Ideas Production and International Knowledge Spillovers: Digging Deeper into Emerging Countries

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Abstract

Research and Development (R&D) activities of emerging countries (EMEs) have increased considerably in recent years. Recent micro studies and anecdotal evidence points to industrialized countries as the sources of knowledge in EMEs. In this context, we examine ideas production and international knowledge spillovers in a panel of 31 EMEs by accounting for six diffusion channels and two types (national versus USPTO) of patent filings. Knowledge spillovers to EMEs accruing from (i) the industrialized world, (ii) the emerging world, (iii) different country and regional groups, (iv) selected bilateral cases, and (v) those within the regional clusters of EMEs, are modeled. Spillovers from the industrialized world appear robust via geographical proximity and disembodied channels only. Other conduits, including trade flows, are either insignificant or not robust. Spillovers from the emerging world are virtually non-existent. Analyses of regional clusters of EMEs do not support any role of language, culture or geographical characteristics in knowledge diffusion. Overall, the breadth and depth of knowledge spillovers to EMEs appear extremely moderate; however, we find pockets (specific countries and certain groups) generating positive spillovers. A carefully choreographed policy focusing on such pockets might be fruitful. We hope that this study (i) complements the micro literature, (ii) furthers the existing macro literature and (iii) provides some new policy insights. Our results are robust to a range of robustness checks, including the estimators – a cointegration approach versus a simple fixed effects OLS estimator.

JEL Classification: O3; O4; O47.

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1. Introduction

In recent years, emerging countries (EMEs) have made a significant headway in their research and development (R&D) activities. Their R&D expenditure has grown by 8.6% per annum (p.a.) in real terms during 1992-2010, rising from $69.3bn in 1992 to $305.6bn in 2010, compared to the growth rate of the Organisation for Economic Co-operation and Development (OECD) countries of 2.8%. Likewise, patent applications filed by the residents of EMEs at their national office grew by 10.4% p.a. during 1992-2011, compared to 2.3% growth for the OECD countries. Consequently, EMEs' world share of R&D expenditure has increased from 12% in 1992 to 26% in 2010 and their share of world resident patent applications has moved up from 11% to 36%. Patent filings by the residents of EMEs at the United States Patent and Trademark Office (USPTO) also increased by 21% (as opposed to 5.5% of OECD countries) p.a. during 1992-2011.[1]

The novelty of EMEs' patents is often called into question. However, recent studies have shed some new light on this issue. Branstetter et al. (2013) report that Chinese generated USPTO patents are as good as those generated by the Multinational Companies (MNCs) in their home countries, evaluated by their forward citations. However, Indian generated USPTO patents do not pass the same quality threshold. These findings highlight a potentially high level of divergence in the quality of EMEs patents ─ which is not surprising ─ yet they also underline that some EMEs are making significant strides in the novelty of their innovations. Branstetter et al. (2013) also discover a strong degree of collaboration between indigenous (Chinese and Indian) firms and MNCs, leading to knowledge spillovers from co-invention teams to purely indigenous teams within the MNCs. However, spillovers from MNCs to indigenous enterprises outside of MNCs appear limited. This implies that knowledge diffusion outside of a bounded conglomerate may be hard to obtain.

China and India, no doubt, are the two major EMEs of the world, yet the recent upsurge in R&D spending and patenting is not limited to them.[2] Moreover, the public (government and higher education) sector still plays a major role in the R&D of most EMEs.[3] For example, the share of the business (private) sector in India's total R&D expenditure was just 35.5% in 2011. The average share of business sector R&D expenditure in our sample of 31 EMEs was 41.9% in 2011. China is a major exception, however. China's business sector R&D is reported as 75.7% of its total R&D in 2011 ─ a ratio which is higher than that of

France (64%), Germany (67.6%), the UK (63.6%) and the US (68.6%). Whether the Chinese business sector R&D is indeed akin to the private enterprise led business sector R&D of the West could be a moot point; nonetheless, these data are from a credible source ─ UNESCO.[4]

Since most EMEs' business sector R&D is small and evolving, it is not hard to deduce that MNCs' R&D in these countries, important though they are, is likely to be rather small. To scrutinize this, a consolidated dataset on the total R&D activities of MNCs in each emerging country is needed which unfortunately is yet to be available. However, the US Bureau of Economic Analysis reports R&D performed abroad by majority-owned foreign affiliates of US parent companies. These data are useful because in some countries US MNCs are the major foreign R&D players ─ e.g., in India eight of the top ten MNCs filing for USPTO are US companies, whereas in China this number is only four (Branstetter et al., 2013). We calculate the R&D stake of majority-holding US MNCs in a range of EMEs using this dataset. [5] The US MNCs' R&D expenditure in BRICS countries (Brazil, the Russian Federation, India, China and South Africa) is just 2.5% and 3.7% of their total and business sector R&D, respectively.[6] Although, US MNCs do not represent the whole universe, nonetheless the collective MNCs' R&D is unlikely to be a high proportion of the total R&D of most EMEs. Based on the mean value of US MNCs' involvement of 2.5% in BRICS countries' total R&D, we hazard a guess that the share of MNCs will be well below 10% of EMEs' total R&D expenditure.[7] Thus, the magnitude of R&D performed by MNCs is still minor relative to the total R&D of most EMEs.

Further, recent micro literature (Blonigen et al., 2012; Branstetter and Drev, 2016; Guadalupe et al., 2012) reports that foreign investors carefully target the largest and most productive local firms ─ "cherry-pick" ─ to invest in and exploit their export networks. It is therefore hardly surprising that the joint venture MNC investments in these cherry-picked domestic firms in EMEs stand out. This raises the concern that what is evident in the labs of these large joint venture private companies in EMEs might not mirror the overall reality of R&D and knowledge spillovers in these countries. Likewise, the firm level evidence of weak knowledge spillover from MNCs to indigenous, outside enterprises, pointed out earlier, also casts doubt on the generality of spillover benefits accruing from MNCs. These micro findings, while important and interesting, do prompt the question: What is the role of knowledge spillover vis-à-vis inventions (production of new ideas) in EMEs at the aggregate level?

This is an important issue from policy perspectives and perhaps best addressed through a macro study.[8] In this context, a rigorous multicountry macro study of ideas production and international knowledge spillovers (IKS), especially focusing on a large panel of EMEs, is both timely and appropriate.[9] The aim here is to do just that. A well-known caveat of macro studies is the issue of aggregation bias, which hides technological heterogeneity, a potentially important issue in assessing knowledge spillover. However, micro studies are also susceptible to sample selection bias as they often select large and R&D active firms. Despite their respective caveats, the importance of both macro and micro assessments of evidence could hardly be over-stressed ─ if micro and macro studies corroborate the same evidence then their policy imperatives become overriding.

We estimate an ideas production function (IPF) and investigate IKS in a comprehensive manner by analyzing a panel of 31 EMEs. We compute both embodied and disembodied measures of potential 'foreign knowledge spillover pools' (FKSPs) ─ the sources of international knowledge spillage ─ by accounting for six different channels of international knowledge transmissions. Five of them are conduits of embodied knowledge transmissions – viz., ratios of total imports, machinery imports, foreign direct investment (FDI), geographical proximity and inventors' mobility – and the sixth is a disembodied measure. We construct separate FKSPs originating from OECD and EME countries. The idea that geographical origin and country heterogeneity might generate diverse FKSPs motivates separate enumerations (details in Section 3).

Countries enjoy special bilateral and/or multilateral relationships (e.g., Griffith et al., 2006). It is also reasonable to assume that certain countries or groups of countries are technologically more sophisticated and/or economically more open than the rest. This raises the possibility that IKS may be specific to country groups and/or country pairs. Hence, we also examine group-specific spillovers by pairing our sample countries with G7 and G3 (Japan, Germany and US), each as a separate group. G7 is the group of most advanced industrialized countries; arguably, Japan, Germany and the US are the most sophisticated technologically within G7, hence our choice as a separate group. For bilateral IKS from industrialized countries, we pair our sample countries with each of the G7 members. However, the choice of country groups and bilateral pairs is not as clear-cut in relation to EMEs. Reflecting their diverse economic strengths, we construct two emerging country groups ─ viz., the Group of Emerging Seven (E7) comprising China, India, Malaysia, Mexico, the Russian Federation, Thailand and Turkey, and the Group of Emerging Two (E2) comprising China and India. Similar to those with G7 and G3, we pair our sample countries separately with E7 and E2 each for group-specific spillovers from EMEs. For bilateral spillovers, we pair our sample countries with each member of E7. We admit some degree of extempore in these (emerging) country selections but nonetheless hope that they shed enough light on the issues of bilateral and group-specific knowledge spillovers across EMEs. Finally, we also scrutinize the aspects of language, culture, historical relations and geographical characteristics in IKS, albeit in a modest way, by regrouping our 31 sample countries into four regional country clusters sharing close ties vis-à-vis these characteristics and analyzing knowledge diffusions between members of each cluster (details in Section 3).

To recap, we model IKS through six different channels. Using these six channels, knowledge spillovers modeled are (i) from the industrialized world (20-OECD countries) to the emerging world (31-EMEs), (ii) from the emerging world (30-EME countries) to each of the sample EMEs, (iii) group-specific spillovers from OECD (G7 and G3) and EMEs (E7 and E2) country groups, (iv) bilateral spillovers from selected OECD and EME countries, and (v) those within the members of each of the four regional clusters. Two measures of the flows and stocks of knowledge based on residents' patent applications filed at the national office and at the USPTO are used. To accomplish this task, we generate 222 different FKSPs: 118 originating from the industrialized world and 104 from the emerging world (details in Section 3). Econometrically, we employ non-stationary panels methods (panel unit root and panel cointegration tests) as well as the heteroskedasticity consistent (HAC) panel fixed-effects OLS; the latter as a robustness check. We hope that the comprehensive nature and rigor of this study will (i) complement the micro literature, (ii) further the existing macro literature and (iii) provide some new policy insights.

We believe that a wide-ranging study such as this one offers important policy insights from several different perspectives. That economic success depends, among other things, on new ideas (innovations), which in turn, depend on network formation, R&D co-operation and IKS, is well-known. This consensus, at the macro level, is built on evidence that mainly emanates from OECD data. However, a strong study on IKS considering EMEs' data is relatively lacking and, at the theoretical level, potential technological rivalry between competing nations cannot be ruled out. Therefore, a policy relevant question would be to inquire what the ground realities are, vis-à-vis IKS, across EMEs. Put differently, what is the empirical evidence concerning technological co-operation versus technological rivalry across EMEs in respect of their R&D upsurge? Information on such issues is vital for policy making. If results reveal significantly positive IKS then that would, at the very least, imply that EMEs have been successful in creating formal or informal knowledge networks which contribute to their learning and innovation. In contrast, if most IKS parameters appear significantly negative then that would suggest technological rivalry across countries (see

Section 4.1). *Mutatis mutandis*, the insignificance of IKS would imply a lack of know-how externalities. This study also provides an implicit appraisal of BRICS countries' declared policy of fostering "technological innovation in developing nations through its financing, capability building, and knowledge sharing".[10] Further, our approach would also reveal if the nature and magnitude of knowledge diffusions originating from industrialized and emerging countries are different. Finally, this study will also shed light on some of the important aspects of IKS, namely, (i) if pockets (group-specific and/or bilateral) of knowledge spillovers exist, (ii) the potential role of social factors (language, culture, historical relations etc.) vis-à-vis IKS, and (iii) the important conduits of IKS. All these insights inform R&D and innovation policy making. Obviously, the exact policy implication very much depends on the existence or otherwise of IKS as well their nature which we shall comment on, following the presentation of our results, in Section 6. The rest of the paper is as follows. Section 2 discusses our sample and data. Measurement issues are covered in Section 3. Section 4 presents the specification of IPF and discusses the main body of results. Section 5 covers some additional robustness checks. Section 6 summarizes the main findings, discusses policy implications and concludes.

2. Sample, Data and Descriptive Statistics

We define the emerging world as comprising over 70 EMEs for which UNESCO maintains R&D data (see footnote 1). Of these countries, due to lack of consistent data on all relevant variables, we analyze 31 major emerging countries (EME-31; see Table 1). Our sample of EME-31 represents the emerging world satisfactorily as they account for 86% of the total R&D expenditure, 89% of the research scientists and engineers employed in the R&D sector (L_A), and 97% of the resident patent applications filed at the national patent offices of the emerging world.

Data on real GDP, R&D expenditure, residents' patent applications at national offices and at the USPTO, scientists and researchers employed in the R&D sector, R&D capital expenditure, total imports, high-tech (machinery) imports, FDI and geographical distances between each capital city are collected for each of the sample countries as well as 20 OECD countries. Likewise, data on international mobility of inventors are also collected. Data frequency is annual. Knowledge stocks are computed using 15% and 20% depreciation rates. R&D expenditure and GDP data are in 2005 purchasing power parity (PPP) US dollars. A detailed account of all data sources is provided in the data appendix.

Our dataset is an unbalanced panel with observations ranging from 509 to 689 across 31 sample countries. However, data on FDI and scientists' mobility are not available for some sample countries, hence data points vis-à-vis these two variables are somewhat shorter. The data covers a maximum time span of 26 years (1985-2010) and a minimum of 17 years (1994-2010). In the literature, patent counts and/or patent citations are widely used to proxy the flow of new ideas (e.g., Battke et al., 2016; Eaton and Kortum, 1996; Griliches, 1990; Nicholas, 2013).[11] We proxy the flow of new ideas by residents' patent applications filed (i) at national offices (i.e., domestic filings), and (ii) at the USPTO. Patent laws, propensities to patent and the importance attached to intellectual property (IP) rights differ across countries, which may contaminate patent qualities and generate noise in cross-country measurements. Our usage of USPTO filings by the residents of EMEs is motivated to mitigate this noise.[12]

Table 1 about here

Table 1 reports some summary statistics. During the sample period, most sample countries show healthy growth rates. The highest average annual growth rate is recorded by China (9.8%) followed by Azerbaijan (6.5%) then India (6.4%). The sample average annual growth rate is 3.7%, which is higher than that of the US (2.6%), Japan (0.8%) and the OECD average (2.6%). Three sample countries (Hungary, Kyrgyzstan and the Russian Federation) grew by less than 2% p.a. during the sample period. The mean R&D intensity across the sample countries is 0.60%, which is much lower than that of the OECD average (1.97%) and the US (2.55%). Five sample countries, namely, China, Czech Republic, Hungary, the Russian Federation and Slovenia have an R&D intensity of above 1%. The mean level of research intensity is 0.23%, which is lower than the OECD average of 0.66%. Chinese research intensity is just 0.12%. India has one of the lowest research intensities of 0.03%. Research productivity, defined as resident patent application per researcher, is quite low (3.6) in EMEs compared with the OECD average (24.5). China surpasses other sample countries by a large margin in R&D activities and we scrutinize this as a robustness check in Section 5.

There is a big difference between domestic and USPTO filings. Sample countries, on average, filed 3,235 patents p.a. domestically whereas the comparable filings at the USPTO are just 116 – a mere 3.6%. Patent applications beyond national jurisdictions are governed by various commercial and strategic decisions ─ e.g., business presence in a foreign country, market size, geographical proximity, patent race etc. Hence, the differences in patent applications at home and abroad are not suggestive of the novelty of one over the other. In fact, Jaffe and Lerner (2014) and the US Government Accountability Office[13] have called into question the quality of the USPTO granted patents. Nevertheless, the USPTO's consistent application of the same patenting rules across all foreign filings is important for our purpose.

3. Construction of Knowledge Stocks and Spillover Pools

The domestic knowledge stock of each sample country is computed by integrating the respective flows of new ideas (domestic and the USPTO filings) through the perpetual inventory method ─ a standard approach in the literature (details in the data appendix). It is also commonplace to compute knowledge stock by integrating the flows of real R&D expenditure. However, R&D expenditure is an input measure whereas patents are outputs; we therefore opted for the latter as we are modeling the generation of new ideas.

Countries differ in their technological sophistication and managerial capability. Branstetter and Drev (2016, p.12) show that "firms in highly advanced countries possess superior managerial and technological expertise than firms in less advanced countries". Likewise, we argue that the sophistication of accumulated ideas between OECD and EMEs might differ, implying a potentially different extent of knowledge spillovers. To capture this potential heterogeneity, we construct separate spillover pools originating from OECD and EMEs.

Macro literature on knowledge spillovers uses total import-ratio widely as one of the conduits of IKS (e.g., Coe and Helpman, 1995; Coe et al., 2009). Following on, the standard measure of total import-ratio weighted FKSPs, originating from the OECD pool, for the i^{th} sample country ($A^{f,tm}_{oecd,i,t}$) is:

$$A^{f,tm}_{oecd,i,t} = \sum_{j=1}^{N} (\mathrm{T}_{ij,t} / Y_{j,t}) * \mathrm{A}^{d}_{j,t} . \qquad (1)$$

where, T_{ij} is the total imports of the i^{th} sample country from the j^{th} OECD trading partner; Y_j denotes the GDP of country j – both measured in nominal terms. Throughout, $\mathrm{A}^{d}_{j,t}$ is the domestic knowledge stock of country j and t denotes the time subscript. This measure of spillover pool follows Lichtenberg and van Pottelsberghe de la Potterie (1998). The parallel spillover pool originating from the emerging world for the i^{th} sample country ($A^{f,tm}_{eme,i,t}; i \neq j)$ is computed analogously. For $A^{f,tm}_{eme,i,t}$, j denotes the emerging partner country.

De Long and Summers (1991) emphasize the importance of machinery investment (imports) for growth. Xu and Wang (1999), among others, argue that trade in capital goods is more appropriate conduit for knowledge spillovers than total imports. The machinery imports-ratio weighted spillover pool originating from OECD countries ($A^{f,mm}_{oecd,i,t}$) is:

$$A^{f,mm}_{oecd,i,t} = \sum_{j=1}^{N} (M_{ij,t} / Y_{j,t}) * \mathrm{A}^{d}_{j,t} \qquad (2)$$

This is similar to (1) except that M_{ij} represents country i 's machinery imports from OECD country j ; the rest of the variables are as defined in (1). The parallel spillover pool originating from the emerging world ($A^{f,mm}_{eme,i,t}; i \neq j)$**)** is computed analogously; country *j* is now one of the trading partners from the pool of 30 EMEs exclusive of the i^{th} country.

FDI, as a conduit of IKS, has received considerable attention in the literature (e.g., Branstetter and Drev, 2016; Keller and Yeaple, 2009). The spillover pool, based on inward FDI as a conduit ($A^{f,FDI}_{oecd,i,t}$) is:

$$A^{f,FDI}_{oecd,i,t} = \sum_{j=1}^{N} (SFD_{ij,t} / K_{j,t}) * \mathrm{A}^{d}_{j,t} \qquad (3)$$

where $SFD_{ij,t}$ denotes the i^{th} sample country's accumulated stock of FDI received from the j^{th} OECD country; $K_{j,t}$ is the non-residential physical capital stock of country j . Time series data on bilateral FDI flows between OECD and EME countries for the full sample period is lacking; hence, we use the mean ratio for the period of 2001-2010; i.e., $SFD_{ij,t}$ and $K_{j,t}$ are mean values. However, to allow for some degree of time variability in the weights used, we also compute separately $A^{f,FDI}_{oecd,i,t}$ using the mean values of weights for sample periods 2001-2005 and 2006-2010; thus, we model three measures of $A^{f,FDI}_{oecd,i,t}$ based on three different weights. Unfortunately, the lack of consistent data on bilateral FDI flows across the majority of sample EMEs precludes us from computing a parallel spillover pool originating from the emerging world.

The geographical proximity weighted spillover pool originating in OECD countries for the i^{th} sample country in the panel ($A^{G-prox}_{oecd,i,t}$ **)** is computed as:

$$A^{G-prox}_{oecd,i,t} = \sum_{j=1,}^{N} (TGD_i / GD_{ij})^{1/2} * \mathrm{A}^{d}_{jt}, \qquad (4)$$

where, TGD_i is the total geographical distance (in kilometers) between country i 's capital city and the capital cities of all partner OECD countries in the knowledge pool. GD_{ij} is the geographical distance between the capital cities of countries i and j. Since the geographical distances between capital cities are constant, the weights are not time varying but A_{jt}^{d} is. Knowledge diffusion is proportional to the square root of the reciprocal of relative geographical distance between countries proxied by the distances of their capital cities. The higher the ratio (.) the closer the geographical proximity. The parallel spillover pool originating from emerging world ($A_{eme,i,t}^{G-prox}$) is calculated analogously using the relative distances between the capital city of country i and those of the partner EMEs j ($j = 1,\ldots, 31$; $i \neq j$) in the sample.

Primarily, skilled migrants emigrate from developing to developed countries. The positive contribution of immigrant inventors to the innovations of industrialized countries has been well documented (Foley and Kerr, 2013; Hunt, 2011; Hunt and Gauthier-Loiselle, 2010; Kerr, 2008). However, evidence on the contribution of overseas inventors' diaspora to their countries of origin is rather mixed – Saxenian (2006) reports positive effects whereas Agrawal et al. (2011), analyzing Indian data, find the opposite. The spillover pool for the i^{th} sample country, weighted by the bilateral ratios of foreign to total inventors engaged in the inventions of OECD countries ($A_{oecd,i,t}^{f,sci}$), is computed as:

$$A_{oecd,i,t}^{f,sci} = \sum_{j=1}^{N} (FINV_{ij,t} / INV_{j,t}) * \mathrm{A}_{j,t}^{d} \qquad (5)$$

where $FINV_{ij}$ denotes the number of inventors who originate from the i^{th} emerging country but are named inventors in the patent application filed by the j^{th} OECD country; INV_{j} is the total inventors named in the total patents filed by j. Time series data on the mobility of innovators for the whole sample period is lacking therefore we use the average ratio for the period of 1995-2010; i.e., $FINV_{ij,t}$ and $INV_{j,t}$ are mean scalars. There is little migration of inventors between EMEs, which rules out a parallel measure of spillover pools from the emerging world.

Finally, we compute disembodied foreign spillover pools originating from OECD ($A_{oecd,i,t}^{f,uw}$ **)** and emerging ($A_{eme,i,t}^{f,uw}$ **)** countries. Disembodied knowledge pools are meant to capture ideas that are diffused beyond diffusion channels. For example, uncodified tacit knowledge and high-concept innovations are diffused via face-to-face contacts (Kloosterman, 2008). Branstetter (1998, p. 523) states, "At the firm level, the most intense knowledge spillovers may be those which take place between direct competitors who buy nothing from one another". The disembodied spillover pool is essentially the unweighted sum of the knowledge stock of partner countries, enumerated as:

$$A^{f,uw}_{oecd,i,t} = \sum_{j=1}^{N} \mathrm{A}^{d}_{j,t} \qquad (6)$$

The $A^{f,uw}_{oecd,i,t}$ is the unweighted sum of domestic knowledge stocks of all 20 countries in the OECD pool. Likewise, a parallel spillover pool originating from the emerging world: $A^{f,uw}_{eme,i,t} = \sum_{j=1}^{N-i} \mathrm{A}^{d}_{j,t}; i \neq j)$ is the unweighted sum of 30 of the 31 EMEs, excluding the i^{th} country under consideration.

We generate six distinct foreign spillover pools originating from the industrialized world based on six conduits (equations 1 through 6). Each of these is constructed by using two streams of patent filings: (i) domestic and (ii) USPTO. This generates 12 (2 patent types x 6 conduits) FKSPs originating from the industrialized world. To explore IKS from groups of industrialized countries, we compute 24 (2 patent types x 2 groups x 6 conduits) different group level FKSPs originating from G7 and G3. Likewise, to explore the bilateral IKS from the industrialized world, we pair our sample countries with each of the seven members of G7 (Online Appendix lists their names). This requires us to generate a further 84 bilateral spillover pools (2 patent types x 7 countries x 6 conduits). Overall, we generate 120 different spillover pools originating from the industrialized world.

Regarding EMEs, due to lack of data on FDI and inventors' mobility, we compute the remaining four corresponding spillover pools originating from the emerging world. This gives us 8 (2 patent types x 4 conduits) FKSPs originating from the emerging world. We then construct FKSPs originating from E7 and E2 groups (as discussed in Section 1) based on the same four conduits and two types of patent filings. This generates 16 (2 patent types x 2 groups x 4 conduits) group-specific spillover pools from the emerging world. Bilaterally, we pair our sample countries with seven individual EMEs (each member of E7) which lead to a further 56 (2 patent types x 7 countries x 4 conduits) bilateral spillover pools from EMEs.

Finally, we examine if parallel geographic, linguistic and cultural characteristics as well as the historical relations influence IKS vis-à-vis our sample of countries. These factors shape the patterns of shared values, beliefs and human interactions, which in turn influence individuals' knowledge set. Geographical characteristics in this context imply 'relational proximity' in forming social practices and institutions. Social psychologists have researched these intricate issues. Hofstede (1980) proposed four empirical dimensions – *power distance*, *uncertainty avoidance*, *individualism and masculinity* – to gauge the cultural mindset of a nation. They have become premises for evaluating the importance of linguistic and cultural characteristics on knowledge spillovers primarily using disaggregated data (e.g., Hussler, 2004).

We pursue a rather subtle and aggregate approach. We regroup our 31 sample EMEs into four regional clusters – Arabian (ARAB), Asian (ASIA), east European (EE), and Latin American (LA) countries.[14] The idea is that member countries of each cluster hail from the same region hence are expected to possess close linguistic, cultural and other geographic affinities, albeit in varying degrees. For example, members of the ARAB cluster share language, culture and geographic proximities and, to a greater or lesser extent, the same can be argued with respect to the member countries of other clusters. Since these regional clusterings capture geographical proximity and data on bilateral FDI flows and inventors' mobility is lacking, we only compute spillover pools based on three conduits ─ total import ratio, machinery import ratio and the disembodied channel. This gives us 24 (2 patent types x 4 clusters x 3 conduits) spillover pools originating from these clusters of EMEs. Overall, we construct a total of 224 spillover pools of which 120 are from OECD and 104 from EMEs. [15]

4. Ideas Production and International Knowledge Diffusions

4.1 Specification

Following the mainstream literature, we specify a log linear knowledge production function in Cobb-Douglas tradition:

$$\ln \dot{A}_{d,i,t} = \alpha_i + \varphi_t + \lambda \ln L_{A,i,t} + \phi \ln A_{d,i,t} + \beta \ln A^{f,\omega_1}_{oecd,i,t-1} + \theta \ln A^{f,\omega_2}_{eme,i,t-1} + e_{i,t} \qquad (7)$$

(i = 1,…,N; and t = 1,…,T).

where subscripts i and t denote the cross-sectional and time series dimensions respectively; $\ln x$ signifies log of x ; $\dot{A}_{d,i,t}$ is the flow of new ideas generated by the i^{th} country; $L_{A,i,t}$ is the number of R&D researchers; $A_{d,i,t}$ represents domestic knowledge stock; $A^{f,\omega_1}_{oecd,i,t}$ and $A^{f,\omega_2}_{eme,i,t}$ are the spillover pools originating from OECD and EMEs. Superscripts $\omega_1(\omega_1 = 1, 2, .., 118)$ and $\omega_2(\omega_2 = 1, 2...., 104)$ indicate the 118 and 104 distinct FKSPs that we have constructed from OECD and EMEs (Section 3). In the estimations, we enter these spillover pools individually, as well as in their equivalent pairs, offering a coherent structure (see Section 4.2).

Micro literature typically models knowledge production as a function of firm's own accumulated knowledge and other firms' accumulated knowledge, measured as spillover pool (e.g., Jaffe, 1986). Depending on the objectives of analyses, measurements of spillover pools take different forms ─ e.g., *intranational* and *international* pools measured domestically and internationally (Branstetter, 2001) or *intersectoral* and *intrasectoral* pools measured across different technology fields (Ramani et al., 2008). In macro literature, domestic production of new ideas is modeled as a function of L_A, A_d and the externality from potential international spillover pool, A^f (Luintel and Khan, 2009; Porter and Stern, 2000). Our specification encapsulates these basic arguments of both micro and macro literature and we extend it by separately treating international spillover pools originating from industrialized and emerging worlds.

We specify a contemporaneous relationship between $\dot{A}_{d,i,t}$ and $A_{d,i,t}$ because inventors (countries) could readily exploit their in-house (domestic) innovations on which to build further. This contemporaneity is also consistent with the micro evidence ─ that firms prefer 'secrecy' to protect profits from their inventions and they take out patents early to preempt rivals from patenting, i.e., 'patent blocking' (Cohen et al., 2000). However, it is sensible to contemplate that international knowledge diffusions take time. Yet evidence suggests that even IKS are realized rather fast ─ within one to two years of invention (Caballero and Jaffe, 1993; Mansfield, 1985). Hence, we set a first order (one year) lag on both foreign spillover pools. Further, our usage of stock measures of domestic knowledge and spillover pools also account for the lags in knowledge flows as well their depreciation rates.

Specification (7) is a fixed effect panel model where α_i captures the country-specific fixed effects and φ_t captures the time effects. The parameter λ measures the elasticity of the flow of new technology (ideas) with respect to R&D researchers. *A priori* λ is expected to be positive and significant; however, a value of $0 < \lambda < 1$ implies duplicative innovation ─ the 'stepping-on-toes' effect. $A_{d,i,t}$, the country-specific knowledge base, is an important factor determining knowledge absorption capacity (Cohen and Levinthal, 1989; Ramani et al. 2008). A significantly positive ϕ implies that $A_{d,i,t}$ facilitates the discovery of new ideas, often interpreted as the 'standing-on-the-shoulders' effect ─ i.e., making new discoveries by building on preceding discoveries. Isaac Newton famously wrote "If I have seen further, it is by standing on the shoulders of giants".[16] Unfortunately, our sample of EMEs lacks such 'giants' domestically to allude to any new invention on their shoulders. However, these countries have put in place respective national innovation systems (NIS) to facilitate the adoption, absorption, production and diffusion of new knowledge domestically. Watkins et al. (2015) elaborate on the genesis of NIS. Therefore, ϕ is best interpreted as the elasticity of innovation with respect to the domestically accumulated knowledge stock and the NIS of EMEs. A $\phi < 0$ implies that the increasing accumulation of domestic knowledge makes the discovery of new ideas harder – the 'fishing out' effect. It would also imply that the cost of subsequent discovery outweighs the incentives offered through the NIS.

Parameters β and θ are spillover parameters associated with the spillover pools originating from OECD and EMEs, respectively. A positive and statistically significant β implies positive IKS from OECD countries. A negative β, however, implies that inventions of OECD countries raise the innovation bar (the threshold of novelty) for EMEs. The parameter θ has a similar interpretation. A distinction is made between 'pecuniary' spillovers and 'pure' knowledge spillovers (Branstetter, 2001; Jaffe, 1986). When a downstream user enhances its ingenuity by reverse engineering the superior upstream technology, then that generates 'pure' knowledge spillover, which is unambiguously positive. However, when the upstream inventor is unable to appropriate the full benefits of its innovation ─ due to hosts of factors inhibiting perfect price discrimination ─ and some benefits leak to downstream users, then that is 'pecuniary' spillover. We do not observe 'pure' technological spillovers. Hence, parameters β and θ capture the combined effects of both of these spillovers. If competitive pressures and technology rivalry are high between countries, then the net spillover effect, and hence the signs of the spillover parameters, could be negative. Therefore, the 'raising-the-bar' effect does not imply that the 'pure' technological spillovers are negative, instead it reflects the spiraling costs of R&D and/or patents blocking by rivals that inhibit discoveries.

4.2 Empirical Results

We follow two empirical approaches. First, we use econometric methods of non-stationary panels which tackle the prominent issue of data non-stationarity. This is imperative because macro panel data relating to specification (7) are widely reported to be non-stationary (unit root) processes in their levels. Specifically, we implement IPS (Im et al., 2003) and Fisher-ADF (Maddala and Wu, 1999) panel unit root tests, and the panel cointegration tests of Pedroni (1999). This is followed by the estimation of long-run (cointegrating) parameters of IPF through the Fully Modified OLS (FMOLS) estimator of

Phillips and Hansen (1990), a widely-used estimator of co-integrating parameters. Second, as a robustness check, we employ the fixed effects (HAC) OLS panel method.[17] The fixed effects approach also affords some modeling flexibility relative to FMOLS which we exploit (see below). In view of the non-stationary panel, FMOLS is more appropriate; hence our preferred estimator.

As expected, both panel unit root tests confirm that logs of $\dot{A}_{d,i,t}$, $L_{A,i,t}$, $A_{d,i,t}$ and all the different measures of spillover pools, generated and used in this paper, are unit root, I(1), processes. These results, available on request, are consistent with those of Coe et al. (2009) and Luintel et al. (2014) who report unit root across similar R&D variables. Given that individual data series in the panel are I(1), we proceed to test if the IPF (7) forms a cointegrating relationship.

Table 2 reports cointegration results encompassing all measures of FKSPs originating from industrialized and emerging worlds based on domestically filed patents. Columns 1 through 10 account for all measures of spillover pools one-by-one. Columns 11 through 14 jointly model the analogous spillover pools originating from OECD and EMEs. While this structure provides a complete picture of the nature of IKS, nevertheless, columns (1) through (10) incorporate only one spillover pool; therefore, they might be construed as suffering from missing variable problems. Hence, the specifications of columns 11 through 14 are our preferred models.

Table 2 about here

Cointegration test statistics ─ t_{adf} and t_{pp} ─ are the Augmented Dickey-Fuller (ADF) and Phillips-Perron between-dimension (Group) panel t-tests under the null that equation (7) is non-cointegrated (see Pedroni, 1999). These Group t-tests, which allow parameter heterogeneity across countries, are preferred over the corresponding Pooled tests due to their lower size distortions and better power properties. Both sets of tests ─ Group and Pooled (the latter not reported) ─ reject the null of non-cointegration at very high levels of precision. Thus, tests unequivocally confirm specification (7) as a robustly cointegrating IPF for our sample of EMEs.

The upper panel of Table 2 reports the long-run (cointegrating) parameters of the IPF estimated by FMOLS. The Group FMOLS shows that the estimates of λ (i.e. $\partial \ln \dot{A}_d / \partial \ln L_A$) across all 14, but two, specifications are positive and statistically significant (mostly at high precisions). The two exceptions are the specifications with spillover pools originating from

EMEs via geographical proximity (column 7) and the disembodied measure (column 10), which appear with insignificant $L_{A,i,t}$. The point estimates of λ are well below unity in all cases, implying that there is duplication in innovations – the 'stepping-on-toes' effect. This finding is consistent with the existing literature on OECD countries (Porter and Stern, 2000; Luintel and Khan, 2009).

The elasticity of $A_{d,i,t}$, ϕ $(= \partial \ln \dot{A}_d / \partial \ln A_d)$, is positive and highly significant. In fact, the point estimates are significantly greater than unity across all specifications. In seven of the 14 cases, these point estimates are above 2.0. Such high magnitudes of ϕ imply increasing returns on $A_{d,i,t}$ – strong evidence that the accumulated knowledge and NIS of these countries beget further innovations. The finding of $\partial \ln \dot{A}_d / \partial \ln A_d > 1$ for EMEs is in sharp contrast to the existing literature based on OECD data – Porter and Stern (2000) find it to be unity ($\phi = 1$) in a sample of 16 OECD countries, whereas Luintel and Khan (2009) report it to be well below unity by using triadic patent families data across 19 OECD countries.

Knowledge spillovers from OECD to EMEs via total imports (column 1) appear negative and significant at 6.7%. The corresponding measure of spillover from the emerging world also appears negative but insignificant (column 3). However, when modeled jointly, both turn statistically insignificant. Spillovers via machinery imports also appear insignificant from both worlds, irrespective of their specifications.

FDI as a conduit of IKS from industrialized to EMEs appears insignificant. The results in Table 2 are based on the $A^{f,FDI}_{oecd,i,t}$ measure computed by using a constant weight for the period 2001-2010 for which we have data. However, the insignificance of FDI remains even when two further separate weights based on the sample periods 2001-2005 and 2006-2010 are used to allow some variability in weights. In the latter two estimates, the FDI weighted FKSPs resume parameters of -0.270 (0.516) and 0.514 (0.167), respectively, both of which appear highly insignificant. Figures within parentheses are respective p-values. Expatriate inventors in industrialized countries appear to contribute knowledge diffusions to their countries of origin – the point elasticity is quite large (1.669) and highly significant. This finding is quite surprising because the proportion of expat inventors (from each emerging country) working for each industrialized country (revealed in patent applications) is very low – the ratio (weight) mostly appears in the third/fourth decimal places. The only exceptions are the Chinese and Indian inventors in the US who respectively form 4% and 3%

of the latter's total inventors. Knowledge diffusions through geographical proximity, when modeled jointly, appear positive and significant (column 13), although the spillovers from the emerging world are significant only at 10%. The coefficient of geographical proximity weighted OECD spillover poll is quite high, suggesting its sizable contribution, like that of $A_{d,i,t}$. Geographically, the closer the emerging country to industrialized ones, the greater the magnitude of knowledge spillover. Disembodied knowledge spillovers, when modeled separately, appear positive and significant from both sources at 10% or better. However, when modeled jointly, disembodied spillover from OECD countries alone remains significant and resumes a very high coefficient. The goodness of fit statistics, ($\bar{R}^2$), show very high fit across all specifications.[18]

To sum up, of the six channels examined, knowledge spillovers from OECD to emerging world via *total imports*, *machinery imports* and *FDI* – the three most widely analyzed conduits in the literature – appear insignificant. The insignificance of FDI is in sharp contrast to the recent micro-based findings of Branstetter and Drev (2016), indicating that micro finding may not be readily generalized – confirming, to an extent, Branstetter's own skepticism on the generality of firm level evidence (see footnote 8). However, there is evidence of strong knowledge spillovers via *geographical proximity* and *disembodied channels* from OECD countries. *Expatriate inventors* from EMEs appear to facilitate knowledge transmissions to their countries of origin. Surprisingly, knowledge spillover across EMEs is virtually non-existent (insignificant); only one spillover parameter via geographical proximity appears marginally significant (at 10%). These results reveal that there are crucial differences in knowledge diffusions accruing from industrialized and emerging worlds.

Does heterogeneity in patent laws and propensities to patent across countries have any bearing on these results? Table 3 reports the results based on measures constructed using patents filed at the USPTO by OECD and EMEs. The significance of $L_{A,i,t}$ improves notably: parameters now have very high precision and high magnitudes across all specifications. Remarkably, in three of the four joint estimates (columns 12-14), the point estimates of λ are above unity, indicating that there is no duplication in innovations leading to USPTO filings; this is also evident in columns 7 and 10, which contrasts with their insignificance vis-à-vis domestic filings. The high point elasticity of $A_{d,i,t}$ — increasing returns to scale — found earlier is upheld by the USPTO filings.

Table 3 about here

With the USPTO filings, knowledge diffusions from OECD via total imports and FDI remain insignificant while those via geographical proximity and disembodied channels continue to appear the strongest ─ results consistent with those from domestic filings. The differences are that spillovers now appear significantly positive via machinery imports but insignificant via inventors' mobility.

Regarding the emerging world, again there is no evidence at all of positive and significant knowledge spillovers across these countries based on USPTO filings. When modeled one-by-one, all spillover parameters but one appear significantly negative. The exception is the spillover via machinery imports, which appears negative but insignificant. When modeled jointly, two spillover parameters (associated with machinery imports and disembodied channels) appear significantly negative at 10% or better and the remaining two (via total imports and geographical proximity) appear negatively signed but insignificant. Not only are the findings of the virtual lack of significantly positive knowledge spillovers, based on domestic filings, largely upheld but the mostly negative and significant spillover parameters indicate a degree of competitive pressures and/or technology rivalry between EMEs, which might be costing their discoveries.

We further probe our results given in Tables 2 and 3 vis-à-vis the estimation method, specification and data measurements. We re-estimate all specifications (columns 1 through 14 of Tables 2 and 3) by using the fixed effects (HAC) OLS panel method. Further, under fixed effects, we augment Tables 2 and 3 by three additional specifications: pooling all FKSPs originating from (i) OECD and (ii) EMEs separately as well as (iii) jointly. On the measurement issue, we evaluate if the lagged values of 'raw' conduits (total and machinery imports, FDI and scientists' diaspora) on their own (devoid of knowledge stock measures) contribute to invention in EMEs. The raw conduits for each sample country are measured by the US dollar value of total imports, machinery imports and total inward FDIs. We model raw conduits using both their nominal and real values (see below). The scientists' mobility, as raw conduit, for the i^{th} sample country is measured by the numbers of inventors located in 20 OECD countries who originate from the i^{th} sample country. The remaining two FKSPs are based on geographical distance which is constant and a disembodied measure which is conduit free, hence our focus on the above four raw conduits. The literature suggests that imports, FDI and scientists' mobility generate know-how externalities. This also serves as a further robustness check of our results in the sense that if raw conduits do not show any higher degrees of positive externalities than those from FKSPs then that will underpin our finding of very modest IKS to EMEs.[19]

For the sake of brevity, we only report selected fixed effect results in the Online Appendix. A complete set of results and their full discussions are available in an earlier version of this paper (Luintel and Khan, 2017). Online Table A1 reports fixed effects results that are parallel to Table 2. Although a full set of results is reported, the most pertinent ones are those in column 5 and columns 11 through 17. Column 5 models FDI; columns 11 through 14 jointly model parallel FKSPs originating from OECD and EMEs; column 15 pools all FKSPs originating from OECD; column 16 does the same for all FKSPs originating from EMEs, and finally column 17 pools all FKSPs originating from OECD and EMEs together.

Results in columns 11 and 12 confirm the insignificance of IKS via both import ratios weighted FKSPs, as reported in Table 2. However, FDI, as a conduit, appears significantly positive irrespective of specifications. Geographical proximities, which appear positive and significant conduits of IKS from OECD and EMEs under FMOLS, now both turn significantly negative under fixed effects. Likewise, the disembodied channel also shows different results: it now appears negative and significant from OECD but positive and significant from the emerging world; under FMOLS, it appears positive and significant from OECD and insignificant from EMEs. Thus, there are some similarities as well as differences between FMOLS and fixed effect results which is not surprising; however, on balance, the fixed effects result shows fewer instances of significantly positive IKS to EMEs than those found under FMOLS across columns 11 through 14. This is because, under fixed effects, not only import ratios continue to remain insignificant but geographical proximities resume negative spillover parameters.

Results in Colum 15, which pools all FKSPs originating from OECD, show positive and significant spillovers via machinery imports, FDI and disembodied channels. These results are different from those of FMOLS (Table 2) which showed significantly positive IKS via scientists' mobility, geographical proximity and disembodied channels. Column 16, which pools all FKSPs originating from EMEs, shows that total imports weighted FKSP is positive and marginally significant (at 10.1%) whereas the disembodied channel is positive and highly significant. Again, these results are also different from those of FMOLS, which showed geographical proximity alone to be positive and marginally significant (at 10%) from EMEs. Finally, column 17, which pools all (OECD and EMEs) FKSPs, reveals *machinery imports*, *FDI* and *disembodied* channels to be the significantly positive conduits from OECD compared to *geographical proximity* and *disembodied* under FMOLS. Regarding spillovers from the emerging world, *machinery imports* and *disembodied* conduits appear to be generating significantly positive spillovers compared to the marginal significance of *geographical proximity* alone under FMOLS. These two estimators show compositional differences in the significance of conduits; however, a comparison of columns 11 through 14 of Table 2 with column 17 of Table A1 reveal that the instances of significantly positive IKS are very close (4 versus 5). To conclude, there are some important variations in results between these two estimators, yet the overall breadth and the depth of IKS do not appear a great deal different. The fixed effects estimator establishes FDI as a significant conduit under domestic filings but, as we shall see, this is not sustained under USPTO filings. [20]

Fixed effect results based on USPTO filings (not reported here but are available in Luintel and Khan, 2017), obtained from the most general specification, show significantly positive spillovers from OECD via *machinery imports* only; spillovers via the remaining five conduits are either significantly negative or insignificant. Thus, FDI loses its significance under USPTO filings. Results of EMEs appear fully consistent with those of FMOLS. There is no evidence of significantly positive IKS from the emerging world; they are either significantly negative or insignificant. Overall, the very modest breadth and depth of IKS reported under FMOLS in Tables 2 and 3 are largely corroborated by the fixed effects estimator and the augmented specifications.

Online Table A2 (Panel A) reports the fixed effects results on raw conduits, measured in nominal US dollars, when innovations are measured by domestically filed patents. IKS via raw conduits are not encouraging either. When both set of raw conduits originating from OECD and EME are pooled (column 11), only total imports from EME are significantly positive; the rest of the raw conduits appear insignificant. Results do not appear much different when innovations are measured by patents filed at the USPTO (Panel B). In their joint estimation, total imports and scientists' mobility from OECD appear significantly positive; the rest of the conduits are either insignificant or significantly negative.

We also scrutinize if real US dollar values of raw conduits (deflated by GDP deflator) produce any different results. It is not entirely clear whether the nominal or real values of these raw conduits should be used. The weights involving different conduits are computed as a ratio of two nominal values; for example, a ratio of imports of country 'i' from country 'j' scaled by GDP of country j. These weights are strictly speaking not real ratios because the required deflators not only differ across countries but also across imports and GDP. Hence, we opted to use both nominal and real values of raw conduits. We comment on the main results, obtained through real values of conduits, without reporting them. With domestically filed patents, parameters of all (real) raw conduits appear either insignificant or significantly negative when modeled one-by-one. When raw conduits from OECD are pooled, only total imports appear significantly positive and the rest appear insignificant. When raw conduits from OECD and EME are pooled, only scientists' diaspora appears significantly positive; the rest of the parameters are either significantly negative or insignificant. The evidence worsens greatly vis-à-vis patents filed at the USPTO. All raw conduits resume significantly negative parameters when modeled one-by-one. When both sets of raw conduits are pooled together, machinery imports from EMEs alone appears positive and significant; the rest appear insignificant. Thus, there is very limited evidence of positive externality spillovers via raw conduits to EMEs which, as argued above, reinforces our finding of a rather modest IKS to EMEs.

Table 4 (Panel A) reports group-specific (G7 versus G3) FMOLS results from industrialized countries based on domestically filed patents. It is evident that knowledge diffusions via geographical proximity, inventors' mobility and disembodied channels are significantly positive from both G7 and G3, which is consistent with the results from the OECD pool as a whole (OECD-20). However, spillovers via FDI appear positive and significant from G7 and G3 with large point elasticities; this is in contrast to the OECD pool where FDI, as a conduit, appears insignificant. Likewise, spillovers via total and machinery imports both appear significantly negative (raising-the-bar effect) from G7 and G3, which is different from their insignificance vis-à-vis the OECD pool. All parameters of $A_{d,i,t}$ are positively signed and significant with magnitudes like those found earlier; the parameters of $L_{A,i,t}$ appear imprecisely estimated in three cases.

Table 4 about here

Table 4 (Panel B) reports the results for the same groups (G7 and G3) based on USPTO filings. Spillovers via two channels – geographical proximity and disembodied – continue to appear significantly positive from both groups, which is consistent with their domestically filed patents. The rest of the spillover parameters from G7 are insignificant. However, spillovers from G3 via machinery imports and FDI are positive and significant. A clear raising-the-bar effect via both import conduits, found from G7 and G3 under domestic patent filings, does not appear robust vis-à-vis the USPTO filings. Thus, there are some important similarities as well as differences in spillover results emanating from G7 and G3 groups vis-à-vis their domestic and USPTO filings.

Online Appendix Table A3 reports the fixed effect results from G7 and G3 groups that are parallel to Table 4 (FMOLS). The structure of the specifications between these two Tables is identical, except that Table A3 contains one extra row of results for each group, estimated by pooling all six FKSPs together. It is evident that the fixed effects spillover results are a lot poorer. Results from domestically filed patents (Panel A) reveal that only scientists' diaspora is significantly positive from G3, irrespective of specifications. From G7, only machinery imports and FDI weighted FKSPs appear significantly positive when all six FKSPs are modeled jointly. Likewise, the results from USPTO filings (Panel B) also confirm only a few instances of significantly positive spillovers. Overall, fixed effects estimates show very little evidence of significantly positive IKS from G7 and G3 groups to EMEs, reinforcing the results found under FMOLS.

We report all results concerning bilateral IKS in the Online Appendix. Table A4, which contains bilateral FMOLS results based on domestic filings, shows significantly positive IKS via geographical proximity from all individual G7 countries except Canada; the latter insignificant. Spillovers via FDI are significantly positive from five of the seven countries; those from Japan and France appear insignificant. Spillovers via total imports appear negative and significant from three (France, Italy and US) and insignificant from the remaining four. Likewise, machinery imports, as a conduit, appear positive and significant from the UK only; they appear significantly negative from Italy and insignificant from the remaining five. Inventors' mobility appears to generate positive and significant spillovers from four countries (Canada, France, UK and US); negative and significant from Germany; and insignificant from Japan. We do not have data on scientists' mobility for Italy. Spillovers via the disembodied channel appear insignificant from Italy but positive and significant (at 10% or better) from the remaining six countries. Results of bilateral spillovers based on USPTO filings (reported in Luintel and Khan, 2017), can be summarized in three main points: (i) knowledge diffusions generally appear thinner than domestic filings because fewer (22 versus 15) spillover parameters appear positive and significant, (ii) the total and the machinery import ratios both appear positive and significant conduits from France and the UK, and (iii) scientists' mobility mostly shows negative externality.

The fixed effects results of bilateral spillovers from G7 members, based on domestically filed patents, show very close similarity to those from FMOLS (Table A4), which reinforces the FMOLS results that there is more evidence of IKS at bilateral levels. In comparison, bilateral spillover results, based on USPTO filings, show some variability; nonetheless, the overall conclusion, derived from FMOLS, is not altered. Again, for brevity, we do not report these fixed effects results but they are reported and fully discussed in Luintel and Khan (2017).

Table 5 reports FMOLS results on knowledge spillovers from emerging country groups (E7 and E2) based on their domestic and USPTO filings, respectively. Results based on domestic filings (Panel A) show no evidence of positive and significant knowledge spillovers from both of these groups with one exception. The spillover parameter associated with machinery imports from E2 is the only one that appears positive and significant; the rest of the spillover parameters are either insignificant or significantly negative. Results from USPTO filings reinforce these findings: all spillover parameters are either significantly negative or insignificant. Overall, there is virtually no evidence of positive and significant knowledge spillovers from E7 and E2 groups to the sample EMEs. These group level results are in line with those from the emerging world (EME-31).

Table 5 about here

Fixed effects results parallel to Table 5, reported in Online Appendix A5, largely corroborate the FMOLS findings. None of the spillover parameters from the E7 and E2 groups, based on domestic filings, appears statistically significant, irrespective of the specifications. Likewise, the results based on USPTO filings show only disembodied FKSPs to be positive and significant at 10% or better from G3 and G7; the rest of the spillover parameters are either significantly negative or insignificant. Thus, the virtual lack of significantly positive knowledge spillovers from EMEs' groups to sample EMEs is robust under both estimators (FMOLS and fixed effects).

However, there is some evidence of bilateral knowledge spillovers across EMEs. The results from domestic filings, based on FMOLS (Online Table A6), reveal that spillovers via geographical proximity are positive and significant from two (Russian Federation and Thailand), negative and significant from three (China, India and Mexico) and insignificant from two (Malaysia and Turkey). Knowledge diffusions via total imports are significantly positive from Malaysia, significantly negative from Mexico (at 10%) and insignificant from the remaining five. Spillovers from machinery imports appear significantly positive from two (China and India), significantly negative from the Russian Federation and insignificant from the remaining four. Likewise, spillovers via the disembodied channel appear significantly positive from the Russian Federation and Thailand; insignificant from China and Malaysia and significantly negative from the remaining three.

Results based on USPTO filings show more (19) cases of significantly positive bilateral spillover parameters than those from domestic filings; the latter show only seven significantly positive spillover parameters. The breadth of positively significant bilateral spillovers is similar under fixed effects. However, the difference between USPTO and domestic filings regarding significantly positive spillover parameters is much reduced to 18 versus 12 in fixed effects compared to 19 versus 7 found under FMOLS. For brevity, these results are not reported but are available in Luintel and Khan (2017). Overall, despite the virtual lack of positive and significant knowledge spillovers emanating from the emerging world and the groups of EMEs (E7 and E2), there is some evidence of bilateral knowledge spillovers across EMEs and this is more so with the USPTO filings. However, results also reveal some spillover parameters (both under domestic and USPTO filings) to be significantly negative, implying technological rivalry. Although significantly negative bilateral spillover parameters are also evident from G7 members, on the whole the negative spillover parameters appear far higher between and across EMEs.

Finally, Table 6 reports the FMOLS results from our regional clusters ─ namely, ARAB, ASIA, EE and LA ─ based on domestic (Panel A) and USPTO (Panel B) filings, respectively. The results based on domestic filings reveal that knowledge spillovers via total and machinery imports are positive and significant within the Arabian and east European clusters of countries but insignificant within Asian and Latin American ones. Spillovers via the disembodied channel are significantly positive between members of the east European cluster, significantly negative for the Arabian and Latin American clusters, and insignificant for the Asian cluster. The evidence weakens vis-à-vis USPTO filings. None of the spillover parameters based on USPTO filings appears significantly positive in any of the regional clusters; they are either significantly negative or insignificant. Fixed effects results (reported in Luintel and Khan, 2017) largely corroborate these findings. Mostly, the breadth and depth of significantly positive spillovers between members of four regional clusters remain very thin.

Table 6 about here

The results of significantly positive spillovers via trade flows within the Asian and EE clusters and those via disembodied conduit within the EE ─ based on domestic filings ─ are starkly different from the complete lack of significantly positive spillovers from E7 and E2 groups. It is tempting to assign these contrasting findings to linguistic, cultural and geographic factors. However, not a single spillover parameter appears positively significant within the Asian and LA clusters vis-à-vis domestic filings. Similarly, no spillover parameter appears significantly positive in relation to USPTO filings under FMOLS. We, therefore, hold back on our temptation. Overall, the results are not systematically convincing enough to support the notion that knowledge spillovers between countries are also shaped by linguistic, cultural and geographic affinities, using regional country clusters as proxy.

5. Further Robustness Checks

We have already scrutinized the sensitivity of our results vis-à-vis two estimators (FMOLS and Fixed Effects) as well as some variations in specifications, especially under fixed effects. We also establish that using the raw conduits of knowledge spillovers does not alter our results of extremely modest IKS to sample EMEs. In this section, we further probe if our results are sensitive to (i) large and small, (ii) high and low growth countries in the sample, and (iii) the rate of depreciation used to calculate domestic and foreign knowledge stocks. China is one of the major players in the R&D activities of the emerging world. We, therefore, evaluate if our results are susceptible to the exclusion of China.

We report a full set of results parallel to Tables 2 and 3 by excluding China from the sample in the Online Appendix (Tables A7 and A8). The exclusion of China does not affect the qualitative nature of our results; all parameter estimates remain fairly close to those of the full sample in their magnitudes, signs and significance. FMOLS results from domestically filed patents (Table A7) remain qualitatively the same for all joint specifications (columns 10-14); only two spillover parameters (reported in columns 6 and 9) appear imprecisely estimated when modeled one-by-one. The findings that $0 < \partial \ln \dot{A}_d / \partial \ln L_A < 1$ and that $\partial \ln \dot{A}_d / \partial \ln A_d > 1$ remain robust. Moreover, results based on USPTO (Table A8) appear almost identical even when China is dropped. Other results also remain robust to the exclusion of China.

We also examine the sensitivity of our results to other large and small countries of the sample, sequentially dropping India, Mexico, Thailand, Turkey, Malaysia, Paraguay and Romania from the panel, as well as the low growth countries (Hungary and Kyrgyzstan). Results remain robust to these sensitivity checks. Finally, we re-estimate our main specifications using domestic and foreign knowledge stocks computed at a 20% depreciation rate and find that results remain robust. Overall, our results are robust to changes in sample sizes (countries), countries with varying growth rates and rates of depreciation of R&D capital.

6. Main findings, Policy Implications and Conclusion.

The emerging world has significantly enlarged its R&D activities in recent years. Against this backdrop, we examine the production of new ideas and IKS in a panel of 31

EMEs. One of the objectives is to gauge empirically if the recent firm level and anecdotal evidence signifying the industrialized world as the primary source of knowledge to EMEs holds at the aggregate level. We account for six different channels of knowledge diffusions and proxy knowledge flows through residents' patent applications filed at their national office and at the USPTO. We empirically scrutinize IKS by using two methods: the FMOLS and fixed effects OLS. Fixed effects results largely corroborate the FMOLS results but, on balance, they show fewer cases of significantly positive knowledge spillovers. As stated in Section 4.2, in view of the non-stationary panel, we lay emphasis on FMOLS results.

Our findings are new and distinctive. We summarize them in four broad points and discuss the potential reasons behind these findings, followed by policy implications. First, IKS from the industrialized (OECD-20) world to emerging world (EME-31) via *total imports, machinery imports* and *FDI* ─ the three most widely analyzed conduits in the literature ─ appear insignificant when measured by domestic patent filings. However, spillovers via *inventors' mobility*, *geographical proximity* and *disembodied channels* appear positive and significant. With USPTO filings, spillovers via *geographical proximity* and *disembodied channels* only appear significant; the remaining four conduits appear insignificant. Thus, spillovers from the industrialized world to EMEs, with respect to both patent filings, appear robust via only two channels ─ *geographical proximity* and *disembodied*. These findings are distinctly different because a large body of literature reports trade flows and FDI as significant conduits of knowledge spillovers. At the group level, significantly positive spillovers from both G7 and G3 are found via *geographical proximity*, *FDI*, *inventors' mobility* and *disembodied channels*, measured by the domestic filings. The *total* and *machinery* import ratios, as conduits, show clear evidence of the raising-the-bar effect from G7 and G3. With respect to the USPTO filings, diffusions via *geographical proximity* and *disembodied channels* alone appear positive and significant from G7; while a further two spillover parameters ─ via machinery imports and FDI – appear significantly positive from G3. The evidence of the raising-the-bar effect via trade flows from G7 and G3, based on domestic filings, does not appear robust with the USPTO filings, nor is the spillover via inventors' mobility. There are a few more instances of significantly positive IKS from G7 and G3 groups than those from OECD pool (OECD-20). Interestingly, more cases of significantly positive IKS from the OECD to EMEs appear at the bilateral level. The higher degree of significant bilateral spillovers echoes the findings of Walsh et al. (2016) who, by analyzing survey data, report that partners in innovation "may vary by the goals of the research" (p. 1669). Despite some evidence of IKS at bilateral levels, overall, the breadth and depth of knowledge spillover externalities from OECD to EMEs appear exceedingly more moderate than the recent firm level and anecdotal evidence would suggest.

Second, positive and significant knowledge diffusions across the emerging world are virtually non-existent. Under FMOLS, only one diffusion parameter from the emerging world, via *geographical proximity*, appears marginally significant (at 10.4%), measured by the nationally filed patents; all remaining diffusion parameters appear insignificant. There is absolutely no evidence of positive and significant knowledge spillovers from the emerging world, based on the USPTO measures. This virtual lack of knowledge spillovers across EMEs is largely corroborated by fixed effects. Significantly positive spillovers are also virtually nil from both groups of EMEs. None of the spillover parameters bar one ─ the diffusion parameter via machinery imports from E2 ─ appears positive and significant from the groups of E7 and E2.

Third, results from the regional clusters of EMEs do not reveal any systematic evidence supporting linguistic, cultural and geographic influences on knowledge diffusions but we caution that the results on the lack of social dimensions should be taken as indicative only in view of the aggregate nature of the analysis. Amid this spillover gloom across EMEs, there is however some evidence of positive knowledge spillovers between EMEs at bilateral levels; and they appear more so vis-à-vis the USPTO filings. Overall, IKS across EMEs is virtually non-existent except in some bilateral cases.

Finally, our results reveal a number of significantly negative IKS parameters from the emerging world, emerging country groups (E7 and E2), emerging country clusters and at the bilateral levels. They indicate some degree of competitive pressure and/or technology rivalry between EMEs, which is not helping their discoveries. Such significantly negative spillovers are also evident from industrialized countries but they are few (confined to bilateral cases only) and nowhere near as pervasive as those from the emerging world. This implies that (i) there is a crucial difference in knowledge diffusions accruing from industrialized and emerging worlds to EMEs, and (ii) technology rivalry is more of an issue between EMEs, rather than between EMEs and industrialized countries. However, a specific country such as China may be a different case.[21]

Brief discussions of potential reasons behind these results and some of their policy implications are in order. The insignificance of trade flows and the lack of FDI as a robust conduit of IKS from the industrialized world to EMEs are not entirely inconsistent with the literature. For example, Keller (1998) and Branstetter (2001) doubt their merit. Trade and FDI flows, as raw measures of conduits, also appear insignificant in explaining innovations in

EMEs. These results might suggest that the R&D focus and processes may be different in EMEs from those of the industrialized countries; probably, the former focusing on a few specific sectors, e.g., Information and Technology, rather than on Manufacturing, which makes it hard to pin down the influence of aggregate trade flows. It is also true that some (major) EMEs stress indigenous innovations keeping several sectors of the economy insulated from foreign investors, thereby reducing the potential influence of international collaboration and spillovers at the aggregate level. For example, India is gradually opening up but very much under its own terms and has kept several sectors of the economy off limits to foreign investors; potential foreign investors often do not appreciate these terms, as we all know. This policy of insulation might, however, not be surprising because even the US firms generate most of their inventions internally (Walsh et al., 2016). In policy terms, our findings indicate that some broadening of R&D strategy by encompassing wider sectors ─ i.e., more opening up of their economies by EMEs ─ may help improve international knowledge linkages.

On the role of FDI, recent micro studies report it as a significant conduit. However, its failure as a robust conduit in our (aggregate) analyses might corroborate the, yet another, parallel micro finding that these firm level positive spillovers may be hard to come by outside of bounded conglomerates. Branstetter et al. (2013) report a strong degree of knowledge spillovers from co-invention teams to purely indigenous teams within the MNCs but spillovers to indigenous enterprises outside of MNCs is virtually non-existent. This also rejuvenates the issue of whether firm level evidence could be generalized for broader policy perspectives and that the firm level evidence may not reflect the aggregate picture. In fact, our results vividly show that firm level findings cannot be generalized and there is lack of correspondence between micro and macro evidence. A policy implication emerging from this is that strategies which might foster a close co-operation (collaboration) between public and private sector R&D might also help develop meaningful linkages and address the lack of correspondence between firm level and aggregate R&D efficacies.

The virtual lack of knowledge spillovers across EMEs at both the global and country group levels also has important policy implications. It suggests a long, hard path ahead in forging any meaningful knowledge linkages across EMEs ─ an issue already spearheaded by the BRICS leaderships with little tangible success to date (successive BRICS Summit declarations emphasize collaborative innovations). As stated earlier, technology rivalry appears a real issue between EMEs. Therefore, there is a case for an active international R&D policy co-ordination between emerging countries, or at least among the BRICS, if they are to achieve their stated goal of increased technological co-operation and collaborative innovation; the current status does not appear to be contributing to their mutual discoveries.

Finally, the existence of pockets (country and/or group of countries) of positive knowledge spillovers from both industrialized and emerging worlds to EMEs suggests that a carefully choreographed policy of synthesizing and focusing on such pockets might be rewarding. Our findings of heterogeneous IKS originating from OECD and EME worlds, as well as those from different countries, country groups and conduits, suggest that the design of R&D and innovation policy requires carefully composed and focused strategy rather than a one-size-fits-all approach.

Besides, we find duplication in knowledge production across EMEs, based on domestic filings; however, this duplication somewhat disappears vis-à-vis USPTO filings. The results show increasing returns to accumulated knowledge, which suggests that EMEs might be in growth transitions. It is, therefore, likely that the high rates of returns to domestic knowledge across EMEs and their high growth rates may gradually decelerate as they mature and become closer to the frontier – a lesson we have learnt from Asian miracle economies.

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Table 1: Descriptive Statistics (Sample Mean)[1]									
	GDP Growth	Filings at the national office	Filings at the USPTO	National filing: research productivity	USPTO filing: Research productivity	R&D expenditure	R&D intensity	L_A	Research intensity
Argentina	3.2	833	89	3.1	0.3	n.a.	n.a.	27,127	0.17
Azerbaijan	6.5	229	2	2.1	0.0	84	0.25	10,741	0.29
Bulgaria	2.5	295	34	2.5	0.3	402	0.60	11,680	0.32
China	9.8	61,854	1,379	7.5	0.2	45,197	1.19	829,562	0.12
Colombia	3.7	99	16	2.5	0.4	541	0.21	3,964	0.03
Costa Rica	4.7	17	10	0.8	0.5	129	0.38	2,010	0.12
Croatia	2.6	331	23	2.5	0.2	513	0.87	13,157	0.65
Czech Republic	2.9	717	79	4.0	0.4	2,375	1.23	18,145	0.35
Ecuador	3.2	10	5	1.0	0.5	105	0.14	945	0.02
Estonia	3.7	34	12	1.0	0.4	158	0.92	3,281	0.47
Georgia	2.6	261	4	2.1	0.0	31	0.23	12,477	0.54
Hungary	1.0	1,402	135	8.7	0.8	1,692	1.18	16,104	0.37
India	6.4	2,887	819	2.2	0.6	12,886	0.72	134,254	0.03
Kyrgyzstan	1.3	133	n.a.	5.8	n.a.	16	0.19	2,280	0.11
Latvia	3.4	157	5	4.5	0.1	117	0.50	3,443	0.29
Lithuania	2.2	110	6	1.4	0.1	267	0.67	7,828	0.46
Malaysia	5.5	433	129	7.0	2.1	1,295	0.49	6,207	0.06
Mexico	2.4	582	143	2.4	0.6	3,559	0.33	24,264	0.06
Morocco	3.9	112	3	0.4	0.0	495	0.52	25,039	0.25
Pakistan	4.2	63	5	0.5	0.0	1,051	0.37	13,619	0.03
Paraguay	2.8	22	1	5.0	0.2	n.a.	n.a.	441	0.02
Poland	4.6	2,528	51	4.5	0.1	2,984	0.64	56,351	0.32
Romania	2.0	1,287	16	5.3	0.1	992	0.55	24,362	0.22
Russian Federation	1.6	24,136	352	4.7	0.1	15,751	1.05	513,984	0.71
Saudi Arabia	2.6	88	43	7.5	3.7	n.a.	n.a.	1,169	0.02
Slovenia	3.4	346	38	6.9	0.8	626	1.53	5,046	0.52
Sri Lanka	5.3	111	4	4.2	0.1	105	0.17	2,661	0.03
Thailand	5.5	459	42	3.9	0.4	673	0.20	11,790	0.03
Tunisia	4.5	43	2	0.4	0.0	434	0.70	10,872	0.34
Turkey	4.1	683	30	2.7	0.1	3,143	0.53	25,102	0.12
Uruguay	2.9	33	7	3.2	0.7	96	0.30	1,030	0.07
Mean (1992-2010)	3.7	3,235	116	3.6	0.46	3,418	0.60	58,676	0.23
Japan (1992-2010)	0.8	344,648	57,868	52.8	8.9	114,666	3.08	652,534	0.97
US (1992-2010))	2.6	168,851	168,851	16.9	16.9	294,273	2.55	1,00,739	0.68
OECD(1992-2010)	2.6	37,400	14,712	24.5	5.2	33,607	1.97	152,533	0.66

GDP growth is the average annual growth rate (%); Research productivity refers to resident patent applications per researcher; R&D expenditure in million 2005 PPP$; R&D intensity refers to R&D expenditure as a percentage of GDP; L_A refers to researchers, scientists and engineers in the R&D Sector; Research intensity refers to researchers as a percentage of the labor force.

[1] We have unbalanced panel data. Reported sample means are calculated over the available data length for each country and each variable. These measures appear very close, even when means are computed for a common sample of 1992-2010.

Table 2: Ideas Production and International Knowledge Spillovers (Domestically Filed Patents)

$$\ln \dot{A}_{d,i,t} = \alpha_i + \varphi_t + \lambda \ln L_{A,i,t} + \phi \ln A_{d,i,t} + \beta \ln A^{f,\omega_1}_{oecd,i,t-1} + \theta \ln A^{f,\omega_2}_{eme,i,t-1} + e_{i,t}$$

Between-dimension (Group) FMOLS estimates

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
$L_{A,i,t}$	0.300 ^{a} (0.000)	0.271 ^{a} (0.000)	0.256 ^{a} (0.001)	0.190 ^{b} (0.022)	0.193 ^{b} (0.025)	0.196 ^{a} (0.008)	0.098 (0.190)	0.145 ^{c} (0.099)	0.199 ^{a} (0.007)	0.063 (0.371)	0.279 ^{a} (0.000)	0.207 ^{a} (0.006)	0.152 ^{b} (0.035)	0.150 ^{b} (0.032)
$A_{d,i,t}$	2.137 ^{a} 0.000)	2.041 ^{a} (0.000)	1.840 ^{a} (0.000)	1.984 ^{a} (0.000)	1.981 ^{a} (0.000)	1.657 ^{a} (0.000)	1.977 ^{a} (0.000)	1.766 ^{a} (0.000)	1.663 ^{a} (0.000)	2.028 ^{a} (0.000)	2.194 ^{a} (0.000)	2.352 ^{a} (0.000)	2.151 ^{a} (0.000)	2.253 ^{a} (0.000)
$A^{f,tm}_{oecd,i,t-1}$	-0.102 ^{c} (0.067)										-0.024 (0.674)			
$A^{f,mm}_{oecd,i,t-1}$		-0.026 (0.509)										0.052 (0.249)		
$A^{f,tm}_{eme,i,t-1}$			-0.002 (0.973)								0.051 (0.366)			
$A^{f,mm}_{eme,i,t-1}$				0.033 (0.149)								0.009 (0.733)		
$A^{f,FDI}_{oecd,i,t-1}$					0.370 (0.286)									
$A^{G-prox}_{oecd,i,t-1}$						0.071 ^{c} (0.078)							2.657 ^{a} (0.000)	
$A^{G-prox}_{eme,i,t-1}$							0.041 (0.187)						0.065 (0.104)	
$A^{f,sci}_{oecd,i,t-1}$								1.669 ^{a} (0.000)						
$A^{f,uw}_{oecd,i,t-1}$									0.081 ^{c} (0.069)					2.840 ^{a} (0.000)
$A^{f,uw}_{eme,i,t-1}$										0.054 ^{c} (0.074)				0.054 (0.212)
$\bar{R}^2$	0.989	0.989	0.989	0.990	0.989	0.990	0.990	0.989	0.990	0.990	0.990	0.990	0.990	0.990
OBS	561	561	561	561	463	561	561	415	561	561	561	561	561	561
Panel cointegration tests														
t_{adf}	-6.934 ^{a} (0.000)	-6.763 ^{a} (0.000)	-6.511 ^{a} (0.000)	-8.126 ^{a} (0.000)	-3.949 ^{a} (0.000)	-8.840 ^{a} (0.000)	-7.880 ^{a} (0.000)	-7.319 ^{a} (0.000)	-9.823 ^{a} (0.000)	-8.342 ^{a} (0.000)	-6.064 ^{a} (0.000)	-8.841 ^{a} (0.000)	-10.462 ^{a} (0.000)	-10.012 ^{a} (0.000)
t_{pp}	-7.828 ^{a} (0.000)	-7.333 ^{a} (0.000)	-8.826 ^{a} (0.000)	-9.055 ^{a} (0.000)	-4.768 ^{a} (0.000)	-12.144 ^{a} (0.000)	-9.198 ^{a} (0.000)	-5.672 ^{a} (0.000)	-13.306 ^{a} (0.000)	-9.915 ^{a} (0.000)	-9.502 ^{a} (0.000)	-14.021 ^{a} (0.000)	-13.277 ^{a} (0.000)	-10.012 ^{a} (0.000)

Where, $L_{A,i,t}$ and $A_{d,i,t}$ respectively denote research scientists employed in the R&D sector and domestic knowledge stock of the i^{th} sample country. Likewise, $A^{f,tm}_{oecd,i,t}$, $A^{f,mm}_{oecd,i,t}$, $A^{f,FDI}_{oecd,i,t}$, $A^{G-prox}_{oecd,i,t}$, $A^{f,sci}_{oecd,i,t}$ and $A^{f,uw}_{oecd,i,t}$, respectively are foreign spillover pools weighted by total imports ratio, machinery imports ratio, FDI ratio, geographical proximity, inventors' mobility and a disembodied measure as explained in Section 3. Equally, $A^{f,tm}_{eme,i,t}$, $A^{f,mm}_{eme,i,t}$, $A^{G-prox}_{eme,i,t}$ and $A^{f,uw}_{eme,i,t}$ are corresponding spillover pools originating from the emerging world. Reported stock measures are calculated at 15% depreciation rate. OBS denotes total observations and $\bar{R}^2$ is goodness of fit statistics. Data on scientists' mobility and FDI are only available for 21 and 25 countries, respectively. t_{adf} and t_{pp} are ADF and Phillips-Perron panel tests of the null of no cointegration (Pedroni, 1999). Lag lengths for cointegration tests are chosen by SIC, setting a maximum lag of 4. Superscripts 'a', 'b' and 'c' respectively denote significance at 1%, 5% and 10%. Throughout all Tables P-values are within parentheses.

Table 3: Ideas Production and International Knowledge Spillovers (Patents Filed at USPTO)

$$\ln \dot{A}_{d,i,t} = \alpha_i + \varphi_t + \lambda \ln L_{A,i,t} + \phi \ln A_{d,i,t} + \beta \ln A^{f,\omega_1}_{oecd,i,t-1} + \theta \ln A^{f,\omega_2}_{eme,i,t-1} + e_{i,t}$$

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Between-dimension (Group) FMOLS estimates														
$L_{A,i,t}$	0.675 [a] (0.000)	0.648 [a] (0.000)	0.700 [a] (0.000)	0.722 [a] (0.000)	0.796 [a] (0.000)	0.576 [a] (0.000)	1.076 [a] (0.000)	0.828 [a] (0.000)	0.531 [a] (0.000)	1.080 [a] (0.000)	0.953 [a] (0.000)	1.125 [a] (0.000)	1.236 [a] (0.000)	1.220 [a] (0.000)
$A_{d,i,t}$	1.813 [a] (0.000)	1.872 [a] (0.000)	1.859 [a] (0.000)	1.795 [a] (0.000)	1.756 [a] (0.000)	1.715 [a] (0.000)	2.141 [a] (0.000)	1.688 [a] (0.000)	1.704 [a] (0.000)	2.124 [a] (0.000)	2.075 [a] (0.000)	2.169 [a] (0.000)	2.238 [a] (0.000)	2.248 [a] (0.000)
$A^{f,tm}_{oecd,i,t-1}$	0.007 (0.935)										0.028 (0.777)			
$A^{f,mm}_{oecd,i,t-1}$		0.082 (0.211)										0.159 [b] (0.027)		
$A^{f,tm}_{eme,i,t-1}$			-0.169 [b] (0.045)								-0.103 (0.280)			
$A^{f,mm}_{eme,i,t-1}$				-0.010 (0.806)								-0.082 [c] (0.098)		
$A^{f,FDI}_{oecd,i,t-1}$					0.160 (0.702)									
$A^{G-prox}_{oecd,i,t-1}$						0.969 [c] (0.059)							1.177 [b] (0.023)	
$A^{G-prox}_{eme,i,t-1}$							-0.247 [b] (0.033)						-0.161 (0.175)	
$A^{f,sci}_{oecd,i,t-1}$								-0.582 (0.317)						
$A^{f,uw}_{oecd,i,t-1}$									1.467 [a] (0.004)					1.245 [a] (0.013)
$A^{f,uw}_{eme,i,t-1}$										-0.255 [b] (0.042)				-0.248 [b] (0.037)
$\bar{R}^2$	0.971	0.971	0.971	0.971	0.975	0.971	0.972	0.970	0.971	0.972	0.971	0.972	0.972	0.972
OBS	665	665	665	664	563	665	665	451	665	665	665	664	665	665
Panel cointegration tests														
t_{adf}	-12.953 [a] (0.000)	-12.613 [a] (0.000)	-11.114 [a] (0.000)	-11.416 [a] (0.000)	-11.714 [a] (0.000)	-12.460 [a] (0.000)	-10.571 [a] (0.000)	-10.013 [a] (0.000)	-12.605 [a] (0.000)	-10.081 [a] (0.000)	-12.727 [a] (0.000)	-13.323 [a] (0.000)	-13.402 [a] (0.000)	-11.870 [a] (0.000)
t_{pp}	-15.203 [a] (0.000)	-16.928 [a] (0.000)	-14.233 [a] (0.000)	-15.082 [a] (0.000)	-11.571 [a] (0.000)	-13.206 [a] (0.000)	-11.516 [a] (0.000)	-9.917 [a] (0.000)	-13.325 [a] (0.000)	-10.366 [a] (0.000)	-14.905 [a] (0.000)	-21.365 [a] (0.000)	-15.253 [a] (0.000)	-14.030 [a] (0.000)

For all variable definitions, reported test statistics and other details, please refer to the notes to Table 2. Tables 2 and 3 contain the same structure of specifications but they differ in measurements of variables. Table 2 utilizes measures based on patents filed at the national patent office, whereas measures in Table 3 are based on their USPTO filings.

Table 4: Knowledge Spillovers from G7 and G3 Groups of Industrialized to Emerging Countries

$$\ln \dot{A}_{d,i,t} = \alpha_i + \varphi_t + \lambda \ln L_{A,i,t} + \phi \ln A_{d,i,t} + \beta \ln A^{f}_{i,t-1} + e_{i,t}$$

Groups	$L_{A,i,t}$	$A_{d,i,t}$	$A^{f,tm}_{i,t-1}$	$A^{f,mm}_{i,t-1}$	$A^{f,FDI}_{i,t-1}$	$A^{G-prox}_{i,t-1}$	$A^{f,\mathrm{sci}}_{i,t-1}$	$A^{f,\mathrm{uw}}_{i,t-1}$
Panel A: Between-dimension (Group) FMOLS estimates (domestically filed patents)								
G3	0.265 (0.001) [a, 1]	1.979 (0.000) [a]	-0.129 (0.021) [b]					
	0.240 (0.001) [a, 1]	2.070 (0.000) [a]		-0.086 (0.055) [c]				
	0.283 (0.001) [a, 3]	1.690 (0.000) [a]			0.954 (0.008) [a]			
	0.208 (0.005) [a, 1]	2.015 (0.000) [a]				1.444 (0.001) [a]		
	0.143 (0.117) [c, 4]	1.925 (0.000) [a]					0.106 (0.013) [a]	
	0.044 (0.590) [1]	1.891 (0.000) [a]						1.258 (0.005) [a]
G7	0.244 (0.002) [a, 1]	2.056 (0.000) [a]	-0.159 (0.004) [a]					
	0.222 (0.003) [a, 1]	2.049 (0.000) [a]		-0.075 (0.092) [c]				
	0.255 (0.002) [a, 3]	1.818 (0.000) [a]			0.630 (0.053) [b]			
	0.202 (0.007) [a, 1]	2.024 (0.000) [a]				1.473 (0.001 [a])		
	0.176 (0.047) [b, 4]	1.997 (0.000) [a]					0.072 (0.088) [c]	
	0.042 (0.607) [1]	1.900 (0.000) [a]						1.250 (0.006) [a]
Panel B: Between-dimension (Group) FMOLS estimates (patents filed at the USPTO)								
G3	0.690 (0.000) [a, 2]	1.833 (0.000) [a]	-0.101 (0.239)					
	0.621 (0.000) [a, 2]	1.840 (0.000) [a]		0.128 (0.058) [c]				
	0.511 (0.000) [a, 3]	1.736 (0.000) [a]			0.738 (0.084) [c]			
	0.537 (0.000) [a, 2]	1.770 (0.000) [a]				1.541 (0.001) [a]		
	0.611 (0.000) [a, 4]	1.618 (0.000) [a]					-0.012 (0.875)	
	0.624 (0.000) [a, 2]	1.785 (0.000) [a]						1.527 (0.001) [a]
G7	0.690 (0.000) [a, 2]	1.818 (0.000) [a]	-0.058 (0.525)					
	0.647 (0.000) [a, 2]	1.899 (0.000) [a]		0.091 (0.180)				
	0.576 (0.000) [a, 3]	1.703 (0.000) [a]			-0.091 (0.828)			
	0.538 (0.000) [a, 2]	1.742 (0.000) [a]				1.317 (0.006) [a]		
	0.619 (0.000) [a, 4]	1.638 (0.000) [a]					-0.113 (0.159)	
	0.609 (0.000) [a, 2]	1.750 (0.000) [a]						1.450 (0.002) [a]

This Table reports the results of 24 models (specifications) which estimate knowledge spillovers from G7 and G3 Groups of Industrialized countries to EMEs based on six channels of diffusions. G7 consists of Canada, France, Germany, Italy, Japan, the UK and the US; G3 consists of Germany, the US and Japan. Italy does not have complete data on inventors' mobility, hence the results for this conduit are based on G6 countries (G7 minus Italy). Superscript 1 denotes specifications with total observations (OBS) ranging from 561 to 586 (561-586); superscript 2 denotes models with OBS=665-688; superscript 3 denotes models with OBS=463-563; and superscript 4 denotes models with OBS=338-380. Data points vary across specifications due to different observations across each data series. The $\bar{R}^2$ across these 24 modules is very high, ranging between 0.971 and 0.993, which is not surprising given that the panel is non-stationary. We implemented the same panel cointegration tests (t_{adf} and t_{pp}), reported in Table 2, on each of these 24 models. Tests reject the null of non-cointegration in all cases with a very high precision (P-values=0.000). For brevity, we do not report these results. Superscripts 'a', 'b' and 'c' respectively denote significance at 1%, 5% and 10%.

Table 5: Knowledge Spillovers from Emerging Country Groups (E7 and E2) to Individual Emerging Countries in the Panel						
$\ln \dot{A}_{d,i,t} = \alpha_i + \varphi_t + \lambda \ln L_{A,i,t} + \phi \ln A_{d,i,t} + \theta \ln A_{i,t-1}^{f,\omega_2} + e_{i,t}$						
Panel A: Between-dimension (Group) FMOLS estimates (Domestic Filing)						
Groups	$L_{A,i,t}$	$A_{d,i,t}$	$A_{i,t-1}^{f,tm}$	$A_{i,t-1}^{f,mm}$	$A_{i,t-1}^{G-prox}$	$A_{i,t-1}^{f,uw}$
E2	-0.075 (0.365)	1.956 (0.000) [a]	0.036 (0.168)			
	0.002 (0.978)	1.900 (0.000) [a]		0.090 (0.000) [a]		
	-0.068 (0.365)	2.588 (0.000) [a]			-0.147 (0.005) [a]	
	-0.032 (0.645)	2.582 (0.000) [a]				-0.195 (0.000) [a]
E7	0.085 (0.311)	1.657 (0.000) [a]	0.082 (0.115)			
	0.160 (0.064) [c]	1.973 (0.000) [a]		0.015 (0.478)		
	-0.170 (0.023) [b]	2.237 (0.000) [a]			0.025 (0.555)	
	-0.052 (0.477)	2.160 (0.000) [a]				-0.008 (0.833)
Panel B: Between-dimension (Group) FMOLS estimates (USPTO Filing)						
E2	0.650 (0.000) [a]	1.943 (0.000) [a]	-0.121 (0.000) [a]			
	0.665 (0.000) [a]	1.909 (0.000) [a]		-0.077 (0.001) [a]		
	0.797 (0.000) [a]	1.661 (0.000) [a]			0.045 (0.536)	
	0.925 (0.000) [a]	1.795 (0.000) [a]				-0.120 (0.127)
E7	0.627 (0.000) [a]	1.838 (0.000) [a]	0.075 (0.276)			
	0.794 (0.000) [a]	2.004 (0.000) [a]		-0.138 (0.000) [a]		
	1.055 (0.000) [a]	2.037 (0.000) [a]			-0.313 (0.006) [a]	
	1.024 (0.000) [a]	2.153 (0.000) [a]				-0.350 (0.001) [a]

The group of emerging seven (E7) consists of China, India, Malaysia, Mexico, the Russian Federation, Thailand and Turkey; and the group of emerging two (E2) is made up of China and India. This table contains 16 models based on two emerging country groups, four conduits and two types of patent filing (Domestic and the USPTO) by the EMEs. Again, we implemented the same panel cointegration tests (t_{adf} and t_{pp}), reported in Table 2, on each of these 16 models. Tests reject the null of non-cointegration in all cases with a very high precision (in all cases, P-values=0.000); results are available on request. All specifications reported under domestic filings contain 586 data points (OBS). Each model shows a very high $\bar{R}^2$ of 0.990 which again is not surprising between non-stationary variables. Likewise, all models reported under USPTO filings have OBS of 665-666; and a very high $\bar{R}^2$ of 0.972.

Table 6: Knowledge Spillovers within Countries of each Regional Cluster					
$\ln \dot{A}_{d,i,t} = \alpha_i + \varphi_t + \lambda \ln L_{A,i,t} + \phi \ln A_{d,i,t} + \theta \ln A^{f,\omega_2}_{eme,i,t-1} + e_{i,t}$					
Panel A: Between-dimension (Group) FMOLS estimates (domestic filings)					
	$L_{A,i,t}$	$A_{d,i,t}$	$A^{f,tm}_{i,t-1}$	$A^{f,mm}_{i,t-1}$	$A^{f,uw}_{i,t-1}$
ARAB	0.819 (0.021) [b]	3.387 (0.000) [a]	0.163 (0.043) [b]		
	0.335 (0.390)	2.855 (0.000) [a]		0.332 (0.000) [a]	
	0.380 (0.329)	2.910 (0.000) [a]			-0.600 (0.000) [a]
ASIA	0.499 (0.001) [a]	0.970 (0.000) [a]	-0.024 (0.702)		
	0.543 (0.000) [a]	1.003 (0.000) [a]		0.044 (0.402)	
	0.480 (0.003) [a]	0.901 (0.000) [a]			-0.050 (0.673)
EE	0.609 (0.000) [a]	0.610 (0.000) [a]	0.422 (0.002) [a]		
	0.496 (0.000) [a]	0.366 (0.000) [a]		0.111 (0.038) [b]	
	0.333 (0.009) [a]	0.387 (0.000) [a]			1.302 (0.000) [a]
LA	0.756 (0.121)	1.675 (0.003) [a]	-0.125 (0.422)		
	0.470 (0.302)	1.438 (0.005) [a]		0.020 (0.802)	
	0.517 (0.042) [b]	1.214 (0.000) [a]			-2.579 (0.000) [a]
Panel B: Between-dimension (Group) FMOLS estimates (USPTO filings)					
ARAB	0.609 (0.195)	1.921 (0.000) [a]	-0.284 (0.048) [b]		
	-0.030 (0.947)	1.929 (0.000) [a]		-0.389 (0.282)	
	0.240 (0.649)	2.055 (0.000) [a]			-0.569 (0.059) [c]
ASIA	0.044 (0.788)	1.458 (0.000) [a]	0.021 (0.832)		
	0.119 (0.540)	1.509 (0.000) [a]		0.117 (0.110)	
	0.994 (0.000) [a]	1.962 (0.000) [a]			-0.607 (0.001) [a]
EE	0.825 (0.000) [a]	1.851 (0.000) [a]	0.063 (0.553)		
	1.124 (0.000) [a]	1.834 (0.000) [a]		0.074 (0.275)	
	0.951 (0.000) [a]	2.262 (0.000) [a]			-0.038 (0.876)
LA	0.299 (0.012) [a]	2.311 (0.000) [a]	-0.099 (0.593)		
	0.372 (0.002) [a]	2.417 (0.000) [a]		-0.301 (0.002) [a]	
	-0.106 (0.496)	2.163 (0.000) [a]			0.677 (0.316)

31 sample countries are grouped into four regional clusters ─ Arabian (ARAB), Asian (ASIA), east European (EE) and Latin American (LA) with four, six, 14 and seven member countries, respectively (footnote 14 lists the country names). Spillovers between members of each cluster are modeled. Group t_{adf} and t_{pp} tests confirm all models as cointegrated at 5% or better except for the Arabian cluster under disembodied conduit (results available on request). However, the pooled t_{adf} and t_{pp} tests confirm the latter as cointegrated. The small number of countries in the ARAB cluster might explain non-cointegration by Group tests. Under the domestic filings, reported models of (i) ARAB cluster has 57 observations (OBS); (ii) ASIA has 120 OBS; (iii) EE has 233 OBS; and (iv) LA has 131 OBS. $\bar{R}^2$ of these specifications range between 0.980 and 0.995. Likewise, under USPTO filings, (i) ARAB cluster has 87 OBS; (ii) ASIA has 164 OBS; (iii) EE has 269 OBS; and (iv) LA has 163 OBS. $\bar{R}^2$ of these specifications range between 0.980 and 0.995.

Data Appendix

Our sample consists of 31 EMEs. Data frequency is annual with a maximum time span of 26 years (1985-2010) and a minimum time span of 17 years (1994-2010). The sample period differs across countries due to data availability. Domestic knowledge stocks for each sample country based on residents' domestic ($A^{H}_{d,i,t}$) and USPTO ($A^{USPTO}_{d,i,t}$) patent applications are calculated from the respective country's patent flows ($\dot{A}^{H}_{d,i,t}$) and ($\dot{A}^{uspto}_{d,i,t}$) using the Perpetual Inventory method. Initial knowledge stock for the i^th country, $A^{H}_{d,i,0}$, is calculated as:

$$A^{H}_{d,i,0} = \frac{\bar{\dot{A}}^{H}_{i,d,t}}{g_i + \delta} \qquad \text{(A1)}$$

where δ denotes the depreciation rate of knowledge; g_i is the average annual growth rate of $\dot{A}_{i,d,t}$ over the sample. We use the mean value of the first five years of $\dot{A}_{i,d,t}$ as the initial value, $\bar{\dot{A}}_{i,d,t}$. We compute alternative measures of R&D capital stocks based on two depreciation rates (15 and 20%). Calculations of domestic knowledge stocks of the i^{th} sample country based on USPTO filings follows the same approach. After the generation of initial knowledge stock, the subsequent stock calculations are straightforward. We acknowledge that the Perpetual Inventory method requires assumptions about the average life of capital stocks, depreciation rates as well as taxes on capital assets, which are not straightforward. Nevertheless, this approach is widely used in the literature hence we follow it. The precise sources of each of the data series used are listed below.

Data	Sources
Resident patent applications at national patent office; Patent applications filed at the US Patent and Trademark Office.	Word Intellectual Property Organization (WIPO), Statistics Database, http://ipstats.wipo.int/ipstatv2/index.htm
Research scientists and engineers employed in the R&D Sector	OECD, Main science and technology indicators (MSTI database), and UNESCO Institute for Statistics, http://data.uis.unesco.org/
Bilateral total and machinery imports, US$	UN Comtrade Database - http://comtrade.un.org/
Bilateral FDI stocks and flows, US$	UNCTAD Bilateral FDI Statistics - http://unctad.org/en/Pages/DIAE/FDI%20Statistics/FDI-Statistics-Bilateral.aspx

Distance between capital cities	Kristian Skrede Gleditsch, http://privatewww.essex.ac.uk/~ksg/data-5.html
International mobility of inventors	Fink and Miguelez (2013), www.wipo.int/publications/en/details.jsp?id=3952&plang=EN
Total Factor Productivity (TFP)	Penn World Table 8.1, www.rug.nl/research/ggdc/data/pwt/
GDP in US$	World Bank, World Development Indicators, http://data.worldbank.org/data-catalog/world-development-indicators
GDP, GDP per capita, GDP deflator (2005=100), population and labor force	World Bank, World Development Indicators, http://data.worldbank.org/data-catalog/world-development-indicators
Gross domestic expenditure on research and development (R&D)	OECD, Main science and technology indicators (MSTI database), and UNESCO Institute for Statistics, http://data.uis.unesco.org/
R&D performed abroad by majority-owned foreign affiliates of US parent companies	Bureau of Economic Analysis, www.bea.gov/iTable/index_mnc.cfm
R&D expenditure by type of cost	OECD Research and Development Statistics - http://stats.oecd.org/Index.aspx?DataSetCode=GERD_COST

A few countries (e.g., Thailand and Sweden) report R&D data every other year, especially in the initial years of the sample. We filled such gaps by the mean of the adjoining values. In a few cases, we also used linear extrapolation through an R&D intensity variable when the gaps in data points were more than one. Overall, less than 5% of our total sample observations have gaps. Filling gaps by these methods is standard in the discipline.

[1] These world shares and growth rates are the authors' own calculations. OECD consists of 34 member countries some of which are EMEs that joined as recently as 2010 (Chile, Estonia, Israel and Slovenia). For the calculation of world share and growth rates, we define an OECD pool comprised of the following 23 OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Republic of Korea, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States. Luxembourg and Israel lack complete data series. A further nine countries, namely, Chile, Czech Republic, Estonia, Hungary, Mexico, Poland, Slovak Republic, Slovenia and Turkey are also current members of the OECD but we categorize them as emerging economies for this analysis. Exclusion of the latter nine countries from the OECD pool only alters the calculated world share of OECD R&D expenditure by just 1%. For data reasons, while generating spillover pools from the industrialized world (Section 3), we base our computations on 20 OECD countries (henceforth OECD-20) excluding Belgium, Greece and Portugal from the above list. For the world share calculations, the pool of EMEs (emerging world) consists of over 70 countries (i.e., 70 to 80) – including the above nine EMEs which are members of OECD – for which UNESCO maintains R&D data. However, for econometric analysis we analyze a sample of 31 EMEs (see Section 2).

[2] Countries such as China (21.1%), India (11.4%), Malaysia (12.4%), Sri Lanka (10.7%), Thailand (13.2%), Turkey (14.0%) have all recorded average annual patent growth rate in double digits (.) during the sample period. The average annual growth rate of the domestic patent of EMEs, as stated above, is 10.4%.

[3] Mazzucato (2013) provides a catalog of evidence on how the US government basically led major invention breakthroughs in the US. Celebrated high tech firms such as Apple simply integrated the pool of technology either invented by or invented with the key financial support of the US government. The thrust of her arguments is that the role of public sector R&D is vital in big knowledge breakthroughs that require high risk taking and huge resource commitments – something that private sector and venture capital firms tend to shy away from. We would argue that, given their nascent and evolving R&D sector, this is more so in EMEs.

[4] Data are from UNESCO at http://data.uis.unesco.org/; accessed on 04/09/2016 (dd/mm/yy).

[5] As of 2011, the proportion of majority-holding US MNCs' R&D in total (business sector) R&D is 4.7% (17.1%) in Argentina, 5.0% (9.3%) in Brazil, 1.5% (2.1%) in China, 4.0% (6.7%) in Hungary, 12.8% (36.9%) in India, 14.7% (23.0%) in Malaysia, 4.6% (16.1%) in Poland, 0.5% (0.9%) in the Russian Federation, 11.2% (25.3%) in Thailand and 0.8% (2.0%) in Turkey. Source: US Bureau of Economic Analysis. Data are available at www.bea.gov/iTable/index_mnc.cfm; accessed on 04/09/2016.

[6] We acknowledge that South Africa is the smallest among the BRICS members which joined the group in 2010. Until South Africa joined, the acronym was BRICs or BRIC rather than BRICS. The exclusion of South Africa hardly changes the proportions of MNC's R&D expenditure. The US MNC's R&D involvement into the four members of BRICs (i.e., excluding South Africa) is 2.6% and 3.8% of their total and business sector R&D, respectively.

[7] Of course, we acknowledge some individual country exceptions, as calculations in footnote 5 show but our conjecture is for the whole of the emerging world.

[8] Commenting on firm-level studies of knowledge spillovers Branstetter (1998, footnote 23) writes, "It is not clear that the results obtained from such studies apply to the relevant industry or the economy as a whole."

[9] There is a voluminous amount of literature examining the role of IKS on domestic total factor productivity (TFP) mostly utilizing OECD data. However, studies investigating ideas production and IKS in a large panel of EMEs are relatively lacking.

[10] See http://www.chinadaily.com.cn/business/2017-02/27/content_28359192.htm. Accessed on 04/04/2017.

[11] Despite their wider usage, we acknowledge that patents are a noisy measure of innovations. Patents mostly explicate the applied part of R&D and innovation, whereas basic research (associated with fewer patent grants) generates more knowledge spillovers (Trajtenberg et al., 1992). Patents differ widely in their "universality" and "size" (Eaton et al., 1998). All

inventions are neither patented nor are they equally valuable (Battke et al., 2016). As a departure, Walsh et al. (2016) enumerate the quality of inventions through survey by directly asking inventors to rank the technological significance of their inventions relative to others in the field at the time. Yet, the flow of patents is the only available and consistent proxy of new ideas for this set of sample countries.

[12] We thank an anonymous referee for suggesting that we use the patents filed at the USPTO to mitigate this potential noise problem.

[13] United States Government Accountability Office (GAO)'s Report to the Chairman, Committee on the Judiciary, House of Representatives, June 2016 can be found at http://www.gao.gov/products/GAO-16-490; accessed on 28/10/2016.

[14] The Arab cluster consists of four countries: Morocco, Saudi Arabia, Tunisia and Turkey; (ii) the Asian cluster consists of six countries: China, India, Malaysia, Pakistan, Sri Lanka and Thailand; (iii) The east European cluster consists of 14 countries: Azerbaijan, Bulgaria, Croatia, Czech Republic, Estonia, Georgia, Hungary, Kyrgyzstan, Latvia, Lithuania, Poland, Romania, the Russian Federation and Slovenia; and finally, (iv) the Latin American cluster consists of seven countries: Argentina, Colombia, Costa Rica, Ecuador, Mexico, Paraguay and Uruguay.

[15] Italy does not have data on foreign scientists working in her R&D sector. Hence, in actual empirical estimations we use 118 rather than 120 FKSPs originating from the industrialized world, hence the total FKSPs generated is 222.

[16] https://en.wikipedia.org/wiki/Standing_on_the_shoulders_of_giants; accessed on 17/09/2016.

[17] We thank one of the anonymous referees who suggests we use fixed effects methods as robustness checks, on the grounds that integration and cointegration methods are not widely used in the micro R&D literature.

[18] The cointegrating regressions are between non-stationary variables, hence $\bar{R}^2$ statistics are always very high, as is evident across all our estimations. Further, we use a between-dimension FMOLS estimator which addresses the crucial issue of parameter heterogeneity across countries and is a powerful estimator. However, under this estimator the $\bar{R}^2$ measure makes little sense because it will be the average of all individual goodness of fit statistics across all panel units. We therefore report the FMOLS within-dimension $\bar{R}^2$, which is an overall $\bar{R}^2$ akin to that of fixed effects OLS regressions. Given the non-stationary data, these $\bar{R}^2$ must be used with a high degree of caution.

[19] We thank an anonymous referee who encouraged us to do robustness checks along these lines. The three additional specifications that we estimate under fixed effects by pooling FKSPs originating from OECD and EMEs separately as well as jointly, vis-à-vis Tables 2 and 3, are not feasible under the Grouped (heterogeneous) panel FMOLS due to the lack of degrees of freedom. Hence, we estimate them under the fixed effect model only. However, they do help to shed light on the robustness of our FMOLS results.

[20] $\bar{R}^2$ shows a very high degree of fit across all models whereas Durbin-Watson (DW) statistics assume a low value. These twin characteristics of low DW statistics and a very high $\bar{R}^2$ are typical across all fixed effects results reported in the paper. They are also typical characteristics of regressions involving non-stationary data. AR(1) estimates improve DW statistics in the range where the first order residual serial correlation is no longer an issue but do not alter the qualitative nature of other results. Given their close similarity across models, we do not comment on these two statistics in respect of the results tables that follow.

[21] The potential exception of countries such as China is our conjecture, rather than a finding of this paper.