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TECHNOLOGY DIFFUSION TOWARDS EMERGING MARKETS: A COMPARATIVE PANEL DATA ANALYSIS

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TEKNOLOJİNİN GELİŞMEKTE OLAN ÜLKELERE DİFÜZYONU: BİR KARŞILAŞTIRMALI PANEL VERİ ANALİZİ

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Abstract

This study aims to reveal how absorbable foreign direct investment (FDI) and macroeconomic performance affect technology diffusion along with patent applications, imports and human capital in 14 selected emerging markets (EMs) between 1980-2017. To do this, a new approach for indexing macroeconomic performance is suggested and a strongly balanced panel was investigated with two different econometric approaches. Key findings are as follows: (i) suggested macroeconomic performance index performs well under pooled mean group and dynamic common correlated effects estimations and proves the importance of macroeconomic outlook for developing countries, (ii) the positive effect of human capital on total factor productivity turns to negative when common factors are included in the estimation, meaning that international technology spillovers are a key source of productivity increases for developing countries.

Keywords: *Technology diffusion, emerging markets, productivity, pooled mean group, dynamic common correlated effects.*

Öz

Bu çalışma, patent başvuruları, ithalat ve beşerî sermayenin yanında absorbe edilebilir doğrudan yabancı yatırımlar (DYY) ve makroekonomik performans verilerini de dikkate alarak seçilmiş 14 gelişmekte olan ülke için 1980-2017 döneminde teknoloji difüzyonunu incelemektedir. Bu amaç bağlamında makroekonomik performansı endekslemeye yönelik farklı bir yaklaşım önerilmiş ve dengeli bir panel veri seti üzerinde iki ayrı ekonometrik yaklaşım ile çalışılmıştır. Elde edilen bulgular şunlardır: (i) önerilen makroekonomik performans indeksi karma ortalama grup ve dinamik ortak korelasyonlu etkiler tahminlemeleri kapsamında iyi performans sergilemiş ve makroekonomik görünümün gelişen ülkeler için önemini ortaya koymuştur, (ii) beşerî sermayenin toplam faktör verimliliği üzerindeki pozitif etkisi ortak faktörlerin analize dahil edilmesiyle negatife dönmektedir. Bunun anlamı, uluslararası teknoloji yayılımı etkilerinin gelişmekte olan ülkeler için anahtar verimlilik kaynaklarından biri olduğudur.

***Anahtar Kelimeler**: Teknoloji difüzyonu, gelişmekte olan ülkeler, verimlilik, karma ortalama grup, dinamik ortak korelasyonlu etkiler.*

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GENİŞLETİLMİŞ ÖZET

Teknoloji difüzyonu gelişmekte olan ülkelerde verimlilik büyümesinin önemli kaynaklarından biridir. Literatür konuya ilişkin olarak temelde doğrudan yabancı yatırımlar, ticaret ve beşerî sermaye kavramlarına odaklanmış olmakla birlikte başka birtakım değişkenler de belirleyici olarak gösterilmektedir. Bu aşamada özellikle gelişmekte olan ülkelerde yabancı finansal yatırımlar/sermaye yatırımları açısından makroekonomik değişkenlere ilişkin trendin önemi açıktır. Öte yandan, uluslararası teknoloji ve bilgi yayılımlarının gelişmekte olan ülkelerce daha iyi değerlendirilebilmesi bakımından ülkelerin bilinen en ileri teknolojiyi kullanan ülkelere olan uzaklığı da belirleyicidir.

Bu çalışmada teknoloji difüzyonunu temsil etmek üzere kullanılan toplam faktör verimliliğini belirlediği varsayılan beşerî sermaye, ticaret ve yerel Ar-Ge çalışmalarının sonucu niteliğinde patent verilerine ek olarak, en ileri teknolojili ülkeye uzaklığa bağlı olarak hesaplanmış bir efektif doğrudan yabancı yatırımlar verisi ile genel makroekonomik görünüme ilişkin bilgi sağlayan bir makroekonomik performans endeksi kullanılmıştır. 14 ülkeye ilişkin olarak 1980-2017 arası 38 yıllık dönemi kapsayan dengeli panel veri seti hem ülkeler arasındaki ortak etkileri göz ardı ederek hem de bu etkileri analize dahil ederek (birinci ve ikinci kuşak tahmin yöntemleri ile) tahminlenmiştir.

Elde edilen sonuçlar ortak etkilerin göz ardı edildiği koşulda tüm açıklayıcı değişkenlerin anlamlı ve beklenen yönde değer vermesi şeklinde olmasına karşın ortak etkilerin dahil edilmesi ile birlikte anlamlılığını koruyan açıklayıcı değişkenler yalnızca beşerî sermaye ve makroekonomik performans endeksi olmuştur. Ancak ortak etkilerin analize dahil edilmesiyle beşerî sermayeye ilişkin tahminlenen katsayı negatife dönmüştür.

Makroekonomik performans endeksinin hem ortak etkileri dışlayan hem de ortak etkileri analize dahil eden modellemelerde anlamlılığını ve yönünü koruması, endeksin gelişmekte olan ülkeler açısından başarılı bir gösterge olarak kullanılabileceğini göstermiştir. Öte yandan, beşerî sermaye endeksinin ortak etkilerin analize dahil edilmesi sonrası negatife dönmesi, incelenen ülkelerin tamamını etkileyen ve büyük oranda uluslararası teknoloji yayılımlarından kaynaklandığı öne sürülebilecek etkilerin ayrıştırılması sonucunda yerel beşerî sermaye endeksi bileşenlerinin (eğitim yılı sayısı ve eğitimin getirisi) toplam faktör verimliliği üzerinde olumsuz etki yarattığını ortaya koymuştur. Diğer bir ifadeyle, uluslararası teknoloji yayılımları incelenen ülkeler açısından önemli ve iyi değerlendirilmesi gereken bir kaynak olarak görünmektedir.

1. INTRODUCTION

The diffusion of technology has been an important topic in macroeconomics and is seen as an important source of long-run growth, particularly in emerging markets. The main reason for this may be the inadequacy in the emerging markets regarding the production of goods and services with high added-value and performance losses due to the utilization of relatively obsolete production techniques. Assuming that the conditions would improve with the diffusion of higher levels of technology, the search for the determinants of mentioned diffusion seems more important than ever. According to Andrews et al. (2016) the insufficient diffusion of technologies is one of the main reasons behind the lean productivity increase seen in the last two decades.

Postulating the basic idea of higher levels of technology primarily diffuses from developed countries to the underdeveloped, main carriers of technology are thought to be foreign direct investment (FDI), trade and human capital. However local R&D efforts are also accepted as important sources of technology diffusion due to the assumption of those efforts would help assimilate new technologies and even create others. Additionally, overall macroeconomic conditions are also important for underdeveloped countries considering the fact that macroeconomic stability affects much needed capital flow towards those countries and it directly shapes expectations for investments.

This study aims to find out how and at what magnitude FDI, trade, macroeconomic performance, local R&D efforts and human capital correlate with total factor productivity in selected emerging countries. In order to do that, a new approach for inclusion of effective FDI and a new type of macroeconomic performance index are employed in the empirical framework.

2. LITERATURE

The literature on the technology diffusion has focused on both tangible carriers (such as produced goods, which constitute embodied technical progress) and intangible carriers (such as skills, know-how, learning-by-doing, which are disembodied technical progress). In this context it is of high importance to account for the internal sources of technology diffusion that increase the ability to absorb new techniques and the possibility to create them in the first place.

The absorptive capacity of destination countries in the context of technology diffusion is a key variable for the diffusion analysis (Driffield and Henry, 2007). A key factor for increasing the absorptive capacity is human capital (Nelson and Phelps, 1966; Cohen and Levinthal, 1989; Engelbrecht, 2002 and Kneller, 2005) but it may come with some problems due to country specific effects (Islam, 1995) or the problems in measurement quality (Griliches, 1998 and Krueger and Lindahl, 1999). Though, the inclusion of a well-specified absorption index or barrier effect is crucial (Parente and Prescott, 1994).

The foreign direct investment (FDI) has been a great source of international technology diffusion (Accolley, 2003) and it still plays a key role in technology diffusion through multinational firms (Geng and Saggi, 2019). As Johnson (2006) and Sarkar (2007) state, the expected effects of FDI are realized only if a country enjoys (i) a certain level of absorptive capacity, (ii) an adequately developed financial system and (iii) a threshold level of education. Thus, an FDI-based index similar to Baltabaev's (2014) for measuring the effective or absorbable level of FDI seems rational.

Trade but more specifically imports, regarding the underdeveloped countries, has also been seen as a key source of technology diffusion. Grossman and Helpman (1990), Keller (2000), Mayer (2001), Hoekman et al. (2005), Teixeira and Fortuna (2010) are among those who employ trade and/or imports as a determinant of technology diffusion. Exports may also be seen as a source of technology diffusion on the grounds of the idea that exporting firms learn new skills and abilities from their counterparts in other countries and then start a self-improvement process internally (Clerides et al. 1998; Bernard and Jensen, 1999 and Hallward-Dremier et al. 2005). Despite the fact that it is a fairly reasonable idea, the import dependence of intermediate goods in underdeveloped countries makes the inclusion of export variable(s) as a determinant of technology diffusion may well end up with significant disturbance in an analysis since at what extent the export goods are produced in a country is not clearly distinguishable. An example of this was shown by Srholec (2007). Ferrier et al. (2016) showed that network effects generated by trade are crucial for technology diffusion and that countries with a stronger connection to the network tend to have higher technology intensity.

Local research and development (R&D) efforts are another important determinant for technology diffusion (Coe and Helpman, 1995 and Lichtenberg and van Pottelsberghe, 1996). R&D stock is also important for technology diffusion (Yildirim, 2013). Patents are realized results of R&D efforts and important sources for firms to increase their market value (Griliches, 1981; Hall et al. 2005) while being proxies for measuring knowledge flows (Almeida and Kogut, 1999; Alcacer and Gittelman, 2006) despite the downside in measuring the quality and/or the heterogeneity of patent registrations. It is possible to overcome the downside by introducing quality measures such as renewal fees (Pakes, 1986; Bessen, 2006) or a patent classification such as IPC of World Intellectual Property Organization, yet there are restrictions in terms of data, especially for underdeveloped countries and for longer time periods. Ertur and Musolesi (2016) found that while richer countries make a better use of local R&D; smaller countries benefit more from the spillovers stemming from trade. That is, smaller countries tend to make more use of embodied technologies. As it might be expected, they also found that the quantity of education is not anymore able to create significant effect on technology diffusion.

As for emerging markets, macroeconomic stability and long-run growth performance is an important issue. This is shown -maybe the best- by Bleaney (1996) among others. According to the World Bank (1993); the macroeconomic stability had been one of the "*two key elements in starting the virtuous circles of high rates of accumulation, efficient allocation and strong productivity growth that formed the basis for East Asia's success*".

Human capital is clearly an important issue regarding productivity (Benhabib and Spiegel, 2005). However, the exact effect of human capital is yet to be found due to inefficiency in current types of human capital indices. The expected effect of human capital is always positive and significant. But the literature seems to be far from consensus on the net effect and the magnitude. Kim and Park (2018) and Habib et al. (2019) found the effect of human capital on productivity consistently positive. Mannasoo et al. (2018) reported that countries that fall further behind the technology frontier tend to benefit less from human capital. Powerful measurement techniques for human capital seem to increase the magnitude of the effect. As Pietrzak and Balcerzak (2016) pointed out, quality of human capital is of a significant influence for developing countries and is more consistent in terms of measurement quality.

Various researchers chose total factor productivity (TFP) as a proxy for technology diffusion and long-run economic growth. Some of them investigated the determinants of TFP including Lee and Hong (2010); Shackelton (2013) and Kim and Park (2018). But in terms of relevancy to this study, current literature for the relation between TFP and trade openness (Yaoxing (2010) and McNeil (2014)), FDI (Bijsterbosch and Kolasa (2010) and Amann and Virmani (2015)) and R&D (Tintin, (2012), Edquist and Henrekson (2017) and Lopez-Rodriguez and Martinez-Lopez (2017)) are worth noting.

3. VARIABLES AND METHODOLOGY

The empirical framework in this study aims to explain technology diffusion through proxies for absorptive capacity, macroeconomic stability, R&D efforts, trade and human capital. The analysis combines those series for 14 emerging markets, namely Argentina, Brazil, Chile, Greece, India, Indonesia, South Korea, Malaysia, Mexico, Portugal, Spain, Thailand, Turkey and South Africa for the time period of 1980-2017, creating a strongly balanced panel. There is a total of 14 observation gaps in the data, due to a calculation of growth rate causing first observations of the same series to be lost in all the countries.

3.1. Dependent Variable

Total factor productivity (TFP) is a widely used proxy for technology diffusion and considering the possible labor-hoarding, it seems to be a more consistent and robust substitute than labour productivity for underdeveloped countries. The related series were obtained from Penn World Table 9.1 (PWT) (see Feenstra et al. 2015) as welfare-relevant levels at current purchasing power parities (USA=1).

3.2. Independent Variables

The absorptive capacity is an important determinant for underdeveloped countries, so is FDI. It seems rational to expect the utilizable positive effects of FDI to strictly depend on a country's potential to adopt new technologies. The measurement for this potential can be done by specifying the distance of a country from the technological frontier. PWT has calculated values for individual TFP levels of countries, holding the USA's level at constant 1. By subtracting each country's level of TFP from 1, the absolute distance to the technological frontier was calculated. Here, a counterargument for using absolute distance may well be the utilization of relative distance by dividing 1 by a country's TFP level but the problem here would be the high correlation between the absorptive capacity and the dependent variable. Thus, it seemed reasonable to employ absolute distances rather than relative ones, especially considering that TFP values were already indices after all. Following that decision, the logarithmic values of absolute distances were multiplied by total FDI/GDP ratios of each country. This approach made it possible to include the distance to technological frontier in the analysis while expanding the effective impact of FDI. At the end, the formula for effective FDI became $\left[log(1-TFP_{it})\,.\,{}^{FDI_{it}}/_{GDP_{it}}\right]$. TFP values were obtained from PWT and FDI data were gathered from World Bank databank (World Bank, 2020) as the total percentage value of net inflows (as a proxy of foreign investment) and net outflows (as a proxy of technology sourcing).

The study also utilizes a new perspective for macroeconomic outlook, similar to the one that Ekren et al. (2017) suggested. Macroeconomic stability is an important issue stated in the related literature and there are indices combining macroeconomic variables to provide a snapshot of macroeconomic situation in a country. Presumably, the best known of them is Barro Misery Index (BMI). However, such indices for aggregated macroeconomic variables have been argued to be defective due to repeated inclusion of inflation. Additionally, such indices rely on data that make it harder or even prevent calculation of the indices for earlier times. In this study, a similar type of index was utilized through a slightly different perspective. PWT includes both employment and population levels, which of course are important for long-run productivity and economic growth. $\left({}^{Employment}/_{Population}\right)$ gives an employment ratio in an economy, which of course is different from the concept *employment ratio* as economists use it, yet it provides information on *dependent population* as it is especially an important issue for underdeveloped countries. Basically, the lack of a standardized unemployment rates for the 14 countries concerning the time period prevents the utilization of actual employment rate but it creates the opportunity to implicitly include the effect of population growth and dependent population ratio within one variable. In that sense, using the growth form of calculated employment ratio, GDP growth rate (also from PWT) and inflation rate (as GDP deflator), (World Bank, 2020) the following *macroeconomic performance index* was calculated:

$$MPI = Employment\ Ratio\ Growth\ Rate + GDP\ Growth\ Rate - Inflation\ Rate$$

In contrast to BMI or other types of misery indices, the suggested index measures stability or prosperity rather than measuring misery while tackling the problem of repeated count for inflation and excluding interest rates as there are no proven significant effects of them on technology diffusion in the long-run. Hence, the direction of a coefficient for MPI is expected to be positive.

In terms of R&D efforts, patents count data were employed as a sum of both sources, residents and non-residents. Patents data are useful due to the fact that patentable techniques feature at least a base level of qualification due to prerequisites for patent applications. Bearing in mind that not all the efforts for R&D are effective, it becomes clearer that patents are realized R&D efforts and inclusion of them in an analysis may increase the potential to derive information from data. The inclusion of patents as realized R&D efforts creates the opportunity of dealing with systematically compiled and standardized -solid- data, however this comes with two costs. The first one is that the largest part of the effect created by a whole patent group actually stems from just a small party of those patents and secondly, not all the knowledge stock is systematically compiled (Acs and Audretsch, 1989; Keller, 2010).

Maybe the most important variable for explaining technology diffusion in short-run is trade and more specifically, imports. The countries that are in the need of new technologies are assumed to be underdeveloped countries and the most rapid way of the diffusion is via materialized goods that carry the embodied technical change. However, services are at least as important considering the fact that not all the technical change are embodied. On the other hand, the proportion of imports in a country's GDP is also important as it provides insight on the country's level of openness. As a result, total imports as a percentage of GDP data (World Bank, 2020) were employed in the analysis.

Lastly, human capital is of high importance for both absorption and creation of new technologies. To be able to obtain reliable results and do comparisons between countries and/or different time periods, utilization of a standardized type of human capital data is crucial. A more efficient way of measuring human capital for underdeveloped countries would arguably include proxies regarding know-how and experience, yet these are not applicable options considering the time period. Thus, the data for human capital were obtained from PWT, which calculates the index on the grounds of years of schooling and returns to education. However, it should be expounded that a customized version of human capital measurement regarding underdeveloped countries would yield in significantly higher estimated coefficients.

3.3. Model Specification

Descriptive statistics showed that the original series had enough standard deviation to derive information. Those are given in Table 1.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min.	Max.
TFP	532	.649029	.2045823	.2606513	1.212558
Effective FDI	532	4.263542	4.543766	-8.726349	26.02516
MPI*	518	-43.67953	255.4553	-3053.834	14.97354
Patents	532	12490.13	31446.59	0	213694
Imports	532	29.11452	17.45623	4.631322	100.5971
Human Capital	532	2.355738	.4647264	1.284942	3.694501

* 14 observation gaps due to growth rate calculation

The series were checked for multicollinearity and the base model to be estimated was designed as the following:

$$lnTFP = c + \beta_1 EffectiveFDI + \beta_2 MPI + \beta_3 lnPatents + \beta_4 Imports + \beta_5 HC + \mathcal{E}_t$$

The indices for effective FDI and MPI were not included as logarithm due to negative values. Similarly, imports and human capital were also not included as logarithms due to the former being percentages and the latter being an index itself. After model specification, the cross-sectional dependency was investigated and the test results according to Pesaran (2004) revealed that there are cross-sectional dependencies in the panel. Thus, the second-generation unit root test of Pesaran (2007) 's CADF was employed in the analysis. Test results for unit roots uncovered that the dependent variable is difference stationary whereas independent variables are a combination of I(0) and I(1). The results for CD test and unit root tests are given in Table 2.

Table 2: Test Results for Cross-Sectional Dependency and Unit Roots

	Cross-Sectional Dependency		**Unit Root Test Results (Pesaran's CADF)**				
Variable	**CD-Test**	**Prob.**		**t-bar**	**Z(t-bar)**	**Prob.**	**Decision**
TFP	3.10	.002	Level	-1.593	.706	.760	I(1)
			1st Diff.	-3.644	-7.461	.000	
Effective FDI	16.71	.000	Level	-2.923	-4.590	.000	I(0)
MPI	10.39	.000	Level	-2.872	-4.386	.000	I(0)
Patents	12.17	.000	Level	-2.022	-1.002	.158	I(1)
			1st Diff.	-4.070	-9.156	.000	
Imports	34.11	.000	Level	-2.294	-2.086	.019	I(0)
Human Capital	56.77	.000	Level	-2.464	-2.762	.003	I(0)

The condition of cross-sectional dependency point pointed out the fact that within the concept of this study, shocks occurred in one of the countries in hand have eventually spread to the others due to either a high rate of integration or globalization. Also, it required the utilization of a second-generation test for cointegration, namely the bootstrap cointegration test suggested by Westerlund and Edgerton (2007), which is shown to provide much more consistent results under cross-sectional dependency. The test results are in Table 3.

Table 3: Bootstrap Test for Cointegration

Test	Value	p-Value	Robust p-Value*
G_T	-2.373	.261	.010
G_a	-4.805	1.000	.620
p_T	-7.219	.442	.040
p_a	-4.333	.959	.160

*Consistent p-values in the presence of common factors in the time series.
100 repeats of bootstrap.

The bootstrap test for cointegration rejected the null hypothesis of no cointegration using the specified appropriate lag length of 1, except for G_a and p_a. At that point, the combination of I(0) and I(1) variables had an implicit deduction towards the utilization of panel ARDL methods, nevertheless for the sake of robustness, also the first generation cointegration tests of Kao (1999), Pedroni (1997) and Westerlund (2007) were performed. All of the tests showed that there is cointegration in the panel. The results with regard to those tests are given in Table 4.

Table 4: Results for First Generation Cointegration Tests

Test Type		Statistic	Prob.
Kao	Modified DF t	-3.0360	.0012
	DF t	-2.4887	.0064
	ADF t	-1.5742	.0577
	Unadjusted Modified DF t	-2.2763	.0114
	Unadjusted DF t	-2.1872	.0144
Pedroni	Modified PP t	3.7513	.0001
	PP t	1.3366	.0907
	ADF t	2.0884	.0184
Westerlund	Variance Ratio	3.1137	.0009

The partial contradiction between the first- and second-generation tests for cointegration raised the question of which method to use for estimation. The right decision under the no-cointegration hypothesis is the utilization of panel ARDL due to the fact that the method is superior for the models in which the regressors are a combination of I(0) and I(1) (Pesaran and Shin, 1998; also see Asteriou et al., 2020). However, in their seminal paper Westerlund and Edgerton (2007) state that most of the distortions observed in the table for rejection rates in Monte Carlo simulations regarding the bootstrap test methodology stems from serial correlation. Considering the fact that cointegration is required for the consistency of the results of DCCE estimation (Kapetanios et al. 2011; Banerjee and Carrion-I-Silvestre, 2017), the data in hand was tested for serial correlation using the techniques suggested by Born and Breitung (2016) and the results proved a strong level of serial correlation. These are represented in Table 5.

Table 5: Test Results for Serial Correlation

Variable	Q(p) Statistic	p-Value
TFP	79.30	.000
Effective FDI	9.42	.009
MPI	2.35	.308
Imports	12.16	.002
Human Capital	57.37	.000
Patents	34.33	.000

The presence of serial correlation in 5 out of 6 variables at 99% level was interpreted as a strong possibility for a *concealed* cointegration due to unmodeled serial correlation patterns (see Herwartz and Lange, 2020), which is consistent with the literature and is expected considering the variables and the length of data in hand.

Concordantly, it was decided that two types of estimation approaches for the data would be appropriate not only for taking the advantage of model comparison but also for the comparison of estimated coefficients in terms of magnitude and direction.

For a shallower panel estimation that ignores the common effects, first the tests for slope homogeneity suggested by Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013) were carried out to determine which type of panel ARDL method to be utilized. The results for both lags included and lags excluded versions exposed that the slope coefficients in the panel are not significantly different from each other, making it a homogenous panel. This is shown in the Table 6.

Table 6: Test Results for Slope Homogeneity

Test		Delta	Prob.
Lags Included	Pesaran&Yamagata	17.679	.000
		19.633 (adj.)	.000
	Blomquist&Westerlund HAC	31.745	.000
		35.255 (adj.)	.000
Lags Excluded	Pesaran&Yamagata	3.746	.000
		4.724 (adj.)	.000
	Blomquist&Westerlund HAC	-4.475	.000
		-5.644 (adj.)	.000

Pesaran and Smith (1995) suggest that as samples get smaller, the probability of heterogeneity in the panel causing a potentially serious bias increase. The considered panel in this study is not actually a short panel but also it is not significantly long. Dynamic fixed effects (DFE) or mean group (MG) type of ARDL estimations require strong homogeneity and only allow for intercepts to vary across groups. Conversely, pooled mean group (PMG) estimation requires the homogeneity condition only for the long-run and allows short-run coefficients, the adjustment rate and error variances to differ among countries. Concordantly, the final form of the model was specified in line with a PMG (ARDL 2, 1, 1, 1, 1, 1) estimation Pesaran et al. (1999) and took the following form:

$$\begin{aligned} logTFP_{it} = {} & \mu_{it} + \delta_{10i}\, EffectiveFDI_{it} + \delta_{11i}\, EffectiveFDI_{it-1} + \delta_{20i}\, MPI_{it} + \delta_{21i}\, MPI_{it-1} \\ & + \delta_{30i}\, logPatents_{it} + \delta_{31i}\, logPatents_{it-1} + \delta_{40i}\, Imports_{it} + \delta_{41i}\, Imports_{it-1} + \delta_{50i}\, HC_{it} \\ & + \delta_{51i}\, HC_{it-1} + \beta_{1i}t + \lambda_i logTFP_{it-2} + \mathcal{E}_{it} \end{aligned}$$

The corresponding error correction model was specified as the following;

$$\begin{aligned} \Delta \log TFP_{it} = {} & \emptyset_i[\log TFP_{it} - \theta_{0i} - \theta_{1i}EffectiveFDI_{it} - \theta_{2i}MPI_{it} - \theta_{3i}logPatents_{it} - \theta_{4i}logImports_{it} \\ & - \theta_{5i}HC_{it} - a_{1i}t] + \delta_{11i}\, \Delta EffectiveFDI_{it} + \delta_{21i}\, \Delta MPI_{it} + \delta_{31i}\, \Delta logPatents_{it} \\ & + \delta_{41i}\, \Delta Imports_{it} + \delta_{51i}\, \Delta HC_{it} + \varepsilon_{it} \end{aligned}$$

The estimation was done using eViews 10+ software and related lag selection was based upon Schwarz information criterion (SIC) and Hannan-Quinn information criterion (HQIC) due to their advantage in rather larger samples (Ayalew et al., 2012) and their consistency regarding the selection of the true lag lengths when working with unit root models (Tao and Yu, 2017). Both SIC and HQIC lag selection criteria gave the same results for all the variables. Yet, a robustness check was carried out using Akaike information criterion (AIC) with larger lags for all the variables but log likelihood values did not improve.

To distinguish and remove the bias of common effects, a more consistent kind of estimation technique, nasmely dynamic common correlated effects (DCCE) estimator was utilized. A common correlated effects estimator adds cross sectional averages as covariates to the mean group estimation, thus accounting for common factors among units (Pesaran, 2006; Chudik and Pesaran, 2013).

4. ESTIMATION RESULTS

The estimation for PMG model was carried out under the assumption of normally distributed residuals and post-estimation diagnostics showed that the assumption was fulfilled. The estimation results for long-run and short-run panel coefficients are given in Table 7.

Table 7: PMG Panel Estimation Results

Variable	Coefficient	t-Statistic	Prob.
Long-run Equation[a]			
Effective FDI	.007120 (.003586)	1.985359	.0478
MPI	.000146 (5.96E-05)	2.453589	.0146
Patents	-.150767 (.041700)	-3.615514	.0003
Imports	-.199614 (.072406)	-2.756862	.0061
Human Capital	.660275 (.121724)	5.424376	.0000
Short-run Equation[a]			
ECT	-.119074 (.029813)	-3.994082	.0001
TFP(-1)	.299925 (.064660)	4.638520	.0000
MPI	.001876 (.000449)	4.180427	.0000
Imports	.107004 (.045185)	2.368144	.0184

a Values with probability levels higher than .10 and constant are not included in the table.
The estimation is based on normal distribution of residuals.

The conducted estimation of specified panel data revealed that for the panel as a whole, effective FDI to be insignificant in short-run but significant and positive in the long-run. More specifically, a unit increase in calculated effective FDI index caused .007% increase in TFP. To exploit the comparison opportunity, the same model was estimated with the sum of inflow (as direct diffusion) and outflow (as technology sourcing) of FDI ratios instead of calculated effective FDI and approximately 50% increase in the coefficient for FDI (.007120 to .010654) was captured along with basically no change in other coefficients. This proved that when considered the distance to technological frontier significantly decreases the magnitude of the effect of FDI in the long-run, contrary to "*the advantage of backwardness hypothesis*". MPI was found to be significant both in short-run and in the long-run, however despite being positive in both, the coefficient was much smaller in the long-run. A unit increase in MPI index was translated into increases in TFP at .001% in the short-run and .0001% in the long-run. A percentage increase in total patents caused a .15% decrease in TFP in the long-run while being insignificant in the short-run. This backed the idea of patents preventing productivity increases due to the impediment to utilize productive techniques at a large scale when innovation is sequential (Bessen and Maskin, 2009) or to retardation effect for commercialization (Sichelman, 2010). Another explanation for this issue may be market uncertainty: Bloom and Reenen (2001) showed that until the condition of higher market uncertainty, the impact of new patents on productivity decreases dramatically. In addition, assuming that a costly investment is a prerequisite in order for new patents to create a full-scale productivity effect, one can easily argue that any obstacle that becloud finance and investment would indirectly cause a decrease in positive effects of patent applications. The estimated coefficients for imports were significant both in the short-run and in the long-run. As expected, the effect in the short-run was positive due to the fact that imports provide direct introduction of embodied technologies into economies. A percentage increase in imports as percentage of GDP caused .10 percent increase in TFP in the short-run. However, the effect was reversed in the long-run, making it a further .19 percent decrease in TFP for a percentage increase in imports. Arguably, this happened due to increasing long-run import dependence for intermediate goods. Human capital was found to be insignificant in the short-run but significant and positive in the long-run. It showed that a unit increase in human capital index would cause .66 percent increase in TFP. Lastly, the error correction rate was estimated to be 11%.

The estimation results for the specified model confirmed the cointegration while revealing only a slight heterogeneity in terms of short-run coefficients across groups which isolates 1 of 14 countries. This, once again, validated the utilization of PMG estimation, in addition to the Hausman (1978) test results, which are given in Table 8.

Table 8: Hausman Test Results

Hausman Test		
Test	**Chi-Squared**	**Prob.**
Cross-section Random	5.899076	0.3162

The test results proved the null hypothesis to be true, which is MG and PMG test results are not significantly different.

The PMG estimation allowing short-run coefficients for individual countries to differ is a valuable advantage. Those results are given in Table 9. Note that the results for India are not provided due to uninterpretable EC term.

Table 9: Cross-Section Short-Run Statistics

Argentina[a]					**Brazil[a]**			
Variable	**Coefficient**	**t-Statistic**	**Prob.**		**Variable**	**Coefficient**	**t-Statistic**	**Prob.**
ECT	-.316186 (.009921)	-31.86994	.0001		**ECT**	-.060884 (.002404)	-25.33055	.0001
Effective FDI	-.003048 (1.53E-05)	-198.7373	.0000		**TFP (-1)**	.489979 (.025906)	18.91359	.0003
MPI	1.01E-05 (4.48E-10)	22594.04	.0000		**Effective FDI**	.004802 (2.46E-05)	195.5570	.0000
Patents	.182092 (.008611)	21.14745	.0002		**MPI**	3.60E-05 (1.73E-10)	207748.8	.0000
Imports	.026614 (.003826)	6.955519	.0061		**Patents**	-.104734 (.006861)	-15.26594	.0006
Chile[a]					**Greece[a]**			
ECT	-.217435 (.001421)	-153.0277	.0000		**ECT**	-.010438 (.000916)	-11.39521	.0015
TFP (-1)	.378191 (.006758)	55.96281	.0000		**TFP (-1)**	.394342 (.023859)	16.52838	.0005
Effective FDI	-.001870 (1.28E-06)	-1462.163	.0000		**Effective FDI**	-.001794 (4.71E-05)	-38.12278	.0000
MPI	.002078 (2.97E-07)	6987.587	.0000		**MPI**	6.91E-05 (2.18E-06)	31.72261	.0001
Patents	.035862 (.000476)	75.28716	.0000		**Patents**	-.027830 (.001022)	-27.23472	.0001
					Imports	.058515 (.008824)	6.631611	.0070

Table 9 (Cont.): Cross-Section Short-Run Statistics

India[b]					**Indonesia[a]**			
ECT	.011116 (.000454)	24.50828	.0001		**ECT**	-.051968 (.001694)	-30.67162	.0001
					TFP (-1)	.475406 (.020397)	23.30816	.0002
					Effective FDI	-.000273 (9.12E-06)	-29.94199	.0001
					MPI	.001887 (4.32E-07)	4372.348	.0000
					Patents	.009166 (.000804)	11.40046	.0014
					Imports	.111163 (.005845)	19.01759	.0003
South Korea[a]					**Malaysia[a]**			
ECT	-.122139 (.004367)	-27.96677	.0001		**ECT**	-.301670 (.007461)	-40.43219	.0000
TFP (-1)	.240868 (.024398)	9.872293	.0022		**TFP (-1)**	.470035 (.013443)	34.96604	.0001
Effective FDI	-.013005 (4.68E-05)	-277.6512	.0000		**Effective FDI**	.002112 (5.05E-06)	418.0370	.0000
MPI	.004062 (5.72E-07)	7099.233	.0000		**MPI**	.004359 (1.81E-06)	2406.873	.0000
Patents	.019620 (.001431)	13.70911	.0008		**Patents**	.065473 (.000329)	198.8972	.0000
Imports	.102354 (.003681)	27.80334	.0001		**Imports**	.636652 (.023583)	26.99599	.0001
Mexico[a]					**Portugal[a]**			
ECT	-.204422 (.001724)	-118.5609	.0000		**ECT**	-.028289 (.000550)	-51.46447	.0000
TFP (-1)	.233677 (.007417)	31.50603	.0001		**TFP (-1)**	.418270 (.018510)	22.59692	.0002
Effective FDI	-.003126 (1.21E-05)	-258.2660	.0000		**Effective FDI**	-.001847 (1.53E-06)	-1209.420	.0000
MPI	.000654 (3.56E-08)	18364.89	.0000		**MPI**	.002969 (2.59E-06)	1145.501	.0000
Patents	.106416 (.000778)	136.8518	.0000		**Patents**	.007567 (.000353)	21.42598	.0002
Imports	-.102727 (.001812)	-56.70074	.0000					
Spain[a]					**Thailand[a]**			
ECT	-.004036 (.000298)	-13.53172	.0009		**ECT**	-.160178 (.003168)	-50.55341	.0000
TFP (-1)	.482474 (.021803)	22.12890	.0002		**TFP (-1)**	.435560 (.018188)	23.94762	.0002
Effective FDI	-.001083 (2.18E-06)	-496.1632	.0000		**Effective FDI**	-.002057 (9.65E-06)	-213.3075	.0000
MPI	.001402 (1.92E-06)	730.4805	.0000		**MPI**	.003661 (2.09E-06)	1749.030	.0000
Patents	-.012833 (.000765)	-16.76797	.0005		**Patents**	.008862 (.001197)	7.405425	.0051
Imports	.052456 (.004430)	11.83981	.0013		**Imports**	.158872 (.006430)	24.70780	.0001

Table 9 (Cont.): Cross-Section Short-Run Statistics

Turkey[a]					South Africa[a]			
ECT	-.177973 (.005392)	-33.00569	.0001		**ECT**	-.022528 (0.000861)	-26.15903	.0001
TFP (-1)	-.411683 (.021290)	-19.33729	.0003		**TFP (-1)**	.276015 (0.022789)	12.11200	.0012
Effective FDI	-.032387 (.000135)	-239.8632	.0000		**Effective FDI**	.004626 (7.68E-06)	602.1342	.0000
MPI	-.000440 (1.45E-07)	-3037.350	.0000		**MPI**	.001636 (1.05E-06)	1564.378	.0000
Patents	.021816 (0.001068)	-20.41969	.0003		**Patents**	.039102 (.000600)	65.17129	.0000
Imports	.188861 (0.004252)	44.42192	.0000		**Imports**	.057574 (.003348)	17.19869	.0004
Human Capital	-1.989396 (.505055)	-3.938968	.0292					

a Values with probability levels higher than .10 and constants are not included in the table.
b Results regarding India are hidden due to uninterpretable ECT value.
Standard errors are given in round brackets under coefficient values.

For about two third of the countries, the effective FDI was found to be significant and negative. This may be due to institutional and/or financial structure (Hermes and Lensink, 2003; Durham, 2004 and Chee and Nair, 2010) or other factors such as investment, political stability etc. (Jayasuriya, 2011). The long-run change in the direction of the effect is thought to be stemming from the economy-wide spillovers as shown in Rodriguez-Clare and Alfaro (2004) and Iacovone et al. (2009). In all the countries except for Turkey, MPI was found to be significant and positive. The result regarding Turkey is thought to be originating from her *relative stagnation since 1950s* as Adamopoulos and Akyol (2006) puts it. Argentina, Brazil and Greece were the countries that have significantly greater coefficients for MPI, supporting the idea that macroeconomic stability has been especially important for those countries in short-run. For a large part of the countries in hand, patents were significant and positively correlated to TFP. Similarly, imports were found to be significant and positive with only three exceptions of Mexico being significant and negative while being insignificant in Brazil and Portugal.

Despite the reasonable results gathered from the PMG estimation, the probably strong effect of cross-sectional dependence poses the need for an improved method for estimation, which can decouple the common factors affecting the time series in the panel. The suggested MPI, regarding the estimation results for DCCE model, resembled consistent results contrary to other variables. By taking the cross-sectional dependencies into account under the assumption of cointegration, it was found that a unit increase in MPI index results in a .003% increase in TFP. However, the estimation results from the DCCE model rendered the coefficients for effective FDI, imports and patents insignificant.

Table 10: DCCE Estimation Results

Variables*	Coefficient	z-Value	P > |z|
TFP (-1)	-.3629074 (.0776969)	-4.67	.000
MPI	.0029214 (.0006137)	4.76	.000
Human Capital	-.3389439 (.1197611)	-2.83	.005
	Test Statistic	p-Value	
CD Test	2.21	.0269	

*Values with probability levels higher than .10 and constants are not included in the table.
Standard errors are given in round brackets under coefficient values.

In addition, with the introduction of DCCE model, the direction of the coefficient of human capital reversed. The results point out that a unit increase in human capital index produces a .34% decrease in TFP. The contradiction between the two methods of estimation regarding human capital is thought to be stemming from the inclusion (or exclusion) of international technology spillovers. Additionally, when the effect of a more quantity based human capital index as in this study considered, a negative effect of human capital may be interpreted as loss of productivity due to inefficient education, which is predominant in most developing countries.

5. CONCLUSION

The estimation results proved that with the utilization of PMG estimation, the effective or absorbable FDI, macroeconomic performance and human capital are positively correlated with TFP in the long-run. Those results are in line with a large part of existing literature and theoretical framework. But for the 14 countries in hand, the panel coefficients for patents and imports are found to be negative in the long-run. This is thought to be due to limitation effects of patents and import-dependent production in those countries respectively. However, when a more consistent estimation technique for cross-sectional dependency -DCCE- was chosen under the assumption of the valid cointegration in the panel, only the MPI was able to keep both its significance and direction while the coefficient for the human capital turned negative and others lost their significance. This showed that even with two different estimation approaches, overall macroeconomic performance is particularly important for developing countries probably due to the fact that the overall macroeconomic indicators are stronger in terms of determining the decisions regarding financial and capital investment. Also, the opposite directions for the estimated human capital coefficients should be seen as a sign of international spillovers being more effective than local sources of human capital accumulation. Since the calculation method for the human capital index in this study is based on years of schooling and returns to education (see, Feenstra et al., 2015), the exclusion of common factors among the countries in this study is implicitly equal to removing the effects of international spillovers that indirectly boost the returns to education. In other words, it seems reasonable that the positive effects of spillovers from the countries that are closer to the current technological frontier to the countries investigated in this study are of greater effects in terms of productivity, compared to local education outcome. This, from a policymaker's perspective, means that in addition to the overall macroeconomic wellbeing, the level of openness is of high importance for a developing country to sustain technology diffusion and to foster long-term economic growth through productivity increases.

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