<td>log $s_{i,t}^d$</td>
<td>0.0809*** (0.0000)</td>
<td>0.0849*** (0.0000)</td>
<td>0.0844*** (0.0000)</td>
<td>0.1026*** (0.0000)</td>
</tr>
<tr>
<td>$G\log s_{i,t}^d$</td>
<td>-0.0364*** (0.0089)</td>
<td>-0.028* (0.0582)</td>
<td>-0.0464*** (0.0018)</td>
<td>-0.0592*** (0.0002)</td>
</tr>
<tr>
<td>log $s_{i,t}^k$</td>
<td>-0.1122*** (0.0000)</td>
<td>-0.1015*** (0.0003)</td>
<td>-0.1093*** (0.0001)</td>
<td>-0.1211*** (0.0001)</td>
</tr>
<tr>
<td>$G\log s_{i,t}^k$</td>
<td>0.1150*** (0.0000)</td>
<td>0.1131*** (0.0000)</td>
<td>0.1162*** (0.0000)</td>
<td>0.1420*** (0.0000)</td>
</tr>
</tbody>
</table>

* The dependent variable is log(total factor productivity), indexed as 1995=1. *, **, *** indicate the parameters that are significant at 10%, 5%, 1% probability level respectively. In parenthesis, p-values are given. All estimations are based on GAUSS procedures provided in NPT version 1.3 that is retrieved from [http://web.syr.edu/~cdkao](http://web.syr.edu/~cdkao).