International technology diffusion, geography and cross-country dependence. A panel data analysis

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Abstract

This paper provides an examination of geographic R&D spillovers with a specific focus on the issue of cross-country dependence. Applying *"first generation"* and *"second generation"* unit roots tests we find strong evidence against the unit root hypothesis. Based on this result, we adopt estimation techniques suitable for stationary variables and, in particular, we compare the estimates obtained from three complementary approaches focusing respectively on the nonparametric covariance matrix estimation, generalised spatial auto-regression and unobserved common correlated factors. This allows shedding some new light on the relative importance of various mechanisms by which technology spillovers across countries may occur.

JEL classification: C23; C5; F0; O3.

Keywords: International technology diffusion; geography; cross-section correlation; spatial panel; factor models; unit roots.

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1 Introduction

Since the seminal paper by Coe and Helpman (1995), henceforth CH (recently revisited by Coe et al., 2009), there has been an increasing interest on international technology diffusion. These authors test the prediction of innovation and growth models (Grossman and Helpman, 1991) where the total factor productivity (TFP) is an increasing function of cumulative R&D and in particular they analyse the role of international trade. By assuming that some intermediate inputs are traded internationally while some others are not, they relate TFP to both domestic and foreign R&D and construct the foreign R&D capital stock as the import-share weighted average of the domestic R&D capital stocks of trade partners. The influence of this approach depends on its plausibility with respect to the (endogenous growth) theory (Keller, 2004) and its versatility by allowing the consideration of alternative channels of international technology diffusion, such as FDI (Lichtenberg and Van Pottelsberghe, 2001), language skills (Musolesi, 2007) or geography (Keller, 2002), henceforth K.

This paper aims to contribute to the empirical literature on international R&D spillovers by focusing on geography as a channel of technology diffusion and by taking into account the role of cross-country correlation when estimating the empirical specification.

The focus on geography as a channel of technology diffusion is motivated by the following reasons. First, it is theoretically consistent as showed by K or by Eaton and Kortum (2002) who respectively show that transport costs or geographical barriers make geographical distance related to international technology diffusion. Secondly, the geographic localisation of international technology diffusion can have relevant economic implications as it can affect the process of convergence across countries (Grossman and Helpman, 1991), how and whether economies agglomerates (Krugman and Venables, 1995) and also the long-run effectiveness of macroeconomic policies that aim at raising the country's technology (K). Finally, in spite of its relevance and theoretical consistency, there is actually much less evidence on geographic international R&D spillovers than on spillovers embodied on other channels such as trade or FDI.

From an econometric point of view, despite that general residual interdependence, global spillovers or omitted common factors (Pesaran, 2006; Breitung and Pesaran, 2008; Lee and Yu, 2009) can be plausibly present in CH–type specifications plaguing standard estimation and inference, to our knowledge, these issues have never been addressed before.

As a preliminary analysis, after having detected the presence of spatial correlation in the data, we study the order of integration of the variables of interest by using new tests allowing for cross section dependence (Choi, 2006; Phillips and Moon, 2004; Bai and Ng, 2004; Pesaran, 2007). We show that when the number of lags of the auto-regressive component of ADF type specifications or the number of common factors is estimated in a model selection framework the variables appear to be stationary. Based on this result, we adopt estimation techniques suitable for stationary variables, and in particular, we compare the estimates obtained from three complementary approaches. First, we allow for general residual interdependence: cross section correlation is simply considered as a special case of non spherical disturbances, producing incorrect statistical inference but not affecting the estimates of the slope parameters. This is handled by using the Driscoll and Kraay (1998) non parametric covariance matrix estimator. Second, cross section correlation is considered as a result of global spillovers and has been modelled and estimated by adopting a generalised spatial panel econometric framework (Lee and Yu, 2010). Finally, cross section dependence is introduced as a result of (unobserved) common factors such as oil prices shocks, technological exogenous modifications, global policies, etc (potentially correlated with the R&D capital stock) producing some effect on productivity and technology diffusion on all economies and therefore the estimation has been carried out using the approach proposed by Pesaran (2006) and named CCE (Correlated Common Factors) estimator. Such a framework can also allow slope heterogeneity which – given the length of the series – could be relevant. Since (to the best of our knowledge) to date, econometric theory does not provide a unified framework allowing simultaneously spatial auto-regression, (correlated) common factors and slope heterogeneity, the above mentioned methods should provide useful and complementary information in the understanding of the process of geographic R&D international spillovers[1].

The remainder of the paper is as follows: section 2 describes the baseline model and provides some preliminary results on both cross-country correlation and stationarity. Section 3 focuses on the estimation of the baseline specification, and in particular, by comparing alternative covariance estimators, provides a measure and the direction of the different biases arising from heteroskedasticity, serial and spatial correlation. Section 4 and 5 extends the benchmark specification by allowing respectively global spillovers and correlated common factors. Finally, section 5 summarizes and concludes.

2 Model specification and preliminary results on cross-country correlation and stationarity

2.1 The benchmark specification with geographic R&D spillovers

The baseline empirical model is an extended version of the one adopted by CH, as modified by Engelbrecht (1997) and Coe et al. (2009) by including human capital in the right hand side of the equation:

$$\log f_{it} = \alpha_i + \beta \log S^d_{it} + \gamma \log S^f_{it} + \delta \log H_{it} + \varepsilon_{it} \tag{1}$$

where $\log f_{it}$ is the logarithm of total factor productivity of country $i = 1, ..., N$ at time $t = 1, ..., T$; α_i are individual fixed effects which take into account unobserved time-invariant characteristics potentially correlated with the R&D capital stock, β is the output elasticity of the domestic R&D capital stock (S^d_{it}), γ is the output elasticity of the foreign R&D capital stock (S^f_{it}) and δ is the output elasticity of the human capital stock (H_{it}). ε_{it} is a white noise error term.

In order to construct foreign R&D capital stock, we follow the theoretical literature on geography spillovers such as K and Eaton and Kortum (2002) and propose a specification of foreign R&D that incorporate the idea that the effectiveness of foreign R&D is negatively related to the geographical

[1] The recent work by Pesaran and Tosetti (2009) is actually in such a direction and in particular it analyses the validity of the CCE effects approach if the true DGP is characterized by an error term which is the sum of a multifactor structure and a spatial process, providing new and interesting results discussed later on.

distance from foreign economies. This is done by weighting foreign R&D capital with an exponential distance decay function:

$$S_i^f = \sum_{j \neq i} exp(-\varphi d_{ij}) S_j^d \tag{2}$$

where d_{ij} represents the distance between country i and j. Finally, to construct the stock of human capital, the average number of years' schooling in the population over 25 years old is used, and following Hall and Jones (1999), this is turned into a measure of human capital stock through the formula:

$$H_{it} = \exp\left[g\left(edu_{it}\right)\right] \tag{3}$$

where edu_{it} is the average number of years' schooling and the function $g\left(edu_{it}\right)$ reflects the efficiency of a unit of labour with edu years of schooling relative to one with no schooling. Following Psacharopoulos (1994) and Caselli (2005), it is assumed that $g\left(edu_{it}\right)$ is piecewise linear with slope 0.134 for $0 < E \leq 4$, 0.101 for $4 < E \leq 8$, and 0.068 for $E > 8$ which implies a log-(piecewise)linear relation between H and edu. Combining equations (1) and (2), we obtain the baseline specification to be estimated:

$$\log f_{it} = \alpha_i + \beta \log S_{it}^d + \gamma \log \sum_{j \neq i} exp(-\varphi d_{ij}) S_j^d + \delta \log H_{it} + \varepsilon_{it} \tag{4}$$

If there are positive geographical spillovers (if foreign R&D enhances domestic productivity, $\gamma > 0$), then a positive estimate of φ indicates that the effectiveness of such spillovers decreases (non linearly) with distance while $\varphi < 0$ suggests that the benefits of foreign efforts for creating technology are increasing with distance. Finally, $\varphi = 0$ indicates that the effectiveness of spillovers does not depend on the distance separating two countries. A simple variant of eq. (4) widely adopted in literature allows the impact of foreign R&D capital to differ between the largest seven countries and the others:

$$\begin{aligned}
\log f_{it} &= \alpha_i + \beta \log S_{it}^d + \gamma_{G7} \mathbf{1}_{G7} \log \sum_{j \neq i} exp(-\varphi_{G7} d_{ij}) S_j^d + \\
&\quad + \gamma_{NOG7} \mathbf{1}_{NOG7} \log \sum_{j \neq i} exp(-\varphi_{NOG7} d_{ij}) S_j^d + \delta \log H_{it} + \varepsilon_{it} \\
with &: \mathbf{1}_{G7} = \begin{cases} 1 & \text{if country } \in \text{ G7 group} \\ 0 & \text{if country } \notin \text{ G7 group} \end{cases}, \\
and &: \mathbf{1}_{NOG7} = 1 - \mathbf{1}_{G7}
\end{aligned}$$

Since one of our main objectives is the comparison of the results with previous studies, our main source is the CH data set which has already been widely adopted in the literature (see table 1). It is a balanced panel of 21 OECD countries plus Israel observed over the period 1971-90. Both TFP and domestic R&D capital stock are from this data source. The average number of years of schooling used to construct our measure of human capital is taken from Barro and Lee (2001) as in Coe et al. (2009). Finally, the distance between 2 countries has been calculated as the spherical distance between capitals.

2.2 Preliminary results

2.2.1 Testing cross-section dependence in panels

First, let us focus on testing and assessing the presence of cross-section correlation in our panel data; the test proposed by Pesaran (2004) is employed. This test is valid asymptotically under very general conditions and can be applied to both stationary and non stationary variables[2] and is based on the average of the pair-wise correlation coefficients $(\widehat{\varrho}_{ij})$ of OLS residuals regressions: $CD = [TN(N-1)/2]^{1/2}\,\overline{\widehat{\varrho}} \xrightarrow{d} N(0,1)$, where $\overline{\widehat{\varrho}} = (2/(N-1)) \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\varrho}_{ij}$. The null hypothesis of no cross section correlation is strongly rejected (pvalue<0.0001)[3].

2.2.2 Panel Unit Root Tests and Cross-Section Dependence

We first present the results obtained using the test proposed by Im, Pesaran and Shin (2003) and the Fisher-type tests introduced by Maddala and Wu (1999) and further developed by Choi (2001). These tests are comparables because they allow the same degree of heterogeneity[4], both tests combine the information obtained from the N independent individual tests and (at least when linear trends are included in the deterministic component and the errors are serially correlated) the asymptotic properties are in both cases obtained by first sending T to infinity and then N to infinity, $(T, N) \rightarrow_{\text{seq}} \infty$[5].

Some issues are at stake. i) Since the series are clearly trended, linear time trends have been included in the deterministic component. ii) The choice of the lag order of the auto-regressive components -k- has to be carefully since it is now a well known fact than ADF-type tests are very sensible to that. There is, of course, a delicate balance between choosing a k that is sufficiently large to allow serially uncorrelated residuals and, at the same time, sufficiently small such that the model is not overparametrized. Therefore, the order of the (individual) AR components has been chosen using alternative criteria (AIC, SBC, HQIC) subject to a maximum lag of 3 which seems a reasonable point of departure given the annual frequency of the data and the observations available for estimation.

The IPS test is based on combining ADF individual t statistics and the reported standardized statistics – the W_{t-bar} – has an asymptotically standard normal distribution and it has been shown to perform well even in small samples. Results in table 2 indicates that i) the test is very sensible to the number of lags of the AR component –k-; ii) when the number of lags k is chosen with AIC, BIC or HQIC, there is strong evidence against the unit roots hypothesis for all the variables; iii) the average

[2]Moreover, it has been shown to have good finite-sample performance in terms of size and power.

[3]The full cross-sectional correlation matrix of residuals can be obtained upon request

[4]We define τ_i the coefficient associated with the autoregressive term in the ADF type regression; Levin, Lin andChu (2002) amog others, propose a test assuming that this coefficient is the same for all cross sections. As pointed out by Maddala and Wu (1999), while the null hypothesis (τ=0) makes sense in some empirical applications, the alternative (τ <0) seems to be too strong to hold in any relevant case. Im, Pesaran and Shin (2003), Maddala and Wu (1999) and Choi (2001) relax the assumption that $\tau_1 = \tau_2 = \ldots = \tau_N$ under the alternative, allowing some of the individual series to have a unit root.

[5]Though the sequential limit results may appear to be more restrictive than the joint limit results obtained by sending T and N to infinity simultaneously, it has been shown that the sequential and joint limit results are identical under additional moment conditions (Phillips and Moon, 1999). As a practical matter, this means that in both cases, a reasonable large number of time periods and cross sections are required to implement these tests.

number of lags obtained with AIC, BIC or HQIC is generally about one and this is consistent with the annual frequency of the data.

Next, we use the Fisher-type tests (Fisher, 1932) provided by Maddala and Wu (1999) and Choi (2001) based on combining the p-value of the N independent test statistics. Two statistics are provided here, labelled P, and Z. They differ in whether they use the inverse chi square and inverse normal of p-values[6]. The Fisher-type statistics (in table 2) fully confirm the IPS tests.

Recently, it has been shown the importance of taking into account cross section correlation for testing the unit roots hypothesis. Pesaran (2007) simulations show that the tests assuming cross-section independence tend to over-reject the null if cross-section correlation is present and Baltagi et al. (2007) find that when spatial auto regression is present, while first generation tests become oversized, the tests explicitly allowing for cross sectional dependence yield a lower frequency of type I error. As pointed out by Pesaran (2007) subtracting the cross-sectional averages from the series before application of the panel unit root test can mitigate the impact of cross-sectional dependence[7]. Since cross-section demeaning could not work in general where the pair-wise cross-section errors' covariances are different across individuals, new panel unit roots tests have been proposed. Let us consider a general specification for contemporaneous correlation in the errors by assuming that they can be decomposed as:

$$u_{it} = \zeta_i^{'}\mathbf{f}_t + v_{it}$$

where $\mathbf{f}_t$ is a $m \times 1$ vector of unobserved common factors and $\zeta_i^{'}$ is the associated vector of country-specific parameters. v_{it} is a idiosyncratic term. In the case of a single unobserved common factor, Pesaran (2007) suggests a test consisting in augmenting the standard (individual) ADF regression with the cross sectional average of first differences ($\Delta\bar{y}_t$) and lagged levels ($\bar{y}_{t-1}$) of the individual series which are $\sqrt{N}$- consistent estimators for $\bar{\zeta} f$ and $\bar{\zeta}\sum_{j=0}^{t-1} f_j$, respectively. This is named the cross-sectionally augmented Dickey Fuller (CADF) and the individual CADF statistics (or eventually the rejection probabilities) are used to develop a modified version of the IPS test (or the Fisher-type tests), named CIPS (CP and CZ). The CADF (CIPS Z_{t-bar}) test has been performed and results are in table 3[8]. Once again, the results are very sensitive to the choice of the lag order and when this is settled using a selection criteria such as the Akaike Information Criteria (or SBC or HQIC), the results about the order of integration are mixed: the TFP and domestic R&D appears to be non stationary while foreign R&D and human capital are found to be stationary. It is worth to note that, as showed by Pesaran (2007), in the case of models with linear time trends (and high cross-section correlation in the data) and $T = 20$, the CIPS tests have a very low power (but correct size)[9], suggesting that the series could be stationary.

[6] Choi (2001) simulation results suggest the use of the Z statistic which offers the best trade-off between size and power. With the aim of comparing Fisher-type tests with the IPS test, Choi (2001) finds that the Fisher tests are more powerful than the IPS test in finite samples and Maddala and Wu (1999) confirm this finding even when the errors are cross-correlated.

[7] We have performed both the IPS test and the Fisher-type tests on the de-meaned series and the (non reported) results are fully consistent with results obtained without demeaning and reported in table 2.

[8] The Z-t-bar statistics is a standardized statistics based on the asymptotic moments of the Dickey-Fuller distribution, while the W-t-bar statistics is based on the means and variances of the individual t statistics. The Z-t-bar and W-t-bar are asymptotically equivalent.

[9] Indeed, Let N=20, for T=20 and high cross-section correlation, the power of CIPS is only 7% (while its size is correct),

Next, in order to further investigate the order of integration of the variables of interest, we follow Moon and Perron (2004) who allow for m unobserved common factors. They consider such factors as nuisance parameters and propose a test statistic that uses defactored data obtained by projecting the data onto the space orthogonal to the factor loadings. They derived two modified t statistics – noted as t_a and t_b - which have a Gaussian distribution under the null hypothesis and propose the implementation of feasible statistics - t_a^* and t_b^*- based on the estimation of long run variances. Since the number of common factors is unknown, a common practice is to estimate it in a model selection framework using a penalized criterion. In doing that, we use the information criteria (IC1) suggested by Bai and Ng (2002) and the BIC3 adopted by Bai and Ng (2004) and Moon and Perron (2004)[10]. In order to assess the robustness of the results to the choice of the kernel function used to estimate the long-run variances, we compute both t_a^* and t_b^* with both Quadratic spectral and Bartlett kernel. In almost all cases (except for foreign R&D) these tests strongly reject the unit roots hypothesis (table 4).

The last test we perform is that proposed by Choi (2006) who uses a two-way error-component model rather than a factor model. The testing procedure is as follows: first, the nonstochastic trend component and cross section correlations are eliminated by GLS detrending (Ellitot et al., 1996) and cross-sectional demeaning. Second, three Fisher type statistics – noted P_m, Z, L^* - are obtained by combing p-values from the ADF test applied to each (detrended and demeaned) time series. From an applied perspective, such approach can be viewed as complementary to Moon and Perron (2004). Indeed, Gutierrez (2006) has showed through Monte Carlo simulation that Moon and Perron's tests have a better size than Choi's when the common factor influences the cross-sectional units heterogeneously but Choi's perform well under the more restrictive assumption that the cross-sectional units are homogeneously influenced by the common factor and in few cases it beats Moon and Perron's in terms of power. Also for such a test (in table 5), the choice of the lags is crucial and when this is done with the AIC (or with other non reported criteria) it clearly indicates that the variables are stationary.

Summarising, the unit roots tests indicates that when the number of lags of the auto-regressive component of ADF type specifications or the number of common factors is estimated in a model selection framework the variables appear to be stationary[11]. This result has the relevant consequence that correct statistical inference can be done without adopting panel co-integration (Kao and Chiang, 1999)[12].

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for T=50, the power increases to 27% and finally for T=100 it is at 93% (Pesaran, 2007, table VII).

[10]The BIC3 is modified BIC criterion has been shown (Bai and Ng, 2002) to perform better than the others when $\min(T, N) \leq 20$ and T and N are roughly of the same size even if it does not satisfy the conditions fr consistency when either N or T dominates the other exponentially. Moon and Perron's (2004) simulation indicates that with 20 or more cross sectional units, their tests provide a precise estimation of the number of factors and show good size, especially the test based on the t_b^* statistic. However, they have low power when deterministic trends are included.

[11]The most of the unit root tests have been performed by using the MATLAB routines kindly provided by C. Hurlin at http://www.univ-orleans.fr/deg/masters/ESA/CH/churlin_R.htm. The CADF (CIPS Z_{t-bar}) test has been performed using the pescadf STATA routine.

[12]In particular, cross section correlation can be allowed in the context of panel cointegration by adopting a SURE framework (Mark et al., 2005), while Kapetanios et al. (2009) extend the Pesaran (2006) CCE approach by examining the case where the unobservable common factors follow unit root processes.

3 General residual interdependence

3.1 A nonparametric covariance matrix estimator

Firstly, cross section correlation is addressed as special case of non spherical disturbances only affecting the estimation of the covariance matrix. Denoting the covariance matrix as Ψ, with typical element ψ_{ij}, we can write:

$$\psi_{ij} = f\left(d_{ij},\boldsymbol{\theta}\right),$$

d_{ij} is the distance separating i and j, $\boldsymbol{\theta}$ is a parameter vector, and f is a distance decay function such that $\frac{\partial f}{\partial d} < 0$ and $\left|f\left(d_{ij},\boldsymbol{\theta}\right)\right| \leq 1$ (Dubin, 1988). In a panel data setting, Driscoll and Kraay (1998) propose a variant of the time series covariance matrix estimator - like that of Newey and West (1987)- which estimates the elements of the variance-covariance matrix non-parametrically, that is, requiring neither a specific functional form for f, nor a precise metric for d. Analytically, Driscoll and Kraay's (1998) -henceforth DK- covariance matrix is obtained as follows. For ease of notation, let us consider a pooled panel data regression model defined by $\mathbf{y} = \mathbf{X}\beta + \boldsymbol{\varepsilon}$ where $\mathbf{y}$ and $\boldsymbol{\varepsilon}$ are NT vectors, $\mathbf{X}$ is the $NT \times K$ matrix and β is a $K \times 1$ vector of parameters. If the disturbances are allowed to be cross-sectionally and serially dependent, β can still be consistently estimated with OLS but the OLS standard errors are inconsistent and the Driscoll and Kraay (1998) covariance matrix is as follows: $Var(\widehat{\beta}) = \Psi = (\mathbf{X}'\mathbf{X})^{-1}\widehat{S}_t(\mathbf{X}'\mathbf{X})^{-1}$, where $\widehat{S}_t$ is the same as in defined as : $\widehat{S}_t = \widehat{\Omega}_0 + \sum_{j=1}^{m(T)} \varkappa\left(j,m\right)\left(\widehat{\Omega}_j + \widehat{\Omega}_0'\right)$. $m(T)$ is the lag length defining the order of autocorrelation and $\varkappa\left(j,m\right) = 1 - j/\left[m(T)+1\right]$ allows smoothness of the sample autocovariance function. Finally, the $K \times K$ dimensional matrix $\widehat{\Omega}_j$ is defined as: $\widehat{\Omega}_j = \sum_{t=j+1}^{T} \mathbf{h}_t(\widehat{\beta})\mathbf{h}_{t-j}(\widehat{\beta})'$, with $\mathbf{h}_t(\widehat{\beta}) = \sum_{i=1}^{N} \mathbf{h}_{it}(\widehat{\beta})$ and $\mathbf{h}_{it}(\widehat{\beta}) = \mathbf{x}_{it}\widehat{\varepsilon}_{it}$. $\mathbf{x}_{it}$ is a $K \times 1$ vector and $\mathbf{h}_{it}(\widehat{\beta})$ are the $K \times 1$ moment conditions of the linear regression model. This estimator has some appealing features: i) it is robust to general forms of cross-sectional dependence not requiring a precise metric for d; ii) it is robust also to serial correlation that, given the time length of 20 years, may be relevant; iii) it remedies the problems which occur in SUR specification when N is larger than T or also when N and T are of similar lengths.

3.2 Benchmark results using alternative covariance matrix estimators

Table 6 summarizes the results obtained by estimating the benchmark specifiactions presented in section 2 with and without correcting the covariance matrix to serial correlation, spatial correlation and heteroskedasticity. Columns (ii) to (v) shows the estimated parameters from the baseline specification in eq.(4), where the model is firstly estimated using NLS (*Nonlinear Least Squares*) without any correction to the covariance matrix. The output elasticity of domestic R&D capital stock, β, is estimated at 0.069 and is significant. This result is in line with the related empirical literature as in Coe and Helpman (1995), Coe et al. (2009), Lichtenberg and Van Pottelsberghe (2001) or Keller (2002). The output elasticity of foreign R&D capital stock incorporated into the geographical technology transfer channel (γ) is estimated at 0.042 and is significant at the 1% level. In other words, we find evidence of positive (but small in magnitude) geographical spillovers across countries. It could be interesting to compare this result with those obtained using alternative technology transfer channels. As pointed out by Lichtenberg and Van Pottelsberghe, 2001, p. 490, *"International technological spillovers have no widely accepted measures"*. According to Keller (2004), the main channels of technological diffusion are trade, FDI and communication skills. There is a large body of literature focusing on Trade and FDI which finds in general a higher value of the point estimate, but which sometime has conflicting results on the statistical significance (table 1). Conversely, analyses of technology diffusion incorporated into communication skills are rare. Musolesi (2007) finds a significant and quite high estimate (about 0.2) for the coefficient associated with foreign R&D incorporated into communication skills. The parameter φ is estimated at 9.64, suggesting that the effectiveness of such spillovers decreases with distance. This result is consistent with Bottazzi and Peri (2003) who find that R&D spillovers are small in magnitude but very localized in European regions. The estimated coefficient of human capital (δ) is highly significant and of the same order of magnitude of that found by Coe et al. (2009)[13]. We finally turn to the results obtained from the estimation of the specification allowing the output elasticity with respect to foreign R&D to differ between large and small countries (table 6, columns vi to xi). Clearly, the effect of foreign R&D on TFP is much higher for G7 than for non G7 countries ($\widehat{\gamma\_G7}$= 0.170,$\widehat{\gamma\_NOG7}$= 0.026 and both are significant). This result is similar to Lichtenberg and Van Pottelsberghe (2001) who focus on FDI spillovers. Another result is that the effectiveness of such spillovers decreases with distance more for G7 than for non G7 countries ($\widehat{\varphi\_G7 > \varphi\_NOG7}$). In other words, the spillovers are more localized for G7 countries than for smaller ones.

Table 6 also provides standard errors obtained using the DK non parametric covariance estimator designed for linear panel data with fixed effects[14]. More generally, we compare the standard errors obtained with NLS (1) with: (2) White (1980) heteroskedasticity consistent standard errors; (3) Newey-West (1987) heteroskedasticity and serial correlation consistent standard errors; (4) DK standard errors with $m(T) = 0$, so that they are robust to heteroskedasticity and contemporaneous spatial correlation; (5) DK standard errors without imposing $m(T) = 0$, so that they are robust to heteroskedasticity, serial and spatial correlation. Comparing these alternative covariance matrix estimators provides a measure and the direction of the different biases arising from heteroskedasticity, serial and spatial correlation.

We note first that for all the variables, the NLS standard errors in (1) are much smaller than the White (2) and Newey-West (3) standard errors which are robust respectively to heteroskedasticity alone and heteroskedasticity and serial correlation. Next we focus on the bias associated to spatial correlation which is the main concern here. Our results clearly indicate that whereas for human capital, spatial correlation –as well as heteroskedasticity and serial correlation - biases downward the LS standard errors, for both domestic and foreign R&D (the main variables of interest here) spatial correlation biases upward the LS standard errors and offsets the downward bias due to heteroskedasticity and serial correlation. Indeed it is worth notning that standard errors in (5) are of the same magnitude as in (1).

[13]The inclusion of human capital is relevant not only because it affects productivity and the ability of firms to absorb information, but also because it is potentially correlated with R&D, and estimating the model without human capital should bias upwards the coefficient associated with R&D. In some previous studies (Barrio-Castro et al., 2002; Frantzen, 2000; Engelbrecht, 1997) such bias has been estimated at about 20% to 30%

[14]The parameters associated with the non linear part of the model $\varphi, \varphi\_G7, \varphi\_NOG$ have been set equal to their estimtes obtained with the NLS estimator.

These results could be quite surprising but are coherent with the Monte Carlo experiments by DK which show that the sign of the bias associated with spatial correlation depends on the off-diagonal elements of the covariance matrix. Finally, it is worth noting that in almost all cases, all variables still remain significant at standard level.

4 Global spillovers: a generalised spatial econometric framework

4.1 Specification, interpretation and estimation

Another strand of the literature has tackled the issue of cross-section correlation by considering models with spatial auto-regression (Baltagi et al., 2007; Lee and Yu, 2009, 2010). In our empirical framework such kind of specifications could be useful since, while in the baseline specification (4), the TFP (which is an output of the unobserved level of technology) of a country depends on the R&D (an input of technology) of the others countries, it could be argued that the TFP of a country depends also on the TFP of other countries which incorporates neighbours' observed and unobserved inputs of technology, such as some socio-economic charactersitics, linked for instance to institutions, culture, history, etc[15].

In order to incorporate this kind of spatial effects in our specification we adopt the Lee and Yu's (2010) generalised specification – named SARAR(1,1) - which considers a SAR (Spatial Auto Regressive) model with spatially auto regressive disturbances and eq. (4) can be rewritten as:

$$\begin{aligned} \log f_{it} &= \alpha_i + \rho \sum_{j \neq i} w_{ij} \log f_{jt} + \beta \log S^d_{it} + \gamma \log \sum_{j \neq i} exp(-\varphi d_{ij}) S^d_j + \delta \log H_{it} + v_{it} \\ v_{it} &= \lambda \sum_{j \neq i} w_{ij} v_{jt} + \varepsilon_{it} \end{aligned} \tag{5}$$

where ρ and λ are the spatial autoregressive parameters. for $\lambda = 0$ and $\rho \neq 0$ eq. (5) converges to a SAR model, conversely with $\lambda \neq 0$ and $\rho = 0$ it is a SEM (Spatial Error Model) and with both $\lambda = 0$ and $\rho = 0$ it reduces to the baseline *"a-spatial"* specification (4). The results obtained from the spatial econometric specifications have to be interpreted by looking at the so-called *reduced form*. Let rewrite (5) by stacking the NT observations:

$$\begin{aligned} \mathbf{y} &= \rho \left(\mathbf{I}_T \otimes W_N \right) \mathbf{y} + \mathbf{X}\beta + Z_\alpha \alpha + \mathbf{v} \\ \mathbf{v} &= \lambda \left(\mathbf{I}_T \otimes W_N \right) \mathbf{v} + \boldsymbol{\varepsilon} \end{aligned} \tag{6}$$

[15] Moreover, it has been shown that such specifications are consistent with theoretical growth models (Ertur and Kock, 2007).

where $\mathbf{y}$ represents the log of TFP, W_N is an $N \times N$ row-normalized matrix[16] where the typical element is $w_{ij} = exp(-\phi d_{ij})/\sum_j exp(-\phi d_{ij})$ which measures the strength of the interaction between countries i and j, $\mathbf{X} = \left[\log(S^d), \log(S^f), \log(H)\right]$ is an $NT \times 3$ matrix and β is the associated 3×1 vector of parameters, $Z_\alpha = (\boldsymbol{\iota}_T \otimes \mathbf{I}_N)$ is a selector matrix of ones and zeros. After some manipulations, eq. (6) can be rewritten in its *reduced form* representation:

$$\mathbf{y} = \mathbf{\Theta}(\rho)\,\mathbf{X}\beta + \mathbf{\Theta}(\rho)\,Z_\alpha\alpha + \mathbf{\Theta}(\rho)\,\mathbf{\Lambda}(\lambda)\,\varepsilon \tag{7}$$

where $\mathbf{\Theta}(\rho) = \left[\mathbf{I}_T \otimes (\mathbf{I}_N - \rho W_N)^{-1}\right]$ is the so-called spatial multiplier and the multiplicative process arises because if $|\rho| < 1$ it follows that $(\mathbf{I}_N - \rho W_N)^{-1} = \mathbf{I}_N + \rho W_N + \rho^2 W_N^2 + \rho^3 W_N^3 + \ldots.$ $\mathbf{\Lambda}(\lambda) = \left[\mathbf{I}_T \otimes (\mathbf{I}_N - \lambda W_N)^{-1}\right]$ is also a spatial multiplier.

This reduced form has three important implications. *First*, in conditional mean, the total factor productivity in a country i will not only be affected by the domestic R&D capital stock in i and by the foreign R&D capital stock for i, but also by those in all the other countries through the inverse spatial transformation $\mathbf{\Theta}(\rho) = \left[\mathbf{I}_T \otimes (\mathbf{I}_N - \rho W_N)^{-1}\right]$. This is the so-called *global interaction effect.* More formally, this can be expressed with the matrix of derivatives of $\mathbf{y}$ with respect to $\mathbf{X}$:

$$\frac{\partial \mathbf{y}}{\partial \mathbf{X}} = \beta\mathbf{\Theta}(\rho) = \beta\left[\mathbf{I}_T \otimes (\mathbf{I}_N - \rho W_N)^{-1}\right]$$

For each block, the diagonal elements contain the direct effects while the off-diagonal elements represent indirect effects which depend on W_N, ρ and β. *Second*, one can easily see that a random shock dues to unobservable factors affecting TFP (i.e. a shock in the disturbances) in a specific country i does not only affect the total factor productivity in i, but also has an impact on the total factor productivity in all the other countries through a more complex mechanism of that presented above: this is the so-called *spatial diffusion process of a random shock,* which, for the SARAR specification, can be expressed as:

$$\frac{\partial \mathbf{y}}{\partial \varepsilon} = \mathbf{\Theta}(\rho)\,\mathbf{\Lambda}(\lambda) = \left[\mathbf{I}_T \otimes (\mathbf{I}_N - \rho W_N)^{-1}\right]\left[\mathbf{I}_T \otimes (\mathbf{I}_N - \lambda W_N)^{-1}\right]$$

where the indirect effects (the off-diagonal elements) depend on W_N , ρ and λ. *Finally*, it is easy to see from equation (6) that this panel data setting with individual fixed effects implies that there is a third multiplier effect on total factor productivity which takes place through the individual time invariant characteristics. In other worlds, total factor productivity of a country i not only depends by its time invariant features but also by those of the other countries, say $\left[\mathbf{I}_T \otimes (\mathbf{I}_N - \rho W_N)^{-1}\right] Z_\alpha\alpha$. This is labelled here as *time invariant characteristics multiplier effect.* Summarizing, spatial spillovers are therefore global since all the observation units are related to each other through the three spatial multiplier effects above mentioned.

A possible and sometimes adopted method for estimating spatial panel econometrics models consists at using the direct maximum likelihood approach (Elhorst, 2009). Lee and Yu (2010) show that this approach provides consistent estimates for regressors coefficients. It however provides estimates of

[16] According to Lee and Yu (2010), it allows to considers as parameter space for both λ and ρ a compact subset of $(-1, 1)$. It also facilitates the interpretation of results.

the variance parameter which are inconsistent when T is finite. They thus propose a quasi-maximum likelihood (QML) approach based on a data transformation that eliminates the individual fixed effects and establish the consistency of the QML estimator. They also demonstrate that except for the variance parameter, the estimates from the direct approach are identical to the corresponding estimates from the transformation approach.

4.2 Specification search

The CD test performed in section 2.2.1 is a general diagnostic test for cross section correlation in panels but it is not designed to discriminate among the different types of spatial correlation. To accomplish this task within the spatial panel regression models with fixed effects, as expressed in eq. (5), we adopt here the testing procedure recently proposed by Debarsy and Ertur (2009) which consists at performing sequentially five LM tests, as follows: A) Joint test: $H_0^a : \rho = \lambda = 0$ against $H_1^a : \rho$ or $\lambda \neq 0$. If the null hypothesis is not rejected none of these two types of spatial correlation -SAR or SEM- is relevant and there is no need to make other tests. Otherwise, to determine the most appropriate specification, first the following two simple tests have to be performed: B) Marginal test $H_0^b : \rho = 0$ $(\lambda = 0)$ against $H_1^b : \rho \neq 0$. Under the alternative, the specifiaction is a SAR; C) Marginal test $H_0^c : \lambda = 0$ $(\rho = 0)$ against $H_1^c : \lambda \neq 0$. Under the alternative, the specifiaction is a SEM. If the null hypothesis is rejected in both cases, then one should discriminate between SAR and SEM. This can be done by using two conditional tests: D) Conditional test $H_0^d : \lambda = 0$ given $\rho \neq 0$ (SAR) against $H_1^d : \lambda \neq 0$. Under the alternative, the specifiaction is a SARAR and E) Conditional test $H_0^e : \rho = 0$ given $\lambda \neq 0$ (SEM) against $H_1^e : \rho \neq 0$. Under the alternative, the specifiaction is a SARAR. If the null is rejected in both cases, the appropriate specification is a SARAR. If the null is rejected only in (D), then the preferred specification is a SEM, otherwise if the null is rejected only in (E), the preferred specification is a SAR.

4.3 SAR(AR) results

We now turn to the presentation of the results obtained adopting the generalised SARAR spatial panel framework (eq. (5)) which has been estimated with the QML approach proposed by Lee and Yu (2010)[17]. Let first focus on the specification search of spatial econometric models presented in the previous section. Results are in table 7. First the joint LM test highly rejects the null of no spatial correlation. Then, looking at the simple marginal tests, it is not possible to discriminate between SAR and SEM since both tests are significant. Finally, using the conditional tests, the results are as follows. For the specification allowing the output elasticity with respect to foreign R&D to differ between G7 and non G7 countries, the spatial autoregressive model (SAR) is the preferred specification whenever the value of ϕ (the exponential decay parameter of the spatail auto-regressive component)[18]. Otherwise, for the basic specification which does not discriminate between G7 and non G7 countries we obtain mixed results. Depending on the choice of ϕ and the significance level the preferred specification is a SAR or a

[17]The exponential decay parameter of the spatail auto-regressive component, ϕ, will takes three different values (1, 5 and 10) in order to check the sensitivity of the results to its value.

[18]Ance an endogenous spatial lag is included there is never evidence of residual spatial correlation, while once residual spatial correlation is included there is still evidence of an endogenous spatial autoregressive component.

SARAR. This clearly indicates that adding to the basic specification an interaction variable G7*foreign R&D is also important to make decrease the spatial error correlation as a result of omitted variables.

Next, the empirical model is estimated and the results are in table 8. Columns (ii) to (vii) present the results for the basic specification while columns (viii) to (xiii) give the outcomes for the specification where the G7 dummy interacts with the foreign R&D. We provide the results obtained from the estimation of both a SAR and a SARAR specification. A general result is that the estimated coefficients and standard errors are quite robust to the choice of ϕ. Let us now focus on the basic specification for which according to the specification search presented before there is not a clear evidence to discriminate between a SAR and a SARAR. First, for the SAR specification (Columns (ii) to (iv)), compared with the results obtained from the benchmark *"a-spatial"* specification presented in Table 6, the estimated coefficients of domestic R&D, foreign R&D and human capital decrease of about 20% to 30%. This clearly indicates the upward bias of the standard CH type specification due to the omission of relevant spatial interactions. The estimation of the spatial autoregressive parameter (ρ) is positive, ranging from 0.24 and 0.44 and highly significant. Then, looking at the SARAR specification (Columns (v) to (vii)) emerges that adding spatial auto-regression in the disturbances makes further decreasing the parameter associated to the explanatory variables. The estimated spatial lag parameter (ρ) rises to about 0.50 while the spatial error parameter (λ) is found to be negative and significant.

Let now focusing on the specification with the G7 dummy in columns (viii) to (xiii) and in particular to the SAR spatial process (columns (viii) to (xi)) which is clearly the preferred one according to our specification search. The parameter associated to domestic R&D is found to be lower than that obtained by using the *"a-spatial"* specification and of the same order of magnitude than those obtained in columns (ii) to (iv) for the SAR without G7*foreign R&D interaction, say 0.055-0.06. The output elasticity with respect to foreign R&D decreases for the G7 countries from 0.17 (the benchmark specification) to 0.14 while for the non G7 countries it is still close to 0.02 but it is now not significant[19]. Finally, the spatial parameter ρ is of the same order of magnitude than that obtained from the specification without G7*foreign R&D interaction: it is ranging form 0.20 to 0.41.

Summarizing, the main results from the spatial econometrics analysis are as follows. (1) Our specification search give unclear results for the basic specification where it seems not easy to discriminate between a SAR and a SARAR but gives a clear indication in favour of a SAR for the specification with incorporate the G7*foreign R&D interaction. This indicates that the omission of G7*foreign R&D interaction is a sources of residual spatial correlation. (2) Allowing spatial auto-regression makes decrease the parameter associated to the R&D capital stocks and indicates the upward bias to the standard CH/K specifications while the estimated spatial auto-regressive parameter (ρ) is positive and highly significant. (3) Finally, the estimation from the specification with G7*foreign R&D interaction seems to indicate that there is evidence of R&D geographical spillovers only for G7 countries (estimated at 0.14) since the parameter associated to non G7 countries (γ_G7) is non significant.

[19] At best it is significant at 11% for $\phi = 10$, column (xi).

5 Unobserved common (correlated) factors

5.1 The CCE approach

Another source of spatial dependence in the data relies on the existence of omitted global variables or common shocks possibly correlated with the R&D capital stock, such as oil prices shocks, technological exogenous modifications, global policies, etc. We therefore adopt the Pesaran (2006) approach that yields consistent estimates even in the presence of correlated unobserved common effects[20]. In order to obtain a more compact notation, let us define: $y_{it} = \log f_{it}$, $\mathbf{x}_{it}= \left[\log(S^d_{it}), \log(S^f_{it}), \log(H_{it})\right]'$ and assume the DGP as follows:

$$y_{it} = \boldsymbol{\alpha}_i' \mathbf{d}_t + \boldsymbol{\beta}_i' \mathbf{x}_{it} + e_{it} \tag{8}$$

where $\mathbf{d}_t$ is an M×1 vector of observed common effects, $\boldsymbol{\alpha}_i'$ is the associated vector of parameters, $\mathbf{x}_{it}$ is a k×1 vector of explanatory variables, and the slope coefficients $\boldsymbol{\beta}_i' = [\beta_i, \gamma_i, \delta_i]$ can be assumed to be fixed and homogeneous across countries, $\boldsymbol{\beta}_i' = \boldsymbol{\beta}'\ \forall\ i$,or assumed to follow the random coefficients specification: $\boldsymbol{\beta}_i = \boldsymbol{\beta} + \mathbf{v}_i$, $\mathbf{v}_i \sim IID\left(\mathbf{0}, \Theta_v\right)$.The errors e_{it} are assumed to have a multifactor error structure:

$$e_{it} = \boldsymbol{\varrho}_i' \boldsymbol{\xi}_t + \varepsilon_{it} \tag{9}$$

where $\boldsymbol{\xi}_t$ is an m×1 vector of unobserved common factors and ε_{it} are idiosyncratic errors assumed to be independently distributed over $(\mathbf{d}_t, \mathbf{x}_{it})$.The common factors $\boldsymbol{\xi}_t$ are allowed to be correlated with $(\mathbf{d}_t, \mathbf{x}_{it})$ according to the following linear relation:

$$\mathbf{x}_{it} = \mathbf{A}_i' \mathbf{d}_t + \boldsymbol{\Gamma}_i' \boldsymbol{\xi}_t + \boldsymbol{\omega}_{it} \tag{10}$$

where $\mathbf{A}_i$and $\boldsymbol{\Gamma}_i$ are n×k and m×k matrices of coefficients and ω_{it} are idiosyncratic errors. These equations can be rewritten compactly as a system of equations:

$$\mathbf{z}_{it} = \mathbf{B}_i' \mathbf{d}_t + \mathbf{C}_i' \boldsymbol{\xi}_t + \mathbf{u}_{it} \tag{11}$$

where:

$$\begin{aligned} \mathbf{z}_{it} &= \begin{pmatrix} y_{it} \\ \mathbf{x}_{it} \end{pmatrix}, \mathbf{B}_i = \begin{pmatrix} \boldsymbol{\alpha}_i & \mathbf{A}_i \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \boldsymbol{\beta}_i & \mathbf{I}_k \end{pmatrix}, \\ \mathbf{C}_i &= \begin{pmatrix} \boldsymbol{\varrho}_i & \boldsymbol{\Gamma}_i \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \boldsymbol{\beta}_i & \mathbf{I}_k \end{pmatrix}, \mathbf{u}_{it} = \begin{pmatrix} \varepsilon_{it} + \boldsymbol{\beta}_i' \boldsymbol{\omega}_{it} \\ \boldsymbol{\omega}_{it} \end{pmatrix}. \end{aligned} \tag{12}$$

[20]Other contributions have been provided by Phillips and Sul (2003) who propose a GLS approach for a autoregressive model with a one-factor structure for the error term and by Coakley et al. (2002) adopt a principal component approach for estimating panel data models with a multifactor error structure. Pesaran (2006) shows that the Coackley et al. (2002) procedure will be not consistent if the unobserved factors are correlated with the included regressors.

Pesaran (2006) suggests using $\begin{pmatrix} \mathbf{d}_t^{'} & \overline{\mathbf{z}}_{wt}^{'} \end{pmatrix}$ as observable proxies for $\boldsymbol{\xi}_t$;where $\overline{\mathbf{z}}_{wt}$ indicates the cross-section average, and $\overline{\mathbf{z}}_{wt} = \sum_{j=1}^{N} w_j \mathbf{z}_{jt}$, w_j are the weights supposed equal to $1/N$. The individual slopes $\boldsymbol{\beta}_i^{'}$ or their mean can be consistently estimated by running ols or pooled regressions of y_{it} on $\mathbf{x}_{it}, \mathbf{d}_t$ and $\overline{\mathbf{z}}_{wt}$. This kind of estimator is referred as a common correlated effect estimator. In particular, Pesaran (2006) proposes two estimators of the individual coefficients' mean , $\boldsymbol{\beta}$: the fixed effect estimator named CCEP and the Mean Group estimator, named CCEMG, which allows slope heterogeneity.

5.2 CCE estimates

Table 9 presents the results of both CCE Mean Group (CCEMG) and CCE Fixed Effects (CCEP) estimates of eq. (11)-(12). In order to check the sensitivity of the results, alternative definitions for the vector $\overline{\mathbf{z}}_{wt}$ of cross sectional averages have been employed (columns (ii) to (v) and (ix) to (xii)). A first result is that the CCE Mean Group estimator which allows for slope heterogeneity[21] gives more plausible estimates of the coefficients associated with domestic and foreign R&D than the CEE Fixed Effects estimator, while the estimated coefficient of human capital is negative in almost all cases. A second result is that the magnitude of the estimated parameters is quite sensitive to the choice of $\overline{\mathbf{z}}_{wt}$: the $\widehat{\beta}_{CCEMG}$ is positive in almost all cases and ranges between -0.263 and 0.119 while $\widehat{\gamma}_{CCEMG}$ ranges between 0.034 and 0.533. In particular, the specifications in columns (iii) to (v) which do not include human capital in the vector of cross sectional averages provides estimates of β and γ not very far from those obtained with the spatial econometric approach. In columns (v) and (vi) the model is re-estimated without human capital as a regressor: this lead (at least for the CEEMG) credible estimates for the parameters associated to domestic and foreign R&D.

Finally, it is worth noting that in almost all cases, the estimated parameters are not significant at standard levels[22].

In order to understand the latter result, it is worth looking at the Monte Carlo simulations by Pesaran (2006) made under the assumption that the DGP is characterised by unobserved common factors. For $N = T = 20$, they indicate that, while the naïve estimators (i.e. the estimators which do not account for cross section correlation as the LSDV or the MG estimators) are oversized but have a quite good power, the CCE estimators have correct size but very low power. Moreover, some new light on the validity of the CCE approach has been provided by Pesaran and Tosetti (2009) (see also Bresson and Hsiao, 2008, for further results) who show that the CCE estimators still provide consistent estimates of the slope coefficient when the DGP is characterised by common factors and spatial error correlation. They also provide interesting simulations under the assumption that the error is generated by a spatial autoregressive model or it is a mixture of a spatial process and a multifactor model. In all cases (for $T = N = 20$), the CCE estimators have a better size than any others (including the ML-SEM estimator) but a very low power compared with any alternative estimators. These simulations also show that the

[21] We also performed the chi-square test statistic proposed by Swamy (1970) of slope homogeneity across cross sections and the null hypothesis has been strongly rejected by the data (p-value<0.0001).

[22] The model has also been estimated with alternative definitions for the vector $\overline{\mathbf{z}}_{wt}$ of cross sectional averages but this does not change the significance level of foreign and domestic R&D.

CCE estimators beat all competitors with respect to the bias when the errors are a mixture of a spatial and a multifactor process. Summarising, these results provide a support to our CCE point estimates and give a clear explanation of the lack of significance.

6 Summary and concluding remarks

This paper provides an empirical analysis of geographic R&D spillovers across countries with a specific focus on the issue of contemporaneous dependence. The empirical model is estimated using complementary econometric methods and many new results are provided. They can be summarized as follows: (i) as a preliminary result, panel units roots tests indicate that when the number of lags of the auto-regressive component of ADF type specifications or the number of common factors is estimated in a model selection framework the variables appear to be stationary. This result indicates that appropriate statistical inference can be done without adopting a panel cointegration approach and consequently sheds a new light on the statistical fondation of estimates on international R&D spillovers using non con-cointegrated estimators such as the LSDV, NLS, heterogeneous slopes estimators, etc, sometimes adopted in previous studies (ii) We find evidence of positive (but small in magnitude) and localized geographic R&D spillovers. They are higher for G7 than for non G7 countries and they decrease with distance more for G7 than for non G7 countries. (iii) Alternative covariance matrix estimators indicate that for both domestic and foreign R&D, spatial correlation biases upward the LS standard errors and offsets the downward bias due to heteroskedasticity and serial correlation. (iv) The spatial econometric estimates indicate that introducing a G7*foreign R&D interaction makes decrease spatial error correlation and the SAR specification is clearly the preferred one. (v) Allowing spatial auto-regression makes decrease the parameter associated to the R&D capital stocks and indicates the upward bias of the standard CH/K specifications while the estimated spatial auto-regressive parameter is positive and highly significant. (vi) The CCE Mean Group estimator which allows slope heterogeneity gives more credible results than the CEE Fixed Effects estimator. (vii) Overall these CCE estimates are quite sensitive to the choice of the vector of cross sectional averages and are often not significant at standard levels. The latter result is probably due to the low power of CCE estimators when the sample size is moderate.

We argue that future applied researches should consider the estimation of more general specifications, allowing simultaneously spatial auto-regression, multifactor errors and slope heterogeneity.

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Table 1. Some previous studies on R&D international spillovers

Author	sample	Technology transfer	Method	ForeignR&D
Coe and Helpman (1995)	22 countries, 1971-90	trade	LSDV	.06-.092
Coe et al. (2009)	22 countries, 1971-90	trade	DOLS	.165-.186
	24 countries, 1971-2004		LSDV	.185-.206
			DOLS	.206-.213
Kao et al. (1999)	22 countries, 1971-90	trade	BC-OLS	.09-.125
			FM-OLS	.075-.103
			DOLS	.044NS-.056NS
Lichtenberg and Van Pottelsberghe (1997)	22 countries, 1971-90	trade	LSDV	.058-.276
Lichtenberg and Van Pottelsberghe (2001)	23 countries, 1971-90	trade	LSDV	.154
		FDI		-.06NS-.072
		trade	FD	.067
		FDI		.006NS-.039
Musolesi (2007)	13 countries, 1981-98	trade	HB	.09
		FDI		-0.01NS-.004NS
		language		.23
Lee (2006)	16 countries, 1981-2000	trade	DOLS	-.02NS-.17
		FDI		-.017NS-.034
		patents		.157-.183
Keller (2002)	14 countries, 1970-95	geographic distance	NLS	.843
		language		.565
Engelbrecht (2002)	21 countries, 1971-85	trade	LSDV	.220-.305
Barrio-Castro et al. (2002)	21 countries, 1971-85	trade	LSDV	.094-.225
	21 countries, 1966-95		LSDV	0.016-0.106
			DOLS	.092-.141

Notes.

LSDV: Least Square Dummy Variable ; DOLS: Dynamic Ordinary Least Square; BC-OLS: Bias Corrected OLS;

FM-OLS: Fully Modified OLS; FD: First Difference; HB: Hierarchical Bayes; NLS: Non Linear Least Square; NS: not significant.

Table 2. IPS (W_{-t-bar}) and Fisher-type statistics (P and Z)

lag order (k)	Test	log f	log S^d	log S^f	log H
1	W_{-t-bar}	-2.14861 (0.0158)	-1.75052 (0.0400)	-2.33921 (0.0097)	-1.55144 (0.0604)
1	P	64.6462 (0.0229)	70.2988 (0.0071)	71.8629 (0.0050)	60.6723 (0.0483)
1	Z	-2.31288 (0.0104)	-1.58178 (0.0569)	-2.47066 (0.0067)	-1.74831 (0.0402)
2	W_{-t-bar}	0.55338 (0.7100)	0.16992 (0.5675)	-1.15137 (0.1248)	-2.36996 (0.0089)
2	P	29.0843 (0.9593)	49.1626 (0.2740)	47.2918 (0.3397)	65.1072 (0.0209)
2	Z	1.31609 (0.9059)	1.30367 (0.9038)	-0.63744 (0.2619)	-1.75297 (0.0398)
3	W_{-t-bar}	-0.25439 (0.3996)	0.21641 (0.5857)	2.09292 (0.9818)	-2.17194 (0.0149)
3	P	46.5330 (0.3685)	39.1391 (0.6797)	15.3795 (1.0000)	66.5139 (0.0158)
3	Z	0.81728 (0.7931)	1.40485 (0.9200)	3.56924 (0.9998)	-1.33588 (0.0908)
aic	W_{-t-bar}	-3.32945 (0.0004)	-1.84356 (0.0326)	-3.58654 (0.0002)	-2.97393 (0.0015)
aic	P	79.1326 (0.0009)	71.8741 (0.0050)	79.3389 (0.0009)	79.8767 (0.0008)
aic	Z	-3.14469 (0.0008)	-1.1403 (0.1271)	-3.58923 (0.0002)	-2.60986 (0.0045)
		$\overline{k}$= 1.00	$\overline{k}$ =1.55	$\overline{k}$ =1.45	$\overline{k}$ =1.36
bic	W_{-t-bar}	-2.57982 (0.0049)	-1.81427 (0.0348)	-3.68351 (0.0001)	-2.91527 (0.0018)
bic	P	70.0827 (0.0074)	73.6950 (0.0033)	80.9023 (0.0006)	79.4714 (0.0008)
bic	Z	-2.41172 (0.0079)	-1.18474 (0.1181)	-3.68534 (0.0001)	-2.58006 (0.0049)
		$\overline{k}$= 0.77	$\overline{k}$ =1.27	$\overline{k}$= 1.32	$\overline{k}$= 1.32
hqic	W_{-t-bar}	-3.32945 (0.0004)	-1.51511 (0.0649)	-3.58654 (0.0002)	-2.97393 (0.0015)
hqic	P	79.1326 (0.0009)	70.5376 (0.0067)	79.3389 (0.0009)	79.8767 (0.0008)
hqic	Z	-3.14469 (0.0008)	-0.77733 (0.2185)	-3.58923 (0.0002)	-2.60986 (0.0045)
		$\overline{k}$= 1.00	$\overline{k}$ =1.41	$\overline{k}$ =1.45	$\overline{k}$ =1.36

Notes.

p-value between brackets.

Table 3. CIPS (Z_{-t-bar})

lag order (k)	Test	$\log f$	$\log S^d$	$\log S^f$	$\log H$
1	Z_{-t-bar}	1.697 (0.955)	-1.381 (0.084)	-2.457 (0.007)	1.414 (0.921)
2	Z_{-t-bar}	1.047 (0.852)	2.841 (0.998)	1.582 (0.943)	0.802 (0.789)
3	Z_{-t-bar}	2.044 (0.980)	3.375 (1.000)	-1.661 (0.048)	-3.486 (0.000)
aic	Z_{-t-bar}	0.758 (0.776)	1.319 (0.906)	-1.702 (0.044)	-2.072 (0.019)

Notes.

p-value between brackets.

Table 4. Moon and Perron test

	m	kernel	$\log f$	$\log S^d$	$\log S^f$	$\log H$
m*(IC1)			4	4	4	4
m*(BIC3)			2	4	4	4
t_a^*	1	QS	-2.6604(0.0039)	-1.7862 (0.0370)	-0.7206 (0.2356)	-0.2279(0.4099)
	1	B	-2.9104(0.0018)	-1.7852 (0.0371)	-0.7889(0.2151)	-0.2382 (0.4059)
	2	QS	-4.2229(1.2057e-005)	-1.6096 (0.0537)	-0.7984 (0.2123)	-4.5750 (2.3815e-006)
	2	B	-4.4621 (4.0585e-006)	-1.6856 (0.0459)	-0.6783 (0.2488)	-4.5750 (2.3815e-006)
	3	QS	-4.3942 (5.5589e-006)	-0.7444 (0.2283)	-4.2315 (1.1605e-005)	-3.5113 (2.2296e-004)
	3	B	-4.5508 (2.6726e-006)	-0.7703 (0.2206)	-3.7149 (1.0164e-004)	-3.6976 (1.0883e-004)
	4	QS	-4.9478 (3.7529e-007)	-3.6826 (1.1544e-004)	-0.4179 (0.3380)	-3.6500 (1.3112e-004)
	4	B	-5.0309 (2.4409e-007)	-4.6880 (1.3792e-006)	-0.5859 (0.2790)	-4.0252 (2.8465e-005)
t_b^*	1	QS	-2.6563 (0.0040)	-1.1354 (0.1281)	-0.6198 (0.2677)	-0.0747 (0.4702)
	1	B	-2.7187(0.0033)	-1.0977 (0.1362)	-0.7003 (0.2419)	-0.0834 (0.4668)
	2	QS	-4.6476 (1.6787e-006)	-0.9969 (0.1594)	-0.8512 (0.1973)	-5.5644 (1.3150e-008)
	2	B	-4.4694 (3.9228e-006)	-1.1119 (0.1331)	-0.7572 (0.2245)	-4.6502 (1.6583e-006)
	3	QS	-4.6777 (1.4502e-006)	-0.3774 (0.3530)	-5.9500 (1.3410e-009)	-6.6819 (1.1796e-011)
	3	B	-4.6046 (2.0666e-006)	-0.4235 (0.3360)	-3.5446 (1.9659e-004)	-6.3602 (1.0077e-010)
	4	QS	-6.3634 (9.8699e-011)	-4.6224 (1.8964e-006)	-0.3629 (0.3583)	-6.2396 (2.1941e-010)
	4	B	-5.1844 (1.0838e-007)	-4.7808 (8.7295e-007)	-0.3591 (0.3598)	-7.2367 (2.2992e-013)

Notes.

p-value between brackets.

Table 5. Choi (2006) Fisher-type statistics (P_m, Z, L^*)

lag order (k)	Test	$\log f$	$\log S^d$	$\log S^f$	$\log H$
1	P_m	1.9495 (0.0256)	7.1271 (5.1237e-013)	10.8056 (0)	0.5401(0.2946)
1	Z	-2.4621 (0.0069)	-3.8111 (6.9186e-005)	-6.7776 (6.1086e-012)	-1.3161 (0.0941)
1	L^*	-2.3866 (0.0085)	-4.6426 (1.7204e-006)	-7.5693 (1.8768e-014)	-1.2233 (0.1106)
2	P_m	-1.3238 (0.9072)	1.5406 (0.0617)	7.3856 (7.5939e-014)	0.3634 (0.3581)
2	Z	0.3686 (0.6438)	0.5268 (0.7008)	-5.4012 (3.3094e-008)	-1.0541 (0.1459)
2	L^*	0.3375 (0.6321)	1.1224 (0.8691)	-5.5847 (1.1708e-008)	-0.9689 (0.1663)
3	P_m	-0.1229 (0.5489)	-0.7096 (0.7610)	-0.6469 (0.7411)	-0.1871 (0.5742)
3	Z	0.0251 (0.5100)	1.1386 (0.8726)	-0.5273 (0.2990)	-0.3876 (0.3492)
3	L^*	-0.0452 (0.4820)	1.4084 (0.9205)	-0.4800 (0.3156)	-0.2621 (0.3966)
aic	P_m	2.6412 (0.0041)	5.9129 (1.6806e-009)	12.2388 (0)	1.9548 (0.0253)
aic	Z	-2.5990 (0.0047)	-2.6092 (0.0045)	-7.7401 (4.9682e-015)	-1.2459 (0.1064)
aic	L^*	-2.5389 (0.0056)	-2.7818 (0.0027)	-8.5914 (4.2945e-018)	-1.1490 (0.1253)

Notes.

p-value between brackets.

Table 6. Benchmark estimates

	Basic specification				Specification with G7 dummy					
	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)
	β	γ	φ	δ	β	γ_G7	φ_G7	γ_NOG7	φ_NOG7	δ
Coefficient	.067	.042	9.649	.538	.069	.170	15.217	.0267	7.042	.375
1) NLS standard errors	.0115***	.0125***	.0125***	.1224***	.0105***	.0183***	.0272***	.0116**	.1801***	.1135***
Standard errors robust to										
2Hetero White.	.0144***	.0155***		.1172***	.0127***	.0214***		.0131*		.1131***
3Hetero. and serial corr NW.	.0188***	.0205**		.149***	.0163***	.0278***		.0170		.1395***
4Hetero. and spatial corr DK, $m(T) = 0$	.0088***	.0082***		.1538***	.0077***	.0092***		.0078***		.1675***
5Hetero., contemporaneous										
and lagged spatial corr.										
DK, $m(T) = 1$	.0105***	.0108***		.1980**	.0090***	.0114***		.0101**		.2136*
DK, $m(T) = 2$	.0115***	.0124***		.2206**	.0098***	.0125***		.0113**		.2358

Notes.

***, **, *: significant at 1%, 5%, 10%, respectively.

standard errors between brackets.

NLS: Non Linear Least Squares.

W, NW and DK: White, Newey-West and Driscoll-Kraay covariance estimator, respectively.

Table 7. Spatial econometric models. LM tests.

	Basic specification			Specification with G7 dummy		
	$\phi = 1$	$\phi = 5$	$\phi = 10$	$\phi = 1$	$\phi = 5$	$\phi = 10$
Joint test. $H_0^a : \rho = \lambda = 0$ against $H_1^a : \rho$ or $\lambda \neq 0$.	105.203	58.67	41.10	59.71	30.80	23.33
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marginal. $H_0^b : \rho = 0$ $(\lambda = 0)$ against $H_1^b : \rho \neq 0$.	60.348	35.23	26.34	59.67	29.82	20.04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marginal. $H_0^c : \lambda = 0$ $(\rho = 0)$ against $H_1^c : \lambda \neq 0$.	18.096	22.75	17.66	44.23	30.10	23.21
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Conditional. $H_0^d : \lambda = 0$ given $\rho \neq 0$ (SAR) against $H_1^d : \lambda \neq 0$.	13.290	2.90	3.81	0.716	0.202	0.237
	(.000)	(0.088)	(0.051)	(0.397)	(0.652)	(0.625)
Conditional. $H_0^e : \rho = 0$ given $\lambda \neq 0$ (SEM) against $H_1^e : \rho \neq 0$.	384.035	362.96	294.81	219.36	112.19	74.03
	(.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Preferred model (5%)	SARAR	SAR	SAR	SAR	SAR	SAR
Preferred model (10%)	SARAR	SARAR	SARAR	SAR	SAR	SAR

Notes.

p-value between brackets.

Table 8. Spatial econometric models. Estimation results

	Basic specification						Specification with G7 dummy					
	SAR			SARAR			SAR			SARAR		
	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)
ϕ	1	5	10	1	5	10	1	5	10	1	5	10
φ	9.649	9.649	9.649	9.649	9.649	9.649						
φ_G7							15.22	15.22	15.22	15.22	15.22	15.22
φ_NOG7							7.04	7.04	7.04	7.04	7.04	7.04
β	0.053***	0.055***	0.056***	0.032***	0.039***	0.040***	0.057***	0.060***	0.062***	0.045***	0.087***	0.090***
	(5.023)	(5.099)	(5.175)	(3.005)	(3.426)	(3.498)	(5.869)	(5.978)	(6.055)	(4.486)	(10.649)	(11.662)
γ	0.020*	0.032***	0.034***	0.0195*	0.020	0.023*						
	(1.782)	(2.659)	(2.804)	(1.686)	(1.520)	(1.696)						
δ	0.191*	0.318***	0.348***	0.208**	0.281***	0.295***	0.074	0.204*	0.235**	0.089	0.064	0.133
	(1.712)	(2.763)	(2.993)	(2.174)	(2.743)	(2.860)	(0.706)	(1.879)	(2.132)	(0.907)	(0.643)	(1.406)
ρ	0.445***	0.286***	0.240***	0.614***	0.504***	0.469***	0.412***	0.247***	0.202***	0.534***	0.629***	0.622***
	(9.391)	(6.480)	(5.859)	(12.765)	(7.154)	(6.948)	(8.735)	(5.683)	(4.984)	(8.750)	(14.122)	(16.167)
λ				-0.402***	-0.293***	-0.286***				-0.229***	-0.448***	-0.484***
				(-4.673)	(-3.049)	(-3.331)				(-2.133)	(-7.003)	(-9.761)
γ_G7							0.134***	0.147***	0.149***	0.115***	0.221***	0.218***
							(7.549)	(8.063)	(8.142)	(6.239)	(14.279)	(15.165)
γ_NOG7							0.006	0.017	0.018	0.004	0.056***	0.052***
							(0.563)	(1.487)	(1.619)	(0.440)	(5.314)	(5.278)

Notes.

***, **, *: significant at 1%, 5%, 10%, respectively.

t statistics between brackets

Table 9. CCE estimates

	CCEMG							CCEP						
	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
φ	9.649	9.649	9.649	9.649	9.649	9.649		9.649	9.649	9.649	9.649	9.649	9.649	
φ_G7							15.22							15.22
φ_NOG7							7.04							7.04
β	-0.263	0.039	0.056	0.060	0.060	0.119	0.073	-0.054	-0.016	0.002	0.004	-0.021	0.003	-0.143
	(-1.619)	(0.224)	(0.291)	(0.331)	(0.295)	(0.580)	(0.308)	(-0.216)	(-0.161)	(0.015)	(0.051)	(-0.275)	(0.044)	(-1.437)
γ	0.533	0.097	0.238	0.034	0.136	0.198		-0.213	-0.101	-0.055	-0.052	-0.111	-0.062	
	(1.187)	(0.306)	0.833	(0.129)	(0.503)	(0.778)		(-0.464)	(-0.741)	(-0.309)	(-0.641)	(-0.574)	(-0.355)	
δ	-3.968**	-0.809	-0.631	-0.667			-3.052*	-0.625	-0.457**	-0.473**	-0.471***			-0.982
	(-2.399)	(-0.968)	(-1.111)	(-1.109)			(-1.752)	(-0.457)	(-1.978)	(-2.059)	(-2.72)			(-0.870)
γ_G7							0.1797							0.251
							(1.316)							(0.878)
γ_NOG7							0.624**							-0.041
							(2.13)							(-0.131)
	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,	$\log f_{it}$,
$\bar{\mathbf{z}}_{wt}$	$\log S^d_{it}$,	$\log S^d_{it}$,	$\log S^d_{it}$,	$\log S^f_{it}$,	$\log S^d_{it}$,	$\log S^d_{it}$,	$\log S^d_{it}$,	$\log S^d_{it}$,	$\log S^d_{it}$,	$\log S^d_{it}$,	$\log S^f_{it}$,	$\log S^d_{it}$,	$\log S^d_{it}$,	$\log S^d_{it}$,
	$\log S^f_{it}$,	$\log S^f_{it}$,			$\log S^f_{it}$,		$\log S^f_{it}$,	$\log S^f_{it}$,	$\log S^f_{it}$,			$\log S^f_{it}$,		$\log S^f_{it}$,
	$\log H_{it}$						$\log H_{it}$	$\log H_{it}$						$\log H_{it}$

Notes.

***, **, *: significant at 1%, 5%, 10%, respectively.

t statistics between brackets. The standard errors are based on the non parametric variance estimator by Pesaran (2006)