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INTERNATIONAL R&D SPILLOVERS AND UNOBSERVED COMMON SHOCKS*

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Abstract

This paper investigates whether returns to domestic R&D and international R&D spillovers should be estimated without considering the heterogeneous impact of unobserved common shocks, as has been done by the literature in this area. Using a panel of 50 economies from 1970-2011, I find that when unobserved common shocks are disregarded, estimates of domestic R&D and foreign R&D weighted by bilateral imports might be biased and inconsistent. Once unobserved common factors are accounted for, by allowing for heterogeneous technology coefficients, significant estimates become more sizable, consistent and not seriously biased in most cases. However, these estimates might be capturing not only returns to domestic R&D and trade-related knowledge spillovers, but also unobserved common spillovers and other effects. This indicates that knowledge spillovers and effects of unknown form cannot be easily separated. Therefore, unobserved common shocks should not be ignored when estimating returns to domestic R&D and international R&D spillovers.

Keywords: Productivity, Spillovers, Cross-Section Dependence, Unobserved Common Shocks.

JEL Codes: C23, O11, O30, O40

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1. Introduction

In the past three decades there has been a great deal of research into international R&D spillovers. A large number of these studies are mainly based on the endogenous economic growth theory, which states that technological evolution and productivity growth can be determined by technology diffusion through international trade relations directed by profit-seeking firms (Romer 1990; Grossman and Helpman 1991; Aghion and Howitt 1992). Since these models suggest that there should be public policies to adopt R&D capital stock through international economic channels, the study of the effects of the technological knowledge flows on the economic performance across countries has become relevant for the economic science.

Keller (2010) states that it is imperative to identify which part of the transfer represents genuine knowledge spillovers in order to assess the case for economic policy intervention. This is because public policy rests on this type of spillovers rather than other sorts of spillovers and effects. The literature on international R&D spillovers has therefore focused on studying how productivity is explained by international R&D spillovers in the global economy by examining the impact of domestic cumulative R&D and the world R&D capital stock that diffuses according to the bilateral economic relations between economies.

A seminal work that empirically corroborates how international R&D spillovers might spread in the world through trade and have an effect on productivity across countries is by Coe and Helpman (1995) (hereafter CH). Following the CH approach the R&D variables are introduced in a TFP function in a separable fashion, many other empirical works have examined the nature of and the channels of transmission for knowledge spillovers. These studies assume that spillovers can be accurately captured by the coefficient of a foreign R&D variable weighted by bilateral trade, FDI, migration and other channels so that the effect of knowledge spillovers on productivity can be consistently estimated.

However, all those studies ignore that unobserved shocks, which may be common across countries[1], can affect the cross-country productivity and R&D investment at the micro and macro level by different magnitudes depending on the country. If unobserved common shocks are treated as omitted factors in the error term within the analyzed econometric framework, and if those shocks are strongly correlated with the domestic and the foreign R&D capital stocks, contemporaneous correlation (or cross-section dependence) among individuals present in the errors could be pervasive and may yield seriously inconsistent and biased estimates and inaccurate inference.

In order to investigate these issues, I first examine how the foreign R&D capital stock weighted by bilateral international trade, namely in bilateral imports, and the domestic R&D capital stock determine the total factor productivity (TFP)[2] in a CH framework where unobserved common shocks are not taken into account. Second, I analyze models where shocks are incorporated in the error term through a multifactor framework so that shocks might affect the productivity and R&D investment of each economy in a heterogeneous fashion[3]. These two cases are studied for a sample of aggregate data across 50 countries and 42 years (1970-2011) in static

[1] Hereafter I will use the terms "unobserved common shocks," "unobserved common factors," "unobserved common effects" and "unobservables" interchangeably.

[2] In the context of the present work, the term "productivity" is tantamount to "total factor productivity."

[3] This means that across the studied time period and using the factor framework, I account for positive and negative unobserved common shocks such as those that appeared during the oil crisis of the 70s, the lost decade of the 80s for Latin America, the standardization of the Internet Protocol Suite (TCP/IP) in the 80s, the downfall of communism at the end of the 80s, the financial and economic crisis that several countries experienced during the 90s, the global financial crisis of 2008 and the emergence of China and India as key world economies during the 21th century, among others.

panel data models which are characterized by homogeneous or heterogeneous technology parameters depending on the case.

What I find is that the CH model might be seriously misspecified due to pervasive or strong cross-section dependence of residuals, and in some cases those models suffer from sever misspecification due to nonstationary residuals. This is also the case when factors are accounted for and technology parameters are homogeneous. Thus, it is demonstrated that the standard literature in this field, which has been largely based on the CH framework, might have stated conclusions which, possibly due to unobserved common shocks, are based on biased and inconsistent estimates of domestic and foreign R&D variables. Hence, they might not be informative at all to assess appropriate economic policy measures on R&D adoption.

Next, when unobserved common factors are regarded and technology parameters are allowed to be heterogeneous, I find consistent, positive and statistically significant estimates of the domestic and foreign R&D capital stock in the majority of cases. However, these results are subject to the presence of weak residual cross-section correlation, which means that even if estimates are significant, what the coefficients have captured are not necessarily pure returns to domestic R&D and knowledge spillovers, but rather a combination of these, unobserved local spillovers and other effects that might characterize the data.

This is an important finding because it supports the fact that knowledge spillovers and other types of spillovers cannot be easily separated in a CH framework as has been assumed in the literature on international R&D spillovers; therefore, common shocks and spillovers of unknown form matter the returns to domestic R&D and international knowledge spillovers with the purpose of assessing economic policy measures. The fact that statistically significant estimates of the domestic and foreign R&D are in the majority of cases more sizable than those obtained from traditional models corroborates these conclusions. Furthermore, this also holds when estimating dynamic panel data models[4] which account for possible feedback effects and lagged values of the covariates and the unobserved common effects.

In addition, I employ the same methodology of dynamic panel data models to examine two subsamples which I have taken from the main sample, one which excludes eleven small emerging economies[5] and another which excludes G7[6] and BRIC[7] countries. To examine both subsamples, I take information on markets from the original sample to model the common factors. Results for the first subsample are in line with the findings from the original sample; however, estimates for the second subsample confirm that, in the presence of unobserved common shocks and feedback effects from productivity onto the regressors, the coefficients of the domestic R&D variable shrinks and their statistical significance diminishes whereas the estimates of the foreign R&D become statistically insignificant. All this is subject to low degrees of residual cross-section dependence.

This shows that the non-separability of the knowledge spillovers from unobserved spillovers and other common effects becomes more evident and that the unobserved common local spillovers and other effects could play a relatively more important role in determining the productivity of these economies than the international R&D spillovers alone. This might be explained by the fact that this subsample comprises a larger proportion of emerging economies than that from the first subsample. I also demonstrate, in static and dynamic panel data estimates, that the rigid foreign R&D weighted variables defined by CH and by Lichtenberg and van Pottelsberghe de la Potterie (1998) (hereafter LP) fail to capture all the cross-sectional dependence present in the data, which in the traditional literature is assumed to arise only from international knowledge spillovers. I

[4] In this respect, I mainly rely on long-run estimates.

[5] Colombia, Costa Rica, Ecuador, Egypt, Indonesia, Malaysia, Panama, Peru, Philippines, Uruguay and Venezuela.

[6] Unites States, United Kingdom, France, Germany, Japan, Italy and Canada.

[7] Brazil, Russia, India and China.

believe that all these findings provide an alternative analysis of the international R&D spillovers realm since they take into account effects of an unknown form that could alter the dynamics of the world productivity and R&D investment.

The rest of this work is organized as follows. Section 2 surveys the literature on the empirical measurement of the international knowledge spillovers that occur in the world through international channels. Section 3 presents a brief theoretical explanation of the econometric multifactor error structure and its econometric relevance. In section 4 I introduce the static and dynamic panel data models that I study here and which relate total factor productivity to domestic and the foreign R&D in the presence of unobserved common shocks. Section 5 describes the data and section 6 gives the unit root and cross-section dependence tests. Section 7 discusses the results of the analysis for the original sample. Section 8 presents the empirical findings of the study of two subsamples and section 9 concludes.

2. Review of the Literature

The empirical literature on international R&D spillovers in which aggregated data is employed has yielded several results for the relationship between spillovers and productivity[8]. The first study on this area was by CH, who used data from 21 OECD countries plus Israel from 1971-1990. Their aim is to see how countries may benefit from imports, in accordance with the level of technology knowledge of their trade partners and their degree of openness. Towards that end, CH apply a country-specific foreign R&D capital stock measure that takes into account technology transfers through trade from all the countries of the sample. This measurement is based on the weighted average of the domestic R&D from country partners where bilateral imports are used as weights, and eventually it is multiplied by the share of imports in the GDP because such weights are fractions which add up to one and cannot accurately measure the role of imports.

Employing pooled cointegrated equations to study the long run relationship of covariates, they find significant returns to domestic R&D and knowledge spillovers; the more open the economy, the larger the effect of knowledge spillovers; and the returns to domestic R&D are larger for the G7 countries, whereas the knowledge spillovers are larger for the smaller advanced countries. Coe et al. (1997) implement the CH framework (although without including a domestic foreign R&D variable) to study the effect of the foreign R&D, openness and human capital stock on productivity across 77 developing countries between 1971 and 1990. They find that these variables affect the TFP of developing countries as long as foreign R&D is interacted with openness, and that North-South spillovers are important even though they might differ across countries.

Although the CH work has inspired several studies, three aspects of it have been criticized: the weighting scheme used for a foreign R&D variable, its econometric implementation, and its inclusion of other determinants of productivity and other weighted R&D variables which could diminish the significance or the magnitude of spillovers captured by a CH weighted foreign R&D variable.

The CH weighting scheme has been used to construct foreign R&D variables based on trade, FDI and others. However, this methodology has not been widely accepted in the literature on international R&D spillovers. Keller (1998), for example, casts doubt on the CH weighting scheme. In Keller's approach, which uses counterfactual estimates by Monte Carlo experiments, CH regressions are repeated by including foreign R&D variables which are computed with random bilateral import weights. Based on OLS models, similar results for true and counterfactual trade patterns are obtained; therefore, it is inferred that the pattern of trade might not be important

[8] For studies that are based on industry or sectorial data see Hall et al. (2009).

to capture R&D spillovers. This is supported by larger spillovers obtained from a proposed foreign R&D variable constructed with the sum of foreign R&D stocks.

Edmond (2001) supports these findings by allowing for heterogeneous technology slopes and using cointegration techniques and the CH sample. However, Coe and Hoffmaister (1999) demonstrate that when alternative random weights are used, spillovers are small, when compared with the original weights from CH. Funk (2001) also criticizes Keller (1998) for using OLS on nonstationary panel data, so his estimates might be biased and provide inadequate information about the randomly weighted foreign R&D stocks. When new cointegration techniques are employed, he finds that the choice of weights might yield information on R&D spillovers. Moreover, Xu and Wang (1999) have shown that Keller's criticism does not apply when a spillover variable based on capital goods imports data is constructed because the inclusion of this variable improves the goodness of fit of the model, so that the weighted variables may yield information on knowledge spillovers.

Another major criticism of the CH weighing procedure is set forth by LP, who find that the CH weighted foreign R&D variable suffers from an aggregation and an indexation biases. To deal with these problems, LP formulate a new weighted foreign R&D variable which is shown to outperform the CH R&D variable. As a response to LP, Coe et al. (2009) expand the CH sample, without indexing the R&D variables, to show that a CH and a LP variables perform equally well when human capital or institutional variables are included; in fact, when a LP and a CH variable are included in the same regression with the human capital, the CH variable performs better.

Other studies which have adopted the LP weighted foreign R&D variable, have found significant knowledge spillovers and that a LP variable does better than a CH variable. This is the case of Xu and Wang (1999), who employ capital and non-capital goods imports in a CH framework; Falvey et al. (2002), who use per capita GDP instead of TFP to analyze the impact of foreign R&D which can be a public or a private good in a donor country and in recipient developing countries; and Madsen (2007), who follows the CH specification and uses patent data and a panel for 16 OECD countries over 135 years to analyze knowledge spillovers and TFP convergence. Further, van Pottelsberghe de la Potterie and Lichtenberg (2001) use the LP procedure to study R&D spillovers embodied in imports and outward and inward FDI finding that only inward FDI is not significant. Other studies, such as that by Guellec and van Pottelsberghe de la Potterie (2004), argue that a foreign R&D variable based on bilateral technology proximity should be preferred because technology may spread without an exchange of goods.

CH 's work sheds light on the proper use of cointegrating regressions without differentiating the data and in the presence of nonstationary covariates which exhibit a time trend. However, Kao et al. (1999) states that since robust panel cointegration techniques were not available at the time of the CH study, CH could not address econometric issues, such as the characterization of the asymptotic distribution of the estimated cointegrating vector in a panel data model and the efficiency of estimates based on a small sample data set. Therefore, Kao et al. (1999) use dynamic OLS (DOLS) models and new cointegration tests to compare their results with those of CH. They show that the CH estimates are biased and foreign R&D spillovers are not significant. However, Zhu and Jeon (2007) and Coe et al. (2009), show that it is possible to find significant and positive trade-related knowledge spillovers when one employs Dynamic OLS models.

Edmond (2001) uses panel cointegration tests in a CH setup which allows for cross-section heterogeneity. He shows that foreign R&D estimates become negative. Moreover, for a sample of 10 OECD countries from 1965-1999 and using multivariate VAR methods under a CH specification, Luintel and Kahn (2004) find heterogeneity in the R&D dynamics so that data cannot be pooled, and normalization of the relationship on TFP for some countries is not valid because there could be reverse causality. By contrast, Coe et al. (2009) show that when allowing for heterogeneity in slopes, the results do not differ from those of the DOLS models. In a more recent study, for a sample of 65 countries over a 40 year period and using Granger causality tests to address simultaneity problems, Bravo-Ortega and Garcia Marin (2011) show that with the inclusion of other covariates such as R&D expenditure, non-linear R&D, openness, scale economies, institutional and cyclical variables, R&D expenditure per capita is significant and that foreign R&D spillovers are insignificant.

Other studies have shown that the significance or the magnitude of international R&D spillovers captured by a CH weighted R&D variable shrinks across countries when other determinants of TFP and other weighted foreign R&D variables are incorporated. Engelbrecht (1997) broadens the CH study by including a human capital variable and subsequently adds an interaction between a human capital variable and a catch-up regressor. His findings show that while the fact that coefficients of domestic and foreign R&D remain statistically significant, overall estimates shrink when human capital is incorporated. Funk (2001), employing the CH framework and data, cointegration techniques and dynamic OLS panel data models, shows that the international R&D spillovers capture by a CH weighted variable are statistically significant while spillovers diffused by bilateral imports are statistically insignificant[9].

Another study by Park (2004) who follows the basic CH specification and weighting scheme, and employs cointegration techniques, shows that domestic R&D and knowledge spillovers through student migration are significant, whereas knowledge flows through trade are insignificant. Lee (2006), who follows the CH framework and uses dynamic OLS for a panel of 16 OECD countries from 1981-2000, shows that knowledge spillovers embodied in inward FDI and disembodied in patent citation and technological proximity are significant, while outward FDI, and CH imports of intermediate goods are insignificant.

More recently, Zhu and Jeon (2007) basing themselves on the CH framework, weighting scheme and sample from 1981-1998, and using OLS and DOLS models, demonstrate that international trade, inward and outward stock-based FDI and information technology are significant and positive channels of knowledge diffusion when they interact with their respective measure of openness (except outward FDI in DOLS models), but trade-related spillovers shrink. Coe et al. (2009) show that when the human capital is accounted for, R&D spillovers shrink. However, when openness and foreign R&D are interacted, they rise. Also, when institutional variables are added (without human capital), the spillovers tend to increase; conversely, they fall when patent protection and human capital are incorporated.

2.1. Doubts about the Conventional Literature on International R&D Spillovers

Despite their intensive analysis of knowledge spillovers from different perspectives, all of these studies assume cross-section independence of errors which may yield biased and inconsistent estimates and inadequate inference if factors are not accounted. I will thoroughly explain the implications of this. Building on Andrews (2005), Pesaran (2006), Coakley et al. (2006), Moscone and Tosetti (2009) and other investigations on macroeconometric panel time series models, we can define cross-section dependence as the contemporaneous correlation among individual units (such as countries) that remains after conditioning for features which are exclusively individual. Such dependence is detected in the error term and may arise from the presence of unobserved common shocks or idiosyncratic correlations.

Focusing on the former, we can identify two main categories of these unobserved common shocks: i) common shocks at the macroeconomic level, such as aggregate financial shocks, real shocks (for example, world demand and supply shocks), global technology effects or structural

[9] However, Falvey et al. (2004), using weighting schemes similar to those of CH and LP find that spillovers through imports are significant (either as a public or a private good) while the evidence of spillovers through exports (which is more likely to be a public good) was less convincing.

changes; and ii) common shocks at the microeconomic level, such as local spillovers[10] which arise from industrial activity and domestic technology development, local consumption and income effects, socioeconomic networks, domestic regulation, institutions, law, environment, sociological patterns, cultural and linguistic heritage, and geographic proximity. The impact of these unobserved commons effects is not the same across units of the whole population. In fact, in extreme cases, they may either affect all units with a strong heterogeneous impact, or have a weak effect (or no effect at all) on a subset of observations. On the other hand, idiosyncratic correlations are those which are not explained by the common shocks and they are represented in the rest of the residuals.

When cross-section independence of errors is assumed, as in the literature on international R&D spillovers, contemporaneous correlation across countries caused by unobserved common effects is disregarded. Nevertheless, if unobserved common effects are present, then they may affect population units differently, in a way that brings about a contemporaneous correlation across units. If the effect of those shocks is weak across cross-section units, the estimates are not seriously biased and the inference is not affected at all, but if their effect is sufficiently strong, then the error cross-section dependence may lead to biased and inconsistent estimation and mistaken inference, as it could happen in the basic CH framework. The study of international knowledge spillovers has neglected this fact which may have resulted in drawing inaccurate conclusions about the effect of R&D spillovers on productivity. This literature assumes that international knowledge spillovers can be studied independently of unobserved spillovers when in reality it is misleading to separate one kind of spillover from the other.

One study in the field of the returns to R&D measurement that has tried to address the issues mentioned above is by Eberhardt et al. (2013) who analyze the private returns to R&D in the presence of unobservables using a panel of twelve manufacturing industries across ten advanced countries from 1980-2005. They study whether ignoring spillovers leads to biased estimates of the private returns to R&D by allowing for heterogeneous technology coefficients across industries and counties, and comparing results from a common factor framework (which accounts for unobserved common effects and does not rely on ad hoc assumptions about the structure of spillovers) with estimates from the approach suggested by Griliches (1979) (where the presence of unobservables is neglected).

Their findings suggest that cross-section dependence is present in the data, which indicates the presence of knowledge and other unobserved spillovers. The Griliches approach, which ignores unobserved common shocks, is thus seriously misspecified due to cross-section correlation or nonstationarity of the residuals. It also yields sizable and significant private returns to R&D. Conversely, when unobserved common effects are accounted for, the magnitude of private returns to R&D falls and the estimates become statistically insignificant. From their viewpoint these findings amount to categorical evidence that R&D and unobserved spillovers are not divisible since such estimates do not distinguish between the effect of R&D and that of unobserved spillovers; therefore, the Griliches framework does not accurately capture returns to domestic R&D. Their findings also suggest that weighted R&D spillover variables fail to capture genuine knowledge spillovers alone and instead reflect data dependencies due to a host of other common factors.

However, the study by Eberhardt et al. (2013) is subject to three drawbacks. First, although they include data on twelve manufacturing industries in ten advanced countries across 26 years which yields 2,637 observations, given a globalized context this may not be a sufficiently representative sample, insofar as it may fail to provide information about a wide variety of common global and local unobserved effects which, in turn, might be possible sources of cross-

[10] In the spirit of Bailey et al. (2014), (local) spillovers might be thought of as positive or negative within a spatial analysis.

section dependence errors. A small country sample in a multifactor framework might exclude cross-section dependencies related to the close interconnectedness of the world brought about by bilateral and multilateral economic interactions between the G10 countries, small advanced economies and emerging economies. The restricted availability of long-term domestic R&D data from emerging economies and small advanced countries makes it difficult to analyze unobserved common effects. Thus, while the limited number of country observations they include is not their fault, they could have collected more information on domestic R&D even in the absence of a complete series of data on this variable for a number of countries. That, in turn, would have provided more information on unobserved common shocks. The same applies to the other covariates. Had their sample included more information on the variables of interest, it would be easier to gauge the reliability of their estimates.

Second, they do not demonstrate that the commonly used weighted R&D spillover variables do not capture genuine knowledge spillovers alone but rather other cross-section dependencies. Even though the data restrictions raise doubts about the reliability of their findings, they also assume, as proven, that the same reasoning can be applied to the weighted R&D spillover variables. However, that might not be the case because the coefficient of a spillover variable may only indicate how rigid those variables could be when trying to capture knowledge spillovers in the presence of weak or strong error cross-section dependence.

Third, although Eberhardt et al. (2013) obtain a favorable outcome from static panel data models, they do not obtain similar results in dynamic models due to the moderate time dimension of their sample, and do not prove long-run cointegration of variables in these models. Therefore, they mainly rely on static panel data results even though dynamic models characterize better the properties of the R&D capital stock and allow for unobserved common effects to react with lags. To obtain reliable estimates, empirical findings on private (or aggregate) returns to R&D should recognize all of those economic features, even in the presence of unobservables. Griliches (1979) supports the inclusion of lagged values of R&D because, first, it takes time for current and lagged values of R&D to result in productivity. This is because projects that involve R&D within firms start at different dates and have to be successfully completed, implemented and accepted by the markets before they yield results. Meanwhile, the associated R&D spillovers take time to spread. We can further assume that the spread of unobserved common local spillovers and global shocks through cross-sectional units and time may be delayed, depending on the characteristics of the units; therefore, they might emerge with lags[11]; and second, there could be a possible causal link between past values of output or other covariates and the R&D capital stock.

[11] Another reason why lagged values of R&D investment should be accounted could be that uncertainty may cause fluctuations in R&D. According to Bloom (2007), the adjustment costs of changing the R&D capital stock might be a response to uncertainty caused by recessions, and economic and political shocks. Such a response is associated with "caution effects" (firms postpone activity since higher uncertainty increases the chances of making a costly mistake; therefore, responsiveness becomes moderate) and "delay effects" (as firms postpone activity at high levels of uncertainty, then uncertainty appears to cause fluctuations in aggregate investment, employment and therefore productivity growth as reallocation of factors of production at the firm level slows) which could have an impact on R&D investment and shape its dynamics through the business cycle. This implies that R&D only may change slowly over time which is coherent with a dynamic link between past and current R&D rates, and thus makes R&D more persistent over time. However, Cesa-Bianchi et al. (2014), assuming that both uncertainty and economic activity are driven by a set of country-specific and global macro-financial (unobserved common) factors, have found that future output growth has an impact on current uncertainty and that uncertainty shocks have little or no effect on GDP. This is not interpreted as saying that uncertainty has no effect on economic activity but rather it seems to be more a symptom than a cause of economic instability. This could provide evidence that uncertainty may not cause fluctuations in aggregates and therefore has no effect on R&D investment, as the concept of delay effects suggests; hence, more research would be needed to see whether in effect uncertainty leads to changes in R&D investment in the presence of unobserved common shocks.

In the present essay, I will address all of these concerns by using aggregate data to study the effects on TFP of returns to domestic R&D and foreign knowledge spillovers in the presence of unobserved common global shocks and local spillovers. In addition to the static panel data approach, I employ a dynamic panel data models which account for possible feedback effects and the lagged effects of covariates and unobserved common shocks.

3. Econometric Framework[12]

3.1 Multifactor Error Structure and Its Implications

One of the ways to deal with the error cross-section dependence is the multifactor error model in which sources of cross-section dependence are assumed to be represented by a few unobserved common factors that affect all the observations with different degrees. Let us write a multifactor error model as follows:

$$y_{it} = \boldsymbol{\beta'}_i \boldsymbol{x_{it}} + u_{it} \tag{1}$$

where $\boldsymbol{x_{it}}$ is a $k \times 1$ vector of regressors specific to cross-section unit i at time t, and:

$$u_{it} = \gamma_{i1} f_{1t} + \cdots + \gamma_{iN} f_{Nt} + \varepsilon_{it} \tag{2}$$

For $i = 1, \dots, N$, and $t = 1, \dots, T$; where each f_{it} is a single unobserved common factor (all of them are fixed relative to N), its j^{th} factor loading is γ_i (each of them can be random or fixed), where $j = 1, \dots, N$, and ε_{it} are the idiosyncratic errors. Observed common factors such as oil prices or deterministics (intercepts or seasonal dummies for instance) are omitted in (2) even though they may be easily included. When we replace (2) in (1) yields:

$$y_{it} = \boldsymbol{\beta'}_i \boldsymbol{x_{it}} + \gamma_{i1} f_{1t} + \cdots + \gamma_{iN} f_{Nt} + \varepsilon_{it} \tag{3}$$

Let us model the correlation between the individual specific regressors, $\boldsymbol{x_{it}}$, and u_{it}, where it is assumed that the former can be correlated with factors as follows:

$$\boldsymbol{x_{it}} = \boldsymbol{\Gamma'}_i \boldsymbol{f_t} + \boldsymbol{v_{it}} \tag{4}$$

where $\boldsymbol{\Gamma_i}$ is a $m \times k$ matrix of factor loadings and $\boldsymbol{v_{it}}$ is the individual component of $\boldsymbol{x_{it}}$ which is assumed to be distributed independently of the innovations u_{it}. Based on Chudik et al. (2011), factor loadings from (3) can be described as:

$$\lim_{N\to\infty} N^{-\alpha} \sum_{i=1}^{N} |\gamma_{ij}| = K < \infty \tag{5}$$

where K is a fixed positive constant that does not depend on N. Given (5), factors in (3) are said to be weak if $\alpha = 0$, semi-weak if $0 < \alpha < 1/2$, and semi-strong if $1/2 < \alpha < 1$. For these sorts of factors (which may be microeconomic shocks or local spillovers) we can say that the factor error structure is cross-sectionally weakly dependent at a given point in time $t \in T$, where T is an ordered time set, if $\alpha < 1$. In this case, weak, semi-weak and semi-strong factors may produce estimates of $\boldsymbol{\beta_i}$ which are not seriously biased and whose consistency and asymptotic normality

[12] I will mention only the main features of the econometric framework that I use here. To see further details, I encourage the reader to take a look at the works I mention in the following lines.

are not affected. These factors affect only a subset of units of the whole sample and the number of affected units rises less than the total units of the sample. On the other hand, factors in (3) are strong if $\alpha = 1$ in (5), so that the factor error structure is cross-sectionally strongly dependent at a given point in time $t \in T$ if and only if there exists at least one strong factor (which might belong to the class of macroeconomic or global shocks)[13]. In that case, the factors might be possibly correlated with $\boldsymbol{x_{it}}$ yielding seriously biased and inconsistent estimates of $\boldsymbol{\beta_i}$. Chudik and Pesaran (2013b) characterize the strong factors as the pervasive effect of cross section in the sense that they affect all units in the sample and their effect is persistent even if N tends to infinite.

3.2. Econometric Estimators of Interest

To define a multifactor framework in different sorts of panel data models to deal with error cross-section dependence, let us follow Chudik et al. (2013) by writing the autoregressive distributed lagged model *ARDL*($p_{y,i}$, $p_{x,i}$) which describes y_{it} with the $p_{y,i}$ and $p_{x,i}$ lag orders[14] as follows:

$$y_{it} = \sum_{l=1}^{p_{y,i}} \varphi_{il} y_{i,t-l} + \sum_{l=0}^{p_{x,i}} \boldsymbol{\beta'}_{il} \boldsymbol{x}_{i,t-l} + u_{it} \tag{6}$$

$$u_{it} = \boldsymbol{\gamma'_i f}_t + \varepsilon_{it} \tag{7}$$

for $i = 1, \dots, N$; $t = 1, \dots, T$, and l=0,...,1; where $\boldsymbol{\gamma_i}$ is a $m \times k$ factor loadings matrix, $\boldsymbol{f_t}$ is a $m \times 1$ matrix of unobserved factors. Once again, to illustrate this point, I do not include deterministics or observed common factors for a purpose of illustration. Now, for different configurations of equation (6) and taking (7) we can deduce different multifactor models, which can be estimated for the present study through three different approaches: (i) the Pesaran (2006) common correlated effects (CCE) estimator in a static panel data model with strictly exogenous regressors; (ii) a CCE approach in a dynamic ARDL panel data model (for convenience it has been transformed into an error correction model (ECM) representation) with weakly exogenous regressors, which has been formulated by Chudik and Pesaran (2013a), and (iii) a CCE estimation procedure in a distributed lagged (DL) model which does not include lags for the dependent variable, in line with by Chudik et al. (2013).

Assuming that $p_{y,i} = p_{x,i} = 1$ and following Chudik and Pesaran (2013a), we obtain the next linear dynamic heterogeneous panel data model, which is covariance stationary:

$$y_{it} = \varphi_i y_{i,t-1} + \boldsymbol{\beta'}_{0i} \boldsymbol{x}_{it} + \boldsymbol{\beta'}_{1i} \boldsymbol{x}_{i,t-1} + u_{it} \tag{8}$$

$$u_{it} = \boldsymbol{\gamma'_i f}_t + \varepsilon_{it} \tag{9}$$

$$\boldsymbol{\omega_{it}} = \begin{bmatrix} \boldsymbol{x_{it}} \\ \boldsymbol{g_{it}} \end{bmatrix} = \boldsymbol{\kappa_i} y_{i.t-1} + \boldsymbol{\Gamma'}_i \boldsymbol{f}_t + \boldsymbol{v_{it}} \tag{10}$$

[13] According to Chudik and Pesaran (2013b) the overall exponent α, which establishes the degree of the impact of factors can be defined as $\alpha = max(\alpha_1, \dots, \alpha_m)$.

[14] The lag orders are chosen for u_{it} to be a process that becomes serially uncorrelated for all i.

for $i = 1, \ldots, N$; $t = 1, \ldots, T$, where $\boldsymbol{x_{it}}$ is a $k \times 1$ vector of regressors specific to unit i at time t, $\boldsymbol{g_{it}}$ is $k_1 \times 1$ vector of covariates specific to unit i, $k + k_1 = k_2$, $\boldsymbol{\kappa_i}$ is a $k \times 1$ vector of unknown coefficients aka the feed-back coefficients, individual fixed effects on ω_{it} are omitted, lags of $\boldsymbol{x_{it}}$, $\boldsymbol{g_{it}}$ and additional lags of the dependent variable are not included, and the regressors are allowed to be correlated with the unobserved common factors. Equation (10) has been introduced in order to explain the difference between strict and weak exogenous regressors, accounting for $\boldsymbol{\kappa_i}$. If we assume that $|\varphi_i| < 1$, and replace (9) and the restriction $\boldsymbol{\beta}_{1i} = -\varphi_i \boldsymbol{\beta}_{0i}$, into (8) we obtain:

$$y_{it} = \boldsymbol{\theta}'_i \boldsymbol{x_{it}} + \boldsymbol{\gamma}^{*\prime}{}_i \boldsymbol{f}^*{}_t + \varepsilon^*{}_{it} \qquad (11)$$

where $\varepsilon^*{}_{it} = (1 - \varphi_i L)^{-1} \varepsilon_{it}$, and $\boldsymbol{f}^*{}_t$ represents a new set of unobserved common factors. Pesaran (2006) has formally established the estimation of (11) as the CCE estimator[15] by including strictly exogenous regressors, i.e. $\boldsymbol{\kappa_i} = \boldsymbol{0}$, which means that estimations are free from feedback effects[16].

The CCE estimation procedure adds cross section averages of the dependent and independent variables as proxies of unobserved common effects[17] where heterogeneous slopes follow a random coefficient model and $\boldsymbol{v_{it}}$ can be serially correlated and cross-sectionally weakly correlated. Cross-section averages are defined as:

$$\bar{\boldsymbol{z}}_{wt} = (\bar{y}_{wt}, \bar{\boldsymbol{x}}'_{wt})' = \sum_{i=1}^{N} w_i \boldsymbol{z}_{it} \qquad (12)$$

where the weights of $\bar{\boldsymbol{z}}_{wt}$, $\boldsymbol{w} = (w_1, \ldots, w_N)$, are a *N X 1* vector of weights which satisfies certain granularity and normalization conditions.

The CCE approach has several advantages. First, it does not require prior knowledge of the number of unobserved common factors (Pesaran 2006); second, CCE estimates are consistent even when there is serial correlation in errors (Coakley et al. 2006); third, it is consistent and asymptotically normal when the idiosyncratic errors are characterized by a spatial process (Pesaran and Tosetti 2011) and when errors are subject to a finite number of unobserved strong effects and an infinite number of weak and/or semi-strong unobserved common effects given that certain conditions on the factor loadings are satisfied (Chudik et al. 2011); fourth, the CCE estimator with either stationary or nonstationary factors have a similar asymptotic distribution when they are cointegrated, and even the latter could be noncointegrated (Kapetanios et al. 2011); and fifth, it can be extended to unbalanced panels (Chudik and Pesaran 2013b).

However, if the restriction $\boldsymbol{\beta}_{1i} = -\varphi_i \boldsymbol{\beta}_{0i}$ does not hold, according to Chudik and Pesaran (2013a) CCE estimations may be seriously biased. As a solution to this inconvenience, they demonstrate that the ARDL model defined by the equations (8), (9) and (10) can be estimated by a dynamic approach of the CCE estimator when i) the aforementioned restriction does not hold, ii)

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[15] In fact, equation (6) for $\varphi_{il} = 0$ and $p_{x,i} = 0$ resembles the model in (11) which can be estimated by the CCE approach in a similar fashion.

[16] Based on Engle et al. (1983), a process that is weakly exogenous is characterized by (i) a reparametrization of the parameters of interest and (ii) a (classical) sequential cut condition. This validates making inference conditional on the regressors; however, it is worth noting that Granger causal feedback effects may implicitly arise in some point. A process that is strictly exogenous, on the other hand, is characterized by weak exogeneity plus Granger noncausality from a dependent variable onto the regressors (the latter is essential to validate forecasting the independent variables and then forecasting the dependent variable conditional on leads of regressors), i.e. there are no Granger causal feedbacks.

[17] This is because cross-section averages pool information on markets, i.e. they pool the past and current views of economic agents on the constitution of covariates. Further, Pesaran and Tosetti (2011) state that the effects of temporal and spatial correlations due to spatial and/or unobserved common factors are eliminated by the addition of cross-section averages.

$\boldsymbol{\kappa_i} \neq \mathbf{0}$, i.e. feedback effects may arise, and iii) the slopes are allowed to be heterogeneous in (8). In addition, other issues are taken into account such as time series bias, the necessary full rank condition of the factor loadings and the existence of infinite lag order relationships between unobserved common effects and cross-sectional averages of the observable factors.

In the present work I emphasize the importance of the long-run relation among the studied variables in order to obtain a steady-state solution of a particular structural economic model. These long-run relations are analyzed with no restrictions on the short-run dynamics on the assumption that there is a single long-run relation between the dependent variable and the independent variables. In addition, heterogeneous technology coefficients and cross-section dependence of errors are taken into account. Therefore, it is important to define the long-run coefficients of interest from the ARDL model defined in (6) by stating for, the sake of simplicity, that $p_{y,i} = 1$ and $p_{x,i} = 0$ as is Chudik et al. (2013), so we can write the next model:

$$y_{it} = \varphi_i y_{i,t-1} + \boldsymbol{\beta}'_i \boldsymbol{x}_{it} + u_{it} \tag{13}$$

$$u_{it} = \boldsymbol{\gamma}'_{\boldsymbol{i}} \boldsymbol{f}_t + \varepsilon_{it} \tag{14}$$

$$\boldsymbol{x_{it}} = \boldsymbol{\Gamma}'_{\boldsymbol{i}} \boldsymbol{f_t} + \boldsymbol{v_{it}} \tag{15}$$

The objective is to estimate the mean long-run coefficients of the variables of interest through the estimate of the short-run coefficients $\boldsymbol{\beta}_i$ and φ_i[18]. This can be done by estimating the vector:

$$\boldsymbol{\theta}_i = \frac{\boldsymbol{\beta}_i}{1 - \varphi_i} \tag{16}$$

Here this coefficient is estimated through the Error Correction Model (ECM) approach which can be easily derived by subtracting $y_{i,t-1}$ from both sides of (13), by adding and subtracting $\boldsymbol{\beta}'_i \boldsymbol{x}_{it-1}$ from the right hand side (RHS) of (13), and by replacing (14) into (13) such that:

$$\Delta y_t = -(1 - \varphi_i)(y_{i,t-1} - \boldsymbol{\theta}_i \boldsymbol{x}_{i,t-1}) + \Delta \boldsymbol{x}_t + \boldsymbol{\gamma}'_{\boldsymbol{i}} \boldsymbol{f}_t + \varepsilon_{it} \tag{17}$$

where $\boldsymbol{\theta}_i$ is defined according to (16). The advantage of the ECM approach is that the mean of the coefficients of the error correction term, denoted by $\lambda_i = 1 - \varphi_i$, measures the speed of convergence towards the long-run equilibrium of steady state and can be consistently estimated under the conditions specified for the ARDL model.

A second approach to estimating $\boldsymbol{\theta}_i$ can be derived from the ARDL model in (13). This is the recently developed DL model, by Chudik et al. (2013). If we replace (14) into (13), subtract $\varphi_i y_{i,t-1}$ from (13), factorize $(1 - \varphi_i L)$ and then divide the whole expression by the latter we can obtain:

$$y_{it} = \boldsymbol{\theta}_i \boldsymbol{x}_{it} + \boldsymbol{\alpha}'_i(L) \Delta \boldsymbol{x}_{it} + \gamma'_i \tilde{\boldsymbol{f}}_{it} + \tilde{\varepsilon}_{it} \tag{18}$$

where $\Delta \boldsymbol{x}_{it} = \boldsymbol{x}_{it} - \boldsymbol{x}_{it-1}$, $\boldsymbol{\alpha}_i(L) = \sum_{l=0}^{\infty} \varphi_1^{l+1} (1 - \varphi_i)^{-1} \boldsymbol{\beta}_i L^l$, $\tilde{\boldsymbol{f}}_{it} = (1 - \varphi_i L)^{-1} \boldsymbol{f}_t$ and $\tilde{\varepsilon}_{it} = (1 - \varphi_i L)^{-1} \varepsilon_{it}$. As can be seen, $\boldsymbol{\theta}_i$ can be consistently estimated directly by the CCE estimation

[18] Short-run coefficients will not be reported; however, they are available upon request.

procedure through a least squares regression of y_{it} on the independent variables, where the lag truncation of order p can be chosen appropriately as an increasing function of the sample size. The consistency of the estimates does not require strict exogeneity since correlations in e_t are allowed. However, a consistent estimation of $\boldsymbol{\Theta}_i$ is subject to the absence of the feedback effects shown in (10) and the roots of $\varphi_i(L)$ have to fall strictly outside the unit circle, otherwise the DL approach is not be consistent. Furthermore, the DL structure does not incorporate lags of the dependent variable.

Estimates of $\boldsymbol{\theta}_i$ through the ARDL or the DL models can be averaged across i in order to estimate the average long-run effects of regressors by $\bar{\theta} = N^{-1}\sum_i^N \hat{\theta}_i$.In addition, cross section averages can be added to the ARDL and DL models as proxies of unobservable common effects, so that the average $\boldsymbol{\Theta}_i$ can be estimated by the CCE procedure. In this case, those models become the cross-sectional ARDL (CS-ARDL) and the cross-sectional DL (CS-DL). Based on Chudik and Pesaran (2013) and Chudik and Pesaran (2013a), cross-section averages for the CS-ARDL model can be defined as:

$$\bar{\boldsymbol{z}}_{wt} = (\bar{y}_{wt}, \bar{\boldsymbol{x}}'_{wt})' = \boldsymbol{\Lambda}(L)\bar{\boldsymbol{\Gamma}}'\boldsymbol{f}_t + O_p(N^{-1/2}) \tag{19}$$

where $\bar{\boldsymbol{\Gamma}} = E(\boldsymbol{\gamma}_i, \boldsymbol{\Gamma}_i)$, $\boldsymbol{\Lambda}(L)$ is the decay rate of the matrix coefficients, and $O_p(N^{-1/2})$ represents the cross-section averages of $\boldsymbol{z}_{it}$ from the equation (6) defined in Chudik and Pesaran (2013a). Cross-section averages for the CS-DL model can be defined as:

$$\bar{\boldsymbol{z}}_{wt} = (y_{wt}, \bar{\boldsymbol{x}}'_{wt})' = \sum_{i=1}^{N} w_i \boldsymbol{z}_{it} \tag{20}$$

The lags of the cross-section averages to be added to the multifactor model are chosen on the basis of the rule of thumb $T^{1/3}$ and that these cross-section averages must be at least as large as the number of unobserved common factors minus one. As the number of unobserved common factors is unknown, a maximum number of unobserved factors (which might be small) is assumed.

4. Econometric Model and Estimation Methodology

The basic econometric model that has been used in literature on international R&D spillovers and was initially formulated by CH is as follows [19]:

$$tfp_{it} = \alpha_i + \boldsymbol{\beta}'_i \boldsymbol{x}_{it} + u_{it} \tag{21}$$

where tfp_{it} is the logarithmic total factor productivity, $\boldsymbol{x}_{it} = (rd_{it}, rf_{it})'$ is the vector of regressors, where rd_{it} is the logarithmic domestic R&D capital stock and rf_{it} is the logarithmic foreign R&D capital stock weighted by bilateral imports. In principle, TFP in equation (21) should be explained by both domestic and foreign R&D, which have been introduced into a productivity function in an additively separable way in order to estimate the coefficients of these variables. As I said above, if unobservables are ignored in (21), and if they are correlated with the R&D variables to a high degree, then the estimates may be biased and inconsistent. This would imply that nothing can be concluded from the magnitude and significance of the coefficients. Now, to see if this occurs, I employ the following models.

[19] As can be seen, openness does not interact with the foreign R&D variable. Instead, I follow the basic framework found in the majority of works on international R&D spillovers because this will be sufficient to show the implications of the effects of unobserved common shocks on a particular CH specification.

4.1. Static Econometric Models

Equation (21) is estimated by employing static models. Here, I use two sorts of estimators. First, I use estimators that restrict homogeneity in the technology parameters and i) assume error cross-section independence, such as pooled OLS (POLS), first difference (FD), and two-way fixed effects (2FE); or (ii) allow for error cross-section dependence, such as the CCE pooled estimator (CCEP). Second, I estimate (21) by allowing for heterogeneity of slopes. Therefore, I use estimators which (i) assume error cross-section independence such as the mean group (MG) estimator and the cross-sectionally demeaned MG (CDMG) estimator; or (ii) that allow for error cross-section dependence such as the CCE MG estimator (CCEMG). CCE estimators include cross-section averages of variables as proxies of unobserved common factors[20]. In this case, (21) becomes:

$$tfp_{it} = \alpha_i + \boldsymbol{\beta}'_i \boldsymbol{x}_{it} + \boldsymbol{\psi}'_{il} \bar{\boldsymbol{z}}_t + \varepsilon_{it} \quad (22)$$

where

$$\bar{\boldsymbol{z}}_t = (\overline{tfp}_t, \bar{\boldsymbol{x}}'_t)'$$

4.2. Dynamic Econometric Models

Three dynamic models are employed to estimate (21). The first model is the traditional ARDL approach (represented as an error correction model (ECM)), where the main purpose is to obtain the long-run estimates of the domestic and foreign R&D variables. The model is defined as follows:

$$tfp_{it} = \alpha_i + \sum_{l=1}^{p} \varphi_{il} tpf_{i,t-l} + \sum_{l=0}^{p} \boldsymbol{\beta}'_{il} \boldsymbol{x}_{i,t-l} + u_{it} \quad (23)$$

I consider $p = 1$ to 3 lags for the ARDL model in order to include sufficiently long lags given the time period of the sample, and to fully account for the short-run dynamics so as to derive the long-run coefficients. Lags are the same across variables and countries. As stated in Chudik et al. (2013), this helps to reduce the adverse effects of the selection of data which may be subject to the use of lag order selection procedures, such as Akaike or Schwarz criteria. I carry out estimations of the ARDL model in (23) by employing the POLS estimator, the 2FE estimator and the MG estimator (all models assume error cross-section independence).

As reported by the same authors, the ARDL structure is valid regardless of whether the independent variables are exogenous or endogenous, or characterized as order one, I(1), or order zero, I(0), processes. In fact, long-run estimates may be consistent when common factors are serially uncorrelated and when they are uncorrelated with the regressors. This favors consistent estimation, especially to reverse causality, i.e. past values for productivity may determine current domestic and foreign R&D capital stocks. It is worth noting this approach has some drawbacks. There could be a large sampling uncertainty due to the restricted time dimension of the panel and the slow speed of convergence towards the long-run. Pesaran and Smith (1995) prove that under a random coefficient model which characterizes heterogeneous dynamic panel data models, pooled OLS estimators are no longer consistent. Also, the ARDL model requires an appropriate choice of lag orders to obtain proper long-run estimates.

[20] In the current study I do not deal with the nature of those unobserved factors.

The second econometric dynamic panel data model which is employed here is the heterogeneous cross-sectional ARDL (CS-ARDL) approach (aka dynamic CCEMG, which is represented by an ECM specification). This is characterized by the following equation:

$$tfp_{it} = \alpha_i + \sum_{l=1}^{p} \varphi_{il} tpf_{i,t-l} + \sum_{l=0}^{p} \boldsymbol{\beta}'_{il} \boldsymbol{x}_{i,t-l} + \sum_{l=0}^{3} \boldsymbol{\psi}'_{il} \bar{\boldsymbol{z}}_{t-l} + e_{it} \tag{24}$$

where

$$\bar{\boldsymbol{z}}_t = (\overline{tfp}_t, \bar{\boldsymbol{x}}'_t)'$$

and where e_{it} is defined by Chudik and Pesaran (2013b) in terms of three aspects: i) ε_{it}, which is the idiosyncratic term, ii) an error component due to the approximation of unobserved common factors, and iii) an error component that is explained by the truncation of possible infinite polynomial distributed lags of $\boldsymbol{\psi}_i(L)$. The CS-ARDL is augmented with contemporaneous and lagged cross-section averages of the dependent and independent variables. I allow for up to $T^{1/3} = 41^{1/3} \approx 3$ lagged cross-section averages of each variable independently of the number of the lags of the variables of (24) for which I include for $p = 1, 2$ and 3 lags.

As can be seen, this ARDL model allows for the possibility that unobserved common shocks react with lags. In addition, contrary to the traditional ARDL model, cross-section averages are included in the CS-ARDL model as proxies of unobserved common global effects and local spillovers in order to account for cross-section dependencies. To ignore the effect of these shocks, as the ARDL approach does, could lead to severely biased estimates if in effect the unobserved factors are highly correlated with the regressors. However, this approach has been formulated only for stationary panels and is subject to sampling uncertainty when the time period is not large enough.

The third dynamic panel data model is the CS-DL mean group (CS-DLMG) approach proposed by Chudik et al. (2013), which can be written in the following way:

$$tfp_{it} = \alpha_i + \boldsymbol{\theta}'_i \boldsymbol{x}_{it} + \sum_{l=0}^{p-1} \boldsymbol{\delta}'_{il} \boldsymbol{x}_{i,t-l} + \omega_{iy} \overline{tfp}_t + \sum_{l=0}^{3} \boldsymbol{\omega}'_{i,xl} \bar{\boldsymbol{x}}_{t-l} + e_{it} \tag{25}$$

where:

$$\bar{\boldsymbol{z}}_t = (tfp_t, \bar{\boldsymbol{x}}'_t)'$$

Here I estimate CS-DLMG models by adding 3 lagged cross-section averages. I take advantage of the fact that it only requires a selection of a truncation lag, in contrast with the ARDL approach, which depends on a correct specification of the lags order. I choose to include $p = 1, 2$ and 3 lags of the regressors. Once cross-section averages are included into the model, it is possible to obtain robust estimations even when the time period is small. It is also robust to the presence of nonstationary variables and factors, regardless of the number of unobserved factors, the presence of weak cross-section dependence, serial correlation or breaks in the idiosyncratic errors, serial correlation in unobserved factors, and heterogeneous or homogeneous short and long-run coefficients. However, the CS-DLMG does not properly tackle the problem of the feedback effects from lagged values of the TFP onto the domestic and foreign R&D, so long-run estimates are consistent only in the absence of this problem. Furthermore, estimations done for small samples are only consistent so long as the eigenvalues of $\varphi(L)$ are not close to the unit circle.

I stress that I have followed Chudik et al. (2013) in the sense that I use different dynamic panel data approaches to deal with several types of econometric problems and to obtain robust results. According to them, although the CS-DLMG estimator produces less biased estimates than the CS-ARDL estimator, the two approaches should be regarded as complementary when dealing with several econometric questions. However, I mainly rely on the CS-ARDL model in a ECM specification, because the cointegration of variables in the long run can be easily observed and this model deals with a variety of problems which are inherent in R&D investment and unobserved common effects: the lagged effects of domestic R&D, foreign R&D and unobserved common shocks, and the feedback effects of past productivity values onto the R&D covariates.

5. Data

The data set contains aggregate data from 1970 to 2011 for 50 advanced and emerging countries, which covers more than the 90% of the world GDP, for an unbalanced panel with $N_{min} = 20$ and $T_{min} = 20$. Information on the data set is reported in Table 1. There are 2042 observations for total factor productivity (TFP), 1873 for the domestic R&D capital stock and 2056 for the foreign R&D capital stock. The methodologies employed to construct the variables and sources are reported in appendix B. The main results of the present work include a weighted foreign R&D capital stock variable defined by LP, whose weights allow for knowledge transmission from all the countries of the sample.

In the appendix A, I include results based on two setups of LP weights that contain information on knowledge transmission from i) 23 OECD countries[21] plus BRICs and ii) all the OECD countries of the sample plus BRICs. In addition, results based on a weighted foreign R&D capital stock variable defined by CH are also included in the appendix A in accordance with the three abovementioned weighting configurations. Table 2 presents descriptive statistics for the variables of interest. Here the foreign R&D capital stock exhibits the highest average growth rate, whereas the total factor productivity growth shows the lowest.

Data for 7 countries are illustrated in Figures 1 to 3. Figure 1 shows that the Chinese TFP registered the largest growth between 1970 and 2011 (3% on average), with a shift in 1980. In contrast, the Brazilian TFP registered a negative growth, at an average rate of 0.5% and coincided with Latin America's "lost decade" in the 1980´s. Thailand, the US, the UK and India show a similar TFP growth rate (0.7%) and increase at an identical rate over time. Although the Russian TFP also grows by 0.7% on average over time, its dynamic is different from that of the other six countries. It falls in the 90s due to a structural change of its political and economic regime, but then it rises steadily from 1999. Moreover, the TFP falls for all countries (except China) in 2008, and later TFP recovers.

Figure 2 displays a positive trend for the domestic R&D capital stock, except for Russia which exhibits a slight U shape evolution. Chinese domestic R&D grows quickly from 2000, while the growth of Brazilian and the Indian domestic R&D accelerate from the mid 80s (with an average growth of 4% from 1970 to 2011). Conversely, the UK domestic R&D registers the smallest growth rate (2%) after Russia, whose growth rate is negative (-0.4%). As seen in Figure 3, foreign R&D capital stock presents a monotonic upward trend, falls for all countries in 2008 and is more volatile across countries than the domestic R&D capital stock and the TFP. The foreign R&D for China, Russia, Thailand and India grow faster than the other countries (15.6%, 13.5%, 9.8% and 7.2% in average respectively). Meanwhile, the UK and the US register the lowest growth rates (which rose about 4%).

[21] All OECD countries from Coe et al. (2009) except Belgium, which is not included here.

6. Unit Root and Cross-Section Dependence Tests

6.1. Unit Root Tests and Stationarity Properties of Variables

In this section I investigate the stationarity of variables in order to understand their time series features before carrying out empirical analysis. To this end, I use the first and the second generation panel unit root tests by Maddala and Wu (1999) and Pesaran (2007) [22], respectively. The disadvantage of the former is that it assumes independently-distributed cross-sectional time series individuals. This is overcome by the latter allowing cross-section dependence across time series observations. This makes an important difference since the first generation panel unit root tests may present substantial size distortions if cross-section dependence is not regarded (Baltagi et al. 2007). Further, the null hypothesis for both tests is that all panels contain unit roots across the observations, which is tested at 5% level of significance.

Later in this work I will only use the Pesaran (2007) unit root test to analyze the time series properties of residuals from each model[23]. Table 3 presents the results of these tests according to two panels, one with logarithmic variables in levels, and other with logarithmic variables in first differences. As can be seen, the Maddala and Wu (1999) unit root test, in which I include a constant, yields unit root in all variables, and when a time trend is added, the only stationary variable is the domestic R&D. However, when one examines the results of the Pesaran (2007) unit root test, whether it only has only a constant or both a constant and a time trend, all variables are nonstationary. In panel 2 all variables in first differences are integrated of order zero (i.e. I(0)), which means that at least from the viewpoint of the Pesaran (2007) unit root test results, all variables are I(1) when they are in levels.

6.2. Cross-Section Dependence Test

The test that I implement to analyze the cross-section dependence of residuals is the cross-section dependence (CD) test by Pesaran (2004), which is based on estimates of pair-wise error correlations. The null of this test is that the average pair-wise error correlations are equal to zero or that there is a cross-section non-correlation of errors. This can be expressed as:

$$H_0: E(u_{it}u_{jt}) = 0 \; for\ all\ t\ and\ i\ where\ i \neq j,$$

Therefore, cross-section correlations of errors are present when $E(u_{it}u_{jt}) \neq 0$. However, as the null hypothesis of the CD test may be restrictive for large panels, Pesaran (2013) it redefined as weak cross section dependence[24]. According to Chudik and Pesaran (2013b), the CD test is valid in the presence of strictly or weakly exogenous regressors, even including lagged covariates.

[22] Pesaran et al. (2013) have demonstrated that the Pesaran (2007) unit root test shows size distortions if there is more than one common factor. Consequently, it would be desirable in future empirical studies to implement either of the next second generation unit root tests proposed by Pesaran et al. (2013) which have been designed to account for multiple unobserved common factors but for which there has not been developed any stata routine yet: the CIPS unit root test in the presence of multifactor error structure, or alternatively, the CSB Sargan-Bhargava, augmented with cross-sectional averages which has better a performance for smaller samples in T.

[23] The results are available upon request.

[24] This test is based on the α exponent of cross-section dependence, introduced by Bailey et al. (2012), and can be used in balanced and unbalanced panels.

7. Results

7.1. Estimates of Static Econometric Models

Table 4 contains the results of the static pooled and mean group estimations. Across models the coefficients of domestic R&D are larger than those of the foreign R&D (except for the CCEMG (i) estimates). More important, all the models with homogeneous slopes (except POLS) yield positive and statistically significant estimates of the domestic R&D at the 1% level, which range between -0.015 and 0.075, whereas the domestic R&D estimates from the MG and CDMG models vary between 0.039-0.061, all being statistically significant at the 10% level. Homogeneous (or Pooled) estimates of the foreign R&D fall between 0.000-0.060, all being statistically significant at the 1% except for the estimate from the first difference model, while the MG and CDMG estimations of foreign R&D range from 0.025-0.031, where the foreign R&D estimate from the MG model is significant at the 10% level.

Even though the majority of the previous estimates which ignore unobservables (or where unobserved effects are accounted for, but technology coefficients are restricted to be homogeneous) seem economically reliable and may be in line with the literature on international R&D spillovers, they are seriously misspecified for two different reasons. First, all models have nonstationary residuals; and second, the large CD statistic reflects the fact that the degree of residual cross-section dependence is very high that R&D estimates may be seriously biased and inconsistent (except for the POLS model). This indicates that there may be substantial error cross-section dependence due to unobserved common micro and macro effects which is ignored by the basic CH model, so those effects might be strongly correlated with the regressors. As a result, this model, which has been fundamental in the study of international R&D spillovers so far, might not be suitable for capturing all the cross-section dependence in the data, because it assumes that all the cross-section dependence is represented by knowledge spillovers, which can lead to seriously biased and inconsistent foreign and domestic R&D estimates.

CCEMG estimates are also reported in Table 4, employing two different setups: (i) a specification without a time trend; and (ii) a model in which a time trend is included. As can be seen, all coefficients of the domestic and foreign R&D variables are statistically significant and range from 0.054-0.090 and 0.057-0.061 respectively. CCEMG models are not misspecified, since they have stationary and not strongly cross-section dependent residuals. Moreover, estimates of the domestic and foreign R&D from the second CCEMG model and foreign R&D coefficients from the first CCEMG model are more sizable when compared with the misspecified pooled and MG models traditionally used in works on R&D spillovers.

According to these results, even if I choose the second over the first CCEMG because the former yields larger significant domestic and foreign R&D coefficients, given that the RMSE is lower, it does not mean that those coefficients merely capture pure returns to R&D and international knowledge spillovers. This is because those coefficients are subject to low degrees of cross-section dependence of residuals, which means that such estimates are capturing additional spillovers and other effects which are not observed. In other words, this shows that international R&D spillovers cannot easily be separated from either unobserved local spillovers or non-observed common shocks, even if the coefficient of the weighted knowledge variable is consistent and not seriously biased. Therefore, the coefficient of the foreign R&D variable which is assumed to only capture knowledge spillovers in a rigid fashion, in reality fails to achieve this purpose. The same applies to the slope of the domestic R&D variable.

Table A1 reports results which include other sorts of weighted foreign R&D variables. Similar conclusions hold for specifications that include a LP foreign R&D variable, because they are characterized by stationarity and low degrees of cross-section correlation of the residuals and yield significant foreign and domestic R&D estimates. This also applies only to the specifications with a CH weighted foreign R&D variable, which allows for knowledge dissemination from all OECD countries plus BRICs and from 23 OECD countries plus BRICs. Conversely, four specifications that include a foreign R&D variable based on CH weights are misspecified, due to strong cross-section dependence of the residuals, despite the fact that all domestic and foreign R&D coefficients are positive and significant at the 1% level. This means that these specifications yield seriously biased and inconsistent estimates, even when unobserved common factors have been accounted for; therefore, a CH weighted variable becomes even more rigid and less explanatory of knowledge spillovers in the presence of common non-observed global shocks and local spillovers.

7.2. Estimates of Dynamic Econometric Models

7.2.1. Dynamic Models That Assume Cross-Section Independence of Errors

Table 5 reports the results of the dynamic ARDL-POLS, 2FE and MG models which assume error cross-section independence. Each model has been estimated with p=1,2 and 3 lags. Coefficients of domestic R&D from the dynamic POLS range from -0.013 to 0.008 and the foreign R&D slopes vary between -0.003 and 0.022. All of these estimates are statistically insignificant and some of them are, indeed, negative. Estimates of the domestic and foreign R&D from the dynamic 2FE fall from -0114-0.005 and 0.031-0.077 respectively, and are significant only for the specification with one lag. Meanwhile, the MG-ARDL estimates of the domestic R&D range from 0.054-0.090 and the coefficients of the foreign R&D fall between 0.057-0.061 where the domestic R&D coefficients are statistically significant to one and two lags.

Variables are cointegrated in the long-run in all models at 1%. Nevertheless, these models are seriously misspecified, because residuals are characterized by strong cross-section dependence, and this misspecification is more severe in the case of the second and third dynamic POLS models, owing to nonstationary residuals. In consequence, none of the models has been chosen. Therefore, we can state that these findings and those from static models provide categorical evidence that the standard CH model may ignore strong error cross-section dependence, possibly caused by unobserved common shocks, which may be correlated with the domestic and foreign R&D, and that leads to biased and inconsistent estimates.

7.2.2. Dynamic Models That Account For Error Cross-Section Dependence

The results of the CS-ARDL models to p=1, 2 and 3 lags, including a time trend, are reported in Table 6 column (i). Estimates of the domestic and foreign R&D variables range from 0.023-0.055 and 0.070-0.082 respectively. Foreign R&D estimates are statistically significant at the 5% level, while the only domestic R&D estimate that is significant (at the 10% level) is that from the model with two lags. None of these models is misspecified, thanks to the fact that low degrees of cross-section correlation of residuals and variables are cointegrated in the long-run at the 1% level. However, only the CS-ARDL specification, which includes two lags, obtains significant coefficients for both domestic R&D and foreign R&D. It may be possible that the CS-ARDL models with one and three lags do not capture statistically significant domestic R&D estimates because of limitations on the time data, especially in the case of countries for which the data does not stretch beyond thirty years.

A more flexible CS-ARDL specification which incorporates a time trend has been estimated. The CS-ARDL (ii) model with 1 and 2 lags includes only two lagged cross-section averages. As can be seen, domestic and foreign R&D coefficients, which range from 0.066-0.085 and 0.065-0.079 respectively, are significant at 5%. Moreover, models with 1 and 2 lags are not missspecified, thanks to a low degree of cross-section dependence of residuals. These results indicate that if there were more observations or more flexibility in the CS-ARDL model, then it might be more feasible to it to yield positive and significant domestic and foreign R&D estimates. However, this flexibility has been introduced at a cost, since only two lagged cross-section averages may not be a suitable way to deal with the problem of reverse causality which may arise in a dynamic model.

The results of the CS-DLMG models which include 1, 2 and 3 lags of the dependent variable and a time trend suggest that all the domestic R&D estimates, which vary between 0.071-0.109, are significant at the 1% level, while the foreign R&D slopes are only significant at 1% for the specification with 2 and 3 lags and at 5% for one lag, falling between 0.052 and 0.080. CS-DLMG models are not misspecified, thanks to low levels of the residual cross-section dependence. Therefore, they do not show seriously biased and inconsistent domestic R&D and foreign R&D estimates so long as feedback effects are not present. Although the RMSE of the CS-DLMG models is larger, compared to the CS-ARDL results, the Monte Carlo experiments in Tables 4 and 8 of Chudik et al. (2013b) show that for that for samples fewer than 100 cross-section and time observations, and in the absence of feedback effects, the CS-DLMG estimator is more efficient and has more power than the CS-ARDL model even when the RMSE of the former is larger.

However, due to the characteristics of the R&D capital stock, it will be necessary to give priority to those dynamic models that account for feedback effects. Given these characteristics, both models might yield complementary results. The CS-ARDL model may indicate that it is possible to obtain consistent, not seriously biased, positive and significant estimates of domestic and foreign R&D, while the CS-DLMG models show that, with more complete data, these results may be more significant and the magnitude larger. Further, long-run cointegration is achieved across CS-ARDL models and the speed of cointegration is higher, compared to the traditional ARDL models from Table 5, even though it is still not very high. The majority of significant domestic and foreign R&D coefficients from Table 6 are more sizable than estimates from the ARDL models, in which error cross-section independence is assumed.

Notwithstanding the fact that all these features describe favorable results for the domestic and foreign R&D coefficients in dynamic models, the presence of weak residual cross-section dependence provides information on the real nature of those estimates. In fact, those coefficients may not capture pure returns to domestic R&D and knowledge spillovers. Instead, they might be capturing these plus unobserved local spillovers and other effects, where both might react with lags. Once again, we can see that a rigid foreign R&D variable may not capture knowledge spillovers as a unique source of cross-section dependence in the data; the same would apply to the domestic R&D variable.

Thus, this confirms that unobservables cannot be easily separated from returns to domestic R&D and knowledge spillovers, as the CH specification has assumed: clear evidence that this specification is not suitable for studying the effect of spillovers on productivity across all the countries in the sample. The fact that, in most cases, domestic and foreign R&D estimates from the static and dynamic models where unobserved common effects are accounted for are more sizable compared to those from a CH specification, indicates that coefficients are capturing more cross-section dependencies than those postulated by the literature on international R&D spillovers; this empirical finding strengthens the abovementioned conclusions.

Tables A2 to A5 show similar findings for models that include different sorts of LP and CH weighted foreign R&D variables. It seems that when the models include a CH foreign R&D variable, the coefficient of this variable is larger than that obtained from models which include LP foreign R&D variables. Further, the coefficient of domestic R&D is significant in most cases, long-run cointegration is significant at the 1% level for CS-ARDL models, and at least three CS-ARDL and all CS-DLMG models yield low degrees of the cross-section dependence of residuals and significant and positive domestic and foreign R&D coefficients, which confirms what was found above. A different situation is presented in Table A6 where a CH weighted foreign R&D variable with information on knowledge transmission from all countries has been incorporated.

Although all CS-DLMG models have low degrees of the cross-section dependence of the residuals, positive and significant estimates for the domestic and foreign R&D variables, and large foreign R&D estimates, only one of the five CS-ARDL models achieves all of this. The other four CS-ARDL models manage to have all these features, but, strangely, none of their domestic R&D coefficients are significant and all are very small compared to the estimates from Tables A4 and A5. This unusual change does not happen when a LP weighted foreign R&D variable is introduced under any of the three knowledge diffusion configurations. As a result, the CS-ARDL and CS-DLMG models from Table A6 are not as complementary as the models in Tables A2 to A5.

This might indicate that results of dynamic models which account for feedback effects and unobserved common effects are sensitive to the inclusion of a CH weighted foreign R&D variable which incorporates the global dissemination of knowledge from all countries (including most of the emerging economies of the sample), which is in line with what I found in the static models. This therefore supports the fact that a CH weighted R&D variable may be too rigid in trying to capture the cross-section dependence which is merely explained by knowledge spillovers, and its inclusion into the model may affect the estimate of the domestic R&D.

8. Comparison between Two Subsamples

In this section I use models such as the CS-ARDL and CS-DLMG (with a time trend) for the estimates of two different subsample sets drawn from the original sample. My aim is to see whether the conclusions from the previous section apply to those subsamples. The first subsample does not include 11 small emerging economies (Colombia, Costa Rica, Ecuador, Egypt, Indonesia, Malaysia, Panama, Peru, Philippines, Uruguay and Venezuela) from the original sample, and the second subsample excludes G7 countries and BRICs. Cross-section averages are based on the original sample. Foreign R&D is based on LP and allows for the transmission of knowledge from all countries of the sample. The results for other configurations of the foreign R&D are included in the appendix A. Table 7 shows the results when 11 small emerging countries are excluded. It can be seen that seven of the eight dynamic models yield not seriously biased, consistent, positive as well as significant domestic and foreign R&D coefficients, although with low degrees of residual cross-section dependence. The estimated CS-ARDL (i) model with two lags is the only model that suffers from a high degree of cross-section dependence of residuals at the 5% level. According to these results, the conclusions of the previous section still apply to the analysis of the first subsample.

Table 8 shows that, when G7 countries and BRICs are excluded, none of the foreign R&D estimates from the CS-ARDL models are significant and only two of five CS-ARDL models yield significant estimates of the domestic R&D in models which are not misspecified. In addition, some of the domestic R&D slopes and all of the foreign R&D estimates are lower compared to the estimates in Table 7. The CS-DLMG model, on the other hand, yield positive and statistically significant estimates of both foreign and domestic R&D variables, even though the significance and magnitude of the foreign R&D coefficients are lower than those coefficients in Table 7. Still, those not misspecified models are subject to low degrees of residual cross-section dependence. It is clear that the CS-ARDL and CS-DLMG estimates from Table 8 are not complementary at all, since the former do not yield at least one model in which both domestic and foreign R&D estimates are statistically significant, as happens with the latter.

Hence, the results of the CS-ARDL model (which from the viewpoint of this study is the most suitable approach to model R&D) for the second subsample suggest that unobserved common local spillovers and other effects could play a relatively more important role in determining the productivity of these economies than the international R&D spillovers alone, subject to the fact that one kind of spillover or effect cannot be separated from the other. Therefore, the role of a weighted foreign R&D variable may be less effective at capturing R&D spillovers in this case. According to all these findings, it seems that the CH specification may not be an accurate way to examine spillovers. It is worth noting that this subsample comprises a larger proportion of emerging economies than that in the first subsample[25]. Similar conclusions, although with different results, can be found in Tables A7 to A10[26].

I have also estimated models by incorporating CH weighted foreign R&D variables. The results for the first subsample are reported in Tables A11 and A13, which account for international knowledge flows from 23 advanced OECD plus BRIC economies and transmission from all OECD plus BRIC countries respectively. These findings agree with those obtained when I included LP weighted foreign R&D variables. Next, Tables A12 and A14, where I exclude G7 plus BRIC countries from the main sample and employ the same CH foreign R&D variables, show that it is possible to obtain positive, consistent, not seriously biased and statistically significant coefficients for both domestic and foreign R&D coefficients from two of the CS-ARDL models and all the CS-DLMG models, so that there is complementarity of results from these models.

This outcome differs from what I previously found when LP foreign R&D variables were included, although both results are subject to low degrees of residual cross-section dependence, which indicates that slopes might be not be capturing pure knowledge spillovers. Nevertheless, if we look at Table A15 (which excludes 11 emerging economies) and Table A16 (which excludes G7 and BRIC countries) - both of which incorporate a CH weighted R&D variable that allows for knowledge transmission from all the countries of the original sample - the results substantially differ from those in Tables A11 to A14, because now none of the CS-ARDL models yields consistent and significant coefficients of domestic R&D and only some of the CS-DLMG models do. This atypical change does not arise when LP foreign R&D variables are included. If we go by the findings from dynamic models where feedback effects and unobserved common factors are accounted, it would seem that the estimates of the domestic R&D are sensitive to the inclusion of a CH foreign R&D variable, particularly when a large number of the emerging economies are added to the weights. Hence, CH weighted variables might be more rigid than the LP variable, and

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[25] A possible explanation for these results may be the fact that the amount of NXT observations in the second subsample was reduced, so the CS-ARDL models may present data constraints which affect R&D estimates. However, results from Table 7 are favorable even though there are fewer observations than those observed from Table 6, and models from Table 8 have almost the same amount of observations as those from the models of Table 7. Then, a reasonable explanation for these results might be the fact that more advanced countries and BRICs in the recent years do more R&D than many of the small advanced countries and emerging economies (see: UNESCO Institute for Statistics 2014), so the impact of the domestic and foreign R&D on productivity is larger and more statistically significant when more advanced countries and BRICs are included in the sample either if 11 of all the emerging economies from the main sample are excluded or not. However, it is clear that when the 11 small emerging economies are included and G7 plus BRICS are excluded, then the formers have a larger share in the sample and that could affect the statistical significance of domestic and foreign R&D estimates from the CS-ARDL models.

[26] Tables A7 and A8 report results for similar setups from Table 7 and 8 respectively but including a LP weighted foreign R&D variable allowing for R&D transmission from 23 OECD advanced economies from the main sample plus BRICs; and Tables A9 and A10 include a LP weighted foreign R&D variable allowing for R&D transmission from all the OECD countries from the original sample plus BRICs.

also fail to capture all the cross-section dependence that exists in the data, whether in static and dynamic models.

9. Conclusion

A vast literature on international R&D spillovers, based on the CH framework, has studied how knowledge spillovers and domestic returns to R&D explain productivity based on the CH framework. However, this paper shows that even if that is the main purpose of the traditional literature on international R&D, unobserved common effects and spillovers should be accounted for. If these are ignored, as in the CH specification, and if they are also correlated with the regressors, estimates may be biased and inconsistent.

These statements are supported by the results of the present work. Conversely, if we allow for heterogeneous technology parameters and shocks are accounted for, we find that statistically significant coefficients of the foreign and domestic R&D capital stock variables are normally asymptotic, consistent , not seriously biased and even more sizable in the majority of cases than the coefficients obtained from the CH framework. However, those coefficients are subject to low degrees of error cross-section dependence which indicates that international spillovers might not be the only sort of spillovers that are captured by the coefficient of the foreign R&D variable. Instead, this coefficient might capture international spillovers plus unobserved spillovers and other common effects; the same applies to the coefficient of the domestic R&D variable.

This clearly explains that knowledge spillovers cannot be easily separated from unobservables and thus should not be solely estimated by employing rigid weighted LP or CH foreign R&D variables in a CH framework where domestic and foreign R&D are introduced into a TFP function in an additively separable fashion, as the conventional literature on international R&D spillovers has assumed. This approach fails to determine which part of the technology transfer can be considered as a R&D spillover. Therefore, economic policies on international technology transfer should be assessed by relying on the results from a more adequate quantitative framework which can account for international technology diffusion spillovers as well as common micro and macro effects of unknown form which might be either related or not related to the cross-country R&D capital stock.

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Table 1: Sample Description

#	Country	TFP	Coverage	Rd	Coverage	Rf	Coverage	#	Country	TFP	Coverage	Rd	Coverage	Rf	Coverage
1	Argentina	42	1970-2011	42	1970-2011	42	1970-2011	26	Italy	42	1970-2011	42	1970-2011	42	1970-2011
2	Australia	42	1970-2011	38	1973-2010	42	1970-2011	27	Japan	42	1970-2011	42	1970-2011	42	1970-2011
3	Austria	42	1970-2011	42	1970-2011	42	1970-2011	28	Korea	42	1970-2011	42	1970-2011	42	1970-2011
4	Brazil	42	1970-2011	38	1973-2010	42	1970-2011	29	Malaysia	42	1970-2011	24	1988-2011	42	1970-2011
5	Bulgaria	42	1970-2011	32	1980-2011	42	1970-2011	30	Mexico	42	1970-2011	42	1970-2011	42	1970-2011
6	Canada	42	1970-2011	42	1970-2011	42	1970-2011	31	Netherlands	42	1970-2011	42	1970-2011	42	1970-2011
7	Chile	42	1970-2011	32	1979-2010	42	1970-2011	32	New Zealand	42	1970-2011	40	1972-2011	42	1970-2011
8	China	42	1970-2011	24	1988-2011	42	1970-2011	33	Norway	42	1970-2011	42	1970-2011	42	1970-2011
9	Colombia	42	1970-2011	41	1971-2011	42	1970-2011	34	Panama	42	1970-2011	25	1986-2010	42	1970-2011
10	Costa Rica	42	1970-2011	38	1974-2011	42	1970-2011	35	Peru	42	1970-2011	34	1971-2004	42	1970-2011
11	Cyprus	42	1970-2011	32	1980-2011	42	1970-2011	36	Philippines	42	1970-2011	38	1970-2007	42	1970-2011
12	Denmark	42	1970-2011	39	1973-2011	42	1970-2011	37	Poland	42	1970-2011	27	1985-2011	42	1970-2011
13	Ecuador	42	1970-2011	39	1970-2008	42	1970-2011	38	Portugal	42	1970-2011	42	1970-2011	42	1970-2011
14	Egypt	42	1970-2011	39	1973-2011	42	1970-2011	39	Romania	24	1988-2011	23	1989-2011	42	1970-2011
15	Estonia	22	1990-2011	20	1992-2011	20	1992-2011	40	Russia	22	1990-2011	22	1990-2011	20	1992-2011
16	Finland	42	1970-2011	42	1970-2011	42	1970-2011	41	Singapore	42	1970-2011	42	1970-2011	42	1970-2011
17	France	42	1970-2011	42	1970-2011	42	1970-2011	42	Spain	42	1970-2011	42	1970-2011	42	1970-2011
18	Germany	42	1970-2011	41	1971-2011	42	1970-2011	43	Sweden	42	1970-2011	42	1970-2011	42	1970-2011
19	Greece	42	1970-2011	38	1970-2007	42	1970-2011	44	Switzerland	42	1970-2011	39	1970-2008	42	1970-2011
20	Hungary	42	1970-2011	42	1970-2011	42	1970-2011	45	Thailand	42	1970-2011	40	1970-2009	42	1970-2011
21	Iceland	42	1970-2011	40	1970-2009	42	1970-2011	46	Turkey	42	1970-2011	42	1970-2011	42	1970-2011
22	India	42	1970-2011	38	1970-2007	42	1970-2011	47	United Kingdom	42	1970-2011	42	1970-2011	42	1970-2011
23	Indonesia	42	1970-2011	38	1972-2009	42	1970-2011	48	United States	42	1970-2011	42	1970-2011	42	1970-2011
24	Ireland	42	1970-2011	42	1970-2011	42	1970-2011	49	Uruguay	42	1970-2011	41	1970-2010	42	1970-2011
25	Israel	42	1970-2011	42	1970-2011	42	1970-2011	50	Venezuela	42	1970-2011	31	1970-2000	42	1970-2011
									Total Obs	2042		1873		2056	

Notes: Variables: Total Factor Productivity (TFP), Domestic R&D (Rd) and Foreign R&D (Rf) capital stocks. All monetary variables are expressed in constant millions of US dollars of 2005 based on purchasing power parity (PPP). Definitions of these variables in the appendix.

Table 2: Summary Statistics					
VARIABLES	Mean	Median	SD	Minimum	Maximum
Levels					
Total Factor Productivity	0.96	0.97	0.14	0.57	1.60
Domestic R&D Capital Stock (million PPP constant 2005 dollars)	70858.70	9109.51	218128.50	48.66	2220345.00
Foreign R&D Capital Stock (million PPP constant 2005 dollars)	9325.21	3062.48	16401.86	4.45	174997.40
Logarithms					
Log Total Factor Productivity	-0.05	-0.03	0.14	-0.56	0.47
Log Domestic R&D Capital Stock (million PPP constant 2005 dollars)	9.20	9.12	2.06	3.88	14.61
Log Foreign R&D Capital Stock (million PPP constant 2005 dollars)	7.99	8.03	1.63	1.49	12.07
Growth					
Δ Total Factor Productivity	0.00	0.01	0.03	-0.25	0.19
Δ Domestic R&D Capital Stock (million PPP constant 2005 dollars)	0.04	0.04	0.06	-0.16	0.34
Δ Foreign R&D Capital Stock (million PPP constant 2005 dollars)	0.07	0.06	0.17	-1.09	3.09

Notes: These descriptive statistics refer to the sample of N = 50 countries from 1970 to 2011.

Table 3: Time-Series Properties						
Panel 1: Logarithmic Variables in Levels						
Maddala and Wu (1999) Fisher Test (Including a Constant)						
Lags	tfp		rd		rf	
	Chi sq	p-value	Chi sq	p-value	Chi sq	p-value
0	79.370	0.936	72.305	0.983	148.420	0.001
1	100.283	0.473	162.193	0.000	48.548	1.000
2	82.956	0.891	111.186	0.209	52.938	1.000
3	72.667	0.982	103.621	0.382	39.330	1.000
Maddala and Wu (1999) Fisher Test (Including a Constant and a Time Trend)						
Lags	tfp		rd		rf	
	Chi sq	p-value	Chi sq	p-value	Chi sq	p-value
0	75.757	0.966	670.225	0.000	376.862	0.000
1	115.222	0.142	198.434	0.000	156.051	0.000
2	86.270	0.834	153.087	0.001	113.769	0.164
3	79.221	0.938	152.661	0.001	105.055	0.345
Pesaran (2007) CIPS test (Including a Constant)						
Lags	tfp		rd		rf	
	Chi sq	p-value	Chi sq	p-value	Chi sq	p-value
0	4.666	1.000	9.486	1.000	-0.669	0.252
1	2.164	0.985	-1.369	0.085	1.787	0.963
2	3.556	1.000	1.335	0.909	4.514	1.000
3	3.777	1.000	2.860	0.998	4.076	1.000
Pesaran (2007) CIPS test (Including a Constant and a Time Trend)						
Lags	tfp		rd		rf	
	Chi sq	p-value	Chi sq	p-value	Chi sq	p-value
0	2.272	0.988	3.296	1.000	-2.317	0.010
1	-0.820	0.206	-3.239	0.001	-0.291	0.386
2	0.274	0.608	0.319	0.625	1.729	0.958
3	1.278	0.899	1.986	0.976	0.933	0.825
Panel 2: Logarithmic Variables in First Differences						
Maddala and Wu (1999) Fisher Test (Including a Drift)						
Lags	Δ tfp		Δ rd		Δ rf	
	Chi sq	p-value	Chi sq	p-value	Chi sq	p-value
0	1027.519	0.000	249.408	0.000	1950.501	0.000
1	698.378	0.000	211.822	0.000	1132.085	0.000
2	466.193	0.000	200.903	0.000	636.864	0.000
3	358.109	0.000	205.921	0.000	593.990	0.000
Pesaran (2007) CIPS test (Including a Drift)						
Lags	Δ tfp		Δ rd		Δ rf	
	Chi sq	p-value	Chi sq	p-value	Chi sq	p-value
0	-20.802	0.000	-3.462	0.000	-26.145	0.000
1	-14.246	0.000	-3.954	0.000	-17.144	0.000
2	-9.186	0.000	-2.829	0.002	-10.203	0.000
3	-6.377	0.000	-1.734	0.041	-7.710	0.000

Notes: The Maddala and Wu (1999) test registers the Fisher statistic results and their associated p-values. Pesaran (2007) tests presents a standardized Z-tbar statistic and its respective p-value . The null hypotheses for both tests refers to all series are nonstationary at the 5% level of significance. Zero to three lags augmentation in the performed Dickey Fuller regressions are included. Panel 1 displays the Dickey Fuller regression for logarithmic variables in levels, including a constant, on the one hand, and, on the other, a constant and a trend. Panel 2 contains the variables in first differences including a drift (constant).

Table 4: Static Panel Data Models								
Estimators	POLS	2FE	FD	CCEP	MG	CDMG	CCEMG	
							(i)	(ii)
tfp dependent variable								
Independent variables								
rd	-0.015***	0.075***	0.060***	0.071***	0.039*	0.061*	0.054**	0.090***
std errors	(0.003)	(0.005)	(0.015)	(0.009)	(0.020)	(0.036)	(0.023)	(0.021)
rf	0.021***	0.060***	0.000	0.037***	0.031*	0.025	0.057***	0.061***
std errors	(0.005)	(0.008)	(0.010)	(0.009)	(0.017)	(0.026)	(0.016)	(0.016)
CD-test	-0.28	119.82†	183.45†	28.1†	13.00†	3.63†	-0.21	-0.59
Order of Integration	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)
RMSE	0.142	0.094	0.029	0.045	0.058	0.066	0.035	0.032
NXT	1871	1871	1821	1871	1871	1871	1871	1871
N	50	50	50	50	50	50	50	50

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for knowledge diffusion from all countries of the sample) are the independent variables. Constant term is included but not reported. Estimators: 1) POLS Pooled OLS (augmented with T-1 year dummies). 2) 2FE: Two-way fixed effects (augmented with T-1 year dummies and N-1 country dummies). 3) FD: First Differences (augmented with T-2 year dummies because when differencing, a year dummy is dropped to avoid perfect multicollinearity). 4) CCEP: Pooled Pesaran (2006) augmented with common country dummies and cross-section averages, 5) MG: Mean Group. 6) CDMG: Cross-sectionally demeaned MG. 7) CMG: Common Correlated Effects MG Pesaran (2006) augmented with cross-section averages is presented in two versions: (i) without a time trend, and (ii) including a time trend. . White heteroskedasticity-robust standard errors are reported in parentheses. Levels of significance are represented by * 10%, ** 5% and *** 1%. **Diagnostics**: (evaluated at the 5% level of significance, full results of the next tests are available on request): 1) CD test: Pesaran (2004) test which is redefined by Pesaran (2013), for which Ho: Cross-section weak dependence of the residuals. 2) CIPS test: Pesaran (2007) test evaluates the order of integration of the residuals where I(0): stationary, I(1): nonstationary. Root mean squared error (RMSE), NXT number of country-time observations and N number of countries are also included. † indicates that null hypothesis of weak cross-section dependence of the residuals at the 5% level is rejected.

Table 5: Dynamic ARDL Panel Data Models Assuming Cross-Section Independence of Errors, in a ECM Representation									
Estimators	POLS			2FE			MG		
	1 lag	2 lags	3 lags	1 lag	2 lags	3 lags	1 lag	2 lags	3 lags
tfp dependent variable									
Independent variables									
rd	-0.013	-0.001	0.008	-0.114***	-0.015	0.005	0.025	0.059**	0.060*
std errors	(0.011)	(0.011)	(0.010)	(0.043)	(0.036)	(0.036)	(0.030)	(0.029)	(0.032)
rf	0.022	0.007	-0.003	0.077*	0.053	0.031	0.024	-0.004	-0.007
std errors	(0.014)	(0.014)	(0.013)	(0.045)	(0.037)	(0.034)	(0.028)	(0.029)	(0.031)
Cointegration coefficients	-0.058***	-0.054***	-0.056***	-0.057***	-0.069***	-0.070***	-0.235***	-0.298***	-0.345***
std errors	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.020)	(0.025)	(0.033)
CD-test	156.35†	122.15†	122.02†	148.78†	115.62†	117.05†	19.26†	16.52†	14.49†
Order of Integration	I(1)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
RMSE	0.028	0.027	0.026	0.028	0.027	0.026	0.023	0.021	0.019
NXT	1821	1771	1721	1821	1771	1721	1821	1771	1721
N	50	50	50	50	50	50	50	50	50

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for knowledge flows from all the countries of the sample) are the independent variables. Constant term is included but not reported. Long run estimates and cointegration coefficients are reported. Estimators for autoregressive distributed lagged (ARDL) panel data specifications, which are represented by a Error Correction Model (ECM), are the following: 1) Dynamic ARDL POLS Pooled OLS (augmented with T-1 year dummies). 2) Dynamic ARDL 2FE: Two-way fixed effects (augmented with T-1 year dummies and N-1 country dummies). 3) Dynamic ARDL MG: Mean Group. White heteroskedasticity-robust standard errors are reported in parentheses. POLS, 2FE and MG models are augmented with p=1, 2 and 3 lagged covariates. Levels of significance are represented by * 10%, ** 5% and *** 1%. **Diagnostics:** (evaluated at the 5% level of significance, full results of the next tests are available on request): 1) CD test: Pesaran (2004) test which is redefined by Pesaran (2013), for which Ho: Cross-section weak dependence of the residuals. 2) CIPS test: Pesaran (2007) test evaluates the order of integration of the residuals where I(0): stationary, I(1): nonstationary. Root mean squared error (RMSE), NXT number of country-time observations and N number of countries are also included. † indicates that null hypothesis of weak cross-section dependence of the residuals at the 5% level is rejected.

Table 6: Dynamic Panel Data Models Accounting for Cross-Section Dependence of Errors, in a ECM Representation								
Estimators	CS-ARDL (ECM)					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.023	0.055*	0.050	0.066**	0.085**	0.071***	0.096***	0.109***
std errors	(0.029)	(0.029)	(0.037)	(0.032)	(0.035)	(0.018)	(0.028)	(0.035)
rf	0.083**	0.070**	0.082**	0.079**	0.065**	0.052**	0.068***	0.080***
std errors	(0.033)	(0.031)	(0.037)	(0.033)	(0.033)	(0.021)	(0.024)	(0.028)
Cointegration coefficients	-0.436***	-0.528***	-0.626***	-0.395***	-0.469***			
std errors	(0.040)	(0.057)	(0.077)	(0.032)	(0.046)			
CD-test	-1.61	0.35	0.70	-1.34	0.34	-1.64	-0.90	-0.30
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.013	0.011	0.013	0.015	0.013	0.021	0.018	0.017
NXT	1720	1640	1579	1791	1735	1758	1741	1687
N	48	45	43	50	48	50	50	48

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for R&D transmission from all the countries of the sample) are the independent variables. Constant term is included but not reported. Long run estimates and cointegration coefficients are reported. Estimators for autoregressive distributed lagged (ARDL) panel data specifications, which are represented by a Error Correction Model (ECM), are the following: 1) Dynamic cross-sectional ARDL (CS-ARDL-i) (augmented with lagged cross-sectional averages of the dependent and independent variables with three lags of these cross-sectional averages). 2) Dynamic cross-sectional ARDL (CS-ARDL-ii) (augmented with lagged cross-sectional averages of the dependent and independent variables with two lags of these cross-sectional averages). 3) Cross-sectional DL Mean Group: CS-DLMG. White heteroskedasticity-robust standard errors are reported in parentheses. All models include a time trend. CS-ARDL (i) and CS-DLMG models are augmented with p=1, 2 and 3 lagged covariates. CS-ARDL (ii) model 2 is augmented with p=1 and 2 lags. Levels of significance are represented by * 10%, ** 5% and *** 1%. **Diagnostics**: (evaluated at the 5% level of significance, full results of the next tests are available on request): 1) CD test: Pesaran (2004) test which is redefined by Pesaran (2013), for which Ho: Cross-section weak dependence of the residuals. 2) CIPS test: Pesaran (2007) test evaluates the order of integration of the residuals where I(0): stationary, I(1): nonstationary. Root mean squared error (RMSE), NXT number of country-time observations and N number of countries are also included. † indicates that null hypothesis of weak cross-section dependence of the residuals at the 5% level is rejected.

Table 7: Dynamic Panel Data Models Accounting for Cross-Section Dependence of Errors, in a ECM Representation and Excluding 11 Middle Income Countries (MICs)

Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.018	0.087**	0.107**	0.089**	0.121***	0.062***	0.102***	0.133***
std errors	(0.040)	(0.037)	(0.042)	(0.038)	(0.034)	(0.023)	(0.035)	(0.036)
rf	0.090**	0.089**	0.086**	0.098***	0.063*	0.057***	0.074***	0.081***
std errors	(0.039)	(0.038)	(0.041)	(0.037)	(0.033)	(0.022)	(0.024)	(0.030)
Cointegration coefficients	-0.401***	-0.483***	-0.587***	-0.377***	-0.474***			
std errors	(0.048)	(0.065)	(0.087)	(0.040)	(0.057)			
CD-test	0.4	2.1†	1.22	1.04	1.92	-0.32	0.19	1.11
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.012	0.019	0.009	0.014	0.012	0.018	0.016	0.015
NXT	1353	1300	1267	1418	1369	1391	1379	1332
N	37	35	34	39	37	39	39	37

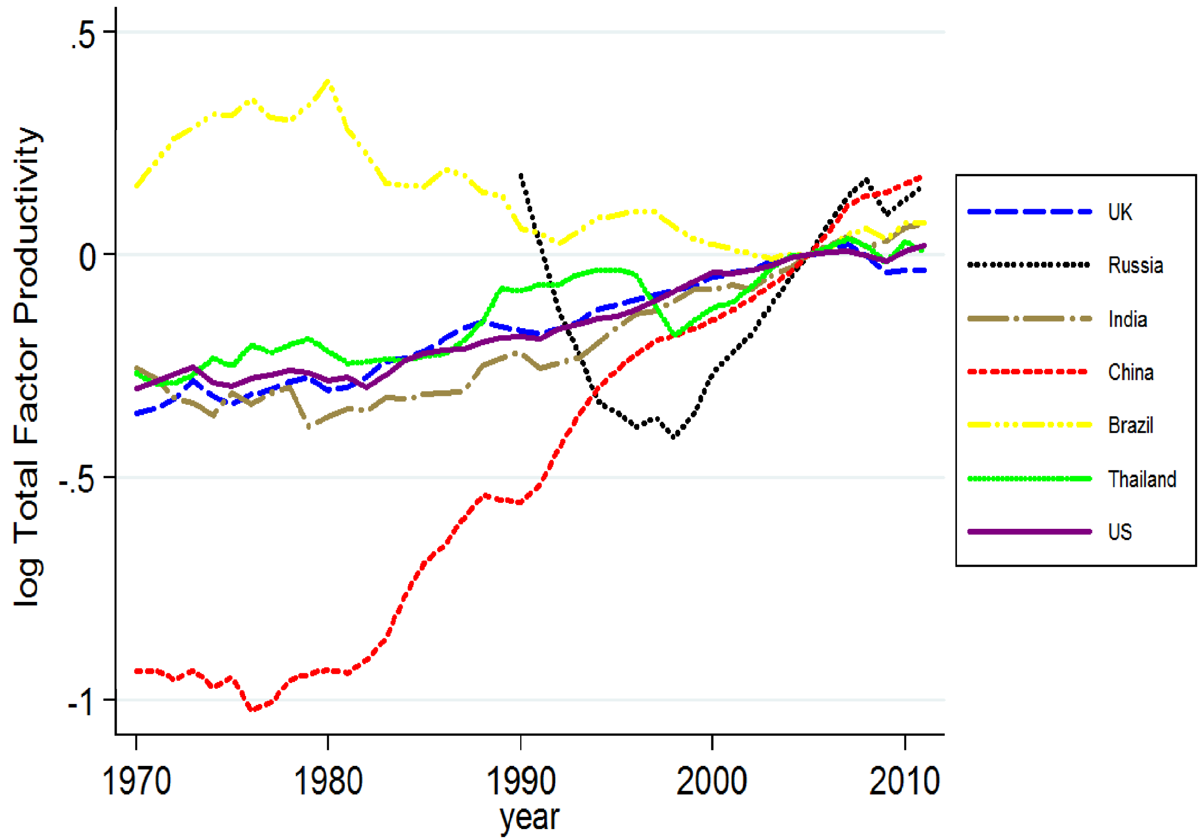
Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for R&D transmission from all the countries of the sample) are the independent variables. See also the notes to Table 7.

Table 8: Dynamic Panel Data Models Accounting for Cross-Section Dependence of Errors, in a ECM Representation and Excluding G7 Countries and BRICS

Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.025	0.059*	0.042	0.070**	0.078**	0.083***	0.111***	0.125***
std errors	(0.028)	(0.031)	(0.034)	(0.032)	(0.035)	(0.024)	(0.031)	(0.041)
rf	0.054	0.041	0.033	0.056	0.033	0.051**	0.053**	0.058**
std errors	(0.033)	(0.033)	(0.037)	(0.035)	(0.036)	(0.023)	(0.025)	(0.030)
Cointegration coefficients	-0.484***	-0.578***	-0.692***	-0.426***	-0.516***			
std errors	(0.040)	(0.060)	(0.084)	(0.033)	(0.051)			
CD-test	-2.72†	-0.78	-0.44	-2.69†	-1.46	-1.88	-1.02	-0.73
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.014	0.012	0.011	0.017	0.014	0.021	0.021	0.018
NXT	1352	1296	1237	1396	1362	1371	1357	1324
N	38	36	34	39	38	39	39	38

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for R&D transmission from all the countries of the sample) are the independent variables. See also the notes to Table 7.

Figure 1: Total Factor Productivity
1970-2010

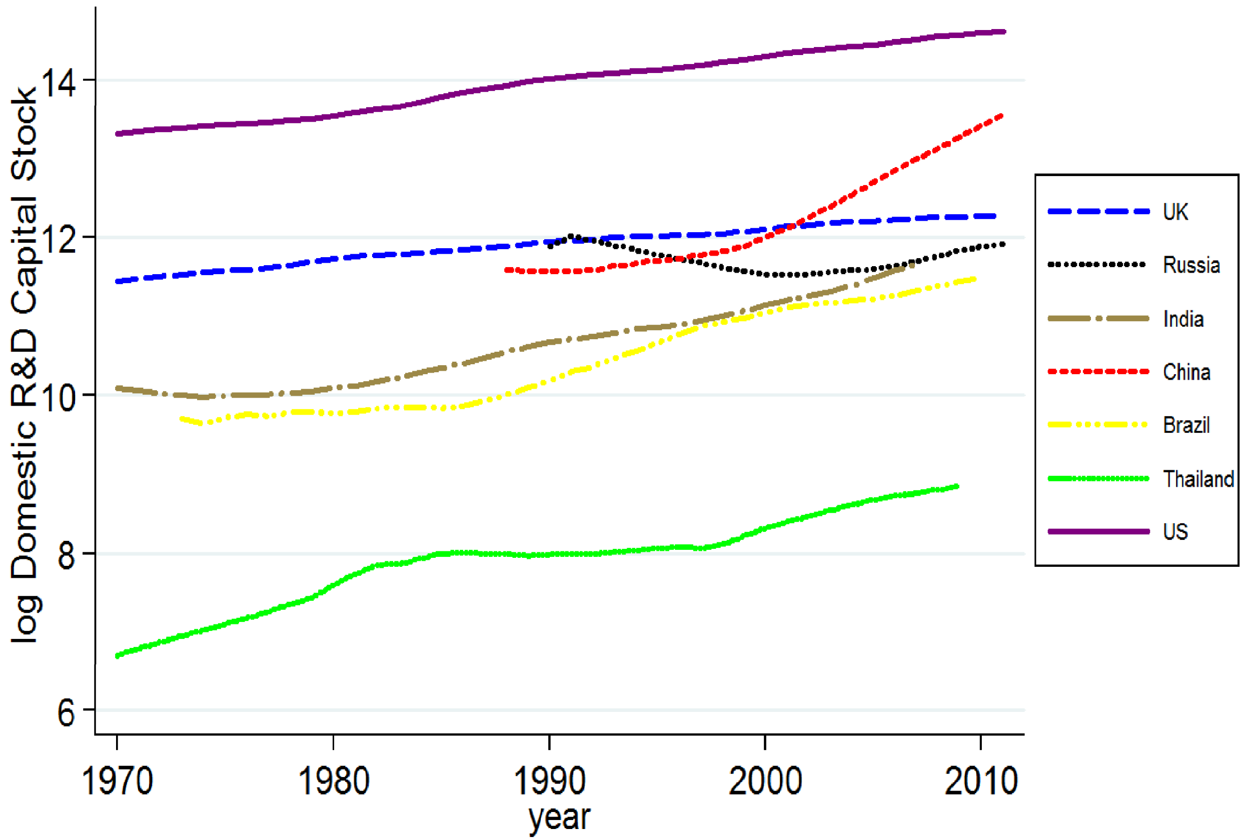


Total Factor Productivity (TFP) derived from national accounts variables (2005=1).

Source: Penn World Table 8.0.

Figure 2: Domestic R&D Capital Stock

1970-2010

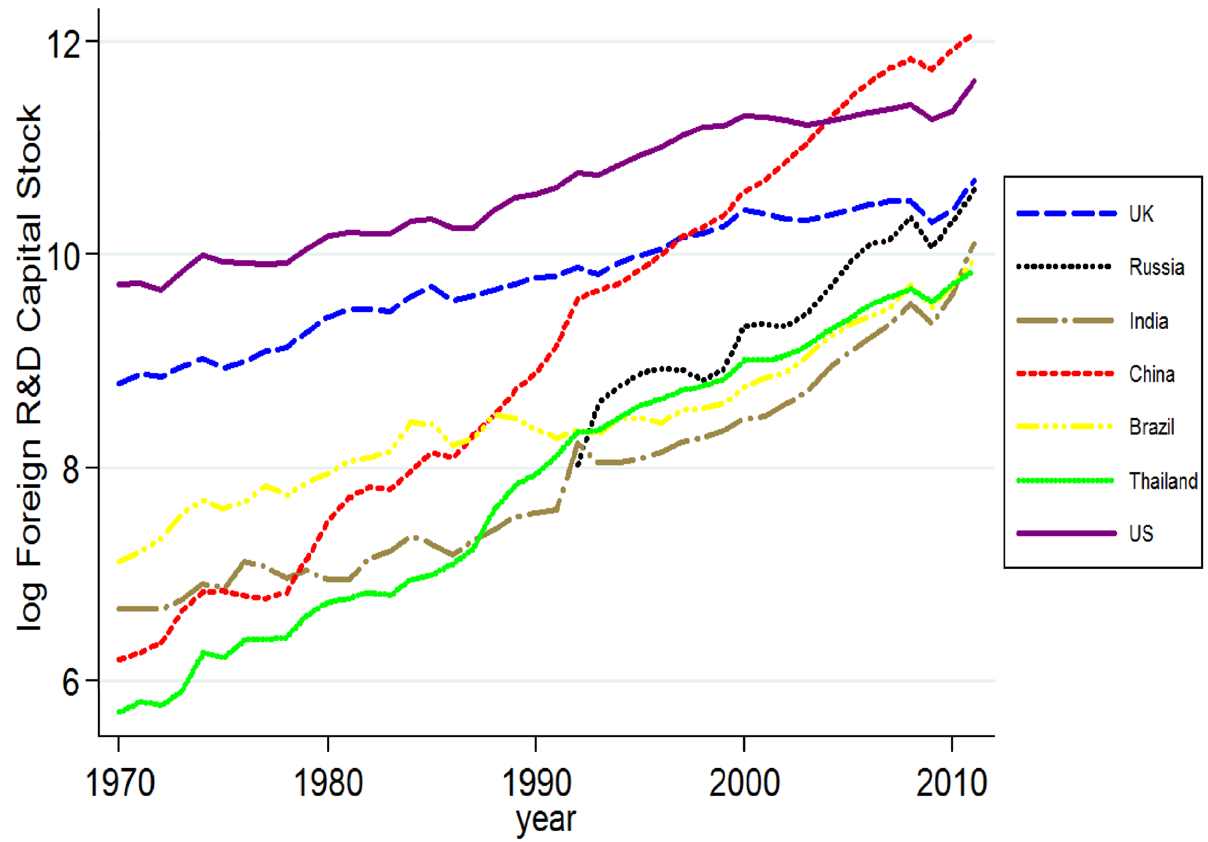


Domestic R&D Capital Stock is defined in terms of constant 2005 million dollars based on purchasing power parity (PPP).

For information about the construction of Domestic R&D Capital Stock refer to the appendix.

Figure 3: Foreign R&D Capital Stock

1970-2010



Foreign R&D Capital Stock in constant 2005 million dollars at PPP is based on Litchtenberg and van Pottelsberghe de la Potterie (1998) bilateral import weights. For more information refer to the appendix.

Appendix A: Additional Results

TableA1: Other Results for Static CCEMG Models										
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
tfp dependent variable										
Independent variables										
rd	0.056**	0.090***	0.056**	0.094***	0.061***	0.063***	0.066***	0.062***	0.068***	0.065***
std errors	(0.022)	(0.022)	(0.023)	(0.021)	(0.018)	(0.024)	(0.020)	(0.021)	(0.018)	(0.021)
rf	0.055***	0.060***	0.057***	0.060***	0.048***	0.057***	0.045***	0.057***	0.043***	0.051***
std errors	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)
CD-test	0.06	-0.39	-0.29	-0.64	1.77	2.06†	1.78	2.11†	2.12†	2.44†
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.034	0.031	0.035	0.032	0.034	0.036	0.035	0.029	0.035	0.029
NXT	1871	1871	1871	1871	1871	1871	1871	1871	1871	1871
N	50	50	50	50	50	50	50	50	50	50
Time Trend	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D (rd) and log foreign R&D (rf) are the independent variables. Constant term is included but not reported. Estimator: CMG, Common Correlated Effects MG Pesaran (2006) augmented with cross-section averages is employed in ten different setups: (i) and (ii) include a rf variable defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (henceforth LP) which allows for knowledge transmission from 23 OECD countries plus BRICs, (iii) and (iv) incorporate a LP-rf variable allowing for knowledge diffusion from all OECD countries of the sample plus BRICs, (v) and (vi) include a rf variable defined by Coe and Helpman (1995) which allows for knowledge flows from 23 OECD countries plus BRICs, (vii) and (viii) incorporate a CH-rf variable allowing for knowledge dissemination from all OECD countries plus BRICs, (ix) and (x) include a CH-rf variable allowing for knowledge diffusion from all the countries of the sample. White heteroskedasticity-robust standard errors are reported in parentheses. Levels of significance are represented by * 10%, ** 5% and *** 1%. **Diagnostics:** (evaluated at the 5% level of significance, full results of the next tests are available on request): 1) CD test: Pesaran (2004) test which is redefined by Pesaran (2013), for which Ho: Cross-section weak dependence of the residuals. 2) CIPS test: Pesaran (2007) test evaluates the order of integration of the residuals where I(0): stationary, I(1): nonstationary. Root mean squared error (RMSE), NXT number of country-time observations and N number of countries are also included. † indicates that null hypothesis of weak cross-section dependence of the residuals at the 5% level is rejected.

Table A2: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and LP Knowledge Diffusion from 23 OECD Countries Plus BRICS

Estimators	CS-ARDL (ECM)					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.035	0.067**	0.064*	0.075**	0.086**	0.077***	0.102***	0.115***
std errors	(0.029)	(0.031)	(0.035)	(0.035)	(0.033)	(0.017)	(0.027)	(0.037)
rf	0.083***	0.064**	0.073*	0.073**	0.059*	0.050**	0.062**	0.082***
std errors	(0.030)	(0.029)	(0.039)	(0.033)	(0.034)	(0.021)	(0.025)	(0.030)
Cointegration coefficients	-0.433***	-0.526***	-0.623***	-0.394***	-0.469***			
std errors	(0.040)	(0.055)	(0.075)	(0.034)	(0.047)			
CD-test	-1.75	-0.06	-0.04	-1.31	0.02	-1.60	-1.04	-0.16
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.013	0.011	0.014	0.015	0.013	0.026	0.018	0.017
NXT	1720	1640	1579	1791	1735	1758	1741	1687
N	48	45	43	50	48	50	50	48

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for R&D transmission from 23 OECD countries of the sample) are the independent variables. Constant term is included but not reported. Long run estimates and cointegration coefficients are reported. Estimators for autoregressive distributed lagged (ARDL) panel data specifications, which are represented by a Error Correction Model (ECM), are the following: 1) Dynamic cross-sectional ARDL (CS-ARDL-i) (augmented with lagged cross-sectional averages of the dependent and independent variables with three lags of these cross-sectional averages). 2) Dynamic cross-sectional ARDL (CS-ARDL-ii) (augmented with lagged cross-sectional averages of the dependent and independent variables with two lags of these cross-sectional averages). 3) Cross-sectional DL Mean Group: CS-DLMG. White heteroskedasticity-robust standard errors are reported in parentheses. All models include a time trend. CS-ARDL (i) and CS-DLMG models are augmented with p=1, 2 and 3 lagged covariates. CS-ARDL (ii) model 2 is augmented with p=1 and 2 lags. Levels of significance are represented by * 10%, ** 5% and *** 1%. **Diagnostics**: (evaluated at the 5% level of significance, full results of the next tests are available on request): 1) CD test: Pesaran (2004) test which is redefined by Pesaran (2013), for which Ho: Cross-section weak dependence of the residuals. 2) CIPS test: Pesaran (2007) test evaluates the order of integration of the residuals where I(0): stationary, I(1): nonstationary. Root mean squared error (RMSE), NXT number of country-time observations and N number of countries are also included. † indicates that null hypothesis of weak cross-section dependence of the residuals at the 5% level is rejected.

Table A3: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and LP Knowledge Diffusion from All OECD Countries Plus BRICS								
Estimators	CS-ARDL (ECM)					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.041	0.063**	0.057	0.059*	0.092**	0.077***	0.096***	0.112***
std errors	(0.030)	(0.031)	(0.037)	(0.033)	(0.037)	(0.018)	(0.025)	(0.034)
rf	0.084***	0.065**	0.054	0.076**	0.067**	0.057***	0.063**	0.084***
std errors	(0.030)	(0.029)	(0.036)	(0.032)	(0.031)	(0.020)	(0.024)	(0.028)
Cointegration coefficients	-0.441***	-0.538***	-0.632***	-0.402***	-0.471***			
std errors	(0.040)	(0.056)	(0.079)	(0.034)	(0.048)			
CD-test	-1.95	0.03	-0.11	-1.51	0.09	-1.88	-1.29	-0.41
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.013	0.011	0.013	0.015	0.013	0.025	0.018	0.017
NXT	1720	1640	1579	1791	1735	1758	1741	1687
N	48	45	43	50	48	50	50	48

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for R&D transmission from all OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A4: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and CH Knowledge Diffusion from 23 OECD Countries Plus BRICS								
Estimators	CS-ARDL (ECM)					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.072**	0.072*	0.084**	0.067*	0.092**	0.124***	0.110***	0.082***
std errors	(0.033)	(0.041)	(0.040)	(0.037)	(0.038)	(0.024)	(0.023)	(0.023)
rf	0.094***	0.066***	0.057**	0.110***	0.082***	0.067***	0.073***	0.091***
std errors	(0.028)	(0.024)	(0.027)	(0.030)	(0.028)	(0.021)	(0.024)	(0.028)
Cointegration coefficients	-0.537***	-0.701***	-0.820***	-0.490***	-0.602***			
std errors	(0.052)	(0.066)	(0.084)	(0.036)	(0.051)			
CD-test	-2.42†	-0.32	-1.15	-0.65	2.08†	-1.16	-1.08	-1.12
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.013	0.018	0.009	0.015	0.013	0.019	0.017	0.015
NXT	1720	1640	1579	1791	1735	1758	1741	1687
N	48	45	43	50	48	50	50	48

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Coe and Helpman (1995) (rf) (allowing for R&D transmission from 23 OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A5: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and CH Knowledge Diffusion from All OECD Countries Plus BRICS								
Estimators	CS-ARDL (ECM)					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.094**	0.056	0.068*	0.075*	0.071*	0.108***	0.092***	0.086***
std errors	(0.044)	(0.042)	(0.039)	(0.039)	(0.039)	(0.030)	(0.030)	(0.032)
rf	0.099***	0.087***	0.092***	0.128***	0.104***	0.067***	0.086***	0.096***
std errors	(0.029)	(0.022)	(0.028)	(0.033)	(0.028)	(0.021)	(0.030)	(0.031)
Cointegration coefficients	-0.573***	-0.736***	-0.885***	-0.507***	-0.633***			
std errors	(0.051)	(0.060)	(0.090)	(0.035)	(0.051)			
CD-test	-1.59	0.19	-0.66	-0.44	1.98†	-0.8	-0.12	-0.75
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.013	0.011	0.009	0.015	0.013	0.019	0.017	0.015
NXT	1720	1640	1579	1791	1735	1758	1741	1687
N	48	45	43	50	48	50	50	48

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Coe and Helpman (1995) (rf) (allowing for R&D transmission from all OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A6: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and CH Knowledge Diffusion from All Countries								
Estimators	CS-ARDL (ECM)					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.082*	0.026	0.031	0.059	0.037	0.108***	0.070**	0.061*
std errors	(0.046)	(0.041)	(0.043)	(0.042)	(0.035)	(0.036)	(0.033)	(0.032)
rf	0.092***	0.083***	0.087***	0.107***	0.091***	0.068***	0.081***	0.102***
std errors	(0.029)	(0.026)	(0.029)	(0.032)	(0.028)	(0.024)	(0.031)	(0.033)
Cointegration coefficients	-0.587***	-0.751***	-0.899***	-0.523***	-0.666***			
std errors	(0.051)	(0.069)	(0.083)	(0.035)	(0.052)			
CD-test	-1.71	0.38	-0.62	-0.34	1.55	-0.67	-0.15	-0.53
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.013	0.019	0.009	0.015	0.012	0.019	0.017	0.015
NXT	1720	1640	1579	1791	1735	1758	1741	1687
N	48	45	43	50	48	50	50	48

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Coe and Helpman (1995) (rf) (allowing for R&D transmission from all countries of the sample) are the independent variables. See also the notes to Table A2.

Table A7: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and LP Knowledge Diffusion from 23 OECD Countries Plus BRICS. 11 Emerging Countries are Excluded from the Main Sample.

Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.040	0.100***	0.122***	0.102**	0.127***	0.079***	0.111***	0.142***
std errors	(0.042)	(0.036)	(0.041)	(0.040)	(0.032)	(0.023)	(0.034)	(0.039)
rf	0.095**	0.085***	0.083*	0.086**	0.059*	0.053**	0.064**	0.081**
std errors	(0.037)	(0.033)	(0.045)	(0.038)	(0.035)	(0.023)	(0.025)	(0.033)
Cointegration coefficients	-0.393***	-0.490***	-0.590***	-0.381***	-0.471***			
std errors	(0.046)	(0.065)	(0.089)	(0.041)	(0.058)			
CD-test	0.20	1.27	0.55	1.22	1.76	-0.10	0.14	1.27
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.012	0.019	0.009	0.014	0.012	0.018	0.016	0.015
NXT	1353	1300	1267	1418	1369	1391	1379	1332
N	37	35	34	39	37	39	39	37

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for R&D transmission from 23 OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A8: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and LP Knowledge Diffusion from 23 OECD Countries Plus BRICS. G7 Countries and BRICS are Excluded from the Main Sample.

Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.042	0.073**	0.060*	0.081**	0.088**	0.086***	0.116***	0.136***
std errors	(0.027)	(0.032)	(0.034)	(0.036)	(0.035)	(0.021)	(0.031)	(0.044)
rf	0.057*	0.036	0.019	0.053	0.025	0.053**	0.049*	0.061*
std errors	(0.030)	(0.030)	(0.038)	(0.034)	(0.037)	(0.023)	(0.027)	(0.033)
Cointegration coefficients	-0.484***	-0.572***	-0.685***	-0.419***	-0.512***			
std errors	(0.040)	(0.057)	(0.082)	(0.034)	(0.053)			
CD-test	-2.91†	-1.41	-0.92	-2.85†	-1.58	-2.03†	-1.24	-0.39
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.014	0.012	0.011	0.017	0.014	0.021	0.020	0.018
NXT	1352	1296	1237	1396	1362	1371	1357	1324
N	38	36	34	39	38	39	39	38

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for R&D transmission from 23 OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A9: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and LP Knowledge Diffusion from All OECD Countries Plus BRICS. 11 Emerging Countries are Excluded from the Main Sample.								
Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.045	0.098**	0.126***	0.091**	0.133***	0.075***	0.108***	0.132***
std errors	(0.042)	(0.039)	(0.047)	(0.040)	(0.037)	(0.023)	(0.032)	(0.036)
rf	0.095**	0.093***	0.062	0.087**	0.066**	0.062***	0.067**	0.084***
std errors	(0.037)	(0.033)	(0.040)	(0.036)	(0.031)	(0.021)	(0.026)	(0.031)
Cointegration coefficients	-0.400***	-0.493***	-0.580***	-0.387***	-0.474***			
std errors	(0.046)	(0.067)	(0.093)	(0.043)	(0.059)			
CD-test	0.02	1.22	0.29	1.12	1.84	-0.34	-0.09	0.99
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.012	0.019	0.009	0.014	0.012	0.018	0.016	0.015
NXT	1353	1300	1267	1418	1369	1391	1379	1332
N	37	35	34	39	37	39	39	37

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for R&D transmission from all OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A10: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and LP Knowledge Diffusion from All OECD Countries Plus BRICS. G7 Countries and BRICS are Excluded from the Main Sample.								
Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.044	0.062*	0.051	0.062*	0.087**	0.085***	0.110***	0.124***
std errors	(0.028)	(0.033)	(0.035)	(0.034)	(0.038)	(0.022)	(0.028)	(0.039)
rf	0.058*	0.037	0.011	0.053	0.029	0.053**	0.048*	0.061**
std errors	(0.030)	(0.030)	(0.035)	(0.034)	(0.034)	(0.024)	(0.027)	(0.030)
Cointegration coefficients	-0.493***	-0.589***	-0.699***	-0.430***	-0.517***			
std errors	(0.039)	(0.059)	(0.088)	(0.035)	(0.054)			
CD-test	-2.93†	-1.18	-0.77	-2.89 †	-1.53	-2.12†	-1.27	-0.68
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.014	0.012	0.011	0.017	0.014	0.021	0.020	0.018
NXT	1352	1296	1237	1396	1362	1371	1357	1324
N	38	36	34	39	38	39	39	38

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998) (rf) (allowing for R&D transmission from all OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A11: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and CH Knowledge Diffusion from 23 OECD Countries Plus BRICS. 11 Emerging Countries are Excluded from the Main Sample.								
Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.082*	0.098*	0.075*	0.079*	0.130***	0.126***	0.119***	0.084***
std errors	(0.048)	(0.053)	(0.043)	(0.041)	(0.047)	(0.029)	(0.028)	(0.026)
rf	0.114***	0.090***	0.083**	0.129***	0.086**	0.085***	0.099***	0.106***
std errors	(0.035)	(0.034)	(0.038)	(0.036)	(0.035)	(0.024)	(0.028)	(0.033)
Cointegration coefficients	-0.496***	-0.648***	-0.741***	-0.479***	-0.572***			
std errors	(0.059)	(0.076)	(0.088)	(0.048)	(0.063)			
CD-test	-1.21	0.03	0.62	1.85	3.83†	-1.06	-1.14	-0.21
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.012	0.012	0.009	0.014	0.012	0.017	0.016	0.014
NXT	1353	1300	1267	1418	1369	1391	1379	1332
N	37	35	34	39	37	39	39	37

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Coe and Helpman (1995) (rf) (allowing for R&D transmission from 23 OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A12: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and CH Knowledge Diffusion from 23 OECD Countries Plus BRICS. G7 Countries and BRICS are Excluded from the Main Sample.								
Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.069**	0.067*	0.096**	0.063*	0.099***	0.101***	0.100***	0.080***
std errors	(0.028)	(0.038)	(0.037)	(0.035)	(0.035)	(0.026)	(0.023)	(0.028)
rf	0.076***	0.047**	0.018	0.079***	0.064**	0.051**	0.051**	0.058**
std errors	(0.028)	(0.024)	(0.019)	(0.029)	(0.027)	(0.022)	(0.024)	(0.025)
Cointegration coefficients	-0.591***	-0.767***	-0.908***	-0.513***	-0.648***			
std errors	(0.060)	(0.074)	(0.095)	(0.038)	(0.058)			
CD-test	-2.55†	-1.48	-2.08†	-2.02†	0.24	-0.21	-0.74	-0.92
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.014	0.011	0.011	0.016	0.014	0.021	0.019	0.017
NXT	1352	1296	1237	1396	1362	1371	1357	1324
N	38	36	34	39	38	39	39	38

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Coe and Helpman (1995) (rf) (allowing for R&D transmission from 23 OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A13: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and CH Knowledge Diffusion from All OECD Countries Plus BRICS. 11 Emerging Countries are Excluded from the Main Sample.								
Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.095*	0.089*	0.064	0.089*	0.106**	0.101***	0.081**	0.081**
std errors	(0.051)	(0.053)	(0.048)	(0.046)	(0.049)	(0.036)	(0.034)	(0.031)
rf	0.119***	0.114***	0.124***	0.160***	0.124***	0.085***	0.115***	0.115***
std errors	(0.034)	(0.033)	(0.040)	(0.038)	(0.036)	(0.021)	(0.033)	(0.034)
Cointegration coefficients	-0.531***	-0.668***	-0.770***	-0.481***	-0.584***			
std errors	(0.056)	(0.070)	(0.091)	(0.045)	(0.062)			
CD-test	0.18	0.30	0.82	1.53	3.35†	-0.89	-0.12	0.31
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.012	0.015	0.009	0.014	0.012	0.018	0.016	0.014
NXT	1353	1300	1267	1418	1369	1391	1379	1332
N	37	35	34	39	37	39	39	37

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Coe and Helpman (1995) (rf) (allowing for R&D transmission from all OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A14: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and CH Knowledge Diffusion from All OECD Countries Plus BRICS. G7 Countries and BRICS are Excluded from the Main Sample.								
Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.071*	0.048	0.080**	0.052	0.065*	0.091***	0.071**	0.080**
std errors	(0.037)	(0.041)	(0.037)	(0.034)	(0.036)	(0.031)	(0.031)	(0.038)
rf	0.091***	0.078***	0.073***	0.101***	0.091***	0.051**	0.059*	0.068**
std errors	(0.030)	(0.024)	(0.028)	(0.033)	(0.028)	(0.023)	(0.032)	(0.032)
Cointegration coefficients	-0.625***	-0.805***	-0.977***	-0.551***	-0.682***			
std errors	(0.054)	(0.066)	(0.100)	(0.037)	(0.054)			
CD-test	-2.49†	-1.2	-1.49	-1.97†	-0.04	0.15	0.09	-0.65
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.014	0.017	0.011	0.016	0.013	0.029	0.019	0.016
NXT	1352	1296	1237	1396	1362	1371	1357	1324
N	38	36	34	39	38	39	39	38

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Coe and Helpman (1995) (rf) (allowing for R&D transmission from all OECD countries of the sample) are the independent variables. See also the notes to Table A2.

Table A15: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and CH Knowledge Diffusion from All Countries. 11 Emerging Countries are Excluded from the Main Sample.

Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.072	0.035	0.024	0.068	0.077	0.114***	0.074*	0.052
std errors	(0.056)	(0.054)	(0.052)	(0.049)	(0.050)	(0.044)	(0.040)	(0.031)
rf	0.121***	0.110***	0.120***	0.137***	0.110***	0.090***	0.103***	0.119***
std errors	(0.034)	(0.036)	(0.037)	(0.036)	(0.036)	(0.026)	(0.036)	(0.037)
Cointegration coefficients	-0.543***	-0.690***	-0.820***	-0.501***	-0.618***			
std errors	(0.055)	(0.082)	(0.082)	(0.043)	(0.063)			
CD-test	-0.50	0.61	0.76	1.57	2.86†	-0.41	-0.02	0.38
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.012	0.013	0.009	0.013	0.012	0.017	0.015	0.014
NXT	1353	1300	1267	1418	1369	1391	1379	1332
N	37	35	34	39	37	39	39	37

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Coe and Helpman (1995) (rf) (allowing for R&D transmission from all countries of the sample) are the independent variables. See also the notes to Table A2.

Table A16: Dynamic Panel Data Models in a ECM Representation Accounting for Cross-Section Dependence of Errors and CH Knowledge Diffusion from All Countries. G7 Countries and BRICS are Excluded from the Main Sample.

Estimators	CS-ARDL					CS-DLMG		
	(i)			(ii)				
	1 lag	2 lags	3 lags	1 lag	2 lags	1 lag	2 lags	3 lags
tfp dependent variable								
Independent variables								
rd	0.045	0.018	0.046	0.041	0.032	0.076**	0.047	0.050
std errors	(0.037)	(0.040)	(0.043)	(0.038)	(0.031)	(0.034)	(0.033)	(0.038)
rf	0.079**	0.070***	0.067**	0.081**	0.067**	0.059**	0.057*	0.089**
std errors	(0.031)	(0.027)	(0.027)	(0.032)	(0.027)	(0.027)	(0.033)	(0.036)
Cointegration coefficients	-0.620***	-0.807***	-0.971***	-0.553***	-0.721***			
std errors	(0.058)	(0.075)	(0.095)	(0.038)	(0.060)			
CD-test	-2.13†	-0.99	-1.48	-1.55	-0.33	-0.08	-0.29	-0.90
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
RMSE	0.014	0.011	0.012	0.016	0.013	0.027	0.019	0.016
NXT	1352	1296	1237	1396	1362	1371	1357	1324
N	38	36	34	36	38	39	39	38

Notes: log total factor productivity (tfp) is the dependent variable. log domestic R&D capital stock (rd) and log foreign R&D capital stock defined by Coe and Helpman (1995) (rf) (allowing for R&D transmission from all countries of the sample) are the independent variables. See also the notes to Table A2.

Appendix B: Definitions, Data Sources and Stata Routines

B.1. Total Factor Productivity (TFP)

Data for TFP at constant national prices (2005=1) have been taken from the Penn World Table (PWT) 8.0 and is defined in terms of the following criteria of Inklaar and Timmer (2013): a general production function, for which output Y is defined by the combination of capital K, labor input L and the productivity level A, is represented as follows:

$$Y = Af(K, L) = AK^{\alpha}(E * hc)^{1-\alpha} \tag{B1}$$

where E is the number of workers in the economy, hc is the average human capital[27], α is the output elasticity of capital and the share that is not earned by labor, and α-1 makes explicit that there are constant returns to scale. A second-order approach of f can be established by the Törnqvist quantity index of factor inputs Q^T which can be used for a given country as:

$$lnQ^T_{t,t-1} = \frac{1}{2}(\alpha_t + \alpha_{t-1}) \ln\left(\frac{K_t}{K_{t-1}}\right) + \left[1 - \frac{1}{2}(\alpha_t + \alpha_{t-1})\right] \ln\left(\frac{L_t}{L_{t-1}}\right) \tag{B2}$$

Therefore, TFP can be approached as a measure of productivity growth in the following:

$$RTFP^{NA}_{t,t-1} \equiv \frac{RGDP^{NA}_t}{RGDP^{NA}_{t-1}} \Big/ Q^T_{t,t-1} \tag{B3}$$

where RTFP and RGDP are the Total Factor Productivity and the GDP, respectively, both based on constant national prices. RTF is constructed by taking data from PWT8.0 on real GDP at constant national prices, capital stock at constant 2005 national prices (in millions of 2005 US dollars), number of persons engaged, index of human capital per person based on years of schooling and returns to education[28]. Feenstra et al. (2013) mention that there are differences between growth rates of real GDP at constant national prices and those from other measures of GDP included in PWT8.0 which arise from discrepancies in the measurement of GDP adjusted to inflation and PPPs. Therefore, in order to distinguish between those measures of GDP and their functionality, the change in real GDP at constant national prices from national accounts in effect measures economic growth. Since it is used taken to construct TFP, then TFP is the best measure of economic growth.

According to Inklaar and Timmer (2013), there are two advantages to following this approach: the first advantage is that labor shares are not forced to be tantamount to 0.7 across countries and over time, as in some studies on economic growth, but rather, labor shares account for labor income of the self-employed and therefore exhibit important variations across countries and over time; and second, capital stock accounts for differences in asset composition across countries and over time, instead of the assumption that investment is an homogeneous asset; as a result, depreciation rates vary across countries and over time rather than being constant. In addition, initial capital stock starts from a capital/input ratio instead of a steady-state setup.

[27] Average human capital can be comparable to the average 'quality' per worker (Griliches 1979) which multiplied by the total number of workers, gives the labor input.

[28] For specific details about the introduction of these data into the RTFP function and the data sources of the returns to education and the index of human capital, see: Inklaar and Timmer (2013).

Capital stock at constant national prices is constructed as a Törnqvist aggregate of the growth of individual assets.

B.2. Domestic R&D Capital Stock ($\mathrm{R^d}$)

$\mathrm{R_{it}}^{\mathrm{d}}$ is the domestic R&D capital stock at constant PPPs of 2005 in millions of US dollars. This is constructed with the perpetual inventory method proposed by Klenow and Rodriguez-Clare (1997), where the initial observation starts in the same way as the capital/input ratio. This is as follows:

$$(R^d/Y)_{i0} = (Rex/Y)_i/(g_i + \delta^{Rd}) \qquad \text{(B4)}$$

where $(R^d/Y)_{i0}$ is the ratio of the domestic R&D capital stock to GDP in the initial period 0 in country i, (Rex/Y) is the average Gross Expenditure on R&D (GERD) to GDP, divided by the domestic R&D capital stock rate of depreciation δ^{Rd} which I set as 0.15, following Griliches (1998); g_i is an estimate of the average growth rate of the GDP of country i from 1981-1990 (for a country whose GDP series begins in 1990 onwards, and average growth is measured by starting at some point between 1990 and 2000). To find the initial domestic R&D capital stock, the right hand side of the last equation is multiplied by the initial GDP[29]. Next, the following equation is used to complete the rest of the series:

$$R_{it}{}^{d} = (1-\delta^R)R_{i,t-1}{}^{d} + Rex_{it} \qquad \text{(B5)}$$

where $R_{it}{}^{d}$ is the domestic R&D capital stock and Rex_{it} the GERD.

To construct these series, I take data on GERD as a percentage of GDP from four different sources in the following order: the first source is the UNESCO Institute for Statistics on Science, Technology and Innovation (IS) Database from 1996-2010. Second, data from 1980-1995 (and for some countries to 1996) were taken from the 1999 UNESCO Statistical Yearbook. This source defines GERD as a percentage of GNP. Therefore, to convert it to a percentage of GDP, it has been multiplied by the Ratio of GNP to GDP (divided by 100) from the PWT 7.1[30]. Third, I have taken data from the OECD Main Science and Technology Indicators Statistics database from 1980 to 2011. The fourth source is the data set from Lederman and Saenz (2005), which includes information on GERD as a percentage of GDP from different series of the UNESCO Statistical Yearbook. I take data from this source between 1970 and 2005. Some data for the period before 1970, taken from the latter source have been interpolated with data post-1970 data to complete the data series from 1970 onwards[31]. Once this was done, pre-1970 observations were dropped. The data collection is summarized in Table B1. Missing data in Table B1 have been interpolated according to the data availability of each country. Since data on GERD as a percentage of GDP were scarce for some economies, I had to interpolate even for time frames without data of seven

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[29] This calculation differs from Klenow and Rodriguez-Clare (1997) because they use per capita GDP in their calculations and the population growth has to be considered to construct the base year of capital stock.

[30] Although this ratio is not reported in PWT8.0, it is still useful and can be adapted to the present work because it has been calculated based on national accounts data.

[31] This is the case of countries such as Finland (1969-1971), Greece (1969-1976), Iceland (1966-1971), Ireland (1969-1971), Portugal (1967-1971), Singapore (1965-1978), Sweden (1969-1971), Thailand (1968-1979), United Kingdom (1961-1972) and Uruguay (1967-1971).

years or more[32]. Despite those interpolations, data for these economies are essential to capture cross-section dependencies of emerging economies and small advanced economies.

Initial data on GERD as a percentage of GDP were used to obtain the first observations for Domestic R&D capital stock. I multiplied this by the output-side real GDP at chained 2005 PPPs in millions of US dollars, a measure of the production possibilities of an economy, from the PWT 8.0. With this I obtained the PPP Converted Expenditure on R&D (GERD) at 2005 constant prices in millions of US dollars, and I used it to construct the rest of the Domestic R&D capital stock series at constant PPP prices in millions of US dollars. The reason why I have used the output-side real GDP at chained 2005 PPPs to compute domestic R&D is because I want to address three important considerations that are mentioned by Feenstra et al. (2013) when deriving this GDP measure: the first is that it is important to ensure that the GDP is comparable across countries by PPPs; the second is that, instead of deflating all final goods, imports and exports by the PPP over final goods, they are deflated by their respective reference prices; and the third is that, to compare GDP over time, it is necessary to account for changes in explicit reference prices for each country.

B.3. Foreign R&D Capital Stock (R^f)

It is the weighted foreign R&D capital stock defined by Lichtenberg and van Pottelsberghe de la Potterie (1998), which is:

$$R_{it}^{f} = \sum\nolimits_{i \neq j} \left(M_{ij}/Y_j \right)_t R_{jt}^{d} \tag{B6}$$

where M_{ij} is country i's imports of goods and services from country j, Y_j is the GDP in country j and R_{jt}^{d} is the domestic R&D capital stock. Data for M_{ij} were taken from the bilateral imports on a c.i.f. basis in US current dollars from the IMF Direction of Trade Statistics (DOTS). To get data for Y_j, I multiplied the GDP at current national prices in local currency times the exchange rate of national currency per USD at the market value, both from the PWT8.0. As a result, the foreign R&D capital stock is defined at constant PPPs of 2005 in millions of US dollars[33].

An alternative measure of foreign R&D capital stock proposed by Coe and Helpman (1995) is also employed here. It is defined as:

$$R_{it}^{f-CH} = \sum\nolimits_{i \neq j} w_{ij}\, R_{jt}^{d} \tag{B7}$$

where $w_{ij} = M_{ij}/\sum_{i \neq j} M_{ij}$ and $\sum_{i \neq j} w_{ij} = 1$.

[32] This is the case of Bulgaria (1982-1988), Colombia (1983-1994), Ecuador (1980-1989), Egypt (1983-1989), Indonesia (2002-2008), Mexico (1975-1983), Philippines (1993-2001), Singapore (1965-1978), and Uruguay (1973-1989).

[33] Countries such as Belgium and South Africa have been excluded because there is no data for bilateral imports for these countries before 1997 and 1998, respectively. According to DOTS, prior to 1997 trade data for Belgium are recorded as trade for the Belgium-Luxembourg Economic Union (BLEU). Belgium and BLEU trade data are not comparable due to the employment of different compilation methodologies.

B.4. Stata Routines

I carried out the empirical study in Stata 12 by using the following econometric routines:

Multipurt by Eberhardt (2011a), Xtcd, by Eberhardt (2011b), Xtmg, by Eberhardt (2012) updated by Eberhardt (2013) (I use this command to carry out all regressions where I allow for heterogeneity in technology parameters), and Xtfisher by Merryman (2005).

Table B1: Data Collection of Gross Expenditure on R&D (GERD) as a Percentage of GDP				
Country	R/Y UNESCO ISS	R/Y UNESCO 1999 S-Yearbook	R/Y OECD Main Science	R/Y Lederman & Saenz (2005)
Argentina	1996-2010	1995	2011	1970-1980 (even years), 1981-1982, 1988, 1990-1994
Australia	1996-2010 (even years)	1981, 1984-1988, 1990, 1992, 1994	-	1973, 1976, 1978
Austria	1996-2011	1981-1995	-	1970, 1972, 1975, 1978
Brazil	2000-2010	1994-1996	-	1973-1978, 1980, 1982, 1985, 1990-1993, 1999
Bulgaria	1996-2011	1992-1994	-	1980-1981, 1989-1991, 1995
Canada	1996-2011	1981-1995	-	1970-1980
Chile	2007-2010	1993-1996	-	1979-2004 (except 1981-1982, 1993-1996)
China	1996-2011	1988-1995	-	-
Colombia	1996-1997, 2000-2011	1982	-	1971, 1978, 1995, 1998-1999
Costa Rica	1996-2000, 2003-2004, 2006-2011	1989-1991	-	1974-1979, 1983, 1985-1986, 1988
Cyprus	1998-2011	1991-1992	-	1980-1984
Denmark	1996-1999, 2001-2011	1981-1993, 1995	-	1973, 1976-1977, 1979
Ecuador	1996-1998, 2001-2003, 2006-2008	1993-1995	-	1970, 1973, 1976, 1979, 1990
Egypt	1996-2000, 2004-2011	1992-1995	-	1973, 1976, 1982, 1990
Estonia	1998-2011	1993-1997	-	1992
Finland	1996-2011	1984-1995	1981, 1983	1971-1979 (even years) (interpolation 1969-1971 to cover 1970)
France	1996-2011	1981-1995	-	1970-1980
Germany	1996-2011	1991-1995	1981-1990	1971, 1974-1975, 1977, 1979-1980
Greece	1997, 1999, 2001, 2003-2007	1981, 1986, 1988-1989, 1991, 1993	1995	1976, 1979-1980, 1982-1983 (interpolation 1969-1976 to cover 1970-1975)
Hungary	1996-2011	1981-1995	-	1970-1971, 1974-1980
Iceland	1996-2003, 2005-2008	1981, 1983-1987, 1989-1996	2009	1971-1979 (even years) (interpolation 1966-1971 to cover 1970)
India	1996-2007	1980-1994	-	1970-1978 (except 1973), 1995
Indonesia	2000, 2001, 2009	1980-1988, 1994	-	1972-1979, 1995
Ireland	1996-2011	1981-1995	-	1971, 1974-1975, 1977, 1979 (interpolation 1969-1971 to cover 1970)
Israel	1996-2011	1989-1995 (except 1991)	1991	1970-1978, 1981-1983, 1985-1986
Italy	1996-2011	1980-1995	-	1970-1979
Japan	1996-2010	1980-1995 (except 1992)	1992, 2011	1970-1979
Korea	1996-2010	1980-1995 (except 1987-1988)	2011	1970-1971, 1974-1979, 1988
Malaysia	1996-2008 (even years), 2009-2011	1992, 1994	-	1988-1989
Mexico	1996-2011	1984-1995 (except 1989-1992)	-	1970-1974 (except 1972), 1989
Netherlands	1996-2011	1980-1995	-	1970-1979
New Zealand	1997-2009 (odd years)	1989-1995 (except 1994)	1981, 1983, 2011	1972-1979 (except 1973, 1978)
Norway	1997, 1999, 2001-2011	1980-1987, 1989-1995 (odd years)	-	1970-1979 (except 1973, 1975-1976)
Panama	1996-2010	1986	-	1990-1995
Peru	1997-2004	1981-1984	-	1971, 1973, 1976, 1985, 1987-1989, 1993-1996
Philippines	2002, 2003, 2005, 2007	1981-1984 (except 1982), 1992	-	1970-1975, 1979-1980, 1982, 1989-1991
Poland	1996-2011	1985-1995 (except 1987, 1993)	1993	-
Portugal	1996-2011	1980-1992 (even years), 1995	1983-1993 (odd years), 1994	1971-1972, 1976, 1978 (interpolation 1967-1971 to cover 1970)
Romania	1996-2011	1991, 1995	1992-1994	1989
Russia	1996-2011	1994, 1995	1989-1993	-
Singapore	1996-2010	1981, 1984, 1987, 1990, 1995	1994, 2011	1978 (interpolation 1965-1978 to cover 1970-1977)
Spain	1996-2011	1981-1995	-	1970-1976 (except 1975)
Sweden	1997, 1999, 2001, 2003-2011	1981-1995 (even years)	-	1971-1979 (odd years) (interpolation 1969-1971 to cover 1970)
Switzerland	1996, 2000, 2004, 2008	1981, 1983, 1992	1986, 1989	1970-1979
Thailand	1996, 1997, 1999-2007, 2009	1980, 1982-1985, 1987, 1989-1991, 1993, 1995	-	1979 (interpolation 1968-1979 to cover 1970-1978)
Turkey	1996-2010	1984-1985, 1990-1995	2011	1970-1972, 1975, 1977-1980, 1983
United Kindom	1996-2011	1981, 1983, 1985-1995	-	1972, 1975, 1978 (interpolation 1961-1972 to cover 1970-1971)
United States	1996-2011	1980-1995	-	1970-1979
Uruguay	1996-2000, 2002, 2006-2010	-	-	1971-1972, 1990-1995 (interpolation 1967-1971 to cover 1970)
Venezuela	-	1980-1992	-	1970, 1973, 1977, 1993-2000