Heterogeneity and Non-Linearities in International Knowledge Spillovers: Evidence Using Novel Panel Estimators

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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 knowledge stocks on TFP. Additionally, the study explores heterogeneity in coefficients caused by a country's proximity to the knowledge 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, Knowledge 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 knowledge 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). International trade is driven by technological differences across countries and facilitates greater access to a variety of markets (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 knowledge 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 knowledge 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) establish that both domestic and foreign R&D stocks significantly impact productivity.

The literature on the subject has seen various improvements relating to the measurement of knowledge 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 test 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. Cross-sectional dependence arising when unobservable factors influencing different countries are correlated, can complicate inference and potentially lead to biased estimates in empirical models (Söderbom et al., 2014).

Empirical literature on productivity also acknowledges that as a country becomes more productive, it reaps diminishing returns to its stock of both domestic and foreign knowledge capital, thus motivating the case of heterogeneity across countries (Fagerberg, 1994; Kneller and Stevens, 2006). 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 arising due to different distances of countries from the leading edge technological frontier. 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 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 knowledge stocks on productivity becomes insignificant. Additionally, the results provide evidence of heterogeneity caused by proximity to the technological frontier, but limited evidence of non-linearities caused by import competition.

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

2 Empirical Literature

The evolution of literature on international knowledge 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. Additionally, Grossman and Helpman (1991b) highlight the importance of trade openness in enhancing productivity growth by facilitating knowledge spillovers through the importation of high-quality inputs. Coe and Helpman (1995) investigate this hypothesis by constructing domestic knowledge stocks using R&D data for 22 OECD countries using the perpetual inventory method, and foreign knowledge 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 knowledge 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 empirical debate on how to measure domestic knowledge 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 knowledge stocks using patent data. They find evidence of domestic and foreign knowledge 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 knowledge 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 knowledge 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 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. 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 knowledge 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)

3 Theory

3.1 Sources of Non-Linearities

Since the the main channel of knowledge spillovers is through imports (Ang and Madsen, 2013), it is also important to acknowledge that import competition, which is directly linked with trade openness (Chen et al., 2009), may have a mediating negative effect on knowledge 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 in the non-linearity thresholds with regards to import competition, depending on each country's distance to the knowledge frontier and other institutional factors that are not within the scope of this study.

To understand the direction of non-linearities, consider a small country with an open economy, with the following production function, assuming Hicks-neutral technical progress:

$$Y = K^{\alpha} L^{1-\alpha} A_d^{\beta_1} A_f^{1-\beta_1} \quad \text{if } m < m^* \tag{1}$$

$$Y = K^{\alpha} L^{1-\alpha} A_d^{\beta_2} A_f^{1-\beta_2} \quad \text{if } m \geq m^* \tag{2}$$

Assuming $\beta_1 > \beta_2$, and hence, $1-\beta_1 < 1-\beta_2$, there is a shift in the relative importance of domestic and foreign knowledge as import intensity changes. The coefficients relating to domestic and foreign knowledge change as m crosses the threshold m^*. Specifically, the marginal impact of domestic knowledge with respect to a change in m, as shown by:

$$\frac{\partial \beta}{\partial m} < 0 \quad \text{for } m \geq m^* \tag{3}$$

which implies that for foreign knowledge stocks, the elasticity parameter $1-\beta$ behaves as follows:

$$\frac{\partial(1-\beta)}{\partial m} = -\frac{\partial \beta}{\partial m} > 0 \quad \text{for } m \geq m^* \tag{4}$$

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 domestic knowledge 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.

The nature of non-linearities of the effect of foreign knowledge stocks on TFP is not explicitly provided in existing literature, but can be theorised using previous studies. Initially, when there is low competition, we see lower adoption rates, labelled as the vintage human capital effect. This can be justified using the vintage human capital models, attributed to the line of literature starting from Chari and Hopenhayn (1991). Using a particular technology builds technology-specific expertise, often referred to as vintage human capital (Comin and Hobijn, 2004). This specialised experience diminishes the motivation to adopt new technologies, as switching would mean forfeiting the benefits derived from this accumulated knowledge (Jovanovic and Nyarko, 1996). As a result, both workers and firms tend to stick with older technologies and continue to invest in them, even when newer and potentially superior alternatives are available. However, with an increase in import competition, over time, firms are forced to adapt and become more resilient (Baldwin, 1992). This results in countries becoming more productive and turning into "early adopters" of new technology (Barro and Sala-i-Martin, 1997). Hence, the coefficient of foreign knowledge may be U-shaped.

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 knowledge, and stock of foreign knowledge. 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 knowledge 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 0.05.

$$S_t^d = S_{t-1}^d + (1-\delta)RD_{t-1} \tag{5}$$

The benchmark knowledge stocks are calculated as,

$$S_{1971}^d = \frac{RD_{1971}}{\delta + g} \tag{6}$$

where g is the annual average logarithmic growth rate from 1971 to 1995, i.e., $g = (log\frac{RD_{1971}}{RD_{1995}})/25$. The benchmark for the data i.e. S_{1971}^d is considered as the stock of knowledge 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 knowledge of a country. This measure is based on the domestic capital stocks of each of the 22 trade partners of the country. This study follows the Lichtenberg and Van Pottelsberghe De La Potterie (1998) measure of foreign knowledge stocks, calculated as follows:

$$S_i^{f:lp} = \sum_j \frac{M_{ij}}{Y_j} {S_j}^d \tag{7}$$

This measure is free from aggregation and indexation issues (see Lichtenberg and Van Pottelsberghe De La Potterie (1998)). However, Coe et al. (2009) find that in terms of statistical performance, the bilateral import weights method given by Coe and Helpman (1995) is superior to the one given by Lichtenberg and Van Pottelsberghe De La Potterie (1998). Hence, the bilateral import weighed stock of knowledge is calculated as follows:

$$S_i^{f:ch} = \sum_j \frac{M_{ij}}{Y_j} S_j{}^d \tag{8}$$

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). Due to its effect on TFP, as proven by Coe et al. (1997), Falvey et al. (2004) and Miller and Upadhyay (2000), this study also controls for trade openness represented by log of trade as a percentage of GDP.

Finally, to understand heterogeneity in coefficients, this study uses a measure of distance to knowledge frontier based on *TFP* levels. A natural proxy for distance to frontier (*DTF*) is "proximity to frontier" for an industry defined as *TFP* in country i at time t divided by the highest *TFP* at time t in the sample (Acemoglu et al., 2006). The variable is then centred around its mean to make econometric interpretations easier. The *DTF* variable is interacted with domestic and foreign knowledge stocks to understand the role played by distance to frontier in determining the dynamics of the estimated coefficients. The signs of the coefficients of these terms are expected to be negative i.e. as the country approaches the knowledge frontier, the rate of technology diffusion declines. In other words, countries that are farther behind experience greater knowledge diffusion and higher growth rates (Abramovitz, 1986; Verspagen, 1991).

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

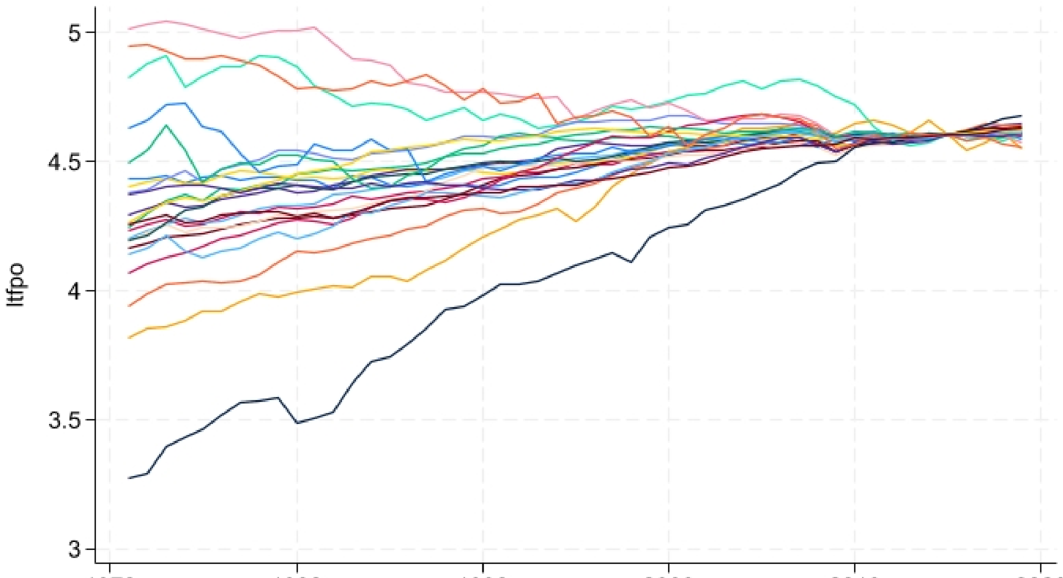

Figure Notes: TFP for 2015 being indexed to 100. The natural log of the variable is presented in the graph. Source: Author

Figure 2 shows the trends in both domestic and foreign knowledge stock accumulation. Stocks of knowledge, both domestic and foreign appears to have a greater growth, and larger variability across countries, compared to TFP growth. Domestic knowledge 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 knowledge.

Figure 2: Knowledge Stocks

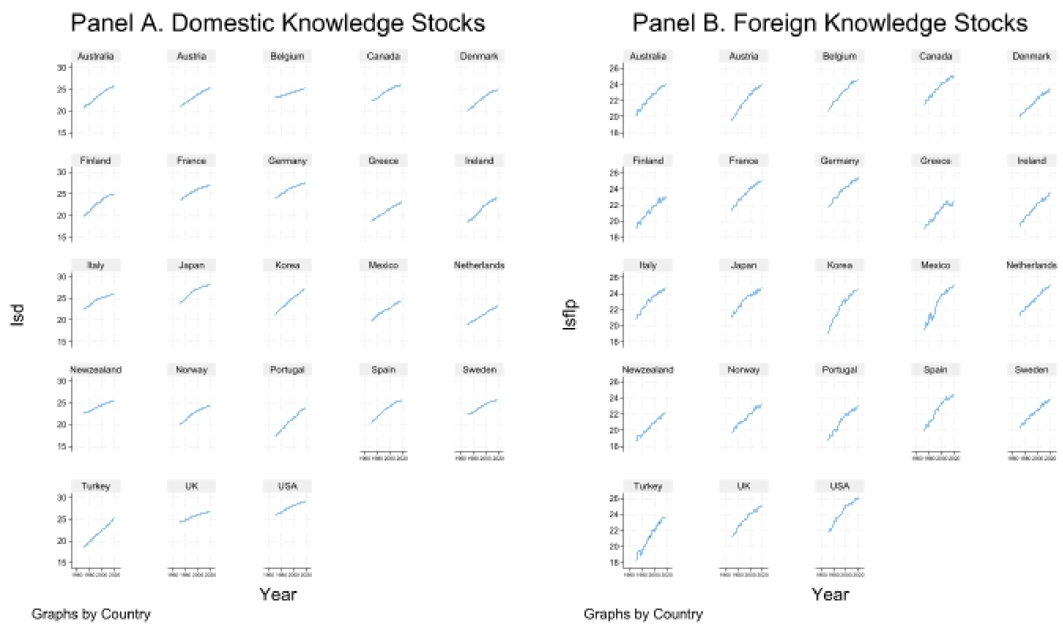

Figure Notes: Domestic knowledge stocks (S^d) and Foreign knowledge stocks $S^{f:lp}$ in natural logarithms. Source: Author

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

Table 1: Summary Statistics

Country	TFP_{2019}/TFP_{1971}	S^d_{2019}/S^d_{1971}	$S^{f:lp}_{2019}/S^{f:lp}_{1971}$	$S^{f:ch}_{2019}/S^{f:ch}_{1971}$
Australia	1.035	112.009	41.694	18.764
Austria	1.087	80.676	79.816	25.054
Belgium	1.083	13.200	105.815	27.867
Canada	1.051	30.006	61.119	19.848
Denmark	1.083	96.916	44.563	22.675
Finland	1.177	121.026	62.595	22.400
France	1.099	23.224	53.395	23.202
Germany	1.113	28.126	65.446	25.946
Greece	0.954	101.169	45.724	26.889
Ireland	1.193	259.975	54.438	13.289
Italy	1.055	28.648	75.976	25.500
Japan	1.102	54.686	63.212	25.385
Korea	1.429	291.476	413.365	29.168
Mexico	0.912	56.780	264.642	21.857
Netherlands	1.098	80.239	42.881	19.917
New Zealand	0.995	18.943	34.099	19.196
Norway	1.131	71.301	41.113	23.615
Portugal	1.031	614.325	112.793	21.280
Spain	1.085	147.478	225.452	22.384
Sweden	1.054	26.164	65.799	24.581
Turkey	0.922	935.474	288.054	21.763
UK	1.114	9.304	51.716	34.554
USA	1.088	19.892	88.620	28.357
Average	1.082	140.045	103.579	23.630
Standard Deviation	0.099	209.317	93.791	4.136

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

two possible explanations for higher variability. Firstly, the preferred method of constructing foreign knowledge 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). 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 knowledge. Table 1 lends further credibility to the graphical inferences, showing that the variability in foreign knowledge stocks are much higher for LP weights than they are for CH weights.

Figure 3: Heterogeneity and Non-Linearities in Knowledge Spillovers

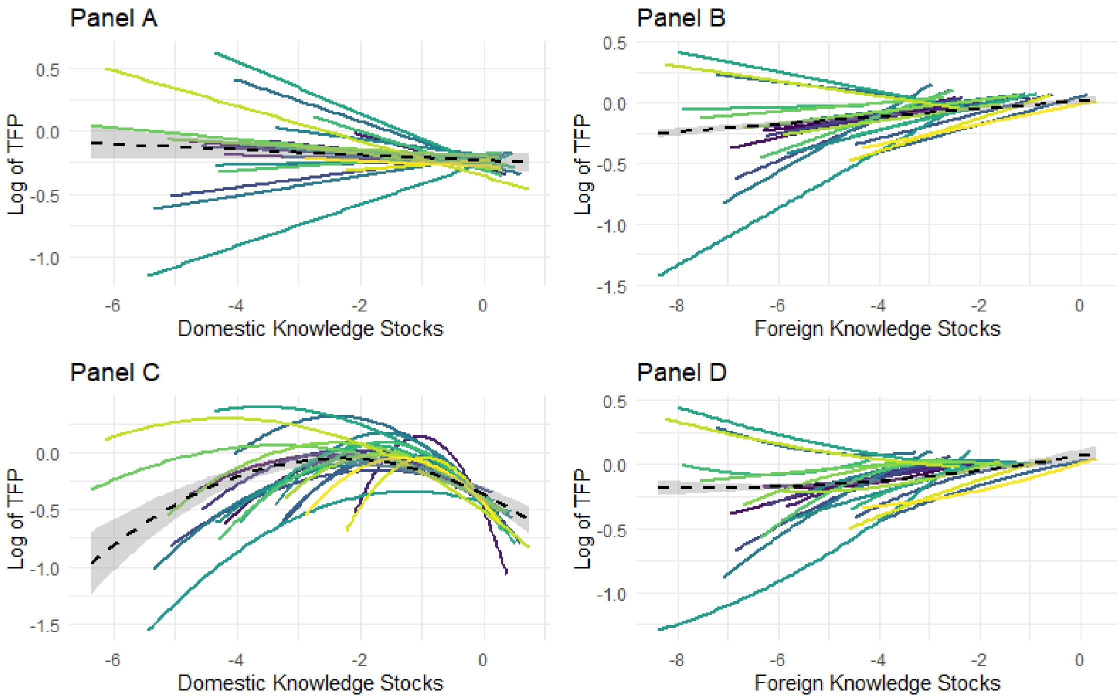

Figure Notes: The coloured lines depict linear plots for each country, while the black dashed line indicates the linear fit for the pooled model. Panel A illustrates the relationship between TFP and domestic knowledge, and Panel B shows TFP against foreign knowledge. Panels C and D present a polynomial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

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 knowledge stocks and TFP. Furthermore, such a stylised presentation of the relationship somewhat validates the inverted U-shaped hypothesis for domestic knowledge stocks (See Figure 3, Panel C), characterised by the escape-competition and Schumpeterian effects as in Aghion et al. (2005). However, the U-shaped hypothesis for foreign knowledge stocks, characterised by vintage human capital effect Chari and Hopenhayn (1991); Jovanovic and Nyarko (1996) and early adoption effects (Barro and Sala-i-Martin, 1997), 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 knowledge 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 these theories using advanced econometric techniques.

5 Empirical Framework

5.1 Dynamic Linear Specifications

Many studies on knowledge 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 uses aggregate data to examine the effects on TFP of domestic R&D and foreign knowledge spillovers, 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 modeling. 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 knowledge spillovers and their impact on economic productivity. Technological knowledge 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. 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 knowledge stocks:

$$TFP_{i,t} = \beta^d S^d_{i,t} + \beta^f S^f_{i,t} + u_{i,t} \tag{9}$$

$$u_{i,t} = \alpha_i + \lambda_i \boldsymbol{l}_t + \epsilon_{i,t} \tag{10}$$

Where LnTFP is the total factor productivity, S^d and S^f are domestic and foreign knowledge stocks respectively, and all variables are taken in their natural logarithms. The coefficient β^j_i, where $j\epsilon${d,f}, is allowed to differ across countries i. The coefficients are therefore heterogeneous, which is the salient feature of this empirical strategy. Here, 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 remaining 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 knowledge 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:

$$\hat{\beta}_{CCEMG} = N^{-1} \sum_{i} \hat{\beta}_i^j, j \epsilon \{d, f\} \tag{11}$$

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:

$$\Delta TFP_{i,t} = \alpha_i + \upsilon_i(TFP_{i,t-1} - \beta_i^d S_{t-1}^d - \beta_i^f S_{t-1}^f - \lambda_i \boldsymbol{l}_t) + \gamma_i^d \Delta S_t^d + \gamma_i^f \Delta S_t^f + \gamma_i^l \Delta \boldsymbol{l}_t + \epsilon_{i,t} \tag{12}$$

$$\Delta TFP_{i,t} = \pi_{0i} + \pi_i^{ECT} TFP_{i,t-1} + \pi_i^d S_{t-1}^d + \pi_i^f S_{t-1}^f + \pi_i^l \boldsymbol{l}_t + \mu_i^d \Delta S_t^d + \mu_i^f \Delta S_t^f + \mu_i^l \Delta \boldsymbol{l}_t + \epsilon_{i,t} \tag{13}$$

β_i^d and β_i^f in Equation (12) represent the long run relationship between TFP and stocks of knowledge, 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 (13) is a reparameterisation of Equation (12), 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 use control variables like human capital (H) and trade openness (TO) 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:

$$\begin{aligned}
\Delta TFP_{i,t} = \pi_{0i} &+ \pi_i^{ECT} TFP_{i,t-1} + \pi_i^d S_{i,t-1}^d + \pi_i^f S_{i,t-1}^f + \pi_i^X X_{i,t-1} \\
&+ \mu_i^d \Delta S_{i,t}^d + \mu_i^f \Delta S_{i,t}^f + \mu_i^X \Delta X_{i,t} \\
&+ \tau_i^{\Delta TFP} \overline{\Delta TFP}_t + \tau_i^{TFP} \overline{TFP}_{t-1} + \tau_i^d \overline{S^d}_{t-1} + \tau_i^f \overline{S^f}_{t-1} \\
&+ \tau_i^X \overline{X}_{t-1} + \rho_i^d \overline{\Delta S_t^d} + \rho_i^f \overline{\Delta S_t^f} + \rho_i^{\Delta X} \overline{\Delta X}_t \\
&+ \sum_{p=0}^{P} \varphi_i^{\Delta TFP} \overline{\Delta TFP}_{t-p} + \sum_{p=1}^{P} \varphi_i^d \overline{\Delta S^d}_{t-p} \\
&+ \sum_{p=1}^{P} \varphi_i^f \overline{\Delta S^f}_{t-p} + \sum_{p=1}^{P} \varphi_i^X \overline{\Delta X}_{t-p} + \varepsilon_{i,t} \qquad (14)
\end{aligned}$$

Equation (14) 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. The model thus accounts for parameter heterogeneity. Although the CCE model accounts for parameter heterogeneity, the estimates for each individual country are derived solely from annual data, and some of these country-specific coefficients are either incorrectly signed, not statistically significant, or both. Hence, this study also accounts for heterogeneity arising out of varying distances to the technological frontier.

5.2 Non-Linear Model

The motivation for non-linearities lies in the mediating effect of import on knowledge spillovers. First, this study hypothesises an inverted U-shaped relationship between domestic knowledge stocks and productivity, justified using the escaping-competition and Schumpeterian effects characterised by Aghion et al. (2005). In addition to domestic knowledge, the theory established in this study states that there may be a U-shaped relationship between foreign knowledge stocks and productivity characterised by the vintage human capital effect and early adoption effect. To test this hypothesis, this study uses an interaction of foreign knowledge stocks and the ratio of nominal imports to nominal GDP to assess non-linearities based on imports (see Equation 15).

$$TFP_{i,t} = \beta^d S^d_{i,t} + \beta^f S^f_{i,t} + \beta^{md} m_{i,t} S^d_{i,t} + \beta^{mf} m_{i,t} S^f_{i,t} + \lambda_i \boldsymbol{l}_t + u_{i,t} \tag{15}$$

Based on the Equation (15), 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. In addition to the non-linearities in the relationships, this study also uses specifications which incorporates heterogeneity using an interaction of knowledge stocks with the distance to the frontier. It also ensures robustness using human capital as a control variable. These specifications provide a holistic picture into the nature of heterogeneity and non-linearities in the spillover literature.

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. As a robustness measure, and to prove the econometric superiority of using the CCE model, this study first presents the results of DOLS model, which has been used widely in the literature that this paper follows.

6.1 Baseline 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 knowledge 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.

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 knowledge stocks. Furthermore, the magnitude of the coefficients are also 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 knowledge 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 knowledge stocks, compared to the 0.035 obtained by Coe et al. (2009). When the LP measure of foreign knowledge is used, the coefficients of both domestic and foreign knowledge stocks are lower compared to the CH specification. When the interaction terms are used (specifications (7) and (8)), foreign knowledge stocks have a negative and significant

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)

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.

Table 3 presents the results of the CCE-ECM model. Specifications (1) and (3) use the CH method of calculating foreign knowledge stocks, whereas specifications (2) and (4) use the LP method. Furthermore, specifications (1) and (2) use the knowledge stocks at levels, and specifications (3) and (4) use an interaction of the knowledge stocks with m as suggested by Coe and Helpman (1995). This study concentrates on the long-run estimates and the coefficient of the lagged error correction term to assess speed of adjustment and investigate evidence of cointegration.

In the four baseline models tested in Table 3, the error correction terms are negative and statistically significant, indicating the presence of a long-run equilibrium relationship between the variables. The results find that except for specification (1), all estimates have magnitudes very similar to Coe et al. (2009); however, they are not statistically significant, except for stock of domestic knowledge in specification (2). These results can also be compared to the DOLS model presented in Table 2. Although the magnitude of the coefficients are very similar in the DOLS and the CCE approaches, the coefficients lose their statistical significance in the latter. Hence, accounting for problems related to cross-sectional dependency is critical in arriving

Table 3: CCE-ECM Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔLnS^{d}	0.238**	0.276**	0.093	0.100	0.239**	0.336**	0.164	0.190
	(0.115)	(0.124)	(0.108)	(0.109)	(0.124)	(0.133)	(0.105)	(0.143)
$\Delta LnS^{f:ch}$	-0.029				-0.041			
	(0.076)				(0.093)			
$\Delta LnS^{f:lp}$		0.044***				0.038**		
		(0.015)				(0.018)		
$\Delta mLnS^{f:ch}$			-0.094**				-0.093*	
			(0.047)				(0.055)	
$\Delta mLnS^{f:lp}$				-0.016				-0.028
				(0.019)				(0.019)
ECT_{t-1}	-0.611***	-0.479***	-0.470***	-0.523***	-0.831***	-0.665***	-0.696***	-0.703***
	(0.055)	(3.326)	(-3.411)	(-3.691)	(-4.571)	(3.326)	(-4.016)	(-4.415)
LnS^{d}	0.008	0.136***	0.061	0.057	-0.155	0.102*	0.087	0.078*
	(0.069)	(0.042)	(0.078)	(0.052)	(0.107)	(0.056)	(0.056)	(0.041)
$LnS^{f:ch}$	-0.099				-0.150			
	(0.167)				(0.277)			
$LnS^{f:lp}$		0.023				0.031		
		(0.029)				(0.023)		
$mLnS^{f:ch}$			0.172				-0.006	
			(0.192)				(0.151)	
$mLnS^{f:lp}$				0.079				-0.001
				(0.082)				(0.092)
LnH					-0.987	0.774	1.035	1.619
					(1.357)	(0.726)	(1.054)	(1.218)
Obs.	1058	1058	1058	1058	1058	1058	1058	1058
CD	-0.08	-2.31	-2.23	-1.93	-1.20	-1.62	-1.91	-1.80
RMSE								

*Results of CCE-ECM regressions. Standard errors are reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels respectively.*

at appropriate statistical inferences.

Table 3 also presents results of the model including human capital (specifications (5) to (8)) as a control variables. When human capital is taken as a control, the long-run coefficients give mixed results. When the CH measure of foreign knowledge is used, the long-run coefficients of domestic knowledge, foreign knowledge, and human capital are all negative and statistically insignificant, which is counterintuitive with respect to the existing literature. However, for the specification (6) which uses the LP method, the magnitude and signs of the coefficients of domestic knowledge, foreign knowledge, and human capital are as expected. When foreign knowledge stocks are interacted with m, the long-run coefficients turn negative, but still statistically insignificant. Although there is sufficient evidence of cointegrating relationships, the empirical results with human capital are not in line with empirical literature following Coe and Helpman (1995) and Coe et al. (2009), or the coefficients in the DOLS model presented in Table 2.

The findings have two major implications on the present R&D led growth literature. Firstly, it suggest that the CH and LP models widely used in the literature may be significantly misspecified due to strong cross-sectional dependence of residuals. Consequently, the standard literature in this field, which has largely relied on these frameworks, may have drawn conclusions based on biased and inconsistent estimates of domestic and foreign R&D variables. This potential bias, likely arising from unobserved common shocks, implies that established findings might not be reliable for assessing appropriate economic policy measures on R&D adoption. This is a crucial finding as it challenges the prevailing assumption in the literature on international R&D spillovers that knowledge spillovers and other types of spillovers can be easily separated within a CH or LP framework. It demonstrates that common shocks and spillovers of unknown forms significantly impact the returns to domestic R&D and international knowledge spillovers, which is vital for informing economic policy measures. Moreover, this conclusion holds when estimating dynamic panel data models that account for potential feedback effects, lagged values of covariates, and unobserved common effects.

Secondly, the results indicate that the non-separability of knowledge spillovers from unobserved spillovers and other common effects is quite pronounced, and that ignoring common shocks would result in misleading results. Unobserved local spillovers and other effects may play a more significant role in determining the productivity of these economies compared to international R&D spillovers alone. Furthermore, the dynamic panel data estimates reveal that the rigid foreign R&D weighted variables defined by CH and LP fail to account for all the cross-sectional dependence present in the data. The traditional literature typically assumes that this dependence arises solely from international knowledge spillovers. These findings provide an alternative perspective on the analysis of international R&D spillovers, considering effects of unknown forms that could influence the dynamics of global productivity and R&D investment.

6.1.1 Heterogeneity

A central feature of this paper is that it attempts to understand how distance to the technological frontier affects coefficients with respect to domestic and foreign knowledge stocks. Hence, this study exploits the country-specific long-run coefficients of the dynamic CCE-ECM model (specifications (1) and (2) in Table 3). The country specific parameters are plotted against the average distance from frontier. This stylistic view enables the reader to understand the relationship between spillover coefficients and distance to frontier.

Figure 4 shows that as the distance from the technological frontier decreases, coefficients for both domestic and foreign knowledge stocks appear to increase. However, upon viewing the figures closely, the slopes do not appear to be very significant and seem to be skewed due to the presence of outliers. While it is clear that there are cross-country differences in how domestic and foreign knowledge stocks affect productivity, such an analysis does not shed light on heterogeneity within countries. Eberhardt and Presbitero (2015) use a similar stylistic analysis to understand non-linearities in their regression specification, and arrive at similar conclusions. However, this study uses these stylised facts as motivation for the presence of within and cross-country heterogeneity, and therefore uses an the interaction of knowledge stocks with a variable representing distance to the knowledge frontier in the subsequent subsection.

Figure 4: Heterogeneity in Spillover Coefficients

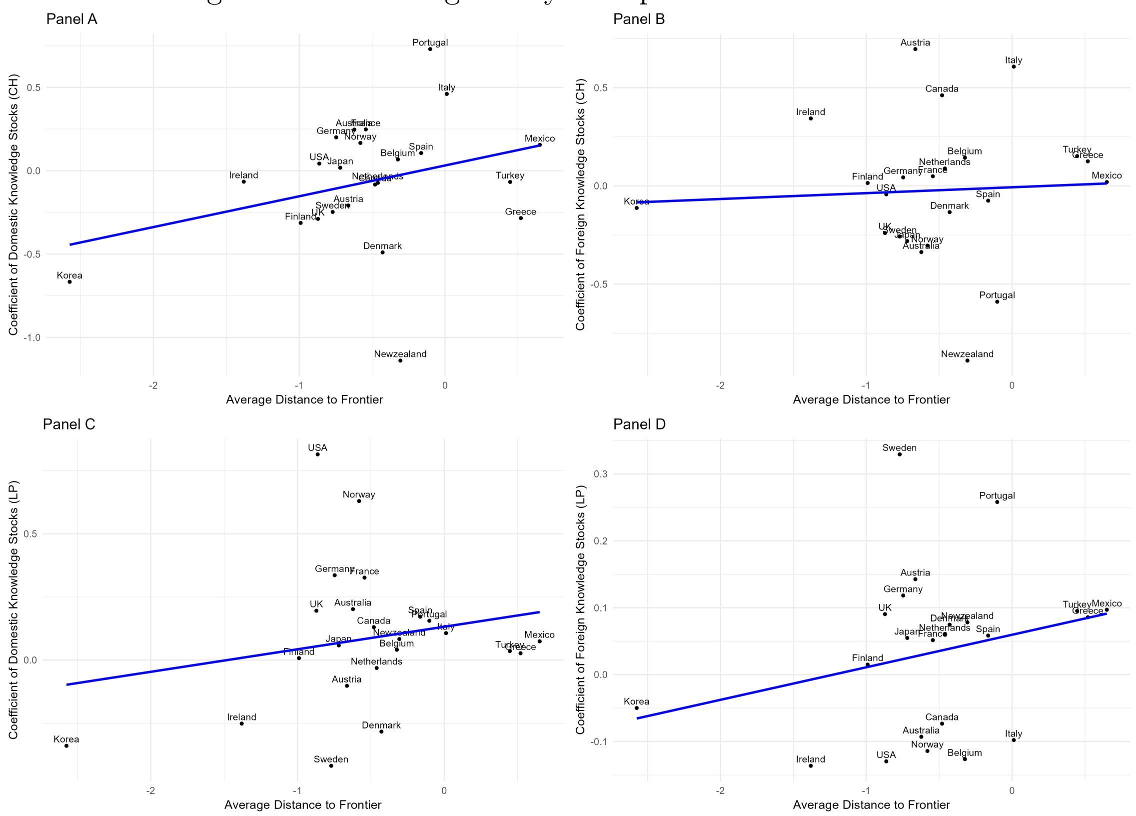

Figure Notes: Panel A and Panel B uses the long-run coefficient for domestic knowledge stocks bilateral import weighted knowledge stocks (Coe and Helpman, 1995) in Model (1) of Table **??**. *Panel C and Panel D shows the plots for the domestic knowledge stocks and Lichtenberg and Van Pottelsberghe De La Potterie (1998) knowledge stocks as in Model (2) of Table* **??**

6.2 Non-Linearities

The regression results of the baseline model, and the model accounting for heterogeneity, like many other papers, yield negative and statistically insignificant coefficients for the elasticity of both domestic and foreign knowledge 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). However, the possibility of negative values for spillover coefficients is motivated using the vintage human capital effect (Chari and Hopenhayn, 1991; Jovanovic and Nyarko, 1996) and the early adoption effect (Baldwin, 1992). The hypothesis tested in this section is that higher imports would lead to lower knowledge spillovers, due to the flooding of domestic markets with foreign inputs and lower motivation to gain knowledge from imported inputs. Furthermore, imports may also eventually reduce the coefficient of domestic knowledge stocks through the escaping-competition and Schumpeterian effect (Aghion et al., 2005). These models empirically test this hypothesis in Table 7.

Table 7 reveals findings for the models that incorporate the non-linear model through the import interaction term. In columns (1) to (4), the model uses specifications that do no use the interactions for distance to frontier, and columns (5) to (8) show the results for specifications with the DTF interaction. Out of the first four models, only model (1) shows evidence that corresponds to the theory. The negative and statistically significant coefficient of $m * LnS^d$, and the positive, albeit insignificant coefficient of LnS^d are evidence for the escaping competition and Schumpeterian effects as in Aghion et al. (2005). However, for the non-linear relationships with foreign knowledge stocks, there appears to be no significant non-linear effects mediated by imports.

In specifications (5) to (8), there is still robust evidence of the coefficients of domestic and foreign knowledge stocks to diminish as countries move closer to the cutting-edge frontier. However, the for

Table 4: Results for Non-Linear Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnS^{d}	0.108*	-0.001	0.101	0.018	-0.003	-0.009	0.011	0.004
	(0.062)	(0.041)	(0.064)	(0.047)	(0.032)	(0.026)	(0.032)	(0.022)
$m * LnS^{d}$	-0.356	0.017	-0.138	0.070	0.010	-0.011	0.092	0.067
	(0.246)	(0.193)	(0.268)	(0.149)	(0.139)	(0.073)	(0.145)	(0.088)
$LnS^{f:ch}$	-0.248***		-0.142***		-0.077*		-0.047	
	(0.081)		(0.067)		(0.040)		(0.036)	
$m * LnS^{f:ch}$	0.631*		0.316		0.031		-0.064	
	(0.359)		(0.378)		(0.212)		(0.204)	
$LnS^{f:lp}$		0.075***		0.075***		0.003		0.005
		(0.020)		(0.022)		(0.015)		(0.013)
$m * LnS^{f:lp}$		-0.050		-0.055		0.042		0.004
		(0.120)		(0.077)		(0.042)		(0.061)
LnH			-0.164	0.805			-0.586	-0.062
			(1.194)	(0.779)			(0.817)	(0.640)
$DTF * LnS^{d}$					-0.028	-0.053***	-0.037**	-0.052**
					(0.018)	(0.010)	(0.015)	(0.009)
$DTF * LnS^{f:ch}$					-0.056***		-0.049**	
					(0.028)		(0.022)	
$DTF * LnS^{f:lp}$						-0.013***		-0.011
						(0.004)		(0.004)
N	1127	1127	1127	1127	1127	1127	1127	1127
CD	-1.54	-2.51	-3.15	-2.81	-0.18	-1.44	0.51	-0.74

*Results of CCE-ECM regressions. Standard errors are reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels respectively.*

foreign knowledge stocks, these findings are not robust. The equations that use the LP measure for foreign knowledge stocks ((6) and (8)), there is evidence of an inverted U-shaped relationship. Particularly, in specification (8), the findings for both domestic and foreign knowledge stocks in terms on non-linearities violate the theoretical predictions. The coefficient for domestic knowledge stocks shows an inverted U-shaped relationship i.e. more imports enable greater coefficients form domestic R&D. The possible reason for this result is that the escape-competition effect is greater than the Schumpeterian effect irresepctive of the volume of imports. In addition to this, one may speculate that the vintage human capital effect trumps the early adoption effect irrespective of import levels. However, in model (8), the coefficient for the interaction fo foriegn knowledge stocks with *DTF* turns positive, but is not statistically significant. In comparison, column (6) shows that there is no significant nonlinear effect, but the *DTF* interaction term is negative and statistically significant for both domestic and foreign knowledge stocks.

7 Conclusion

This paper investigates the presence of international knowledge spillovers in productivity growth, 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 conducted in the are ignore econometric problems arising from cross-sectional dependency, which lead to 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 domestic and foreign knowledge stocks. Short-run coefficients are significant in only a few specifications, and are therefore not robust. The elasticity for foreign knowledge stocks turns positive and statistically significant only when the specification controls for trade-openness and uses an import interaction term.

Second, it studies heterogeneity in spillover coefficients by using an interaction with distance to frontier calculates using proximity to the most productive country. There is conclusive evidence that as the country moves closer to the knowledge frontier, productivity returns to both domestic and foreign knowledge stocks decline. However, there are still some unexplained negative coefficients for knowledge stocks, which can be theoretically justified using the escaping-competition and Schumpeterian effects for domestic knowledge, and vintage human capital and early-adoption effects for foreign knowledge.

Therefore, 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 distance to knowledge frontier. There is mixed evidence of the nature of non-linearities in different specifications tested. The findings are therefore not robust, and it is very difficult to formally comment on the nature of non-linearities in spillovers.

In conclusion, this paper attempts to bring a methodological and theoretical improvement in the literature on international knowledge spillovers. However, the findings of the baseline model is not consistent with the broader empirical growth literature on the subject. Furthermore, it finds that although distance to the knowledge frontier plays an important role which explains why some developing countries benefit more than developed countries, it fails to empirically establish the presence of non-linearities that have been justified using the theoretical 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. Future research could benefit from controlling for institutional factors, as suggested by Coe et al. (2009), in understanding heterogeneity in spillovers by using modern econometric tools.

References

Abramovitz, M. (1986). Catching up, forging ahead, and falling behind. *The Journal of Economic History*, 46.

Acemoglu, D., Aghion, P., and Zilibotti, F. (2006). Distance to frontier, selection, and economic growth. *Journal of the European Economic Association*, 4:37–74.

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.

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.

Barro, R. J. and Sala-i-Martin, X. (1997). Technological diffusion, convergence, and growth. *Journal of Economic Growth*, 2.

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.

Comin, D. and Hobijn, B. (2004). Cross-country technology adoption: Making the theories face the facts. *Journal of Monetary Economics*, 51.

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.

Fagerberg, J. (1994). Technology and international differences in growth rates. *Journal of Economic Literature*, 32.

Falvey, R., Foster, N., and Greenaway, D. (2004). Imports, exports, knowledge spillovers and growth. *Economics Letters*, 85:209–213.

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.

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.

Jovanovic, B. and Nyarko, Y. (1996). Learning by doing and the choice of technology. *Econometrica*, 64.

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.

Miller, S. M. and Upadhyay, M. P. (2000). The effects of openness, trade orientation, and human capital on total factor productivity. *Journal of Development Economics*, 63:399–423.

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. 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.

Verspagen, B. (1991). A new empirical approach to catching up or falling behind. *Structural Change and Economic Dynamics*, 2.

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 5: 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 6.

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.

Table 6: 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**
$LnTO$	78.11***	-2.210**	-5.348***

*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.*

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:

$$TFP_{i,t} = \beta^{d} S^{d}_{i,t} + \beta^{f} S^{f}_{i,t} + \beta^{X} X_{i,t} + u_{i,t} \tag{16}$$

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

Table 7: 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
$TFP, S^d, S^{f:ch}, TO$	-3.335***	-7.647	-10.582***	-6.974**
$TFP, S^d, S^{f:lp}, TO$	-2.530***	-6.446	-8.545**	-4.603
$TFP, S^d, mS^{f:ch}, TO$	-2.048*	-6.042	-8.425*	-4.706
$TFP, S^d, mS^{f:lp}, TO$	-2.077**	-5.962	-8.292*	-4.920

*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.*

7. For robustness, the results of Pedroni (2004) cointegration is presented in Table 8. The tests provide ample evidence of there being a cointegrating relationship between the variables.

Table 8: 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
$TFP, S^d, S^{f:ch}, TO$	0.310	-0.353	-0.266	2.181**	1.022	0.581
$TFP, S^d, S^{f:lp}, TO$	1.88*	0.967	0.827	3.169***	1.786*	0.261
$TFP, S^d, mS^{f:ch}, TO$	1.356	0.136	-0.064	2.582***	1.028	-0.310
$TFP, S^d, mS^{f:lp}, TO$	1.304	0.218	0.067	2.453**	0.963	-0.086