Technology Spillover and TFP Growth: a Spatial Durbin Model

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Abstract

Since 2008 the world economy has been experiencing crisis. This has weakened potential output growth and has increased unemployment and public debt. Returning to economic growth has become an imperative for countries that have seen slowdown or declining economic growth. The best way to promote economic growth is to deal with problems raised by diminishing returns of labour and capital. Therefore, growth should be ensured by an increase in total factor productivity (TFP). This paper aims to contribute to a wide literature on technological spillovers by analysing the major determinants of TFP evolution. We started from a model in which technological progress shows up as an expansion of the number of varieties of products. Based on this model, we decompose TFP into two components: quality component and variety component. We address the quality component by introducing a country’s distance to technological frontier. We assume that quality is a negative function of the technological gap of country $i$ with respect to its own technological frontier. This technological frontier is defined as the geometric means of knowledge levels in all countries. Using R&D expenditure combined with human capital stock, we deal with the variety component. In doing so, we obtain a spatial durbin structure in TFP growth that can be estimated using the spatial econometrics toolbox. We use a sample of 107 countries over the period 2000-2011 to estimate our TFP growth model. The role played by technological spillovers constitutes the main focus of this analysis. In addition to traditional factors such as R&D and human capital stock, also technological spillovers exert a strong impact on productivity growth. The technological spillovers are captured by both the spatial autocorrelation coefficient and the indirect impact of R&D.

KEYWORDS: Diffusion; Productivity; R&D; Spatial Auto-correlation.

JEL: R12; E23; O32; C21.

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1 Introduction

Continued economic growth depends on our ability to maintain and increase current levels of innovation. Therefore, innovation and technological progress are key determinants of economic growth.

Although firms are the main driver of innovation, governments have an important role to play. Governments implement a wide range of policies to promote innovation including in the areas of R&D, intellectual property rights, education, labour markets, financial markets, as well as product market regulations. Improving the business environment for innovation is an especially important policy area and open trade is a key part of the business environment conducive for innovation, allowing for the freer flow of technologies across borders, enhancing competitive pressures and opening new markets. International trade is an important way in which global firms exploit innovations on the one hand, and is an important source of innovations on the other (Grossman and Helpman, 1991) [11].

There is a wide body of theoretical research showing that international openness exerts a positive impact on growth and productivity in various ways (Aghion and Howitt, 2009 Chp. 15) [2]. Trade could raise productivity because producers gain access to new imported varieties of inputs. Moreover, trade and the resulting increase in input variety could reduce the cost of innovation and thus result in more variety creation in the future. Also, the impact of increased product variety on productivity should depend upon the elasticity of substitution among different varieties of a good, and/or upon shifts in expenditures shares among new, remaining, and disappearing goods. In particular, increasing the number of varieties could not have much of an effect on productivity if new varieties are close substitutes for existing varieties or if the share of new varieties is small relative to existing ones (Broda et al., 2006) [5].

Since the seminal paper of Coe and Helpman (1995), several empirical studies have documented that R&D cross-country spillovers, through the channel of trade flows, have been an important engine of TFP growth in the industrialized countries (Coe et al., 1997, Crespo et al., 2004). Coe and Helpman (1995) test the prediction of the trade and growth models of Grossman and Helpman (1991), and Rivera- Batiz and Romer (1991), in which foreign R&D creates new intermediate inputs and perhaps spillovers that the home country can access through imports. The subsequent studies highlight that productivity spillovers arising from international openness are strongly conditioned on host country's innovation and absorptive capabilities. True, a large technology gap between local and foreign firms can indicate a big "catch-up" potential; however, this could also show the very poor absorptive capabilities of the local partners (Blomström and Sjöholm, 1999). Therefore, availability of adequate human capital (Borensztein et al., 1998) and basic infrastructure facilities are found to be crucial for the adoption and development of advanced technologies. Empirical studies have reported that trade
enhances competitive pressures. For instance, fierce competition arising from the entry of MNCs is found to be detrimental to the economy by crowding out the less efficient domestic firms (Kokko, 1996).

Other channels of international technology diffusion have been examined. For example, Keller and Yeaple (2009) have examined R&D spillover by substituting bilateral measures of FDI instead of imports. Lee (2006) has used bilateral technological proximity and patent citations between countries, and geography location has been used by Keller (2002) and Ertur and Musolesi (2013).

While the importance of trade and FDI in the performance of innovation systems is well accepted, not enough is known about how trade affects the innovation process. So, this paper aims to contribute to a wide literature on technological spillovers by analyzing the major determinants of TFP evolution. We put the main focus on the impact of international openness through foreign trade on productivity. We started from a model in which technological progress shows up as an expansion of the number of varieties of products. Based on this model, we decompose TFP into two components: quality component and variety component. We address the quality component by introducing a country’s distance to technological frontier. A country far from technology frontier has a certain advantage backwardness, because it can grow rapidly simply by adopting technologies that have already been developed in more advanced countries. Technology transfer will stabilize the gap between rich and poor countries, thus allowing the poor countries to grow as fast as the rich. We assume that quality is a negative function of the technological gap of country $i$ with respect to its own technological frontier. This technological frontier is defined as the geometric means of knowledge levels in all countries.

Technological knowledge is often tacit and circumstantially specific. It cannot simply be copied and transplanted to another country. Instead, the receiving country must have a certain capacity in order to master the technology and adapt it to local conditions. To deal with the variety component, we use R&D expenditure combined with human capital stock. In doing so, we obtain a spatial durbin model that can be estimated using the spatial econometrics toolbox. This allows us to capture both direct and indirect effects of trade on TFP growth.

We use a sample of 107 countries over the period 2000-2011 to estimate our TFP growth model. The role played by technological spillovers constitutes the main focus of this analysis. In addition to traditional factors such as R&D and human capital stock, also technological spillovers exert a strong impact on productivity growth. The technological spillovers are captured by both the spatial autocorrelation coefficient and the indirect impact of R&D and human capital.

The remainder of the paper has the following structure. In Section 2 we will lay out the theoretical model; Section 3 presents data and estimation results. Section 4 concludes.
2 The theoretical model

We consider models in which technological progress shows up as an expansion of the number of varieties of products (Romer 1987, 1990) [13] [14]. We think of a change in this number as a basic innovation, akin to opening up a new industry. Of course, the identification of the state of technology with the number of varieties of products should be viewed as a metaphor; it selects one aspect of technical advance and thereby provides a tractable framework to study long-term growth.

Another metaphor has been developed in which progress shows up as quality improvements for an array of existing kinds of products (Grossman and Helpman, 1991a; Aghion and Howitt, 1992) [10] [1]. These quality enhancements represent then more or less continuous process of upgrading that occurs within an established industry. Both two metaphors should be viewed as complementary not as two opposite approaches (Barro and Sala-i-Martin, 2003) [3].

2.1 Production relations

Consider a single country in a world economy with $n$ different countries. There is a fixed number $L$ of people, each of whom lives forever and has a constant flow of one unit of labor that can be used in manufacturing. For simplicity we suppose that no one has a demand for leisure time, so each person offers her one unit of labor for sale inelastically (that is, no matter what the wage rate). Her utility each period depends only on consumption, according to the same isoelastic function (Aghion and Howitt, 2009 Chp. 3) [2],

$$u(c) = \frac{c^{1-\varepsilon}}{1-\varepsilon}, \quad \varepsilon > 0$$

and she discounts utility using a constant rate of time preference $\rho$. This means that in steady state the growth rate $g$ and the interest rate $r$ must obey the Euler equation, which can be written as:

$$g = \frac{r - \rho}{\varepsilon}$$

There is one final good $Y_i(t)$, produced under perfect competition by labor $L_i(t)$ and a continuum of intermediate products, indexed by $v$ in the interval $[0, M_i(t)]$. $M_i(t)$ is our measure of product variety. We follow Broda et al. (2006) [5] by writing the production function as

$$Y_i(t) = \left( A_i(t)L_i(t) \right)^{1-\alpha} \left[ \int_0^{M_i(t)} x_{i,v}(t)dv \right]^{\frac{\alpha}{\beta}}$$  \hspace{1cm} (1)

where $A_i(t)$ is a productivity parameter, $\alpha \in [0, 1]$ is one minus the share of labor in output and $\nu \in [0, 1]$ measures the elasticity of substitution between varieties of input goods $x_{i,\nu}(t)$, with a higher $\nu$ corresponding to more substitutable inputs.
All intermediates enter symmetrically into the production function, and all bear the same price. At equilibrium, each intermediate is demanded to the same extent \( x_i(t) = x_{i,\nu}(t) \) (Grossman and Helpman 1991) \(^1\). Using this fact, \(^1\) can be simplified to

\[
Y_i(t) = (A_i(t)L_i(t))^{1-\alpha} M_i(t)^{\frac{\alpha}{2}} x_i^\alpha(t)
\]

Each intermediate product is produced using the final good as input, one for one. That is, each unit of intermediate product \( v \) produced requires the input of one unit of final good (Aghion and Howitt, 2009 Chp. 3) \(^2\). According to this one-for-one technology, the aggregate capital stock is given by \( K_i(t) = M_i(t)x_i(t) \). Using this fact, we can rewrite \(^2\) as

\[
Y_i(t) = A_i(t)^{1-\alpha}L_i(t)^{1-\alpha}M_i(t)^{\frac{1-\nu}{\nu}}K_i(t)\alpha
\]

We follow Coe and Helpman (1995, 2009) \(^6\) \(^7\) and Keller (1998) \(^12\) by specifying the total factor productivity (TFP) as follows:

\[
Z_i(t) = \frac{Y_i(t)}{L_i(t)^{1-\alpha}K_i(t)^{\alpha}} \tag{4}
\]

Substituting \(^3\) to \(^4\) yields:

\[
Z_i(t) = \frac{Y_i(t)}{L_i(t)^{1-\alpha}K_i(t)^{\alpha}} = \frac{A_i(t)^{1-\alpha}L_i(t)^{1-\alpha}M_i(t)^{\frac{1-\nu}{\nu}}K_i(t)^{\alpha}}{L_i(t)^{1-\alpha}K_i(t)^{\alpha}} = A_i(t)^{1-\alpha}M_i(t)^{\frac{1-\nu}{\nu}}\alpha
\]

Unlike Coe and Helpman (1995, 2009) \(^6\) \(^7\) and Keller (1998) \(^12\), this measure of TFP has two components: a product-variety component captured by the term in \( M_i(t)^{\frac{1-\nu}{\nu}}\alpha \) and a quality component embodied in the term in \( A_i(t)^{1-\alpha} \).

### 2.2 Distance to frontier and quality of innovation

Equation \(^5\) shows that TFP depends on quality of innovation and on product-variety. In order to capture the quality component, we follow (Ertur and Koch, 2007; 2011) \(^8\) \(^9\) by defining \( A_i(t)^{1-\alpha} \) as:

\[
A_i(t)^{1-\alpha} = \zeta \prod_{j=1}^{n} \left( \frac{Z_j(t)}{Z_i(t)} \right)^{\gamma w_{ij}} \tag{6}
\]

where \( \gamma \in [-1, 1] \) captures the degree of technology diffusion. We suppose that quality is a negative function of the technological gap of country \( i \) with respect to its own technological frontier. This technological frontier is defined as the geometric mean of knowledge levels in all countries denoted by \( Z_j(t) \), for \( j = 1, 2, ..n \). We assume that the interaction terms \( w_{ij} \) are non-negative, finite and non-stochastic. The gap with respect to technological
frontier determines the quality of productivity. Indeed, the closer is a country to its own technological frontier the higher is its productivity quality.

Substituting (6) to (5) yields:

\[ Z_i(t) = \zeta \prod_{j=1}^{n} \left( \frac{Z_j(t)}{Z_i(t)} \right)^{\gamma_{wij}} M_i(t)^{(1-\gamma)\alpha} \]  

(7)

As regards, the product variety component, we follow Grossman and Helpman (1991) by assuming that in a world with international trade in goods and services, foreign direct investment, and an international exchange of information and dissemination of knowledge, a country’s productivity depends on its own R&D as well as on the R&D efforts of its trade partners. In other words, a country’s level of productivity will be related to the number of contacts that local agents have with their counterparts in the international and Business communities. Expressly, we have:

\[ M_i(t)^{(1-\gamma)\alpha} = R_i^\theta(t)H_i^\psi(t) \prod_{j=1}^{n} \left( R_j^\theta(t)H_j^\psi(t) \right)^{\gamma_{wij}} \]  

(8)

where \( \theta > 0 \) and \( \psi > 0 \) are the elasticities of R&D and human capital stock. We therefore suppose that country i’s product variety depends on its own R&D expenditures \( R_i(t) \) and on R&D of all countries denoted by \( R_j(t), j = 1, 2, ..n \). The term \( H_i \) captures country’s i ability and absorption capacity which is measured by human capital stock.

Substituting (8) into (7) yields:

\[ Z_i(t) = \zeta \prod_{j=1}^{n} \left( \frac{Z_j(t)}{Z_i(t)} \right)^{\gamma_{wij}} R_i^\theta(t)H_i^\psi(t) \prod_{j=1}^{n} \left( R_j^\theta(t)H_j^\psi(t) \right)^{\gamma_{wij}} \]  

(9)

Taking (9) in logarithm forms yields:

\[ \ln Z_i(t) = \ln \zeta - \ln Z_i(t) + \gamma \sum_{j=1}^{n} w_{ij} \ln Z_j(t) + \theta \ln R_i(t) + \psi \ln H_i(t) + \gamma \theta \sum_{j=1}^{n} w_{ij} \ln R_j(t) + \gamma \psi \sum_{j=1}^{n} w_{ij} \ln H_j(t) \]

Arranging the terms, we obtain:

\[ \ln Z_i(t) = \frac{\ln \zeta}{2} + \frac{\gamma}{2} \sum_{j=1}^{n} w_{ij} \ln Z_j(t) + \theta \ln R_i(t) + \frac{\psi}{2} \ln H_i(t) + \frac{\gamma \theta}{2} \sum_{j=1}^{n} w_{ij} \ln R_j(t) + \frac{\gamma \psi}{2} \sum_{j=1}^{n} w_{ij} \ln H_j(t) \]  

(10)

Equation (10) can be rewrite as:

\[ \ln Z_i(t) = \beta_0 + \beta_1 \ln R_i(t) + \beta_2 \ln H_i(t) + \rho \sum_{j=1}^{n} w_{ij} \ln Z_j(t) + \lambda_1 \sum_{j=1}^{n} w_{ij} \ln R_j(t) + \frac{\gamma \psi}{2} \sum_{j=1}^{n} w_{ij} \ln H_j(t) \]  

(11)
where $\beta_0 = \ln \zeta_2$; $\beta_1 = \theta_2$; $\beta_2 = \psi_2$; $\rho = \gamma_2$; $\lambda_1 = \gamma \theta_2$ and $\lambda_2 = \gamma \psi_2$.

In matrix form we obtain:

$$Z = \beta_0 I + \beta_1 R + \beta_2 H + \lambda_1 WR + \lambda_2 WH + \rho WZ \tag{12}$$

where $Z = Z_i(t)$, a matrix $(n \times 1)$ of TFP growth; $I$, a matrix $(n \times 1)$ of 1; $R = \ln R_i(t)$ a matrix $(n \times 1)$ of R&D; $H = h_i(t)$, a matrix $(n \times 1)$ of human capital stock; $W = \sum_{j=1}^{n} w_{ij}$ is our interaction matrix $(n \times n)$. We obtain a version of the well known specification in the spatial econometric literature referred to as the Spatial Durbin Model (SDM). This kind of econometric specification includes spatial lags of all the exogenous variables in addition to the spatial lag of the endogenous variable

$$y = X\beta + WX\theta + \gamma Wy + \epsilon$$

### 3 Empirical Implementation

#### 3.1 Data

Our study uses a sample of 107 countries over the period 2000-2011. We extract our basic data from the Feenstra et al. (2013) Penn World Table (PWT version 8.0). This database contain information on TFP growth, Index of human capital per person (among many other variables) for a large number of countries. We measure all variables for $i = 1, ..., n$ as the average over the period 2000-2011. Our index of human capital person is based on years of schooling (Barro/Lee, 2012) and returns to education (Psacharopoulos, 1994). R&D expenditures are from the United Nations Educational, Scientific and Cultural Organization and Trade data are from world bank database.

The interaction matrix $W$ corresponds to the so-called spatial weights matrix commonly used in spatial econometrics to model spatial interdependence between observations (LeSage and Kelly, 2009). More precisely, each country is connected to a set of neighbouring countries by means of a purely spatial pattern introduced exogenously in $W$. Elements $w_{ii}$ on the main diagonal are set to zero by convention, whereas elements $w_{ij}$ indicate the way country $i$ is spatially connected to country $j$. In order to normalize the outside influence upon each country, the weight matrix is standardized such that the elements of a row sum up to one. For the variable $x$, this transformation means that the expression $Wx$, called the spatial lag variable, is simply the weighted average of the neighbouring observations. It is important to stress that the friction terms $w_{ij}$ should be exogenous to the model (Ertur and Koch, 2007). Traditionally, connectivity has been understood as geographical proximity, and various weights matrices based on geographical space have thus been used in the spatial econometric literature, such as contiguity, nearest neighbours and geographical distance-based matrices. However the definition is
in fact much broader and can be generalized to any network structure to reflect any kind of interactions between observations. This is why we prefer to use the terms interaction matrix for $W$.

We specify our interaction matrix $W$ using import from $j$ to $i$. This interaction matrix is defined as follow:

$$ w_{ij} = \begin{cases} 
0 & \text{if } i = j \\
X_{ji} & \text{if } i \neq j 
\end{cases} $$

### 3.2 Estimation results

As explanatory variables in our SDM regression model we use R&D, a constant term, and human capital index over the period 2000-2011. Since this is a spatial Durbin model, the explanatory variables also include the average of these variables from neighbouring counties, which we label as W-R&D and W-hc. Table 1 displays the full results:

<table>
<thead>
<tr>
<th>Model</th>
<th>OLS</th>
<th>SDM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent V.</td>
<td>TFPG</td>
<td>TFPG</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>0.007**</td>
<td>0.007**</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>hc</td>
<td>0.024 *</td>
<td>0.034**</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>w-R&amp;D</td>
<td>0.026*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td></td>
</tr>
<tr>
<td>w-hc</td>
<td>0.089</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td></td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.184***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.42</td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>-2.815</td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>-2.690</td>
<td></td>
</tr>
</tbody>
</table>

*Notes:* Standard errors are given in parentheses. *** significant at 1%; ** significant at 5% and * significant at 10%. AIC and BIC stand for the Akaike and the Schwarz information criteria, respectively.

Table 1 presents least-squares and SDM model estimates based on trade interaction matrix. Since the estimate for the parameter $\rho$ is significantly different from zero, least-
squares estimates are biased and inconsistent. This coefficient means spatial autocorrelation that captures technological diffusion from neighbouring counties’ TFP growth.

The SDM model estimates cannot be interpreted as partial derivatives in the typical regression model fashion. To assess the signs and magnitudes of impacts arising from changes in the two explanatory variables, we turn to the summary measures of direct, indirect and total impacts presented in Table 2.

<table>
<thead>
<tr>
<th>Model</th>
<th>X-impacts</th>
<th>R&amp;D</th>
<th>hc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct</td>
<td>0.007**</td>
<td>0.033*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.018)</td>
<td></td>
</tr>
<tr>
<td>Indirect</td>
<td>0.036**</td>
<td>0.098</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.080)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>0.043**</td>
<td>0.132</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.156)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Standard errors are given in parentheses. *** significant at 1%; ** significant at 5% and * significant at 10%.

From the table we see that the direct impact of R&D is positive and significant, suggesting an positive impact on TFP growth. Also, the indirect effect of R&D is positive and significant. This suggests that R&D in neighbouring counties has a positive impact on TFP growth, which seems intuitively plausible. The total effect from R&D is positive and comprised mostly of the indirect impact, a large R&D spillover.

The direct impact of human capital is positive and significant, suggesting an positive impact on TFP growth. However, the indirect effect of human capital is not significant. This means that we don’t have an impact of human capital from neighbouring counties. The total effect from human capital is positive and comprised mostly of the indirect impact.

We can interpret the total impact estimates as elasticities since the model is specified using logged growth of TFP, R&D and human capital. Based on the positive 0.043 estimate for the total impact of R&D, we would conclude that a 10 percent increase in R&D would result in 0.43 percent in TFP growth.

4 Conclusions

In this we have analysed the major determinants of TFP evolution by decompose it into two component: quality component ant variety component. To deal with both components, we have introduced country’s distance to technological frontier and variable
that captures international R&D spillover. In doing so, we have obtained a spatial durbin model. When spatial autocorrelation is modeled, OLS is no longer appropriate: the estimators obtained by this method are not convergent if there is a lagged endogenous variable and they are inefficient in the presence of spatial autocorrelation of errors. In this study the spatial autocorrelation coefficient is positive and significant suggesting international technological diffusion through trade.

The results of our estimation show a positive direct impact of R&D and a positive indirect impact suggesting R&D spillover from neighbouring countries through trade. The total impact of R&D show that a 10 percent increase in R&D results in 0.43 percent in TFP growth.

The results also highlight a positive impact of human capital but no spillover from neighbouring countries' human capital.

References


