Heterogeneity and Non-Linearities in International R&D Spillovers: Evidence Using Novel Panel Estimators

Shreesh Chary[1]

School of Economics, University of Nottingham, NG1 2RD

Submitted in partial fulfilment of the degree of Master of Science in Development Economics

Submission Date: 19 September 2024

Supervisor: Professor Facundo Albornoz Crespo

Word Count: 8011

[1]lexsc28@nottingham.ac.uk

Abstract

This study examines how domestic and foreign R&D effort influences total factor productivity for a panel of 23 OECD countries from 1971 to 2019. This study updates and expands upon existing literature by addressing frequently disregarded unobserved common spillovers and shocks by utilising advanced panel-time series techniques. It uses a dynamic common correlated effects estimators using linear specifications and a static common correlated effects estimator for non-linear specifications to understand underlying dynamics. The findings reveal statistically insignificant long-run effects of both domestic and foreign R&D stocks on TFP. Additionally, the study explores heterogeneity in coefficients caused by a country's proximity to the R&D frontier, finding that productivity returns diminish as countries approach the frontier. Furthermore, despite the theoretical motivations for non-linearities, empirical evidence for such effects is inconclusive.

Keywords: *Dynamic CCE, Growth Empirics, Heterogenous Coefficients, R&D Spillovers, Technological Frontier*

JEL Classification*: O31, O33, O40*

Contents

1 Introduction

Economic growth has always been a central concern for economists and policymakers. Since the industrial revolution, economic growth has allowed people to afford a lifestyle that only a few ultra-rich people could afford before (Aghion and Howitt, 1998). The foundational work of Solow (1956) identified technical progress as the primary driver of such economic growth, setting the stage for subsequent theoretical advancements that emphasise the role of innovation. Building on Solow's seminal work, growth literature argues that incentivised innovation drives technical progress, enhancing productivity growth across countries (e.g., Aghion and Howitt (1992), Grossman and Helpman (1991a), Romer (1990)). Therefore, a country's productivity, which reflects its level of technical advancement, is intrinsically tied to its R&D investments and innovation efforts. For this reason, firms are motivated to innovate inputs to produce goods that are supplied for final consumption. This innovation can be thought of in two ways: the first being an innovation in the number of inputs, or "horizontal" innovation, as illustrated by Romer (1990); the second is an innovation in the quality of inputs, where each innovation leads to R&D creation on a technological frontier (see Aghion and Howitt, 1992; Grossman and Helpman, 1991a). These innovation efforts, when aggregated, explain why countries experience varying stages of economic growth based on the extent of their R&D activities.

The narrative of economic growth is not confined to the internal dynamics of innovation alone. It can also be achieved through greater openness to international trade (Grossman and Helpman, 1991b), which is driven by technological differences across countries (Dornbusch et al., 1977). Furthermore, "new" trade theories, pioneered by Krugman (1979), and built upon by Melitz (2003), argue that trade facilitates access to a variety of markets and products, which, in turn, enables consumers to satisfy their love for variety in the Dixit and Stiglitz (1977) sense. It also enables firms to access inputs of higher quality that have been developed in foreign countries. When firms utilise inputs of greater quality, they are able to produce a higher output, and experience greater levels of productivity.

Endogenous growth models show that R&D efforts significantly explain variations in total factor productivity. However, countries do not rely solely on their domestic firms for production inputs; they also import inputs from abroad. Due to access to foreign markets through international trade, domestic productivity depends on both domestic and foreign R&D effort (Grossman and Helpman, 1991b). This viewpoint motivates the possibility of R&D spillovers in the sense that R&D effort undertaken by one country influences the productivity of another. The rationale behind the use of the phrase "spillover" is that R&D is a non-rival good i.e. the marginal cost of an additional firm or individual using a technology is negligible (Keller, 2004; Romer, 1990).

The seminal empirical paper of Coe and Helpman (1995) establishes that both domestic and foreign R&D stocks significantly impact a country's productivity. The literature on the subject has seen various improvements relating to the measurement of R&D stocks (see for e.g.

Lichtenberg and Van Pottelsberghe De La Potterie, 1998; Madsen, 2007) and methodological innovations (see for e.g. panel cointegration techniques used by Kao et al., 1999). Coe et al. (2009) justify heterogeneity in coefficients using dummy variables representing institutional factors, using a panel covering 34 years. Their empirical model uses panel time-series techniques with heterogeneous coefficients, and tests for unit-roots and cointegration. However, with the development of novel panel-time series techniques, econometric inferences can be made more robustly than ever before. So far, econometric methods like panel dynamic OLS have been used to estimate spillover coefficients (see for e.g. Coe et al., 2009; Madsen, 2007). Furthermore, the frameworks used in previous studies operate under the assumption of cross-sectional independence of errors, meaning that the interplay between international R&D spillovers and other unobserved common spillovers and shocks does not result in contemporaneous correlations (cross-sectional dependency) across countries. There is also an argument to be made for possible non-linearities in spillovers caused by productivity losses due to import competition (Aghion et al., 2005), or lags in adoption of new technologies (Chari and Hopenhayn, 1991). Such non-linearities have never been explored empirically in the spillover literature before.

This paper contributes to the existing literature by filling two crucial gaps. First, it fills an empirical gap by accounting for cross-sectional dependency arising out of heavy interdependence between countries, and heterogeneity across countries. Second, it raises the theoretical motivation for the presence of non-linearities in spillovers and attempts to test it empirically. Using data from 23 OECD countries spanning from 1971 to 2019, this study employs the common correlated effects estimator given by Pesaran (2006), and further developed by Chudik and Pesaran (2015). The findings indicate that when employing techniques robust to cross-sectional dependency, the impact of R&D stocks on productivity becomes insignificant. Additionally, the results provide evidence of heterogeneity caused by differences in human capital, as well as G7 and non-G7 countries, as well as non-linearities for countries having average imports of less than 15% of GDP.

The remainder of this paper is organised as follows: Section 2 provides a review of pertinent literature. Section 3 motivates the possibility of non-linearities from existing theoretical and empirical literature. Section 4 describes the construction of variables, and uncover patterns in the data which further motivate heterogeneity and non-linearities in a stylistic fashion. Section 5 elaborates on the methodology used in the paper. Section 6 presents the results of the econometric model and discusses its implications on the broader growth literature. Section 7 concludes.

2 Empirical Literature

The evolution of literature on international R&D spillovers can be classified into three broad themes. First, theoretical frameworks and empirical evidence highlight the crucial role of deliberate, incentivised R&D efforts in driving productivity growth. Grossman and Helpman (1991b) highlight the importance of trade openness in enhancing productivity growth by facilitating R&D spillovers through the importation of high-quality inputs. Coe and Helpman (1995) investigate this hypothesis by constructing domestic R&D stocks using R&D data for 22 OECD countries using the perpetual inventory method, and foreign R&D stocks using bilateral import weights of domestic R&D stocks of the exporter. They find that both domestic and foreign R&D stocks successfully explain more than half of the variation in TFP between 1971 and 1990. However, Lichtenberg and Van Pottelsberghe De La Potterie (1998) state that the Coe and Helpman (1995) weighing scheme for foreign R&D stocks suffers from aggregation and indexation issues. They construct a unique weighing scheme where they choose weights based on the ratio of bilateral imports to the exporting partner's nominal GDP. However, they arrive at results that are very similar to Coe and Helpman (1995).

Second, there is an methodological debate on how to measure domestic R&D stocks. Technology is difficult to measure directly. The commonly used approaches include assessing inputs in the form of R&D expenditures, and outputs in the form of patents. The OECD has provided internationally comparable R&D data, but this data mostly represents wealthier countries and excludes many middle-income and poorer nations, which spend more on technology adoption than innovation (Keller, 2010). Most empirical works on the subject have used R&D stocks based on the perpetual inventory method using OECD's R&D expenditure data (Coe and Helpman, 1995; Lichtenberg and Van Pottelsberghe De La Potterie, 1998; Coe et al., 1997, 2009). On the other hand, patents offer another approach and are more inclusive of poorer countries. However, patent data can be misleading since a few patents account for most value, not all innovations are patented, and non-codifiable technologies are excluded (Jaffe and Tajtenberg, 2002). Madsen (2007) use a panel of 16 OECD nations for a time-period of 135 years and construct R&D stocks using patent data. They find evidence of domestic and foreign R&D stocks heavily influencing productivity growth in their sample, and conclude that there is a genuine relationship between the variables rather than just common trends dictating variations in productivity. Furthermore, Ang and Madsen (2013) also use patent data and show that there have been R&D spillovers through various channels such as FDI, patent flows, imports, exports, and geographic proximity. They find that of all channels, imports have the greatest intensity of R&D spillovers.

Third, growth literature has stressed on the role of human capital in determining growth characteristics of nations (Benhabib and Spiegel, 1994). Furthermore, Nelson and Phelps (1966) state that human capital may also affect the level and intensity of technology diffusion as it influences the absorptive capacity of countries to adopt foreign R&D. Although Benhabib and Spiegel (1994) state that human capital may not enter the production function directly, Kneller and Stevens (2006) find that human capital does affect productivity through both direct and indirect effects. Coe et al. (1997) re-estimate the Coe and Helpman (1995) model by including a variable for educational attainment to represent human capital. On the other hand, Engelbrecht (1997) use the Barro and Lee (2001) data based on average years of schooling in their regressions. Both find that human capital yields a positive and statistically significant estimate, and gives more stable estimates for elasticities of domestic and foreign R&D stocks. Some form of human capital has been used in most empirical papers on the topics ever since (Coe et al., 2009; Frantzen, 2000; del Barrio-Castro et al., 2002; Ang and Madsen, 2013)

Despite the extensive literature estimating R&D spillovers across countries, in the last fifteen years, studies have departed from cross-country regressions and shifted to micro-level data which covers firms and industries (see for e.g. Eberhardt et al. (2013)). However, it is important to acknowledge that studies like Coe et al. (2009) and Ang and Madsen (2013) use methods that are quite outdated in the context of panel time-series literature. These methods typically assume cross-sectional independence of errors, implying that international R&D spillovers and other unobserved common shocks and spillovers do not induce contemporaneous correlations across countries. Furthermore, studies have assumed that R&D stocks enhance productivity in a linear fashion. Hence, this study uses the Coe et al. (2009) paper as a reference point and attempts to update it by: i) updating the panel to include 49 years (a long panel of countries enables us to use mean group models to account for heterogeneity); ii) updating the econometric methodology to accommodate common shocks and spillovers; iii) Motivating the presence of non-linearities and empirically testing it.

3 Non-Linearities in R&D Spillovers

Since the the main channel of R&D spillovers is through imports (Ang and Madsen, 2013), it is also important to acR&D that import competition, which is directly linked with trade openness (Chen et al., 2009), may have a mediating negative effect on R&D spillovers. To that end, there are two contrasting, yet totally plausible outcomes of increased import competition: one, it may retard productivity growth by reducing profitability of domestic innovation (Feenstra, 1996); and two, import competition may be productivity enhancing, by incentivising domestic firms to ramp up their innovation to meet import competition (Baldwin, 1992). Various studies have used firm level data to empirically understand this relationship. While Bloom et al. (2016) and Ding et al. (2016) find evidence of import competition to have a positive productivity effect, Friesenbichler et al. (2024) and Autor et al. (2020) find that the effect is, indeed, negative. Furthermore, Aghion et al. (2005) theorise that competition from imports drives productivity growth and increases R&D spending among domestic firms and industries that are closer to the global technological frontier. However, for firms and industries that are trailing behind, such competitive pressure tends to reduce their motivation to invest in productivity enhancements and R&D. Evidence suggests that there may, therefore, be an inverted U-shaped non-linear relationship between import competition and productivity growth (Aghion et al., 2009). One may therefore suspect that there may be severe heterogeneity and non-linearity with regards to R&D spillovers due to the mediating effect of imports.

The above non-linearities can be theoretically justified using existing literature. As imports rise, the influx of foreign goods increases competitive pressure on domestic firms, potentially leading to market distortions and productivity losses. The justification for the effect of R&D stocks on TFP being a decreasing function in imports can be attributed to two relationships specified by Aghion et al. (2005). They theorise that in a low-competition environment, a greater proportion of sectors tend to feature incumbents that are closely matched, making it more probable that as "escape-competition" effect will prevail, suggesting that firms innovate to avoid losing market share to close competitors. Conversely, in a high-competition context, the "Schumpeterian" effect is more likely to take precedence because a larger number of sectors are characterised by lagging firms with initially low profits taking the lead in innovation. Here, The Schumpeterian effect emphasises that intense competition encourages less profitable firms to innovate as a means to catch up or survive in the market.

4 Data

4.1 Construction of Variables

A heterogeneous coefficients model would require a large T to estimate country-specific coefficients and cointegrating relationships. Hence, this study uses a panel of twenty-three OECD countries (see Appendix A for full list) and a time period of forty-nine years.

The main variables of the analysis are total factor productivity, domestic stocks of R&D, and stock of foreign R&D. The total factor productivity *(LTFP)* is the log of output minus a weighted average of capital and labour inputs, with factor shares serving as the weights. The data for TFP have been borrowed from the OECD productivity database and consists of business-sector TFP only, normalised to country specific values for 2015. Missing values have been interpolated. Where interpolation was not possible, the estimated values using OLS regressions of $LTFP$ on the TFP of the total economy as in Feenstra et al. (2015) were used to estimate missing observations for $LTFP$. A time trend (T) was also added if it was significant. The regressions had R^2 values between 0.95 and 0.99, signifying a high degree of fit.

Domestic R&D stocks have been constructed using R&D expenditure data from the ANBERD database published by the OECD (2024). Current business sector R&D expenditure is taken in US Dollars. Missing values in R&D were statistically interpolated where possible. Where interpolation was not possible, the estimated values using OLS regressions of log R&D on logGVA, where GVA is the real value-added in the business sector, were used to estimate missing observations for R&D. A time trend (T) was also added if it was significant. The regressions had R^2 values between 0.95 and 0.99, signifying a high degree of fit. A similar method was employed by Coe et al. (2009) to fill their missing values. The perpetual inventory method was used to compute R&D capital stocks in the business sector (S^d), where the depreciation rate (δ) is assumed to be 5%.

$$S_t^d = S_{t-1}^d + (1-\delta)RD_{t-1} \tag{1}$$

The benchmark R&D stocks are calculated as,

$$S_{1971}^d = \frac{RD_{1971}}{\delta + g} \tag{2}$$

where g is the annual average logarithmic growth rate from 1971 to 1995, i.e., $g = (log\frac{RD_{1971}}{RD_{2019}})/49$. The benchmark for the data i.e. S_{1971}^d is considered as the stock of R&D for 1971. To convert nominal R&D stocks to real R&D stocks, the values of S^d have been normalised to 1 for each country's 2015 value.

A number of alternate measures have been devised to construct the stock of foreign R&D of a country, namely the bilateral imports weights given by Coe and Helpman (1995) and the weights given by Lichtenberg and Van Pottelsberghe De La Potterie (1998) based on nominal imports and nominal GDP. Lichtenberg and Van Pottelsberghe De La Potterie (1998) state that the bilateral import weights suffer from aggregation and indexation issues. However, Coe et al. (2009) find that the bilateral import weights method introduced performs better in their econometric models. Recognizing these limitations, this study sticks to the Lichtenberg and Van Pottelsberghe De La Potterie (1998) weights to ensure simplicity and accuracy, while avoiding the methodological flaws associated with the bilateral import weights approach. The measure of foreign R&D stocks can be calculated as follows:

$$S_i^{f:lp} = \sum_j \frac{M_{ij}}{Y_j} {S_j}^d \tag{3}$$

For robustness in the specification, we also adopt control variables that may influence total factor productivity. One significant determinant of productivity is human capital (Kneller and Stevens, 2006; Romer, 1990). Following Coe et al. (2009), an index of human capital per worker based on average years of schooling given by Barro and Lee (2013) is used, which is adapted in the Penn World Tables constructed by Feenstra et al. (2015).

4.2 Data Description

This section further attempts to understand underlying patterns in the variables constructed. It begins with understanding the evolution of TFP over time to understand its growth and variability across countries. Figure 1 shows the trends in total factor productivity. By construction, the real TFP for each country for 2015 is indexed to 100, and the values for the remaining years are calculated on a relative scale. With the exception of Greece, Turkey, and Mexico, all countries appear see a positive trend in TFP.

Figure 1: Trends in Total Factor Productivity

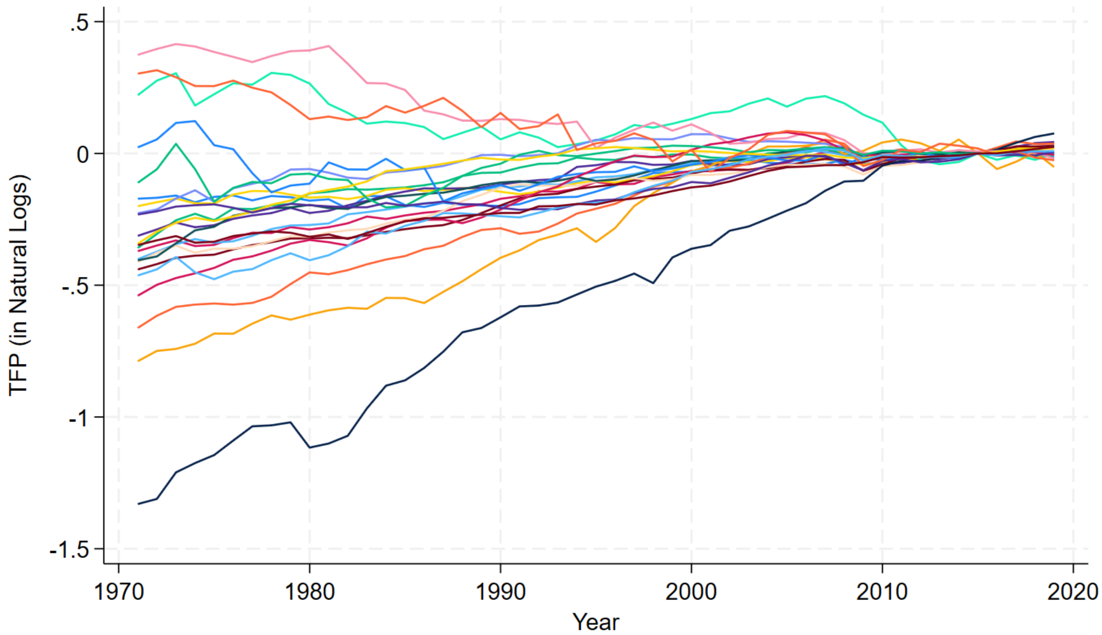


Figure Notes: TFP for 2015 being indexed to 100. The natural log of the variable is presented in the graph. Source: Author

Figure 2 shows the trends in both domestic and foreign R&D stock accumulation. Stocks of R&D, both domestic and foreign appears to have a greater growth, and larger variability across countries, compared to TFP growth. Domestic R&D stocks start from a low level in 1971, and have a clear and monotonic upward trend, which can also be seen in 34 year of data collected by Coe et al. (2009). The exception to this trend can be seen in Belgium and the United Kingdom, who start at a high point but do no grow much over the 49 years. The US, the UK, Germany, France, Korea, and Japan and the countries with the highest stocks of domestic R&D.

Figure 2: R&D Stocks

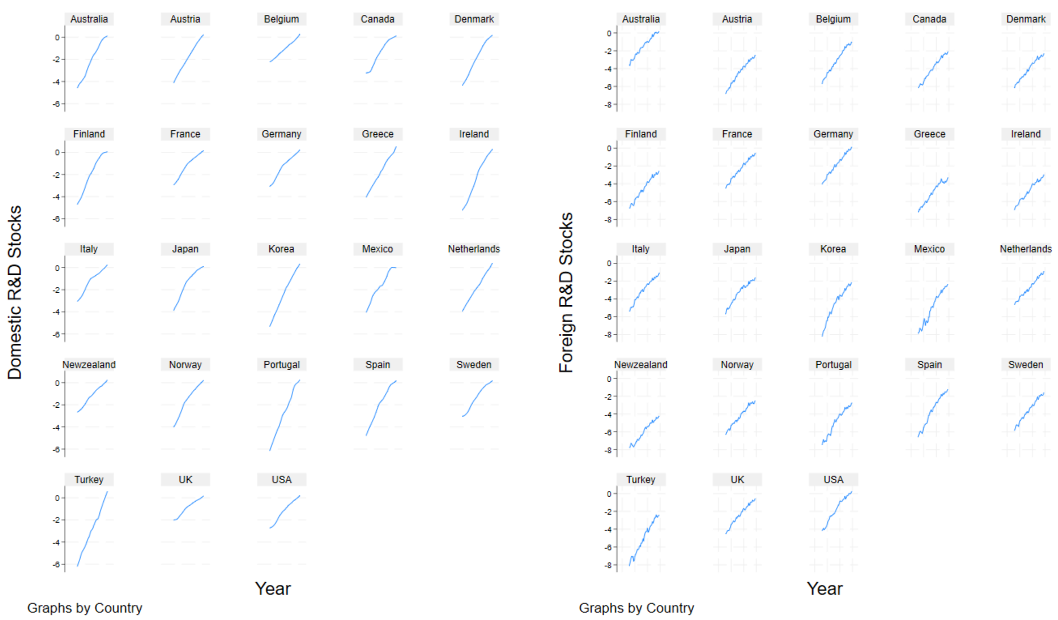


Figure Notes: Domestic R&D stocks (S^d) *and Foreign R&D stocks* $S^{f:lp}$ *in natural logarithms. Source: Author*

A similar trend can be seen where stocks of foreign R&D start at a low level, and increase rapidly over time. Foreign R&D stocks appear to be more uniform across countries, compared to domestic R&D stocks. This is in contrast to Coe et al. (2009), who find that foreign R&D stocks are more uniform across countries. There are two

Table 1: Summary Statistics

Country	TFP_{2019}/TFP_{1971}	S^d_{2019}/S^d_{1971}	$S^{f:lp}_{2019}/S^{f:lp}_{1971}$
Australia	1.035	112.009	41.694
Austria	1.087	80.676	79.816
Belgium	1.083	13.200	105.815
Canada	1.051	30.006	61.119
Denmark	1.083	96.916	44.563
Finland	1.177	121.026	62.595
France	1.099	23.224	53.395
Germany	1.113	28.126	65.4466
Greece	0.954	101.169	45.724
Ireland	1.193	259.975	54.438
Italy	1.055	28.648	75.976
Japan	1.102	54.686	63.212
Korea	1.429	291.476	413.365
Mexico	0.912	56.780	264.642
Netherlands	1.098	80.239	42.881
New Zealand	0.995	18.943	34.099
Norway	1.131	71.301	41.113
Portugal	1.031	614.325	112.793
Spain	1.085	147.478	225.452
Sweden	1.054	26.164	65.799
Turkey	0.922	935.474	288.054
UK	1.114	9.304	51.716
USA	1.088	19.892	88.620
Average	1.082	140.045	103.579
Standard Deviation	0.099	209.317	93.791

Table Notes: Variables taken in levels values and not in natural logs. The table shows heterogeneity in the evolution of TFP and R&D stocks across the sample.

possible explanations for higher variability. Firstly, the preferred method of constructing foreign R&D stocks is using the Lichtenberg and Van Pottelsberghe De La Potterie (1998) method rather than the

Coe and Helpman (1995) method used by Coe et al. (2009). Secondly, due to vast differences in output across countries, and therefore vast differences in the ratio of imports to output, there is less uniformity in the evolution of foreign R&D. Table 1 presents summary statistics relating to the main variables of analysis of this study. It shows the variability in growth rates across countries but does not show the temporal variable across countries. Figure 2 is a better depiction of differences across countries as well as time.

Lastly, a stylistic description is used to motivate both heterogeneity and non-linearities in the relationships being studied. Figure 3 clearly shows differential relationships among the sample of countries. Panels C and D show evidence of a non-linear relationship between R&D stocks and TFP. Furthermore, such a stylised presentation of the relationship somewhat validates the inverted U-shaped hypothesis for domestic R&D stocks (See Figure 3, Panel C), characterised by the escape-competition and Schumpeterian effects as in Aghion et al. (2005). However, the inverted U-shaped hypothesis for foreign R&D stocks is not very evident from Panel D of Figure 3.

This stylised descriptive analysis offers valuable insights, but it is essential to acknowledge that economic development is influenced by numerous factors beyond those depicted in these plots. Moreover, such visualisations cannot establish causal relationships, whether from foreign R&D stocks to growth or the reverse. While this discussion is not definitive, these visual representations raise questions about the strict implicit assumptions of linear relationship that are commonly found in existing literature. Hence, it is important to formally test

Figure 3: Heterogeneity and Non-Linearities in R&D Spillovers

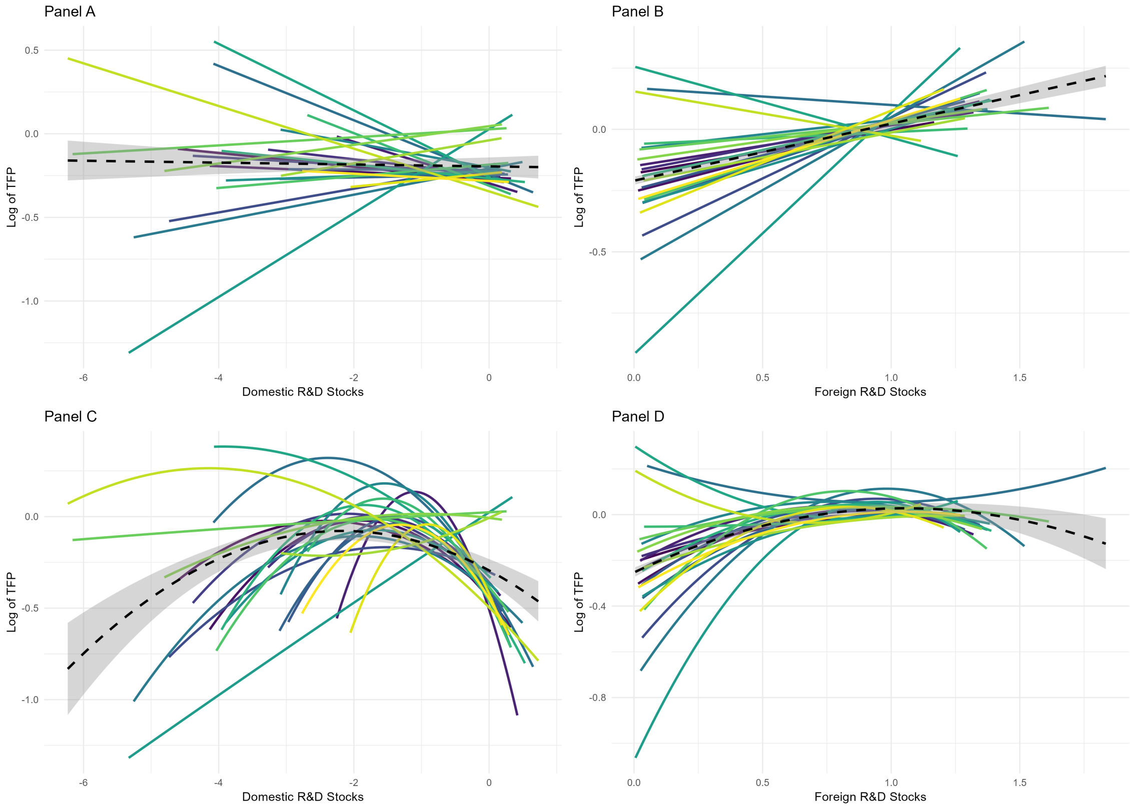


Figure Notes: The coloured lines depict linear plots for each country, while the black dashed line indicates the linear fit for the pooled model. Panel A illustrates the relationship between TFP and domestic R&D, and Panel B shows TFP against foreign R&D. Panels C and D present a polynomial fit for the variables. Source: Authors

these theories using advanced econometric techniques.

5 Empirical Framework

5.1 Dynamic Linear Specifications

Many studies on R&D spillovers assume cross-section independence of errors, potentially leading to biased and inconsistent estimates if unobserved common factors are not accounted for. Cross-section dependence, the contemporaneous correlation among countries after conditioning on individual features, may arise from unobserved shocks. Ignoring these common effects can result in misleading conclusions. For instance, Eberhardt et al. (2013) found that ignoring spillovers leads to biased estimates of R&D returns, suggesting that unobserved spillovers significantly impact these returns. Therefore, this study examines the effects domestic and foreign R&D stocks on TFP by considering unobserved common shocks and local spillovers through dynamic panel data models.

The Common Correlated Effects (CCE) estimator is particularly suited for this analysis, as it accounts for unobserved common effects, handles heterogeneous impacts across units, and supports dynamic modelling. By using the CCE estimator, this study aims to provide more accurate and reliable estimates of the effects of R&D on TFP, offering a comprehensive understanding of international R&D spillovers and their impact on economic productivity. Technological R&D is genuinely global since it is made available to individuals worldwide through new telecommunications and internet technologies, growing economic interconnectedness, and new forms of communication (Keller, 2000). This interconnectedness has profound implications on cross-sectional dependency between the panel units, in the form of unobserved common shocks and spillovers. Therefore, this study departs from the standard estimation of long-run coefficients and cointegrating regressions and resorts to long-run coefficients estimated using the Pesaran (2006) common correlated effects (CCE) estimator. Due to the dynamic specification and the inclusion of an autoregressive element of the dependent variable in the list of regressors, the dynamic CCE estimator following Chudik and Pesaran (2015) is used. The CCE model's superiority compared to the DOLS model, that has been commonly used in the existing literature, lies in its ability to accommodate cross-sectional dependency between panel units and its resilience against the unit-root properties of the variables.

The baseline equation of interest is a growth equation characterised by total factor productivity being a function of domestic and foreign R&D stocks:

$$TFP_{i,t} = \beta^d S^d_{i,t} + \beta^f S^f_{i,t} + u_{i,t} \tag{4}$$

$$u_{i,t} = \alpha_i + \lambda_i \boldsymbol{l}_t + \epsilon_{i,t} \tag{5}$$

Where LnTFP is the total factor productivity, S^d and S^f are domestic and foreign R&D stocks respectively, and all variables are taken in their natural logarithms. The coefficient β^d_i and β^f_i are allowed to differ across countries i. The coefficients are therefore heterogeneous, which is the salient feature of this empirical strategy. Equation 5 shows the multi-factor error structure that we assume $u_{i,t}$ in Equation 4 to have. α_i represents the country-specific fixed effects that capture unobserved heterogeneity across countries. These fixed effects account for time-invariant characteristics unique to each country. The term λ_i $\boldsymbol{l}_t$ denotes the unobserved common factors, where $\boldsymbol{l}_t$ is a vector of common shocks affecting all countries at time t, and λ_i is a vector of factor loadings that measure the sensitivity of each country to these common shocks. Finally, $\epsilon_{i,t}$ is the idiosyncratic error term that captures the idiosyncratic variability unexplained by the other components. This multifactor error structure is crucial as it captures unobserved spillovers that affect multiple countries simultaneously, including technological advancements, global economic trends, or international policy changes that impact TFP across countries. By incorporating common factors, the model accounts for common shocks, such as global financial crises or widespread technological disruptions, allowing for isolation of the impact of domestic and foreign R&D stocks from these overarching influences. The factor loadings λ_i enable the model to account for the varying impact of common shocks across countries, recognising that different countries may respond differently to the same global event. This approach improves estimation accuracy by addressing cross-sectional dependence, leading to more accurate and consistent estimates of the coefficients β^d and β^f, thus providing better inference regarding the impact of domestic and foreign R&D efforts on productivity.

In models with heterogeneous slopes, the mean group estimator is used to make inferences about the whole panel. The CCEMG estimator is given by:

$$\hat{\beta}^j_{CCEMG} = N^{-1} \sum_i \hat{\beta}^j_i, j \epsilon \{d, f\} \tag{6}$$

Due to the importance of using a dynamic analysis when dealing with panels with a large T, and the importance of selecting models that are robust to the unit-root properties of the data, this study uses an error correction representation of the model. Eberhardt and Presbitero (2015) point towards three reasons why an error correction specification is superior to static or restricted dynamic models: (a) they distinguish between short-run and long-run relationships; (b) they allow inferences of the speed of adjustment of the model in response to an exogenous shock in the previous period; (c) in the case of mixed order of variables, the statistical significance of the error correction term is evidence of an equilibrium long-run relationship between the selected variables. The error correction representation can be obtained as follows:

$$\Delta TFP_{i,t} = \alpha_i + \upsilon_i (TFP_{i,t-1} - \beta_i^d S_{t-1}^d - \beta_i^f S_{t-1}^f - \lambda_i \boldsymbol{l}_t) + \gamma_i^d \Delta S_t^d + \gamma_i^f \Delta S_t^f + \gamma_i^l \Delta \boldsymbol{l}_t + \epsilon_{i,t} \tag{7}$$

$$\Delta TFP_{i,t} = \pi_{0i} + \pi_i^{ECT} TFP_{i,t-1} + \pi_i^d S_{t-1}^d + \pi_i^f S_{t-1}^f + \pi_i^l \boldsymbol{l}_t + \mu_i^d \Delta S_t^d + \mu_i^f \Delta S_t^f + \mu_i^l \Delta \boldsymbol{l}_t + \epsilon_{i,t} \tag{8}$$

β_i^d and β_i^f in Equation (7) represent the long run relationship between TFP and stocks of R&D, and γ_i^d and γ_i^f represent the short run relationships. υ_i represents the error correction coefficient which signifies the speed of adjustment of the model to its long run equilibrium. Equation (8) is a reparameterisation of Equation (7), and is the error correction representation of the model. π_i^{ECT} is the speed of adjustment parameter, which shows the speed at which the economy converges to its long-run equilibrium.

According to Pesaran (2006), the CCE model entails taking cross-sectional averages of all variables included in the model to account for latent components and omitted parts in the cointegration relationship. However, Chudik and Pesaran (2015) have highlighted the vulnerability of this approach to small sample bias, which is especially obvious in dynamic panels with modest time series dimensions. Furthermore, they relaxed the strong exogeneity condition for observables. This departure calls into question the consistency of the original Pesaran (2006) paradigm. To overcome these concerns, it is advised that additional lags be added to the cross-section averages of all model variables. The model also uses log of human capital (H) as a control variable in natural logs to make the empirical specification robust. These control variables are embedded in the vector X. Thus, the estimation equation is changed as follows:

$$\begin{aligned}\Delta TFP_{i,t} = \pi_{0i} + \pi_i^{ECT} TFP_{i,t-1} + \pi_i^d S_{i,t-1}^d + \pi_i^f S_{i,t-1}^f + \mu_i^d \Delta S_{i,t}^d + \mu_i^f \Delta S_{i,t}^f \\ + \tau_i^{\Delta TFP} \overline{\Delta TFP}_t + \tau_i^{TFP} \overline{TFP}_{t-1} + \tau_i^d \overline{S^d}_{t-1} + \tau_i^f \overline{S^f}_{t-1} + \rho_i^d \overline{\Delta S_t^d} \\ + \rho_i^f \overline{\Delta S_t^f} + \sum_{p=0}^{P} \varphi_i^{\Delta TFP} \overline{\Delta TFP}_{t-p} + \sum_{p=1}^{P} \varphi_i^d \overline{\Delta S^d}_{t-p} + \sum_{p=1}^{P} \varphi_i^f \overline{\Delta S^f}_{t-p} \\ + \varepsilon_{i,t} \qquad (9)\end{aligned}$$

Equation (9) is the complete specification of the error correction model as in Chudik and Pesaran (2015). They demonstrate that when augmented with an adequate number of lagged cross-section averages (where $P = int(\sqrt[3]{T})$ is proposed as a rule of thumb), the CCE Mean Group estimator exhibits strong performance even within a dynamic model featuring weakly exogenous regressors. Hence, the number of lagged cross-sectional averages is set to $P = int(\sqrt[3]{49}) = int(3.659) = 3$. Furthermore, the mean group estimate takes into account the coefficient of each cross sectional unit, thereby accounting for parameter heterogeneity.

5.2 Non-Linear Static Model

The motivation for non-linearities lies in the mediating effect of import on R&D spillovers. This study hypothesises an inverted U-shaped relationship between R&D stocks and productivity, justified using the escaping-competition and Schumpeterian effects characterised by Aghion et al. (2005). It is expected that both domestic and foreign stocks of R&D will have a diminishing effect on productivity as imports increase. To test this hypothesis, this study uses an interaction of foreign R&D stocks and the ratio of nominal imports to nominal GDP to assess non-linearities based on imports (see Equation 10).

$$TFP_{i,t} = \beta^d S^d_{i,t} + \beta^f S^f_{i,t} + \beta^{md} m_{i,t} S^d_{i,t} + \beta^{mf} m_{i,t} S^f_{i,t} + \lambda_i \boldsymbol{l}_t + u_{i,t} \tag{10}$$

Based on the Equation (10), this study makes statistical inferences about the presence on non-linearities using the static CCE model, because the inclusion of cross-sectional dependence and parameter heterogeneity in an error correction specification would introduce a level of complexity that extends beyond the scope of this analysis. It also ensures robustness using human capital as a control variable. However, modelling non-linearities within individual countries may not reveal a consistent pattern across the sample. It is challenging to tie spillover effects to specific import thresholds, just as it would be unreasonable to assert that economic growth will be steady at 14% imports-to-GDP ratio but significantly worse at 16%, or to claim that a car accident is unlikely at 54 mph but almost certain at 56 mph (adapted from Eberhardt and Presbitero, 2015). Hence, the panel is disaggregated based on various thresholds of the ratio of imports to nominal GDP. The minimum average import to GDP ratio is of Japan (3.793%), and the maximum is of Belgium (50.755%). Hence, a thresholds is used to disaggregate the panel, which is set at 15%, which is the average of the average country-wise imports excluding outliers (Belgium and New Zealand). This thresholds has been arbitrarily set in order to maintain a roughly equal number of countries in each sub-sample.

6 Results and Discussion

This study carries out the cross sectionally augmented Im-Pesaran-Shin (Pesaran, 2007) test for testing panel unit-roots, and the Pesaran (2004) test to detect cross-sectional dependency in the variables, the results of which can be found in Appendix B. The results suggest mixed order of integration and considerable cross-sectional dependence among the variables. Furthermore, results of Westerlund (2007) and Pedroni (2004) tests reveal evidence for cointegration, the results of which can be found in Appendix C. However, due to mixed order of integration, it is more appropriate to use methods that are resilient to unit-root properties of the data, motivating the use of a CCE-ECM specification. To test whether the data follows the standard economic intuitions and is coherent with previous studies when common shocks are not accounted for, this study first presents the results of DOLS model, and then error correction models using a two-way fixed-effects estimator (2FE), a pooled CCE model (CCEP), a mean group (MG) model.

6.1 Baseline Model

6.1.1 DOLS Model

For the baseline model, this study begins by attempting to replicate the results of the baseline specification given by Coe and Helpman (1995), with additional controls, using the dynamic OLS (DOLS) method as suggested by Coe et al. (2009). In doing so, this study attempts to verify whether extending the time frame from the 34 years taken by Coe et al. (2009), to 49 years in this study, significantly changes the magnitude of coefficients obtained for domestic and foreign R&D stocks. The prerequisites for using a DOLS model are variable non-stationarity and the presence of cointegration among the variables. The results for the unit-root and cointegration tests are presented in Appendices B and C. The results of the DOLS model for the various specifications tested in this study are presented in Table 2. For just the DOLS model, to facilitate comparison with past studies, this study also employs the bilateral import weights method for constructing R&D stocks. In Table 2, $S^{f:ch}$ represents bilateral import weights and $S^{f:lp}$ represents the weights based on GDP inspired by Lichtenberg and Van Pottelsberghe De La Potterie (1998).

The results of the DOLS model presented in Table 2 are in line with the empirical results of Coe et al. (2009). Specifications (1) to (4) replicate the baseline specification as in Coe and Helpman (1995), without using any control variables. In each case, there is a positive and statistically significant coefficient for both domestic and foreign R&D stocks. Furthermore, the magnitude of the coefficients are also

Table 2: Panel Dynamic OLS

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnS^{d}	0.094***	0.062***	0.018***	0.038***	0.135***	0.057***	0.069	0.083
	(12.900)	(8.084)	(5.607)	(4.531)	(17.27)	(-4.398)	(-1.193)	(1.589)
$LnS^{f:ch}$	0.248***				0.263***			
	(7.928)				(9.254)			
$LnS^{f:lp}$		0.043***				0.120***		
		(-3.948)				(12.91)		
$mLnS^{f:ch}$			0.277***				-0.447***	
			(8.400)				(-12.39)	
$mLnS^{f:lp}$				0.060***				-0.226***
				(9.868)				(-11.67)
LnH					-0.419***	0.100***	0.486***	0.260
					(-3.418)	(-6.575)	(7.007)	(1.48)

very similar to Coe and Helpman (1995) and Coe et al. (2009). In addition to the baseline specifications, human capital is used as an additional control variable to make the regression specification more robust in specifications (5) to (8). The regression result in column (5) yields a coefficients for domestic R&D stocks that is higher than Coe et al. (2009), who obtain a coefficient of 0.098. It also reports a coefficient of 0.268 for foreign R&D stocks, compared to the 0.035 obtained by Coe et al. (2009). When the LP measure of foreign R&D is used, the coefficients of both domestic and foreign R&D stocks are lower compared to the CH specification. When the interaction terms are used (specifications (7) and (8)), foreign R&D stocks have a negative and significant coefficient, which is completely contrary to the findings of Coe et al. (2009). Even though the DOLS model yields results that are similar to Coe et al. (2009), the estimation technique does not accommodate cross-sectionally dependent residuals, and unobservable common shocks and common spillover effects. Hence, the common correlated effects estimator is used to obtain more robust results.

6.1.2 Error Correction Models

The results of the DOLS model in the previous subsection is in line with the previous literature on the subject. However, due to mixed order of integration among the variables, it is best to use methods that are resilient to unit root properties of the data. Table 3 presents an error correction representation of the baseline specification using a pooled OLS (POLS), two-way fixed effects (2FE), pooled common correlated effects (CCEP), mean group (MG) estimator, and common correlated effects mean group (CCEMG) estimator. The POLS and 2FE models assume homogeneous coefficients across countries; the latter considers country and time fixed-effects to capture unobserved heterogeneity. The CCEP model uses cross-sectional averages to account for unobserved common shocks, but does not impose heterogeneous coefficients. The MG model assumes heterogeneous coefficients but does not account for cross-sectional dependency. Finally, the results of the CCEMG model is presented, using contemporaneous cross-sectional average terms, but does not use lagged cross-sectional averages for simplicity. Simply put, this section presents an alternative way of modelling the variables and comparing coefficients to ensure robustness. For ease in representation, the table shows only long run coefficients, and uses only the Lichtenberg and Van Pottelsberghe De La Potterie (1998) method to calculate R&D stocks

The results from Table 3 reveal that there is strong evidence for error correction in all the models tested; the lagged error correction term is statistically significant in all the models. The long run coefficient of domestic R&D stocks is positive throughout, but statistically significant in only the CCEP and MG models. The coefficients for foreign R&D stocks are mixed in signs: the MG model is the only one which reveals a statistically significant coefficient for foreign R&D stocks. In cases where domestic R&D stocks are significant, the magnitude of the coefficient is much higher than those reported in the DOLS model, and the coefficient for foreign R&D stocks turn insignificant in four out of five models.

The diagnostic tests highlight that the use of cross sectional aver-

Table 3: Linear Dynamic Models (ECM)

Variables	POLS	2FE	CCEP	MG	CCEMG
S^d	0.042*	0.070	0.111***	0.174**	0.019
	(1.79)	(1.16)	(3.37)	(2.22)	(1.24)
S^f	0.001	0.008	-0.022	-0.076**	0.022
	(0.09)	(0.007)	(-0.77)	(-2.04)	(1.31)
ECT_{t-1}	-0.044***	-0.029***	-0.207***	-0.209***	-0.382***
	(-7.66)	(-3.48)	(-8.79)	(-7.41)	(-8.57)
Observations	1104	1104	1104	1104	1104
CD	50.65	70.70	45.22	19.82	7.75
$RMSE$	0.021	0.019	0.018	0.018	0.017

Error Correction representation based on a sample of N=23 countries. t-statistics reported in parentheses. Short run variables included in regressions but not reported.

ages in the models with heterogeneous parameters considerably reduces residual cross-sectional dependence, as demonstrated by the decrease in the Pesaran (2004) CD statistic from 19.82 in the MG model to 7.75 in the CCEMG model. Although the null hypothesis of cross-sectional independence still cannot be rejected in the CCEMG model, the results are quite encouraging for the subsequent section, where the modelling strategy employs further lagged cross-sectionally averaged regressors. The presence of cross-sectional dependence in the residuals is an indicator that the unobserved common shocks and spillovers have been incorrectly specified. This seems to be the case in all the models tested, motivating the use of models with more lags of cross-sectionally averaged regressors.

6.1.3 Common Correlated Effects Estimator

This section is dedicated to the error correction version of the common correlated effects estimator with three lagged cross-sectional averages. Furthermore, it uses the baseline specification and the specification with log of the Barro and Lee (2013) human capital index. The sample is also disaggregated into G7 and non-G7 countries, following the empirical exercise performed by Coe and Helpman (1995) to understand how the effect of domestic and foreign R&D capital stocks affect both groups differently. Since G7 countries are more advanced, and are closer to the technological frontier, they may experience smaller returns to foreign R&D capital and larger returns to domestic R&D capital Coe and Helpman (1995); Coe et al. (1997); Lichtenberg and Van Pottelsberghe De La Potterie (1998). Each model emphasises both the long-run estimates and the error correction term coefficient to examine cointegration and identify evidence of a long-run relationship. This approach leverages the panel aspect of the data to (i) initially calculate the long-run coefficient for each country (ALR)[2], which is subsequently averaged, and (ii) first average the ECM coefficients and then determine the long-run average (LRA). This empirical strategy is inspired by Eberhardt and Presbitero (2015).

For all the models tested in Table 4, the error correction term is statistically significant, showing that there is an equilibrium long-run relationship between the variables. The findings of the CCEMG model also reveals that there is a positive and statistically significant long-

[2]Note that the average long-run coefficient is very sensitive to positive outliers in the group-specific EC-coefficients.

Table 4: Linear Dynamic Models (ECM)

Variables	Full Sample		G7		Non-G7	
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic R&D						
LRA	0.061**	0.046	0.117***	0.193**	0.034	-0.029
	(0.030)	(0.056)	(0.036)	(0.087)	(0.036)	(0.055)
ALR	0.233	0.005	0.094**	0.058	0.294	-0.017
	(0.231)	(0.075)	(0.048)	(0.201)	(0.334)	(0.068)
Foreign R&D						
LRA	0.035	0.008	0.030	0.032**	0.038	-0.004
	(0.026)	(0.007)	(0.029)	(0.013)	(0.037)	(0.049)
ALR	-0.370	0.014	-0.001	0.044	-0.531	0.001
	(0.420)	(0.007)	(0.050)	(0.032)	(0.606)	(0.058)
Human Capital						
LRA		1.015		0.205		1.429
		(1.255)		(2.404)		(1.487)
ALR		-0.183		-1.615		0.443
		(0.007)		(2.655)		(1.255)
ECT_{t-1}	-0.457***	-0.684***	-0.499***	-0.759***	-0.439***	-0.650***
t-statistic	-7.95	-8.71	-3.38	-3.33	-7.91	-10.76
$\bar{t}$-statistic	-3.17	-3.65	-3.49	-3.94	3.037	-3.521
Observations	1058	1058	322	322	736	736
CD	-2.34	1.48	-0.37	-0.25	-2.26	-1.66
RMSE	0.011	0.009	0.006	0.004	0.013	0.011

*The first set of t-statistics are non-parametric statistics derived from the country-specific coefficients following Pesaran and Smith (1995) The second set represents averages across country-specific t-statistics. Statistical significance of ECT based on Gengenbach et al. (2016). RMSE is the root mean squared error, CD test reports the Pesaran (2004) test. *, **, and *** represent staitistical significance at the 10%, 5%, and 1% respectively.*

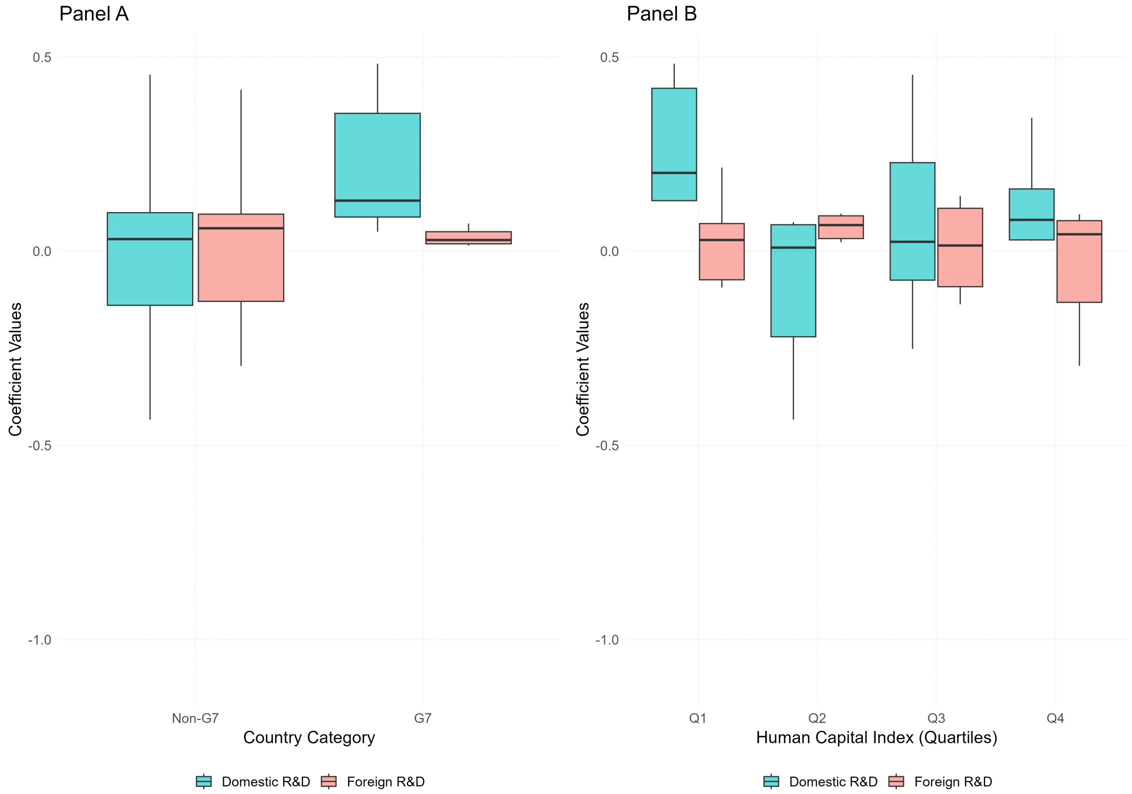
run average coefficient for domestic R&D stocks, but this coefficient turns insignificant when human capital is used as a control. The long-run average is highly sensitive to outliers in the error correction terms, making it difficult to obtain coherent results. The long run average coefficients are statistically significant in both the models for the sub-sample of G7 countries, with a coefficient higher than the coefficients reported in the DOLS model in Table 2 and the results of Coe et al. (2009). However, the coefficient for the long-run average effect for non G-7 countries are statistically insignificant; in fact, for the model with human capital, the coefficient is negative.

There isn't very compelling evidence of foreign R&D capital having a statistically significant impact on productivity, except the long-run average coefficient for G7 countries when human capital is used as a control. Hence, there is no evidence of international R&D spillovers from imports when the empirical strategy accommodates common unobserved shocks and spillovers that causes cross-sectional dependency. However, it is crucial to note that insignificant coefficients do not indicate that significant effects are absent; instead, it emphasises the heterogeneity among countries, with varying dynamics that tend to cancel each other out on average.

The CCEMG model uses the averaged country-specific long run coefficients to arrive at mean group results. Heterogeneity in country level coefficients can arise from three possible sources that have been previously explored in the literature. First, the relative size of the economy may affect the size of coefficients; Coe and Helpman (1995) find that in smaller countries, foreign R&D capital stock might be at least as crucial as domestic R&D capital stock, and in larger countries (G7 countries) domestic R&D capital stock may hold greater significance. Second, the level of human capital may affect the absorptive capacity of countries. Starting with Arrow (1969), countries vary in both their commitment and capacity to adopt new technologies. Growth literature has stressed on the role of human capital in determining growth characteristics of nations (Benhabib and Spiegel, 1994). Furthermore, Nelson and Phelps (1966) state that human capital may also affect the level and intensity of technology diffusion as it influences the absorptive capacity of countries to adopt foreign knowledge. Although Benhabib and Spiegel (1994) state that human capital may not enter the production function directly, Kneller and Stevens (2006) find that human capital does affect productivity through both direct and indirect effects. Lastly, import intensity may cause heterogeneity, and perhaps non-linearities (investigated in the subsequent section), in country coefficients. Coe and Helpman (1995) suggest that foreign R&D capital stocks have stronger effects on domestic productivity the larger the share of domestic imports in GDP.

Panel A of figure 4 reveals that when countries are classified into G7 and non-G7 countries, domestic R&D stocks appear to have a higher coefficient, on average, than countries that do not fall into G7 nations. This is in corroboration with the results of Coe and Helpman (1995), but in contrast with the results found by Coe et al. (2009), who report that countries in the G7 countries have a lower coefficient for domestic R&D stocks. However, there is no discernible differences in the coefficients for foreign R&D stocks in G7 and non-G7 nations.

Figure 4: Boxplots to Assess Heterogeneity

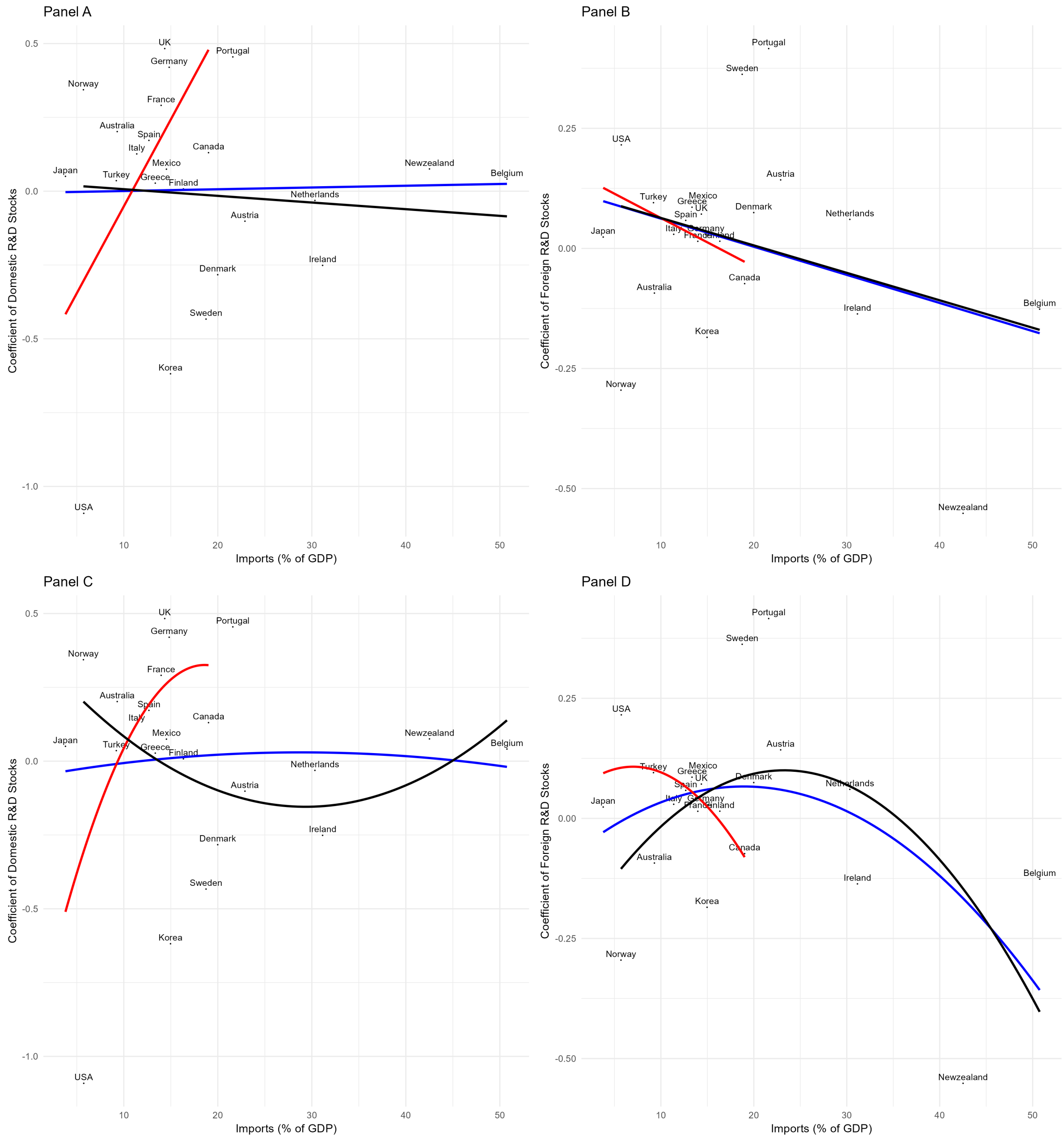


The boxplot uses country specific coefficients of specification (2) of the CCEMG model in Table 4. Panel A classifies the countries into G7 and non-G7 countries. Panel B classifies countries based on their human capital index into quartiles: quartile 1 being countries with the highest human capital and quartile 4 being the lowest

Panel B of Figure 4 shows a higher coefficient for domestic R&D stocks for countries in the first quartile of human capital index. However, even there are no discernible differences in the coefficients of domestic and foreign R&D stocks for countries in the three other quartiles.

Figure 5 plots the country specific coefficients against import intensity measured as the percentage of nominal imports with respect to nominal GDP. Panel A of Figure 5 shows that there is very little

Figure 5: Heterogeneity Based on Import Intensity



Panels A and B show the linear plot of country specific coefficients of domestic and foreign R&D stocks respectively. Panels C and D show the polynomial plot of country specific coefficients for domestic and foreign R&D stocks respectively. To add another dimension of heterogeneity, the blue line represents the full sample, the red line represents G7 countries and the black line represents non-G7 countries.

heterogeneity across country coefficients of domestic R&D stocks with respect to imports. Panel B reveals that as import intensity increases, the coefficient of foreign R&D stocks decreases. This is in contrast with the findings of Coe and Helpman (1995), who find that countries with higher import intensity experience higher R&D spillovers. To add another dimension of heterogeneity, the effect of import intensity on the coefficient of foreign R&D stocks is similar for the full sample, the sub-sample of G7 countries, and the sub-sample of non-G7 countries. In contrast, for domestic R&D stocks, G7 countries appear to experience greater spillovers as imports rise, as apposed to the slightly negative slope seen in non G7 countries and the full sample.

Finally, Panels C and D present the non-linear plots for country specific coefficients against import intensity. Although there is no clear pattern of non-linearities for domestic R&D stocks, the coefficients for foreign R&D stocks reveal a clear inverted U-shaped relationship, that is consistent for all sub-samples, in line with the expectations of the earlier established theory through the escaping competition and Schumpeterian effects. The analysis conducted so far aimed to explore whether there is a non-linear relationship between R&D stocks and TFP across different countries. Various empirical models found evidence of significant heterogeneity in long-run coefficients among countries. Moving forward, the focus will be on empirical models that accommodate both varying long-run relationships across countries and potential threshold effects within individual countries.

6.2 Non-Linearities

The regression results of the baseline model, and the model accounting for heterogeneity, like many other papers, yield negative coefficients for the elasticity of both domestic and foreign R&D stocks in certain specifications. A negative coefficient is not theoretically justified according to endogenous growth models given by Romer (1990) and Aghion and Howitt (1992). The hypothesis tested in this section is that higher imports would lead to lower R&D spillovers, due to the flooding of domestic markets with foreign inputs and lower motivation to gain R&D from imported inputs. Furthermore, imports may also eventually reduce the coefficient of R&D stocks through the escaping-competition and Schumpeterian effect (Aghion et al., 2005). Non-linear models are presented in Table 5. The specifications are tested for three sub-samples: the full sample of 23 countries, the sub-sample of countries with an import intensity of less than 15%, and the sub sample of countries with import intensity of greater than 15%. The models tested include specifications including and excluding the human capital control variable. The 15% threshold has been set arbitrarily.

On average, the coefficient for foreign R&D is positive and statistically significant for the full-sample and for the sample of countries that have an import intensity of less than 15%. However, the coefficient for S^f turns statistically insignificant for the sub-sample of countries with import intensities of greater than 15%. Furthermore, the results show the presence of non-linearities for the sub-sample of countries in the low import regime ($m < 15\%$). It can be inferred that countries that are in the low import regime face non-linearities in R&D spillovers

Table 5: Non-Linear Model

Variables	Full Sample		$m < 15\%$		$m > 15\%$	
	(1)	(2)	(3)	(4)	(5)	(6)
S^d	-0.001	0.018	0.061	0.082*	-0.094	-0.110
	(0.041)	(0.047)	(0.048)	(0.044)	(0.080)	(0.063)
S^f	0.075***	0.075***	0.061***	0.061**	0.066	0.082*
	(0.020)	(0.022)	(0.021)	(0.024)	(0.051)	(0.046)
$m * S^d$	0.017	0.070	0.449	0.336	0.072	0.026
	(0.193)	(0.149)	(0.292)	(0.221)	(0.095)	(0.115)
$m * S^f$	-0.050	-0.055	-0.388*	-0.286**	-0.008	0.029
	(0.120)	(0.077)	(0.206)	(0.127)	(0.046)	(0.047)
H		-0.805		-0.246		-0.824
		(0.779)		(0.965)		(0.681)
N	1127	1127	637	637	490	490
CD	-2.51	-2.81	-3.88	-2.90	-2.39	-3.28
RMSE	0.020	0.018	0.020	0.016	0.019	0.016

as imports increase, but as a country reaches a high import regime ($m > 15\%$), the non-linearities vanish, but so does the statistically significant coefficient for S^f.

The findings reveal evidence of both escaping competition and Schumpeterian effects for countries in the low-import regime. However, there is no evidence for such an effect in the case of domestic R&D stocks for all sub-samples, and foreign R&D stocks for the full sample and high import regime sub-sample. Hence, the non-linearities appear to be driven by countries in the low-import regime.

Table 6: Country-specific coefficients and thresholds

Country	S^f	$m * S^f$	Threshold
Australia	0.129	-1.782	0.072
Austria	0.010	-0.058	0.175
Belgium	-0.042	-0.104	-0.407
Canada	0.016	-0.075	0.214
Denmark	0.129	0.030	-4.261
Finland	0.148	0.141	-1.043
France	0.055	-0.051	1.082
Germany	0.065	0.231	-0.280
Greece	0.256	0.349	-0.732
Ireland	-0.061	-0.018	-3.435
Italy	0.013	-0.298	0.043
Japan	0.086	-0.645	0.133
Korea	0.042	-0.309	0.136
Mexico	0.141	-0.262	0.539
Netherlands	0.054	-0.464	0.117
New Zealand	0.161	0.039	-4.102
Norway	0.082	-0.718	0.114
Portugal	0.255	0.034	-7.491
Spain	-0.133	0.820	0.162
Sweden	0.193	0.245	-0.790
Turkey	0.095	-0.141	0.673
UK	0.086	1.024	-0.084
USA	-0.050	0.856	0.058

Figure 6: Non-Linearity Threshold

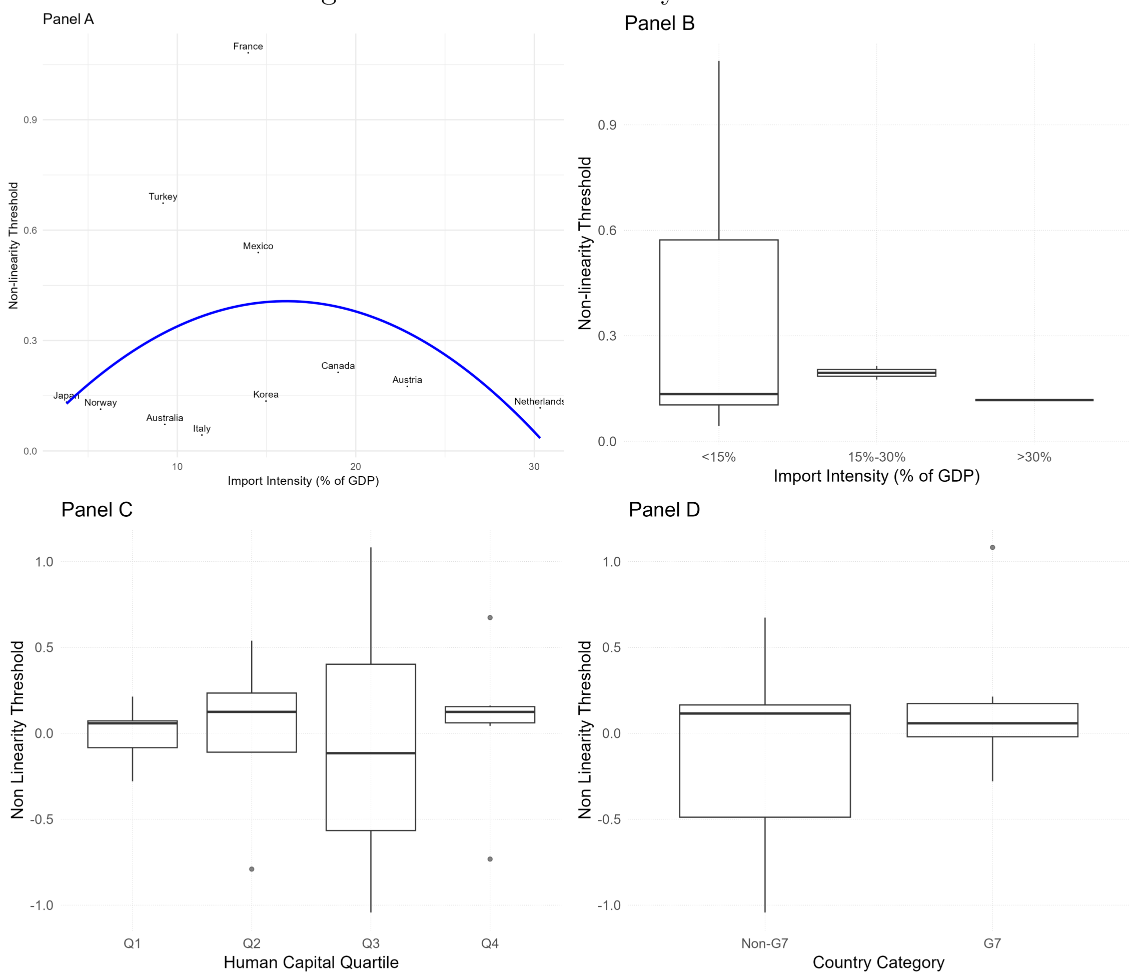


Figure Note: The above graphs plot the non-linearity threshold calculated as $\beta_i^f/\beta_i^{m*f}\ \forall\ i$. Panels A and B use a sub-sample of countries that reveal an inverted U shaped relationship between TFP and S^f. Panels C and D use sub-samples excluding heavy outliers in Denmark, Finland, Ireland, Newzealand, and Portugal, but including countries with thresholds below 0. They plot the non-linearity threshold against categories based on import intensity, human capital (in quartiles), and G7/Non-G7 countries.

The mean group estimator can be exploited to study country-specific coefficients. The non-linear coefficients can be used to identify country specific thresholds where R&D spillovers will eventually decline for countries demonstrating an inverted U-shaped relationship. Panel A of Figure 6 shows that of the countries that reveal an inverted U-shaped relationship, there appears to be an inverted U-shaped relationship between the import intensity and non-linearity threshold. As the average import intensity increases, the non-linearity threshold rise, but eventually declines as the intensity goes on rising. Panles B, C, and D attempts to understand heterogeneity in the thresholds by classifying countries into categories based on their import intensity, their human capital index, and their status as a G7 or non-G7 country. On average, countries with medium import in the range of 15% to 30%, the threshold for non-linearity is higher than for countries with import intensity less than 15% or greater than 30%. However, there is not much heterogeneity in the thresholds on the basis of relative human capital levels. Intuitively, countries with a higher human capital index would have a higher absorptive capacity, and therefore, a higher threshold (Kneller and Stevens, 2006), these differences cannot be seen in the selected sample of countries. There also does not appear to be any heterogeneity in the thresholds based on the countries' categorisation into G7 and non-G7 nations.

Lastly, the sample also contains countries that have a the same sign in the coefficient for both S^f and $m * S^f$ (Belgium, Denmark, Finland, Germany, Greece, Ireland, New Zealand, Portugal, and the UK), leading to a negative non-linearity threshold , and countries that have a negative coefficient for S^f but positive coefficient for $m * S^f$ (Spain, USA), leading to a positive threshold but a U-shaped relationship. Such relationships arise due to other institutional factors (beyond the scope of this study), like ease of doing business, patent protection, and legal systems (Coe et al., 2009). Countries may therefore experience negative spillovers, which are further exacerbated by higher imports (for e.g. Belgium and Ireland), or positive spillovers, which are intensified by higher imports (for e.g. Denmark, Finland, Germany, Greece, New Zealand, Portugal, UK). The latter is in line with the results of Coe and Helpman (1995).

Hence, it can be concluded that the threshold of non-linearities are heterogeneous across countries. Most countries in the sample reveal an inverted U-shaped relationship as earlier hypothesised, heterogeneity in which is determined by their import intensity. There are also countries which show a non-linear exponential relationship, that is, the direction of spillovers are intensified with greater imports. Countries may also show a U-shaped relationship, which may be because of country specific institutional factors like legal systems, patent protection, and ease of doing business.

7 Conclusion

This paper investigates the presence of international R&D spillovers sparked by the work of Coe and Helpman (1995). This article makes three contributions to the existing literature on the subject.

First, this article updates the time-period taken by Coe et al. (2009) by taking a time-period of 49 years and a cross-section of 23 OECD countries. Previous studies ignore unobserved common shocks leading to cross-sectional dependency, which causes an upward bias in estimates. This paper explores various specifications using the dynamic CCE estimator given by Chudik and Pesaran (2015), and reports statistically insignificant long-run coefficients for both foreign R&D stocks, bust significant positive coefficient for domestic R& stocks, especially for G7 countries. It leads one to question the validity of the conclusions drawn by previous studies, and highlights that spillovers effects turn insignificant when the specifications accommodate common shocks and spillovers.

Second, it studies heterogeneity in spillover coefficients graphically, based on three factors that have been previously explored in the literature: G7/non-G7 categorisation, level of human capital, and import intensity. The results show that G7 countries experience higher returns to domestic R&D stocks, as do countries in the top quartile of human capital index. Further it shows that foreign R&D stocks appear to decline with an increase in imports, but such an effect cannot be seen for domestic R&D stocks.

The third and final contribution of this study lies in disentangling negative coefficients by understanding non-linearities arising due to imports. It also accounts for heterogeneity arising from human capital index, import regimes, and categorisation into G7 and non-G7 countries. The results suggest that there is a significant non-linear relationship for foreign R&D in countries with an average import to GDP ratio of less than 15%, but not for other countries. The results also show that the non-linearity threshold is also non-linear and forms an inverted U-shape as import intensity rises. However, there does not appear to be any heterogeneity in the thresholds based on human capital and no differences between G7 and non-G7 countries.

In conclusion, this paper attempts to improve the empirical rigour in the literature on international R&D spillovers. However, the findings of the econometric models are not consistent with the broader empirical growth literature on the subject. Furthermore, there appear to be non-linearities in the spillovers, which have not been explored earlier in the literature. The nature of spillover effects varies by country, so policies effective in one nation may be ineffective or harmful in another due to differing national contexts. Therefore, a limitation of this paper is that it ignores other institutional factors such as patent protection, ease of doing business, and legal systems, which have been established to cause heterogeneity in the previously established literature.

References

Aghion, P., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and innovation: an inverted-u relationship. *The Quarterly Journal of Economics*, 120:701–728.

Aghion, P., Blundell, R., Griffith, R., Howitt, P., and Prantl, S. (2009). The effects of entry on incumbent innovation and productivity. *Review of Economics and Statistics*, 91:20–32.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60.

Aghion, P. and Howitt, P. (1998). *Endogenous Growth Theory*. MIT University Press.

Ang, J. B. and Madsen, J. B. (2013). International r and d spillovers and productivity trends in the asian miracle economies. *Economic Inquiry*, 51.

Arrow, K. J. (1969). Classificatory notes on the production and transmission of technological knowledge. *American Economic Review*, 59.

Autor, D., Dorn, D., Hanson, G. H., Pisano, G., and Shu, P. (2020). Foreign competition and domestic innovation: Evidence from us patents. *American Economic Review: Insights*, 2.

Baldwin, R. (1992). On the growth effects of import competition. *NBER Working Paper*.

Barro, R. J. and Lee, J.-W. (2001). International data on educational attainment: updates and implications. *Oxford Economic Papers*, 53:541–563.

Barro, R. J. and Lee, J. W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics*, 104:184–198.

Benhabib, J. and Spiegel, M. M. (1994). The role of human capital in economic development evidence from aggregate cross-country data. *Journal of Monetary Economics*, 34.

Bloom, N., Draca, M., and Reenen, J. V. (2016). Trade induced technical change? the impact of chinese imports on innovation, it and productivity. *Review of Economic Studies*, 83.

Chari, V. V. and Hopenhayn, H. (1991). Vintage human capital, growth, and the diffusion of new technology. *Journal of Political Economy*, 99:1142–1165.

Chen, N., Imbs, J., and Scott, A. (2009). The dynamics of trade and competition. *Journal of International Economics*, 77.

Chudik, A. and Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188:393–420.

Coe, D. T. and Helpman, E. (1995). International r&d spillovers. *European Economic Review*, 39:859–887.

Coe, D. T., Helpman, E., and Hoffmaister, A. W. (1997). North-south r&d spillovers. *Economic Journal*, 107.

Coe, D. T., Helpman, E., and Hoffmaister, A. W. (2009). International r&d spillovers and institutions. *European Economic Review*, 53.

del Barrio-Castro, T., López-Bazo, E., and Serrano-Domingo, G. (2002). New evidence on international r&d spillovers, human capital and productivity in the oecd. *Economics Letters*, 77:41–45.

Ding, S., Sun, P., and Jiang, W. (2016). The effect of import competition on firm productivity and innovation: Does the distance to technology frontier matter? *Oxford Bulletin of Economics and Statistics*, 78.

Dixit, A. K. and Stiglitz, J. E. (1977). Monopolistic competition and optimum product diversity. *American Economic Review*, 67.

Dornbusch, R., Fischer, S., and Samuelson, P. A. (1977). Comparative advantage, trade, and payments in a ricardian model with a continuum of goods. *The American Economic Review*, 67.

Eberhardt, M., Helmers, C., and Strauss, H. (2013). Do spillovers matter when estimating private returns to r&d? *Review of Economics and Statistics*, 95.

Eberhardt, M. and Presbitero, A. F. (2015). Public debt and growth: Heterogeneity and non-linearity. *Journal of International Economics*, 97.

Engelbrecht, H.-J. (1997). International r&d spillovers, human capital and productivity in oecd economies: An empirical investigation. *European Economic Review*, 41:1479–1488.

Feenstra, R. C. (1996). Trade and uneven growth. *Journal of Development Economics*, 49.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the penn world table. *American Economic Review*, 105.

Frantzen, D. (2000). R&d, human capital and international technology spillovers: A cross-country analysis. *The Scandinavian Journal of Economics*, 102:57–75.

Friesenbichler, K. S., Kügler, A., and Reinstaller, A. (2024). The impact of import competition from china on firm-level productivity growth in the european union*. *Oxford Bulletin of Economics and Statistics*, 86.

Gengenbach, C., Urbain, J., and Westerlund, J. (2016). Error correction testing in panels with common stochastic trends. *Journal of Applied Econometrics*, 31:982–1004.

Grossman, G. M. and Helpman, E. (1991a). Quality theory ladders of in the growth. *The Review of Economic Studies*, 58.

Grossman, G. M. and Helpman, E. (1991b). Trade, knowledge spillovers, and growth. *European Economic Review*, 35.

Im, K. S., Pesaran, M., and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115:53–74.

Jaffe, A. and Tajtenberg, M. (2002). *Patents, Citations & Innovations: A Window on the Knowledge Economy*. MIT Press.

Kao, C., Chiang, M. H., and Chen, B. (1999). International r&d spillovers: An application of estimation and inference in panel cointegration. *Oxford Bulletin of Economics and Statistics*, 61.

Keller, W. (2000). Do trade patterns and technology flows affect productivity growth? *World Bank Economic Review*, 14.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, 42:752–782.

Keller, W. (2010). *International trade, foreign direct investment, and technology spillovers*, volume 2.

Kneller, R. and Stevens, P. A. (2006). Frontier technology and absorptive capacity: Evidence from oecd manufacturing industries. *Oxford Bulletin of Economics and Statistics*, 68.

Krugman, P. R. (1979). Increasing returns, monopolistic competition, and international trade. *Journal of International Economics*, 9.

Lichtenberg, F. R. and Van Pottelsberghe De La Potterie, B. (1998). International r&d spillovers: a comment. *European Economic Review*, 42.

Madsen, J. B. (2007). Technology spillover through trade and tfp convergence: 135 years of evidence for the oecd countries. *Journal of International Economics*, 72:464–480.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71.

Nelson, R. R. and Phelps, E. (1966). Investment in humans, technological diffusion, and economic growth. *The American Economic Review*, 56.

OECD (2024). Analytical business enterprise r&d by isic rev.4 industry (anberd database).

Pedroni, P. (2004). Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the ppp hypothesis. *Econometric Theory*, 20.

Pesaran, M. and Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68:79–113.

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. *SSRN Electronic Journal.*

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74:967–1012.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22:265–312.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70:65.

Söderbom, M., Teal, F., Eberhardt, M., Quinn, S., and Zeitlin, A. (2014). *Empirical development economics.* Routeledge.

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics*, 69:709–748.

Appendices

A List of Countries

The current study uses a sample of countries that is slightly different from earlier studies by CH, LP, and CHH. The country list is in the table below:

Table 7: List of Countries

Australia	Austria	Belgium	Canada
Denmark	Finland	France	Germany
Greece	Ireland	Italy	Japan
Korea Republic	Mexico	Netherlands	New Zealand
Norway	Portugal	Spain	Sweden
Turkey	United Kingdom	United States	

B Unit Root Tests

When employing panel data over time, it is critical to address three time-series-related issues in model specification (Söderbom et al., 2014): slope-heterogeneity, cross-sectional dependency, and non-stationarity. Furthermore, the specified regression equations may face the problem of spuriousness because both explanatory and dependent variables are generally non-stationary. Hence, the unit root properties and cross-sectional dependency of variables is tested for the econometric strategy to yield meaningful results. Cross-sectional dependence in some variables could potentially give unreliable results if first-generation panel unit-root tests are used. Hence, the cross-sectional Im-Pesaran-Shin

(CIPS) test for unit root provided by Pesaran (2007), which augments the unit root test given by Im et al. (2003) (IPS), is used. It tests the null hypothesis that all panels follow a unit root process against the alternate of some panels being stationary. Results are presented in Table 8.

Table 8: Results of CD and CIPS Tests

Variable	CD	CIPS	
		I(0)	I(1)
LnTFP	48.27***	-1.912	-5.598***
LnS^d	110.76***	-2.675***	-2.163**
$LnS^{f:lp}$	110.33***	-2.660***	-5.941***
$LnS^{f:ch}$	111.24***	-1.994	-5.403***
$m * LnS^{f:lp}$	75.50***	-2.843***	-6.120***
$m * LnS^{f:ch}$	102.34***	-3.146***	-6.086***
LnH	107.63***	-2.000	-2.189**

*The table presents the unit-root properties of the variables and results for cross-sectional dependence. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels respectively.*

It is important to note that while panel unit root tests are deemed necessary, it typically fails to provide a comprehensive understanding of the unit-root properties of the data. For instance, rejecting the null hypothesis merely indicates that some panel units lack a unit root, which may not sufficiently elucidate the underlying dynamics. Consequently, a greater reliance is placed on estimation methods that are resilient to unit root behaviour, which would yield more robust and informative results.

C Cointegration

It is also important to understand whether there is an equilibrium long-run equilibirum (cointegrating) relationship between the variables in the various models tested. The baseline models involve the following specification:

$$TFP_{i,t} = \beta^d S^d_{i,t} + \beta^f S^f_{i,t} + \beta^X X_{i,t} + u_{i,t} \tag{11}$$

Table 9: Westerlund Cointegration Test Results

Model	G_t	G_a	P_t	P_a
$TFP, S^d, S^{f:ch}$	-3.243***	-12.142***	-12.449***	-9.791***
$TFP, S^d, S^{f:lp}$	-2.402***	-7.021	-7.833***	-4.686**
$TFP, S^d, mS^{f:ch}$	-2.102***	-6.982	-9.203***	-6.621***
$TFP, S^d, mS^{f:lp}$	-2.193***	-6.793	-9.570***	-5.507***
$TFP, S^d, S^{f:ch}, H$	-3.342***	-5.677	-9.337**	-5.765
$TFP, S^d, S^{f:lp}, H$	-2.777***	-4.350	-8.066*	-3.440
$TFP, S^d, mS^{f:ch}, H$	-2.99***	-4.218	-8.261*	-4.547
$TFP, S^d, mS^{f:lp}, H$	-2.923***	-4.585	-8.805**	-3.498

*The table presents the results for the variance ratio given by Westerlund (2007). I use the option of testing against the alternative hypothesis for all panels being cointegrated. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels respectively.*

Where X is a vector of control variables, including Human Capital (H) and Trade Openness (TO), both in natural logarithms. The cointegrating relationships are tested using both first and second generation methods. To account for cross-sectional dependency, the Westerlund (2007) error-correction based panel cointegration test is used in Table

9. For robustness, the results of Pedroni (2004) cointegration is presented in Table 10. The tests provide ample evidence of there being a cointegrating relationship between the variables.

Table 10: Pedroni Cointegration

Model	Panel			Group		
	ρ	t	ADF	ρ	t	ADF
$TFP, S^d, S^{f:ch}$	0.189	-0.663	0.313	1.755*	0.511	-0.033
$TFP, S^d, S^{f:lp}$	0.496	-0.325	-0.120	2.19**	0.727	-0.655
$TFP, S^d, mS^{f:ch}$	-0.467	-1.78*	0.255	1.252	-0.560	0.755
$TFP, S^d, mS^{f:lp}$	-0.600	-2.029**	-1.913**	1.041	-0.724	-2.153**
$TFP, S^d, S^{f:ch}, H$	-0.271	1.176	-0.901	1.241	-0.201	-0.849
$TFP, S^d, S^{f:lp}, H$	0.454	-0.843	-1.001	1.77*	-0.196	-1.000
$TFP, S^d, mS^{f:ch}, H$	1.026	-0.125	-0.718	2.575***	0.893	-0.168
$TFP, S^d, mS^{f:lp}, H$	-1.733*	0.826	-0.006	2.964***	1.586	0.340