ECONSTOR
Make Your Publications Visible.

A Service of
ZBW
Leibniz-Informationszentrum Wirtschaft
Leibniz Information Centre for Economics

Luintel, Kul Bahadur; Khan, Mosahid

Working Paper

R&D, scale effects and spillovers: New insights from emerging countries

Cardiff Economics Working Papers, No. E2016/4

Provided in Cooperation with:
Cardiff Business School, Cardiff University

Suggested Citation: Luintel, Kul Bahadur; Khan, Mosahid (2016) : R&D, scale effects and spillovers: New insights from emerging countries, Cardiff Economics Working Papers, No. E2016/4, Cardiff University, Cardiff Business School, Cardiff

This Version is available at:
https://hdl.handle.net/10419/174117

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

WWW.ECONSTOR.EU

Mitglied der Leibniz-Gemeinschaft

Cardiff Economics Working Papers

Cardiff Business School
Cardiff University

Ysgol Fusnes Caerdydd
Prifysgol Caerdydd

Working Paper No. E2016/4

R&D, Scale Effects and Spillovers: New Insights from Emerging Countries

Kul B Luintel and Mosahid Khan

April 2016

ISSN 1749–6101

Cardiff Business School
Aberconway Building
Colum Drive
Cardiff CF10 3EU
United Kingdom
t: +44 (0)29 2087 4000
f: +44 (0)29 2087 4419
business.cardiff.ac.uk

This working paper is produced for discussion purpose only. These working papers are expected to be published in due course, in revised form, and should not be quoted or cited without the author's written permission.
Cardiff Economics Working Papers are available online from:
http://econpapers.repec.org/paper/cdfwpaper/ and
business.cardiff.ac.uk/research/economics/working-papers
Enquiries: EconWP@cardiff.ac.uk

R&D, Scale Effects and Spillovers: New Insights from Emerging Countries

Kul B Luintel*
Cardiff Business School
Aberconway Building, Colum Drive
Cardiff, CF10 3EU
Tel: +44 (0)292 087 5534
Fax: +44 (0)292 087 4419
LuintelK@cardiff.ac.uk

AND

Mosahid Khan
World Intellectual Property Organization
Geneva, Switzerland.
Mosahid.khan@wipo.int

Abstract

There has been a concomitant rise in R&D and the rate of economic growth in emerging countries. Analyzing a panel of 31 emerging countries, we find convincing evidence of scale effects which make government policies potent for long-run growth. This contrasts sharply with the well known findings of Jones (1995a). Innovations show increasing returns to knowledge stock, implying that the diminishing returns assumed by some semi-endogenous growth models might not be generalized. International R&D spillovers raise the innovation bar. The observed growth rates of emerging economies appear in transition therefore their growth rates may recede with the passage of time.

JEL Classification: O3; O4; O47.

Key Words: Scale Effects; Ideas Production; Diffusion; Panel Integration and Cointegration.

*Corresponding author.

R&D, Scale Effects and Spillovers: New Insights from Emerging Countries

1. Introduction

Historically, world research and development (R&D) activity has been almost entirely concentrated in the Organisation for Economic Co-operation and Development (OECD) countries; they accounted for 88% of world R&D expenditure (R&DEXP) in 1992. While OECD countries still account for the lion's share (about 74%) of world R&DEXP, emerging countries are making a significant headway. The latter's share in world R&DEXP increased from 12% in 1992 to 26% in 2010. Over the last two decades or so, emerging countries' R&DEXP has grown by 8.6% per annum (p.a.) in real terms, rising from $69.3bn in 1992 to $305.6bn in 2010, whereas the growth rate of OECD R&DEXP was only 2.8% p.a.

The flow of new-to-the-country knowledge (new ideas) – proxied by resident patent applications ($\dot{A}_d$) – also paints a similar picture. OECD and emerging countries respectively accounted for 89% and 11% of worldwide resident patent applications in 1992; however, this has dramatically changed over the last two decades – the proportion of resident patent applications by OECD countries has gradually reduced to 64%, whereas the proportion of emerging countries has increased to 36% by 2011. The growth in resident patent applications mimics the patterns of R&DEXP – resident patent applications filed by emerging countries rose by 10.4% p.a. during 1992-2011, whereas applications filed by OECD countries grew by only 2.3% during the same period.

The number of research scientists and engineers employed in the R&D sector (L_A) worldwide was about 4.5 million in 1994 of which 2.8 million (62%) were in OECD countries and 1.7 million (38%) in emerging countries. Between 1994 and 2010, the world total of L_A increased from 4.5 million to 6.7 million of which the OECD accounted for 4.1 million (61%) and emerging countries 2.6 million (39%). L_A grew annually by 2.4% in OECD countries and 2.7% in emerging countries which is far less contrasting than the growth rates of R&DEXP and $\dot{A}_d$ between these two groups of countries.[1]

Overall, the level of R&D activities is still much greater in OECD countries but the momentum is clearly higher in emerging countries in recent decades. The rapid rise

in the level of R&D activities is potentially important for emerging countries. The first generation of R&D-based endogenous growth models (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1998) postulate that innovations drive productivity and long-run economic growth. In these models, permanent changes in government policies – e.g. subsidy to R&D – lead to permanent change in growth rate through increased R&D intensity. These models predict that knowledge creation, domestic total factor productivity (TFP) and real income per head of labor grow proportionately with the level of R&D (the level of resources devoted to R&D) – the well known scale effects. Jones (1995a, b) rigorously scrutinizes these predictions of scale effects and concludes that they are "inconsistent" with the time series evidence from industrialized countries and hence "counterfactual". Following Jones' critique, two variants of second-generation R&D-based growth models have evolved in attempting to explain (reconcile) the absence of scale effects. One variant of these models assumes decreasing returns to knowledge stock to decipher the scale effects (Jones 1995a, b; Kortum, 1997; Segerstrom, 1998; Aghion and Howitt, 2005; Ha and Howitt, 2007).[2] The other variant of second-generation models adopts a highly disaggregated approach and focuses on the firm level R&D activities (Young, 1998; Peretto 1998; Howitt, 1999; Dinopoulos and Thompson, 1998).[3]

In this context, three issues motivate this paper. First, to the best of our knowledge, the predictions of scale effects have not been scrutinized vis-à-vis the emerging countries. This is not just an issue of country extensions; instead, it has important policy ramifications. Suppose emerging countries' growth experiences show scale effects. This implies that governments in these countries could influence the rate of growth of technology, productivity and per capita output through their R&D policies even at the aggregate level. In essence, this is what the first generation of R&D-based endogenous growth models preached until Jones found them empirically "counterfactual" vis-à-vis the industrialized countries. However, industrialized countries, examined by Jones, are developed and mature; in contrast, emerging countries are still very much in the course of industrialization and development. It is therefore valid to ask if the scale of R&D activities and hence the R&D policies have the potential for growth augmenting effects in the emerging world. This is also important from the perspectives of the increased levels of R&D and patenting activities followed by some of the emerging countries – e.g. China. If there are no clear benefits, then one wonders why policy makers in emerging countries are vigorously pursuing

such policies. Affirmative findings would imply that scale effects are consistent when countries are industrializing and/or are at the take-off stage of economic growth and development, even though this has not been found to be the case with the mature economies. To this end, we rigorously scrutinize R&D-based endogenous growth models using 31 emerging countries' data and document some new results.

We also address an important estimation (econometric) issue in testing the scale effects. Theoretically, scale effects are the relationships between a stationary, I(0), regressand (viz., growth rates of technology, productivity and the real per capita output) and non-stationary, I(1), regressors (namely, measures of the scale of R&D activities (see Section 2)) which make econometric methods based on standard distributions invalid. We augment the scale effect specifications by proposing the joint use of two measures of the level of R&D activities – the number of R&D researchers (L_A) and fixed capital expenditure in the R&D sector (K_A) – which has the potential of generating a valid balancing (co-integrating) scale effect relationship between I(0) and I(1) variables (details in Section 4). Further, the joint use of the R&D researchers and the fixed R&D capital expenditure also captures the level of R&D inputs more accurately. To our knowledge, scale effects have not been econometrically tested in this manner in previous literature.

Second, emerging countries' ideas production function has not received scrutiny, despite the upsurge in their R&D activities. Parameters of ideas production function allow us to evaluate, among other things, if growth rates of emerging countries are along the balanced growth path (BGP) from the perspectives of knowledge-based endogenous growth models (details in Section 2). We model an ideas production function for these countries and investigate the role of international knowledge spillovers. A body of literature (Coe and Helpman 1995; Keller, 1998; Porter and Stern, 2000; Luintel and Khan, 2004; Coe et al., 2009; to name but a few) focuses on international knowledge spillovers across OECD countries. However, each emerging country faces potential competition and collaboration from the emerging world as well as the industrialized world vis-à-vis its production of new ideas domestically. We, therefore, explicitly model the role of domestically accumulated knowledge stock and the potential spillovers from two sources of foreign knowledge stocks, namely, knowledge originating in the emerging world and in the advanced industrialized world (mature OECD countries). These two sources of international knowledge spillovers are

important because they may have potentially different effects on the domestic production of new ideas in emerging countries – we explain below (in Section 2) why this may be the case.

We allow for two channels of international knowledge transmissions: bilateral total import ratios and bilateral high tech (machinery) import ratios. Further channels of knowledge transmissions, such as R&D collaborations, foreign direct investment (FDI) flows etc., exist in the literature but data limitations vis-à-vis a relatively large number of emerging economies preclude us from their usage.

Third, we are also motivated by one of the issues raised by Jones (1995a). In presenting his influential time series evidence against the scale effects – which has received well over 1,600 scholarly citations at the time of this paper – Jones states "To the extent that technology defuses quickly across international boundaries, testing the R&D equation country-by-country may produce misleading results. Perhaps the correct unit of analysis is the entire OECD or even the world instead of an individual country" (page 519). Literature widely documents that technology diffuses internationally and promptly (Coe and Helpman, 1995; Coe et al., 2009; Luintel and Khan, 2009). Jones (1995b) addresses his concern by presenting time series evidence from France, Germany, Japan and the US – all of which reject the scale effect. He then conjectures that his results are unlikely to be "overturned" by including more countries in the analysis. Our analysis of a panel of emerging countries may go some way toward addressing Jones' concern, albeit with different countries and dataset. To our knowledge, this is probably the first ever study that examines the "scale effects" as well as the ideas production function, allowing two sources of international knowledge spillover on emerging countries' data.

A brief preview of our findings is in order. Unlike the findings of Jones (1995a) vis-à-vis industrialized countries, we find support for scale effects in emerging countries. Formal tests confirm that technology, productivity and real per capita income growth rates are proportionally related to the level of R&D inputs, proxied by the number of scientists and engineers employed and the level of real fixed investment in the R&D sector. We also find that ideas production shows increasing returns to domestic knowledge stock – a strong 'standing-on-the-shoulders' effect. This finding goes against the assumptions of decreasing returns to knowledge contained in some of the semi-endogenous growth models (e.g. Jones 1995a, b; Segerstrom, 1998). We find that ideas production in emerging countries is duplicative – there are diminishing

returns on researchers in the R&D sector. Foreign knowledge stocks originating in OECD and emerging countries both raise the innovation bar for emerging countries. Economic growth in emerging countries appears to be in a transitional phase (far from a BGP from the perspectives of R&D-based endogenous growth models). Our results are put through extensive sensitivity checks with respect to various emerging countries including China.

The rest of the paper is organized as follows. The following section sets out an analytical framework and specifies test equations for scale effects and the ideas production function. Our sample and data are discussed in Section 3. Section 4 presents our results on the scale effects. In Section 5, the results of the ideas production function and international R&D spillovers are presented. Section 6 discusses the robustness of our results and Section 7 concludes.

2. Analytical Framework

Drawing from Romer (1990), Grossman and Helpman (1991), Jones (1995a) and Aghion and Howitt (1998), we present a simple analytical framework to investigate (i) the scale effects and (ii) domestic ideas production that allow distinct international knowledge diffusions from OECD and emerging countries. We model output (Y) in a standard neo-classical (Cobb-Douglas) tradition with labor augmenting technology (A), and constant returns to physical capital stock (K) and labor (L):

$$Y = K^{\alpha}[A(1-a_l)L)]^{1-\alpha} \qquad (2.1)$$

Time subscripts are suppressed for convenience. Note that in (2.1) doubling capital and labor inputs will double the output. If the stock of knowledge is also doubled then (2.1) is clearly increasing returns to scale, which reflects the non-rivalrous nature of knowledge. The economy consists of two sectors: (i) goods producing sector and (ii) knowledge producing sector; a_l is the fraction of L used in the R&D sector. The R&D-based endogenous growth models specify the flow of 'new ideas' ($\dot{A}$) as:

$$\dot{A} = \delta A^{\phi} L_A^{\lambda} \qquad (2.2)$$

Where, δ is the scale parameter and A is the accumulated knowledge stock; $L_A (= a_l L)$ is the number of R&D researchers. Parameters ϕ and λ, respectively, measure the sensitivity of the flow of new ideas (knowledge) to A and L_A. In Romer (1990), A is

taken to be the global knowledge stock – each country can draw from the pool of world knowledge stock. He assumes $\phi = 1$ and $\lambda = 1$, which gives the following relationship for the growth of new ideas (technology):

$$\frac{\dot{A}}{A} = g_A = \delta L_A . \qquad (2.3)$$

Equation (2.3) states that knowledge (technology) growth is proportional to the number of units of labor (scientists and engineers) devoted to the R&D sector (L_A) hence the "scale effect". The scale parameter δ denotes that technology grows at a fixed proportion of L_A. As will be evident below, R&D-based endogenous growth models also imply that, in the steady state, output per labor grows at the rate of g_A (i.e. proportional to L_A). However, Jones (1995a) shows that scale effects are "counterfactual" to the growth experience of industrialized countries. In a similar vein to Stokey (1995), Jones (1995a) allows diminishing returns in L_A ($0 < \lambda < 1$) and A ($0 < \phi < 1$), and proposes a semi-endogenous R&D-based growth model of the form:

$$\frac{\dot{A}}{A} = \delta \frac{L_A^{\lambda}}{A^{1-\phi}} \qquad (2.4)$$

Equation (2.4) eliminates the scale effects as long as L_A and $A^{1-\phi}$ grow at the same rate, which is what one would expect along the BGP. The key implication of Jones' semi-endogenous growth model is that while it removes the scale effects, the R&D or conventional government policies no longer affect the growth rate in the steady state.

The analysis above assumes a global pool of knowledge and does not distinguish between domestic and foreign knowledge stocks; in reality, they are likely to contain different elements of technology and their level of sophistication may vary. This is because the world is far from being technologically homogeneous. For example, motor vehicles produced in Germany are well known for their quality, epitomizing the excellence of German car technology the world over. However, it makes little sense to assume that a competitor – e.g. Hyundai Motor Group of South Korea – has access to the same pool of car technology as that of German car manufacturers. [4] This is why a separate treatment of domestic and foreign knowledge stocks is important in modeling domestic innovations, productivity and growth. Similar arguments apply in respect of different pools of foreign knowledge stocks. Foreign knowledge stock originating from

technologically advanced (industrialized) countries may contain more sophisticated technology than that originating from the emerging world. Put differently, the sophistication of knowledge (accumulated ideas) between OECD and emerging countries may differ, implying potentially different types and the extent of R&D spillovers. It is conceivable that OECD innovations, due to their technological sophistication, may raise the innovation bar for emerging countries. Further, international R&D spillovers also depend on the congruity of domestic and foreign know-how, and the absorptive capacity of the recipient country. The degree of congruency of foreign knowledge stocks originating in OECD and emerging countries may also be different. In order to capture the potentially different effects of domestically accumulated knowledge stock and different sources of foreign knowledge stocks, we modify (2.2) and specify the following model of domestic production of new ideas:

$$\dot{A}_d = \delta L_A^{\lambda} A_d^{\phi} A_{fO}^{\beta} A_{fE}^{\theta} \qquad (2.5)$$

In (2.5), the domestic flow of new knowledge ($\dot{A}_d$) depends on the number of researchers employed in the domestic R&D sector (L_A), domestic knowledge stocks accumulated in the past (A_d), and foreign knowledge stocks originating in OECD (A_{fO}) and emerging (A_{fE}) countries. We differentiate between domestic and two sources of foreign knowledge stocks and allow for their potentially different effects on the domestic ideas production of emerging countries. Parameters λ, ϕ, β and θ are to be discussed shortly. From (2.5) the growth rate of domestic technology is:

$$\frac{\dot{A}_d}{A_d} = g_{A,d} = \delta L_A^{\lambda} A_d^{\phi-1} A_{fO}^{\beta} A_{fE}^{\theta} \qquad (2.6)$$

Taking logs of (2.6), differentiating with respect to time and rearranging:

$$\frac{\dot{g}_{A,d}}{g_{A,d}} = \lambda n + (\phi - 1) g_{A,d} + \beta g_{A,fO} + \theta g_{A,fE} \qquad (2.7)$$

Where, g_x denotes a growth rate of x and $n = \frac{\dot{L}}{L}$. Setting $\dot{g}_{A,d} / g_{A,d} = 0$ and solving for growth ($g^*_{A,d}$) along a BGP:

$$g^*_{A,d} = \frac{\lambda}{1-\phi} n + \frac{\beta}{(1-\phi)} g_{A,fO} + \frac{\theta}{(1-\phi)} g_{A,fE} \qquad (2.8)$$

This BGP is defined if $\phi < 1$, which is in the spirit of Jones' (1995a) semi-endogenous growth model with one key difference. In Jones (1995a), $g^*_{A,d}$ only depends on n but in our formulation it also depends on the externalities associated with $g_{A,fO}$ and $g_{A,fE}$. Theoretically, these externalities may take any value: positive, negative or zero, on which we elaborate below. From (2.7):

$$\dot{g}_{A,d} = \lambda n(g_{A,d}) + (\phi - 1) g^2_{A,d} + \theta g_{A,fO} * g_{A,d} + \beta g_{A,fE} * g_{A,d} \qquad (2.9)$$

If $\phi > 1$ then $\dot{A}_d$ increases more than proportionately with A_d and there is no steady state solution. Whether steady state exists is an empirical issue, which we tackle in Section 5. If $\phi < 1$ then it can readily be shown that, at the steady state, output and output per labor grow respectively at the rate of ($g_{A,d} + n$) and $g_{A,d}$. Given that $g_{A,fE}$, $g_{A,fO}$ and n are exogenous, the dynamics of $g_{A,d}$ and the economy's steady state growth path depend on the value of ϕ.

To estimate these parameters for a panel of emerging countries, we log-linearize the ideas production function (2.5) as:

$$\ln \dot{A}_{d,i,t} = \alpha_i + \varphi_t + \lambda \ln L_{A,i,t} + \phi \ln A_{d,i,t} + \beta \ln A_{fO,i,t} + \theta \ln A_{fE,i,t} + e_{i,t} \qquad (2.10)$$

(i = 1,…,N; and t = 1,…,T).

Where $\ln x$ denotes log of x. Specification (2.10) is a fixed effect panel model. The subscripts "i" and "t" denote the cross-sectional and time series dimensions respectively; 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 the number of researchers working in the R&D sector (L_A). 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. The parameter ϕ measures the sensitivity of domestic flow of new ideas to domestically accumulated knowledge stock. A significantly positive ϕ implies that the accumulated domestic knowledge stock facilitates the discovery of new ideas – the 'standing-on-the-shoulders' effect. On the other hand, $\phi < 0$ implies that the increasing accumulation of domestic knowledge

makes the discovery of new ideas harder – the 'fishing-out' effect. As shown above, a ϕ>1 also implies that economic growth rates of sample countries are not on the BGP.

A positive and statistically significant β implies positive international knowledge spillovers' externality from OECD countries. A negative β, however, implies that the accumulated inventions of OECD countries raise the innovation bar for emerging countries, making it hard for them to innovate domestically. Likewise, a positive and statistically significant θ implies positive international knowledge spillovers across emerging countries, whereas a negative and significant θ means the 'raising-the-bar' effect.

3. Sample and Data

We define emerging world as comprising of 71 emerging countries for which UNESCO maintains R&D data. [5] Of these 71 countries, due to lack of consistent data on all relevant variables, we analyze 31 major emerging countries (emerging-31; see Table 1). Our sample of emerging-31 countries represents the emerging world satisfactorily as they account for 86% of the total R&DEXP, 89% of the research scientists employed in the R&D sector and 97% of the resident patent applications field at the national patent offices of the emerging world. Our patent data are domestically filed patent data from each of the sample countries.

Data on real GDP, R&DEXP, resident patent applications, TFP growth, labor force, the number of research scientists engaged in R&D sector and R&D capital expenditure are collected for each of the sample countries. Data frequency is annual. Our dataset is an unbalanced panel consisting of observations ranging from 508 to 657 (see Table 2) covering a maximum time span of 26 years (1985-2010) and a minimum of 17 years (1994-2010). Knowledge is tacit and difficult to measure. Nonetheless, patent counts and/or patent citations are widely used to proxy the flow of new ideas in the literature. One of the earliest uses of patent data to proxy innovation is by Schmookler (1966). Griliches (1990) viewed patents as a "good index of inventive activity" and Eaton and Kortum (1996) regard patents as widely accepted measures of innovation. Following the literature, we proxy the flow of new ideas by resident patent applications. [6] The domestic knowledge stock for each sample country ($A_{d,i,t}$) is computed by integrating the respective flow of new ideas through the perpetual inventory method – a standard approach in the literature. We compute two alternative

measures of foreign knowledge stocks originating from OECD countries based on two channels of knowledge diffusions: bilateral total import ratios weighted ($A^{TM}_{fO,i,t}$) and bilateral high tech (machinery) import ratios weighted ($A^{MM}_{fO,i,t}$). De Long and Summers (1991) emphasize the importance of machinery investment (imports) for growth. Due to data constraints we could only compute bilateral total import ratios weighted foreign knowledge stock ($A_{fE,i,t}$) originating in emerging countries. Thus, we model the effects of two sources of foreign knowledge diffusions – those originating from advanced industrialized countries and those from the emerging countries – and two channels of international knowledge transmissions. Knowledge stocks are computed using 15% and 20% depreciation rates. R&DEXP and GDP data are converted to 2005 purchasing power parity (PPP) US dollars. We provide details of our data, their sources and computation methods in the data appendix.

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 5.8%, which is much higher when compared to the US (2.6%), Japan (1.7%) and the OECD countries' average (2.1%) during the same period. However, 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 (R&DEXP as a percentage of GDP) across the sample countries is 0.83%, which is much lower than that of the OECD average (2.37%) and the US (2.9%). 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 (R&D researchers as a percentage of the total labor force) is 0.13%, which is also quite low compared to the OECD average of 0.74%. The size of Chinese L_A is close to 1 million but due to China's population of over a billion, the Chinese research intensity is just 0.12%. India experienced a high growth rate of 6.4% during the sample period yet its research intensity is one of the lowest (0.03%). China and India respectively have 1.4 and 1.2 billion population each, yet China appears well ahead of India vis-à-vis R&D and research intensities. Research productivity, defined as resident patent application per R&D research scientist, appears quite low (5.9) in emerging countries

compared with the OECD average (22.3). China surpasses other sample countries by a large margin in terms of the numbers of resident patent applications and we scrutinize this issue as a robustness check of our results in Section 6.

Figure 1 plots the time series data on the share of OECD-23 and emerging-31 countries' R&DEXPs in the world total. The share of OECD-23 gradually declined from 88% in 1992 to 74% in 2010, while the share of emerging-31 countries increased from 8% to 22% in the same period. Figure 2 shows the world share of resident patent applications between OECD-23 and emerging-31 countries – the world share of emerging-31 is sharply increasing while the share of OECD-23 is declining. The OECD-23's share has declined from 89% in 1992 to 64% in 2011, whereas the share of emerging-31 has increased from 10% to 35% during the same period.

Figure 3 plots the total number of scientists and engineers engaged in the R&D sector along with the total R&DEXP (in real terms) of 31 sample countries. The number of R&D employees has increased sharply: from 1.5 million in 1992 it peaked at 2.7 million in 2008 – an average annual increase of 3.8% – then slightly subsided to 2.3 million by 2010. The fall in L_A in the last two years of the sample is explained by the fall in Chinese R&D research scientists by 0.38 million. The plot of total real R&DEXP is sharply upwardly trended; it climbed from $47.3bn in 1992 to $254.1bn in 2010 – a growth rate of 9.8% p.a. Overall, R&D activities are still well below the OECD level in emerging countries; nonetheless, the level is far from trivial and shows higher momentum.

China has appeared as one of the major players in R&D activities in recent years. It shows the fastest rate of growth of R&DEXP and domestic patent applications amongst all the sample countries in the panel. China's share in the total R&DEXP of the 31 sample countries increased from 24.6% in 1992 to 62.6% in 2010. As expected, the exclusion of China from the sample makes the plots of emerging countries across Figures 1 through 3 much flatter. However, as shown below, our empirical results are robust to the exclusion of a range of sample countries, including China.

4. Are there Scale Effects?

The first generation R&D-based growth models predict that the rates of growth of technology (new knowledge), TFP and per capita real income are proportionally related to the level of resources devoted to R&D – often proxied by the number of

research scientists working in the R&D sector (L_A). As is well known, these predictions of scale effects are not supported by the growth experiences of industrialized countries (Jones, 1995a). We assess evidence of scale effects in our sample of emerging countries. We begin with the *prima facie* evidence followed by rigorous formal tests of scale effects.

In Figure 4, we report pair-wise scatter plots of L_A and the three growth rates – g_A, g_{TFP} and g_y – as well as their respective regression lines as *prima facie* evidence of scale effects. The top left quadrant shows the scatter plots of growth rate of technology ($\frac{\dot{A}_d}{A_d} = g_A$) and L_A along with the regression line. The regression line is fitted by regressing g_A on a constant and L_A. The scatter plots, as well as the regression line, are both upwardly trended, albeit mildly, suggesting support for scale effects between g_A and L_A. The top right quadrant shows the plots of real GDP per capita growth rate (g_y) and L_A which are trended upwards. The bottom left quadrant shows scatter plots and the regression line for TFP growth and L_A, which are also mildly positively trended. [7] Finally, the bottom right hand quadrant depicts the scatter plots and regression line for the flow of technology ($\dot{A}_d$) and L_A – the productivity of R&D researchers – which is sharply upwardly trended, implying that researchers' productivity has been increasing. When we exclude China, the regression line relating to the plots of g_A and L_A appears somewhat flatter but the other three plots remain qualitatively the same (almost identical). These scatter plots are useful in that they provide a bird's-eye view of the scale effects but they cannot be substitutes for a formal statistical scrutiny. Moreover, the regression lines, generated by ordinary least squares (OLS), do not address the intricacies of data generation processes as L_A is non-stationary. In the following, we provide a formal and rigorous assessment of scale effects.

We begin by assessing the integratedness of our panel data through panel unit root tests. We apply IPS (Im, Pesaran and Sin, 2003) and Fisher-ADF (Maddala and Wu, 1999) panel unit root tests, which are widely used in the literature. Table 2 reports the results of these tests. For the tests of scale effects, only growth variables (reported

in Panel B) and measures of the level of R&D inputs – L_A and K_A (fixed capital expenditure in the R&D sector) – reported in Panel A are of relevance. Other variables in Table 2 relate to the ideas production function, which we discuss in the next section. As expected, both tests decisively (at a very high level of precision) reject the null of the unit root in all three growth variables of our interest. Emerging countries' panel data on $g_{A,i,t}$, $g_{TFP,i,t}$ and $g_{y,i,t}$ are stationary, I(0). Expectedly, both tests also confirm $L_{A,i,t}$ and $K_{A,i,t}$ as unit root, I(1), processes. [8] Our findings are consistent with the results of Jones (1995a), who reports TFP growth and real per capita income growth to be stationary but L_A as exponentially increasing and a unit root process for industrialized countries.

The estimation of a relationship involving an I(0) dependent variable and an I(1) regressor, as shown in equation (2.3) for the scale effect, must generate an I(1) error term. Besides, the OLS and/or the IV estimate of scale parameter in (2.3) must approach zero asymptotically due to the non-stationarity of L_A. Therefore, an estimation of scale effects in a bivariate framework is fraught with statistical problems. However, if there can be at least two mutually cointegrated I(1) explanatory variables then this would provide a sensible model for the I(0) dependent variable as the error term would then be I(0). In order to estimate scale effects authentically we augment specification (2.3) by K_A. This has two clear advantages: (i) it makes the estimation of scale effect valid if L_A and K_A are cointegrated (and this is what we find),[9] and (ii) the inclusion of K_A also captures the level of R&D inputs more accurately since both labor and fixed capital employed in the R&D sector are accounted for. Thus, our empirical tests of scale effects address the issue of unbalanced regression and they account for both labor and capital inputs of the R&D sector. Our approach also largely tackles the issue of endogeneity. This is because endogeneity arises from stationary disturbances and it becomes less of an issue (may be ignored) in reasonably large samples when the variables are I(1) due to super consistency. Except for the growth variables, all our data are I(1), hence we apply cointegration methods to estimate scale effects and ideas production function. We have a reasonable sample size of 508 to 657 panel observations with low frequency (annual) data. Hence, our econometric methods go some way to addressing any potential endogeneity bias. In the following we regress

technology growth (g_A), TFP growth (g_{TFP}), and real per capita income growth (g_y), in turn, on L_A and K_A .

We employ the Dynamic OLS (DOLS, Stock and Watson, 1993) – as shown by Kao, Chiang and Chen (1999) for panel data – which is a simple yet powerful and efficient estimator of a cointegrating relationship when the regression model contains a mixture of stationary and non-stationary variables. The DOLS approach augments the cointegrating regression by leads and lags of regressors that eliminate endogeneity. Stock and Watson (1993) allow for variables with different orders of integration – e.g. I(0), I(1), I(2) – in the regression equation; however, they always maintain the dependent variable to be non-stationary. Our dependent variable is stationary, hence our augmentation to a trivariate specification, incorporating two mutually cointegrated regressors, is important, as discussed earlier.

Table 3 reports the estimates of scale parameters obtained through the DOLS estimator. It is evident that L_A and K_A both exert a positive and significant effect on all three growth variables of our interest. Dependent variables are growth rates (expressed as ratios, i.e. 5% as 0.05) and R&D inputs (regressors) are measured in log levels, hence the reported parameters are semi-elasticities. Typically, under the DOLS, the significance tests of these parameters are conducted by Wald tests. All but one of the Wald tests assume very small p-values under the null, suggesting that all but one estimated scale parameters are highly significant. The exception is the effect of K_A on g_A, which appears insignificant.

The magnitude of the scale parameter for real per capita GDP growth rate is 0.034. This means a 1% increase in the number of research scientists employed in the R&D sector increases real per capita GDP growth rate by 0.034. Likewise, the scale parameter of g_y associated with K_A is 0.062. These are large growth effects (scale effects) of R&D inputs. To give some perspective, Chinese real per capita GDP, on average, grew by 9.8% (Table 1). These estimates imply that a 1% increase in Chinese L_A would increase Chinese real per capita growth rate by 0.35% (point elasticity). Likewise, a 1% increase in K_A increases Chinese g_y by 0.63%. The scale parameters of TFP growth vis-à-vis L_A and K_A are 0.038 and 0.069; these point estimates respectively imply point elasticity of 0.39 and 0.70 for Chinese TFP growth. These

estimates also imply that India could increase her real per capita income, TFP and technology growth rates respectively by 0.53%, 0.59% and 0.28% through increasing the number of research scientists employed in the R&D sector by 1%. Finally, the scale parameter for technology growth associated with L_A is also positive and statistically highly significant. However, the magnitudes of implied point elasticity turn out to be much smaller than those for g_{TFP} and g_y – the point elasticity of g_A with respect to L_A for China (India) is 0.18 (0.28). Surprisingly, K_A appears insignificant in explaining g_A. Countries with lower growth rates are set to benefit more through expanding their R&D sector. The IPS and the ADF-Fisher tests (Panel B of Table 3) confirm (at very high levels of precision) that the error-correction term (cointegrating vector) of all the estimated models of scale effects is stationary, implying that the estimated models of scale effects are indeed cointegrated.

Overall, the picture that emerges from the growth experience of emerging countries appears very different from that of industrialized countries vis-à-vis the scale effects. It is true that the degree of persistence between R&D inputs and the three growth variables of interest (g_y, g_{TFP} and g_A) is very different. L_A and K_A show permanent persistence (unit root) whereas the growth variables have short-lived persistence (stationary processes). Despite difference in their persistence levels, cointegration tests on a suitably specified model of scale effect by econometric method that accounts for I(0) and I(1) variables in the model undoubtedly show that these growth rates and R&D inputs, in turn, are cointegrated, i.e. they are tied together by an equilibrating long-run relationship. The magnitudes of scale parameters for TFP growth and per capita income growth are sizable. The findings that these scale parameters are indeed cointegrating parameters between I(0) and I(1) variables lay to rest any concern that they might be spurious. Unlike the time series evidence from industrialized countries, the growth experience of a large panel of emerging economies supports the scale effects predicted by the first generation of R&D-based growth models.[10]

Ideas Production and International Knowledge Diffusion

The ideas production function (2.10) allows distinct international knowledge spillovers from OECD and emerging countries. Panel data relating to this type of

specification are widely reported to be non-stationary (unit root) processes in levels (see, among others, Coe et al., 2009; Luintel et al., 2014). Table 2 reports the results of panel unit root tests on these variables. As expected, the results confirm that all variables are level non-stationary (see also footnote 8). Tests on the first differences of the data unequivocally reject non-stationarity (unit root). Hence, the panel dataset we have is a first order-integrated process.

We, therefore, test if the ideas production function (2.10) forms a cointegrating relationship for the sample countries at hand. Cointegration implies a long-run equilibrating relationship between the flows of new ideas and its determinants, as specified in equation (2.10). In order to account for the three different measures of foreign knowledge stocks, individually as well as jointly, we estimate four different specifications of ideas production function. They are clearly shown in columns (1) through (4) of Table 4. Columns (1) and (2) incorporate two alternative measures of the OECD originated foreign knowledge stocks; column (3) incorporates the foreign knowledge stock originating from emerging countries; and column (4) jointly models both the OECD and emerging foreign knowledge stocks. [11] While these specifications provide a complete picture of the nature of international knowledge spillovers, nevertheless columns (1) through (3) incorporate only one source of international knowledge spillovers, hence they might be construed as suffering from missing variable problems. The most general specification is column (4) which incorporates both sources of international knowledge spillovers and is hence our preferred model.

Cointegration tests corresponding to these specifications are reported in the lower panel of Table 4. We report a battery of panel cointegration tests to ensure the robustness of our results. Test statistics t_{adf} and t_{pp} are the Augmented Dickey-Fuller (ADF) and Phillips-Perron panel t-tests under the null that equation (2.10) is non-cointegrated. [12] The between-dimension (Group) tests allow model parameters (cointegrating parameters) to be different (heterogeneous) across countries in the panel while testing the null of non-cointegration. The within-dimension (Pooled) tests assume homogeneous cointegrating vectors across countries under the null. It is worth noting that the Group tests exhibit lower size distortions than the Pooled tests and that the Group t-statistic is shown to be the most powerful amongst these tests (Pedroni, 2004). Hence, we attach more value to the Group tests.

Both sets of tests ─ Group and Pooled ─ reject the null of non-cointegration at very high levels of precision. We also report the panel cointegration test proposed by Kao (1999) which only allows for heterogeneity in intercepts but assumes homogeneous slope parameters across countries in the panel. Kao's test also rejects the null of non-cointegration of ideas production function. This array of tests, which vary considerably in their underlying assumptions, unequivocally confirms a robust cointegrating ideas production function for the panel of 31 emerging countries in our sample.

The upper panel of Table 4 reports the long-run (cointegrating) parameters of ideas production function estimated by the Fully Modified OLS (FMOLS) estimator of Phillips and Hansen (1990). [13] The Group FMOLS shows that the estimates of λ (i.e. $\partial \ln \dot{A}_d / \partial \ln L_A$) across all specifications are positive and statistically significant at 5.2% or better; however, their magnitudes are well below unity, implying that research scientists do produce 'new ideas' but there is duplication in innovation – the 'stepping-on-toes' effect. This finding is consistent with the existing literature on OECD countries. Porter and Stern (2000) and Luintel and Khan (2009) report that the elasticity of the flow of new ideas with respect to R&D research scientists is positive and statistically significant but less than unity. The elasticity of domestic knowledge stock, ϕ $(= \partial \ln \dot{A}_d / \partial \ln A_d)$, is positive and significantly greater than unity across all specifications. In fact, in columns (3) and (4), the Group estimates of ϕ are above 2.0. Such high magnitudes of ϕ imply a very strong standing-on-the-shoulders effect – inventions stimulating further inventions in emerging countries. The finding of $\partial \ln \dot{A}_d / \partial \ln A_d > 1$ for emerging countries is in complete 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 statistically significant but well below unity using Triadic Patent data across 19 OECD countries.

Foreign knowledge stocks that originated from the OECD – (columns 1 and 2) – resume negative and statistically significant parameters. These results remain intact even when foreign knowledge stocks originating from emerging countries are incorporated in the equation (column 4). Thus, embodied international R&D spillovers from the OECD appear to raise the innovation bar for emerging countries. This may

also reflect the rivalry (competition) in the technology market between these two groups of countries. The results in Column (3) reveal that there is no significant international R&D spillover between emerging countries. However, column (4), which jointly models two sources of foreign knowledge stocks, shows that both sources of foreign knowledge stocks raise the innovation bar for the domestic innovation of emerging countries.[14] The existing evidence on international knowledge spillovers, vis-à-vis domestic innovation in OECD countries, is mixed. Porter and Stern (2000) find significantly negative international spillovers, whereas Luintel and Khan (2009) find the opposite. Our findings, that ideas production by OECD and emerging countries raises the innovation bar for emerging countries, are consistent with the findings of Porter and Stern vis-à-vis OECD countries.

The Pooled FMOLS estimates are qualitatively similar to Group estimates. The results of the first three columns are qualitatively the same except for the magnitudes of the parameters – the magnitudes of Pooled estimates are smaller than the Group estimates – and that L_A marginally fails significance at 10% in column (3). In contrast to Group estimates, the parameter ϕ resumes a value of unity statistically across columns (1) to (3). However, the most general specification (column (4)) rejects the null of $\phi = 1$ in favor of $\phi > 1$ at 10%. [15] The results in column (4) show that international R&D spillovers from OECD countries continue to appear negative but knowledge spillovers from emerging countries are at best insignificant. In view of the relatively weak power performance of the Pooled estimator, we attach more importance to the Group estimates.

5. Robustness

We scrutinize 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. As stated in Section 3, 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 Chinese data.

Our results for scale effects are robust to the exclusion of China from the panel. Of the three specifications of scale effects reported in Table 3, results pertaining to TFP growth and technology growth equations remain robust (very close parameter magnitudes and positive and statistically significant). In fact, the exclusion of China

improves the significance of the parameter of K_A in the technology growth equation – this parameter appeared insignificant in Table 3 but now turns significant at 10%. For the per capita real GDP growth equation, the scale parameter of K_A remains robust (positive and significant) but the parameter of L_A loses its precision (becomes insignificant).

Table 5 reports the full set of the cointegrating parameter of ideas production function for the panel of 30 countries, i.e. excluding China from the sample. As is evident, the exclusion of China does not affect the qualitative nature of our results; all parameter estimates remain pretty close to those of the full sample in their magnitudes, signs and significance. A minor difference is some reductions in the precision of the parameter of L_A in columns (3) and (4) under Group estimates. The findings that $0 < \partial \ln \dot{A}_d / \partial \ln L_A < 1$ and that $\partial \ln \dot{A}_d / \partial \ln A_d > 1$ are upheld, and so are the negative externalities associated with the two sources of foreign knowledge stocks.

Further, we also examine the sensitivity of our results to other large and small countries of the sample, sequentially dropping India, the Russian Federation, 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 – all parameters appear identical in signs and statistically significant. Finally, we re-estimate all models (specifications) using domestic and foreign knowledge stocks computed at a 20% depreciation rate. The results remain robust to this change in depreciation rate. Overall, our results are robust to changes in sample sizes (countries), countries with varying growth rates and the rates of depreciation of R&D capital.

7. Conclusion

We observe that emerging countries have significantly increased their R&D activities in recent years. As a result, the relative share of emerging countries in world R&DEXP increased from 12% in 1992 to 26% in 2010; and their relative share of resident patent applications increased from 11% in 1992 to 36% by 2011. This upsurge in R&D activities coincides with their impressive rate of economic growth. Although the sample countries show different rates of growth, the panel of 31 sample countries

grew by 5.8% p.a. during 1992-2010 – a striking growth performance from the perspective of OECD economies.

This concomitant rise in the levels of R&D activity and the rate of economic growth in emerging countries is interesting from the perspective of the pioneering R&D based endogenous growth models (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1998; among others). These models predict scale effects – i.e. technology, TFP and per capita real income, should grow proportionally with the level of resources devoted to R&D. However, the time series evidence from the growth experiences of industrialized countries does not support these predictions of scale effects.

Against this backdrop, we rigorously examine the scale effects and domestic knowledge creation (ideas production) in a panel of 31 emerging countries.[16] Our sample countries account for 86% of total R&DEXP and 89% of R&D scientific communities of the emerging world. Typically, the scale effect is a relationship between a stationary (respective growth rates) and a non-stationary (level of R&D) variable. However, statistically, a bivariate relationship involving a stationary regressand and an I(1) regressor is problematic because it generates a non-stationary, I(1), residual and the (scale) parameter must be zero asymptotically. We suggest a solution to this issue by specifying a scale effect relationship incorporating two mutually cointegrated R&D inputs. We employ an econometric method that addresses the issue of unbalanced regressions involving I(0) and I(1) variables while estimating the scale parameters. We also estimate the ideas production function for emerging countries by explicitly allowing for the distinct international knowledge spillovers from the pools of OECD and emerging countries' knowledge stocks.

Our findings are unique and interesting. We find evidence in support of the scale effects of R&D in emerging countries. The pair-wise scatter plots of real per capita GDP growth, TFP growth, technology growth and the level of R&D, proxied by researchers employed in the R&D sector, are upwardly trended. This is in sharp contrast to the time series plots reported by Jones for the USA and a few other industrialized countries. More formally, econometric tests of scale effects – which address the issue of unbalanced regression – reveal a statistically significant proportional relationship between the level of R&D inputs (L_A and K_A) and the growth rates of per capita real GDP, TFP and technology.

With respect to idea creation, we find duplication in knowledge production – the 'stepping-on-toes' effect. This is consistent with the existing literature, albeit based on the OECD data. Innovations in emerging countries show increasing returns to knowledge, which suggests that the assumption of diminishing returns to knowledge contained in semi-endogenous growth models (e.g. Jones, 1995a) may not be data consistent vis-à-vis emerging countries. We find that the two sources of international knowledge spillovers – originating from OECD and emerging countries – raise the innovation bar for the domestic production of ideas by emerging countries. Our results are robust to sensitivity checks with respect to country sizes, countries with varying growth rates, as well as the depreciation rates employed in the computation of knowledge stocks.

At the policy level, the implications of our findings are consistent with the well known prescriptions of the pioneering first generation R&D-based endogenous growth models – that government policies, especially by subsidizing the R&D sector, could enhance economic growth rates in emerging countries. This apparent difference in results between industrialized and emerging countries vis-à-vis the scale effect may be due to the structural differences in these economies. Industrialized countries are developed, mature and have well-developed markets. However, emerging countries are in the course of industrialization and development, and they lack well-developed markets, which may potentially provide a role for government policies in influencing growth. One of our findings is that growth rates observed in emerging countries appear to be part of a transition process and are not on the BGP. It is, therefore, likely that the increasing returns to domestic knowledge stock and high growth rates of these economies may decelerate as they mature and become closer to the frontier – a lesson we have learnt from Asian Miracle economies. In the context of our findings, an interesting research agenda would be to explore the role of R&DEXP on the transition dynamics of emerging countries, which we hope to scrutinize in the future.

References

Aghion, Philippe and Peter Howitt, Endogenous Growth Theory, Cambridge, MA: MIT Press (1998).

Aghion, Philippe and Peter Howitt, "Growth with Quality Improving Innovations: An Integrated Framework." In P. Aghion and S. Durlauf (Eds.), Handbook of Economic Growth. Amsterdam: North Holland, 2005.

Coe, David T., and Elhanan Helpman, "International R&D Spillovers," European Economic Review 39(1995), 859-887.

Coe, David. T., Elhanan Helpman, and Alexander W. Hoffmaister, "International R&D Spillovers and Institutions," European Economic Review 53(2009), 723-741.

De Long, Bradford, J., and Lawrence H. Summers, "Equipment Investment and Economic Growth," Quarterly Journal of Economics 106(1991), 445-502.

Dinopoulos, Elias, and Peter Thompson, "Schumpeterian Growth without Scale Effects," Journal of Economic Growth 3(1998), 313-35.

Eaton, Jonathan, and Samuel Kortum, "Trade in Ideas Patenting and Productivity in the OECD," Journal of International Economics 40(1996), 251-278.

Eaton, Jonathan, Eva Gutierrez, and Samuel Kortum, "European Technology Policy," Economic Policy 13(1998), 403-438.

Gengenbach, Christian, Franz C. Palm, and Jean-Pierre Urbain, "Panel Unit Root Tests in the Presence of Cross-Sectional Dependencies: Comparisons and Implications for Modelling," Econometric Rev 29(2010), 111-145.

Griliches, Zvi, "Patent Statistics as Economic Indicators: A Survey," Journal of Economic Literature 28(1990), 1661-1707.

Grossman, Gene M., and Elhanan Helpman, Innovation and Growth in the Global Economy, Cambridge, MA, and London: MIT Press (1991).

Ha, Joonkyung, and Peter Howitt, "Accounting for Trends in Productivity and R&D: A Schumpeterian Critique of Semi-Endogenous Growth Theory," Journal of Money, Credit and Banking 39(2007), 733-774.

Howitt, Peter, "Steady Endogenous Growth with Population and R & D Inputs Growing," Journal of Political Economy 107(1999), 715-730.

Im, Kyung So, Hashem M. Pesaran, and Yongcheol Shin, "Testing for Unit Roots in Heterogeneous Panels," Journal of Econometrics 115(2003), 53-74.

Johansen, Soren, "Estimation and Hypothesis Testing of Cointegrating Vectors in Gaussian Vector Autoregression Models," Econometrica 59(1991), 1551-1580.

Jones, Charles I., Introduction to Economic Growth (Second Edition), W.W. Norton & Company Ltd., 2002.

Jones, Charles I., "R&D-Based Models of Economic Growth," Journal of Political Economy 103(1995a), 759-784.

Jones, Charles I., "Time Series Tests of Endogenous Growth Models," Quarterly Journal of Economics 110(1995b), 495-525.

Kao Chihwa., Chiang Min-Hsien and Bangtian Chen "International R&D spillovers: an application of estimation and inference in panel cointegration," Oxford Bulletin of Economics and Statistics 61(1999), 691-709.

Kao, Chihwa D., "Spurious Regression and Residual-Based Tests for Cointegration in Panel Data," Journal of Econometrics 90(1999), 1-44.

Keller, Wolfgang, “Are International R&D Spillovers Trade-Related?: Analyzing Spillovers Among Randomly Matched Trade Partners,” European Economic Review 42(1998), 1469-1481.

Kortum, Samuel S., “Research, Patenting, and Technological Change,” Econometrica 65(1997), 1389-1419.

Lichtenberg, Frank. R., and Bruno van Pottelsberghe de la Potterie, “International R&D Spillovers: A Comment,” European Economic Review 42 (1998), 1483-1491.

Luintel, Kul B., and Mosahid Khan, “Are International R&D Spillovers Costly for the US?,” Review of Economics and Statistics 86 (2004), 896-910.

Luintel, Kul B., and Mosahid Khan, “Heterogeneous Ideas Production and Endogenous Growth: An Empirical Investigation,” Canadian Journal of Economics 42(2009), 1176-1205.

Luintel, Kul B., Mosahid Khan, and Konstantinos Theodoridis, “On the Robustness of R&D,” Journal of Productivity Analysis 42(2014), 137-155.

Maddala, Gangadharrao S., and Shaowen Wu, “A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test,” Oxford Bulletin of Economics and Statistics 61(1999), 631-652.

Pedroni, Peter, “Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors,” Oxford Bulletin of Economics and Statistics (Special Issue) (1999), 653-670.

Pedroni, Peter, “Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis,” Econometric Theory, Cambridge University Press (2004), 597-625.

Peretto, Pietro F., “Technological Change and Population Growth,” Journal of Economic Growth 3(1998), 283-311.

Pesaran, Hashem M., “A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence,” Journal of Applied Econometrics 22(2007), 265-312.

Phillips, Peter C. B., and Bruce E. Hansen, “Statistical Inference in Instrumental Variable Regression with I(1) Processes,” Review of Economics Studies 57(1990), 99-125.

Porter, Michael, and Scott Stern, “Measuring the “ideas” production function: evidence from international patent output,” National Bureau of Economic Research, Working Paper No. 7891 (2000).

Romer, Paul M., “Endogenous Technological Change,” Journal of Political Economy 98(1990), 71-102.

Schmookler, Jacob, Invention and Economic Growth, Cambridge: Harvard University Press (1966).

Segerstrom, Paul S., “Endogenous Growth without Scale Effects,” American Economic Review 88(1998), 1290-1310.

Stock, James H., and Mark W. Watson, “A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems,” Econometrica 61(1993), 783-820.

Stokey, Nancy L., “R&D and Economic Growth,” Review of Economic Studies 62(1995), 469-489.

Van Pottelsberghe de la Potterie, Bruno, and Frank Lichtenberg, “Does Foreign Direct Investment Transfer Technology across Borders?,” Review of Economics and Statistics 83(2001), 490-497.

Young, Alwyn, “Growth without Scale Effects,” Journal of Political Economy 106(1998), 41-63.

Table 1: Descriptive Statistics (Sample Mean)[1]

	GDP Growth	Patents	Research Productivity	R&D Expenditure	R&D Intensity	L_A	Research Intensity
Argentina	3.2	833	3.1	n.a.	n.a.	27,127	0.17
Azerbaijan	6.5	229	2.1	84	0.25	10,741	0.29
Bulgaria	2.5	295	2.5	402	0.60	11,680	0.32
China	9.8	61,854	7.5	45,197	1.19	829,562	0.12
Colombia	3.7	99	2.5	541	0.21	3,964	0.03
Costa Rica	4.7	17	0.8	129	0.38	2,010	0.12
Croatia	2.6	331	2.5	513	0.87	13,157	0.65
Czech Republic	2.9	717	4.0	2,375	1.23	18,145	0.35
Ecuador	3.2	10	1.0	105	0.14	945	0.02
Estonia	3.7	34	1.0	158	0.92	3,281	0.47
Georgia	2.6	261	2.1	31	0.23	12,477	0.54
Hungary	1.0	1,402	8.7	1,692	1.18	16,104	0.37
India	6.4	2,887	2.2	12,886	0.72	134,254	0.03
Kyrgyzstan	1.3	133	5.8	16	0.19	2,280	0.11
Latvia	3.4	157	4.5	117	0.50	3,443	0.29
Lithuania	2.2	110	1.4	267	0.67	7,828	0.46
Malaysia	5.5	433	7.0	1,295	0.49	6,207	0.06
Mexico	2.4	582	2.4	3,559	0.33	24,264	0.06
Morocco	3.9	112	0.4	495	0.52	25,039	0.25
Pakistan	4.2	63	0.5	1,051	0.37	13,619	0.03
Paraguay	2.8	22	5.0	n.a.	n.a.	441	0.02
Poland	4.6	2,528	4.5	2,984	0.64	56,351	0.32
Romania	2.0	1,287	5.3	992	0.55	24,362	0.22
Russian Federation	1.6	24,136	4.7	15,751	1.05	513,984	0.71
Saudi Arabia	2.6	88	7.5	n.a.	n.a.	1,169	0.02
Slovenia	3.4	346	6.9	626	1.53	5,046	0.52
Sri Lanka	5.3	111	4.2	105	0.17	2,661	0.03
Thailand	5.5	459	3.9	673	0.20	11,790	0.03
Tunisia	4.5	43	0.4	434	0.70	10,872	0.34
Turkey	4.1	683	2.7	3,143	0.53	25,102	0.12
Uruguay	2.9	33	3.2	96	0.30	1,030	0.07
Mean	5.8	112,831	5.9	3,418	0.83	1,925,063	0.13
Japan	1.7	344,648	52.8	114,666	3.27	652,534	0.99
US	2.6	168,851	13.3	293,128	2.91	1,265,880	0.90
OECD	2.1	749,956	22.3	683,866	2.37	3,367,628	0.74

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

[1] We have an 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.

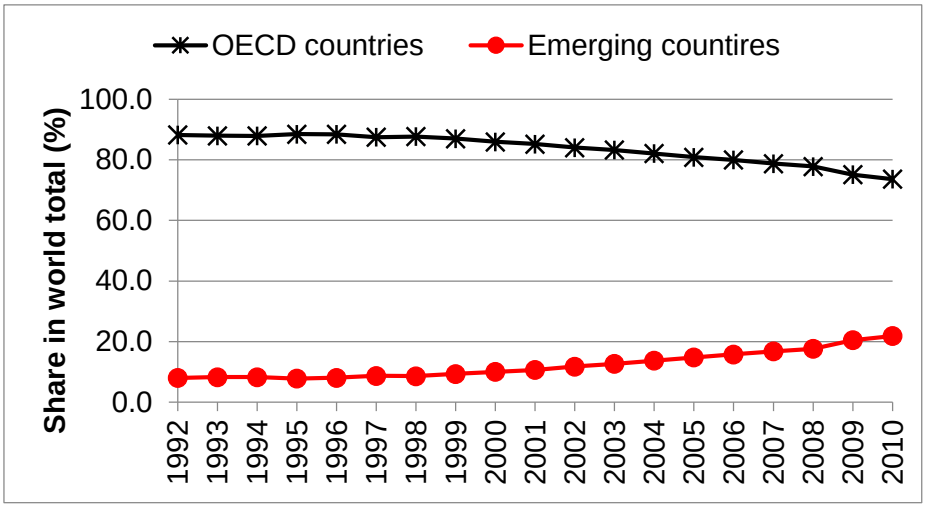


Figure 1: R&D Expenditure Share (%). OECD 23 and emerging 31 sample countries.

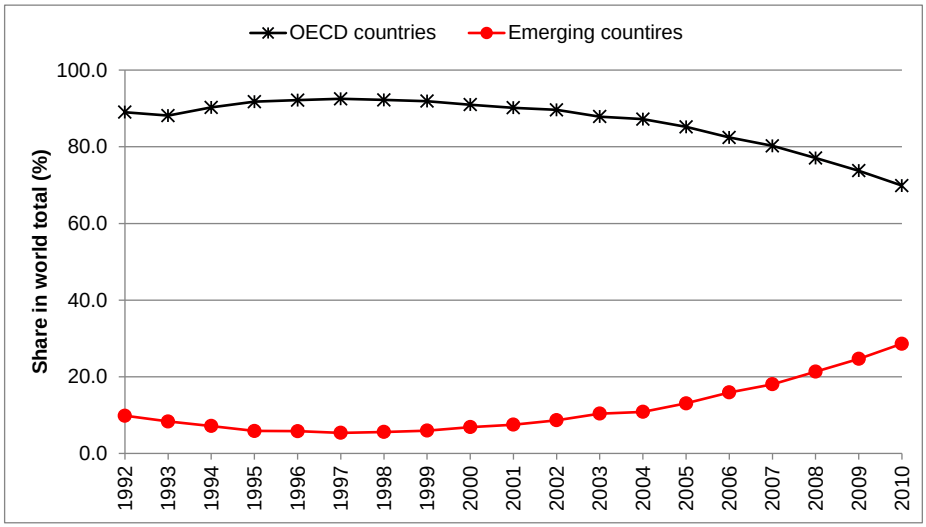


Figure 2: Patent Applications Share (%). OECD 23 and emerging 31 sample countries.

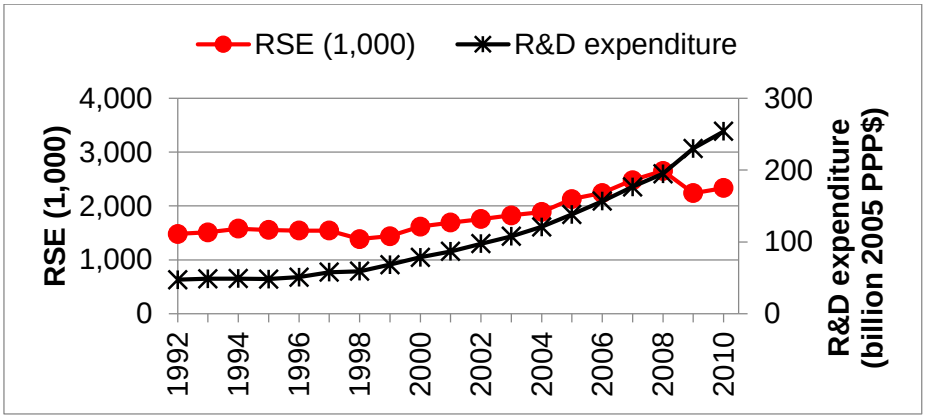
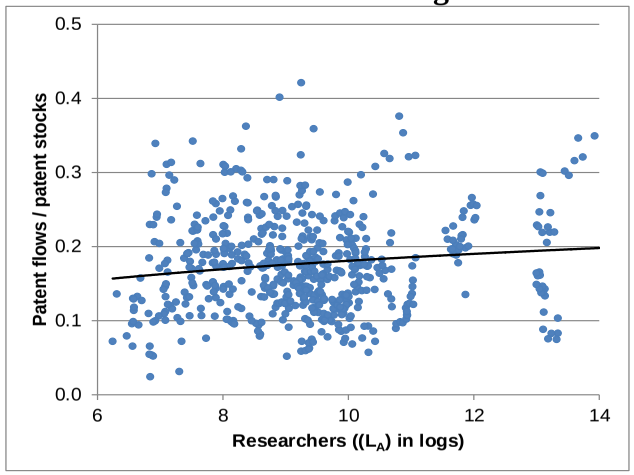
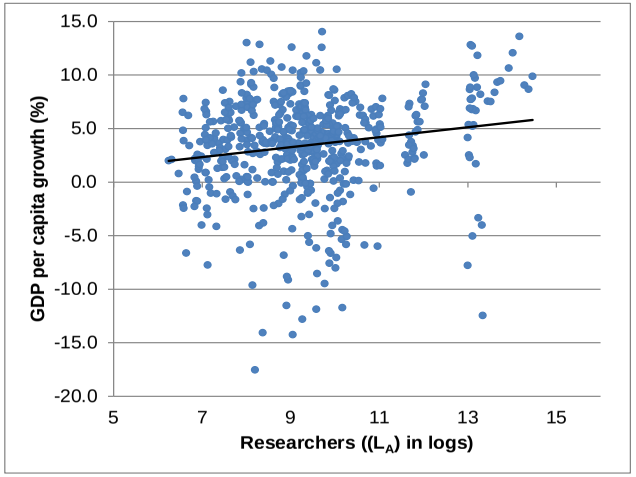


Figure 3: R&D Researchers and R&D Expenditure for 31 sample emerging countries; in '000'.

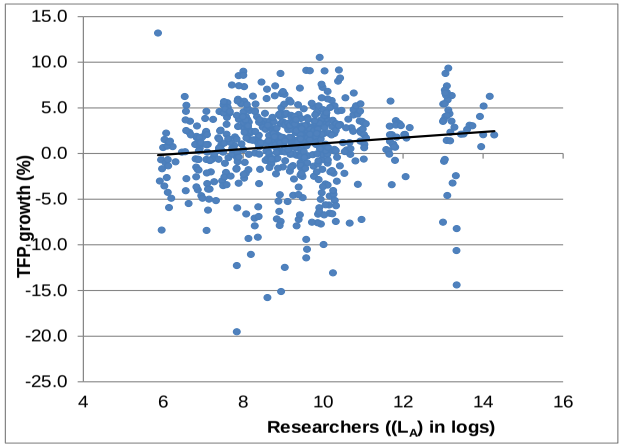
Figure 4: Some cross-country plots and scale effects



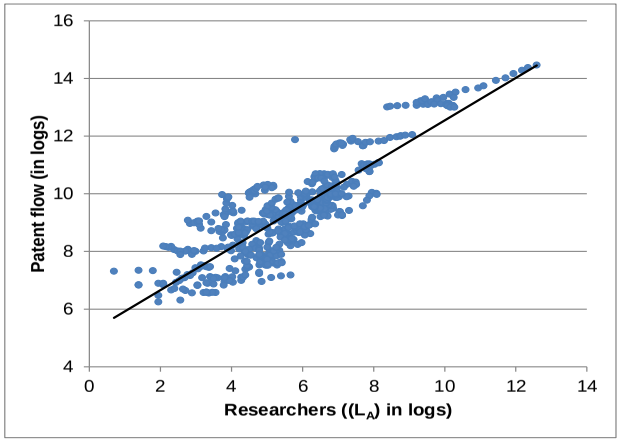
31 sample emerging countries



31 sample emerging countries



28 sample emerging countries



31 sample emerging countries

Table 2: Results of Panel Unit Root Tests

	Panel A: Level Variables							Panel B: Growth Variables		
	$\dot{A}_{d,i,t}$	$L_{A,i,t}$	$A_{d,i,t}$	$A^{tm}_{fO,i,t}$	$A^{mm}_{fO,i,t}$	$A^{tm}_{fE,i,t}$	$K_{A,i,t}$	$g_{y,i,t}$	$g_{tfp,i,t}$	$g_{A,i,t}$
IPS	0.981	0.901	0.999	0.789	0.320	1.000	1.000	0.003	0.000	0.000
ADF-Fisher	0.942	0.909	0.904	0.474	0.268	0.996	1.000	0.038	0.000	0.000
OBS	617	617	617	617	617	617	508	586	657	617

For both tests, p-values under the null of unit root are reported. In all test equations, individual effects are included as exogenous variables. Including a linear time trend in level regressions does not alter the qualitative nature of reported results. A third order lag length is used in all estimations except for $g_{A,i,t}$ and results are robust to any lag lengths of 1 to 3. The results for $g_{A,i,t}$ appear slightly sensitive to the third order lag hence the reported results pertain to the first order lag length which are robust to second order lag length as well. IPS test is the standardized $\bar{t}_{NT}$ test of Im et al. (2003). $L_{A,i,t}$ denotes the number of research scientists employed in the R&D sector; $A_{d,i,t}$ is the domestic knowledge stock of ith sample country; $A^{tm}_{fO,i,t}$ and $A^{mm}_{fO,i,t}$ are OECD originating foreign knowledge stocks weighted respectively by total imports and machinery imports; $A^{tm}_{fE,i,t}$ denotes the emerging country originating total imports weighted foreign knowledge stock and $K_{A,i,t}$ is the fixed capital expenditure in the R&D sector. $g_{y,i,t}$ is the growth rate of per capita real GDP; $g_{tfp,i,t}$ denotes TFP growth rate and $g_{A,i,t} = \frac{\dot{A}_{i,t}}{A_{i,t}}$. Row OBS denotes total panel observations by each variable. Subscripts ‘i’ and ‘t’ respectively denote the cross-sectional and time series dimensions. Data on $g_{tfp,i,t}$ and $K_{A,i,t}$ are only available for 28 and 27 countries, respectively (see notes to Table 3). Other data series are available for 31 countries. For most countries, data on $g_{tfp,i,t}$ start in 1986 hence the largest number of observations (OBS) despite only 28 countries.

Table 3: Panel Estimates of Scale Effects

Panel A			
Regressors	Dependent variables		
	$g_{y,i,t}$	$g_{tfp,i,t}$	$g_{A,i,t}$
$L_{A,i,t}$	0.034 [a] {0.004} [0.000]	0.038 [a] {0.003} [0.000]	0.018 [a] {0.003} [0.000]
$K_{A,i,t}$	0.062 [a] {0.003} [0.000]	0.069 [a] {0.004} [0.000]	0.010 {0.007} [0.154]
Panel B Panel cointegration tests of scale relationship			
IPS	[0.000] [a]	[0.000] [a]	[0.000] [a]
ADF-Fisher	[0.000] [a]	[0.000] [a]	[0.000] [a]
N (OBDF)	24 (324)	21 (285)	27 (384)

All variables are are defined in the notes to Table 2. We estimate the following second order DOLS cointegrating regression:

$$y_{i,t} = \alpha_i + \gamma_t + \beta_1 \log L_{A,i,t} + \beta_2 \log \mathrm{K}_{A,i,t} + \sum_{j=-2}^{2} \theta_j \Delta \log L_{A,i,t-j} + \sum_{j=-2}^{2} \varphi_j \Delta \log \mathrm{K}_{A,i,t-j} + e_{i,t} .$$

Where $y_{i,t} \in (\mathrm{g}_{A,i,t}, g_{tfp,i,t}, g_{y,i,t})$. Numbers within { } are standard errors and those within [ ] are p-values of Wald tests under the null that the coefficient is zero. Fixed and time effects both appear significant hence are maintained in the estimations. Due to collinearity, results for $g_{A,i,t}$ pertain to a second order lag and a first order lead. Azerbaijan, Georgia and Pakistan do not have data on $g_{tfp,i,t}$; further, Paraguay, Saudi Arabia, Sri Lanka and Turkey do not have data on $K_{A,i,t}$. First differencing consumes 31 observations; and the leads and lags consume a further 124 observations. Due to degree of freedom problems, Croatia, Estonia and Slovenia are dropped from DOLS estimations, hence the different number of sample countries (N) and degrees of freedom (OBDF). Superscripts ‘a’, ‘b’ and ‘c’ respectively denote significance at 1%, 5% and 10%.

Table 4: Parameter Estimates and Panel Cointegration Tests of Knowledge Production Function.

$$\log \dot{A}_{d,i,t} = \alpha_i + \gamma_t + \lambda \log L_{A,i,t} + \phi \log A_{d,i,t} + \beta \log A_{fO,i,t} + \theta \log A_{fE,i,t} + e_{i,t}$$

	Between-dimension (Group) FMOLS estimates				Within-dimension (Pooled) FMOLS estimates			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$L_{A,i,t}$	0.157[b] (0.048)	0.193[a] (0.014)	0.165[c] (0.052)	0.162[c] (0.052)	0.082[c] (0.069)	0.085[c] (0.059)	0.073 (0.111)	0.078[c] (0.085)
$A_{d,i,t}$	1.899[a] (0.000)	1.889[a] (0.000)	2.133[a] (0.000)	2.387[a] (0.000)	1.098[a] (0.000)	1.088[a] (0.000)	1.083[a] (0.000)	1.132[a] (0.000)
$A^{tm}_{fO,i,t}$	-0.230[a] (0.000)	-	-	-0.197[a] (0.000)	-0.073[c] (0.083)	-	-	-0.086[b] (0.043)
$A^{mm}_{fO,i,t}$	-	-0.073[b] (0.042)	-	-	-	-0.060[c] (0.066)	-	-
$A^{tm}_{fE,i,t}$	-	-	-0.070 (0.334)	-0.113[c] (0.078)	-	-	0.013 (0.695)	0.057 (0.119)
Panel Cointegration tests								
t_{adf}	-6.934[a] (0.000)	-6.763[a] (0.000)	-6.511[a] (0.000)	-6.064[a] (0.000)	-6.129[a] (0.000)	-5.611[a] (0.000)	-5.345[a] (0.000)	-4.446[a] (0.000)
t_{pp}	-7.828[a] (0.000)	-7.333[a] (0.000)	-8.830[a] (0.000)	-9.502[a] (0.000)	-6.947[a] (0.000)	-6.237[a] (0.000)	-5.615[a] (0.000)	-6.062[a] (0.000)
t_{kao}	NA	NA	NA	NA	-10.389[a] (0.000)	-10.755[a] (0.000)	-10.766[a] (0.000)	-10.939[a] (0.000)

t_{adf} and t_{pp} are ADF and Phillips-Perron tests of the null of no cointegration in the panel as shown by Pedroni (1999). t_{kao} is the Kao (1999) test which only allows for country-specific intercepts (α_i) in pooled data. They are asymptotically standard normal left-sided tests. P-values are within parentheses. Lag lengths for cointegration tests are chosen by SIC setting a maximum lag of 4. All estimates have 31 countries and 586 degrees of freedom. Please refer to the notes of Table 2 for variable definitions. Superscripts 'a', 'b' and 'c' respectively denote significance at 1%, 5% and 10%.

Table 5: FMOLS Estimates of Knowledge Production Function (Excluding China)

$$\log \dot{A}_{d,i,t} = \alpha_i + \gamma_t + \lambda \log L_{A,i,t} + \phi \log A_{d,i,t} + \beta \log A_{fO,i,t} + \theta \log A_{fE,i,t} + e_{i,t}$$

	Between-dimension (Group) FMOLS estimates				Within-dimension (Pooled) FMOLS estimates			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$L_{A,i,t}$	0.130 [c] (0.100)	0.171 [b] (0.033)	0.140 (0.107)	0.137 (0.107)	0.084 [b] (0.065)	0.087 [b] (0.058)	0.075 (0.107)	0.078 [b] (0.088)
$A^{d}_{i,t}$	1.947 [a] (0.000)	1.934 [a] (0.000)	2.189 [a] (0.000)	2.450 [a] (0.000)	1.107 [a] (0.000)	1.095 [a] (0.000)	1.088 [a] (0.000)	1.134 [a] (0.000)
$A^{tm}_{fO,i,t}$	-0.236 [a] (0.000)	-	-	-0.205 [a] (0.000)	-0.074 [b] (0.082)	-	-	-0.088 [b] (0.040)
$A^{mm}_{fO,i,t}$	-	-0.077 [b] (0.035)	-	-	-	-0.060 [b] (0.068)	-	
$A^{tm}_{fE,i,t}$	-	-	-0.072 (0.339)	-0.117 [b] (0.078)	-	-	0.009 (0.793)	0.055 (0.149)
Panel Cointegration tests								
t_{adf}	-7.349 [a] (0.000)	-7.177 [a] (0.000)	-6.907 [a] (0.000)	-6.536 [a] (0.000)	-7.032 [a] (0.000)	-5.736 [a] (0.000)	-5.478 [a] (0.000)	-4.743 [a] (0.000)
t_{pp}	-8.213 [a] (0.000)	-7.704 [a] (0.000)	-9.214 [a] (0.000)	-9.985 [a] (0.000)	-6.254 [a] (0.000)	-6.325 [a] (0.000)	-5.708 [a] (0.000)	-6.251 [a] (0.000)
t_{kao}	NA	NA	NA	NA	-9.911 [a] (0.000)	-10.306 [a] (0.000)	-10.393 [a] (0.000)	-10.496 [a] (0.000)

Results pertain to 30 sample countries, i.e. excluding China. ( ) are p-values. For the details of tests, please refer to the notes to Table 4. All estimates have 546 degrees of freedom. Superscripts 'a', 'b' and 'c' respectively denote significance at 1%, 5% and 10%.

[1] OECD consists of 34 member countries some of which are emerging countries that joined as recently as 2010 (Chile, Estonia, Israel and Slovenia). For this exposition of relative shares, the total OECD R&D activities comprise those of the following 23 OECD countries (henceforth OECD-23): 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. Complete datasets for Luxemburg and Israel are lacking. A further nine countries, namely, Chile, Czech Republic, Estonia, Hungary, Mexico, Poland, Slovak Republic, Slovenia and Turkey are also the current members of OECD but we categorize them as emerging economies for the present analyses. In any case, inclusion of the latter nine countries within the OECD pool does not alter the picture much – the proportions of OECD R&DEXP become 89% in 1992 and 75% in 2010. R&DEXP are in real (2005) PPP US dollars. Likewise, for this exposition, the pool of emerging countries consists of 71 countries – including the above nine emerging countries which are members of OECD – for which UNESCO maintains R&D data. Due to lack of consistent data on all relevant variables, econometric analyses cover the 31 major emerging countries (henceforth emerging-31). This sample of emerging-31 countries highly satisfactorily represents the emerging world's R&D activities. Specific details are provided in Section 3.

[2] These models are called "semi-endogenous" growth models where the steady-state level of productivity is policy dependent, while the productivity growth rate is not. Consequently, policy changes have only level effects on per capita income, not growth effects.

[3] In these models, growth rate becomes a function of R&D employment per firm (average R&D) which is scale invariant. The average firm size must grow to achieve growth rate in per capita income.

[4] Not to mention the rivalry for market shares amongst different German auto firms. Hyundai is currently the fourth largest vehicle manufacturer in the world. http://en.wikipedia.org/wiki/Hyundai_Motor_Company; accessed on 10/07/2014.

[5] As explained in footnote 1, nine of these 71 countries are young (recent) members of the OECD. In view of the nature of these countries' economy, we treat them as emerging countries in this analysis.

[6] We acknowledge that patents are a noisy measure of innovations. They widely differ in their "universality" and "size" (Eaton, Gutierrez and Kortum, 1998). Several ideas are neither patented nor produced by using official R&D resources (Jones, 2002). Yet, the flow of patents is the only available and consistent proxy of new ideas for this set of sample countries.

[7] We use separate measures of technology growth and TFP growth. Technology growth is measured as $\frac{\dot{A}_d}{A_d}$ whereas data on TFP growth are obtained from Penn World Table Edition 8. Azerbaijan, Georgia and Pakistan do not have data on TFP growth, hence 28 countries in the plot.

[8] IPS and Fisher-ADF tests of unit root assume cross-sectional independence. Recently, panel unit root tests addressing cross-sectional dependence – the second-generation tests – have been proposed. The cross-sectionally augmented IPS (CIPS) test (Pesaran, 2007) is one of the powerful such tests (Gengenbach, Palm and Urbain, 2010). We also implemented CIPS tests and the results confirm that all level variables in Table 2 are I(1). We do not report CIPS tests but use them only as complementary evidence because the CIPS test is quite costly in terms of the degrees of freedom in a panel such as ours where its T_i dimension is not very large. Nonetheless, the results of the CIPS tests are available on request.

[9] Panel ADF and Phillips-Perron cointegration tests decisively reject the null of non-cointegration between L_A and K_A. ADF test statistic is -9.052 (0.000) and Phillips-Perron statistic is -7.619 (0.000); figures within parentheses are p-values.

[10] We also directly estimated (by OLS) equation (2.3) by regressing g_A, g_{TFP} and g_y, in turn, on L_A by adding an additive error term. In all cases, L_A appears positively signed

and highly significant. The parameters of g_A, g_{TFP} and g_y respectively are 0.0182(0.0003), 0.0011(0.0002) and 0.004(0.0002); (.) are standard errors. Since these regressions contain a stationary, I(0), regressand and a non-stationary, I(1), regressor, as discussed above, these parameters must approach zero asymptotically.

[11] Column 4 incorporates total import weighted foreign knowledge stock originating from OECD and emerging countries. Due to data constraints, we could not compute high tech (machinery) imports weighted foreign knowledge stock originating in emerging countries.

[12] Pedroni (1999), which has received wide usage in the literature, proposes these panel cointegration tests.

[13] We used the DOLS estimator in estimating the scale effects because we needed to address the issue of an unbalanced regression equation involving I(0) and I(1) variables. DOLS requires augmentations by leads and lags of regressors in their suitable differences, which could be costly in terms of the degrees of freedom. Unlike the scale effect equation, the ideas production function (2.10) involves all I(1) variables, hence is a balanced equation. The use of DOLS for (2.10) could prove costly in terms of the loss of degrees of freedom, as it has multiple regressors. For example, the general model with four regressors (column 4 of (2.10)) requires an estimation of 16 parameters excluding the fixed effects with just the first order augmentations. A second order augmentation involves estimating 24 parameters excluding the fixed effects, which is simply not feasible within a between-dimension framework – hence the choice of FMOLS.

[14] The foreign knowledge stock originating in emerging countries ($A^{tm}_{fE,i,t}$) is highly correlated with the other two measures of knowledge stocks ($A_{d,i,t}$ and $A^{tm}_{fO,i,t}$) with correlation coefficients of 0.65 and 0.66, respectively. Therefore, we regressed $A^{tm}_{fE,i,t}$ on the latter two and used the residual as the orthogonalized $A^{tm}_{fE,i,t}$.

[15] The standard errors of ϕ parameter across columns (1) through (4), under the Pooled estimator, are respectively 0.078, 0.078, 0.079 and 0.080.

[16] Of course, as explained in notes to Table 3, sample countries for scale effects range between 21 and 27 due to data constraints but the ideas production function is estimated with 31 countries.

Data Appendix

As stated above, our sample consists of 31 emerging countries. 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 for each country varies due to data availability. Domestic knowledge stocks for each sample country ($A_{d,i,t}$) are calculated from the respective country's domestic patent flows ($\dot{A}_{i,d,t}$), using the Perpetual Inventory method. Initial knowledge stock for the ith country, $A_{d,i,0}$, is calculated as:

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

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 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. We compute alternative measures of R&D capital stocks based on two depreciation rates (15 and 20%). We use two channels of international knowledge transmissions: bilateral total imports and bilateral high tech (machinery) imports and use them as weights. The relevant weights for all foreign knowledge stocks are computed using three-year moving averages to avoid yearly fluctuations.

Two measures of foreign knowledge stocks: (i) originating in OECD countries and (ii) originating in emerging countries, are computed in order to model potentially different knowledge transmissions from these two sources. The total import ratio-weighted foreign knowledge stock originating from OECD countries for the ith country of our sample ($A^{tm}_{fO,i,t}$) is:

$$A^{tm}_{fO,i,t} = \sum_{j=1}^{N-i} (M_{ij,t} / Y_{j,t}) * \mathrm{A}^{d}_{j,t} \qquad \text{(A2)}$$

where, M_{ij} is the total imports of (sample) country i from country j; Y_j denotes the GDP of country j; and $\mathrm{A}^{d}_{j,t}$ is the domestic knowledge stock of country j. Throughout,

‘t’ denotes the time subscript. This measure of foreign knowledge stock is due to Lichtenberg and van Pottelsberghe de la Potterie (1998).

The bilateral machinery import weighted foreign knowledge stock ($A^{mm}_{fO,i,t}$) is computed as shown in (A2) above, except that $M_{i\,\mathrm{j,t}}$ now denotes machinery imports of country i from country j. Finally, the total import weighted foreign knowledge stock originating from emerging countries is computed as:

$$A^{tm}_{fE,i,t} = \sum_{k=1}^{N-i} (M_{ik,t} / Y_{\mathrm{k},t}) * \mathrm{A}^{d}_{\mathrm{k},t}$$

where, M_{ik} is the total imports of (sample) country i from partner emerging country k; Y_k denotes the GDP of country k; and $\mathrm{A}^{d}_{k,t}$ is the domestic knowledge stock of country k. Due to data unavailability for the majority of sample countries we could not compute the machinery import-ratio weighted foreign knowledge stock originating in emerging countries. All the relevant data series used and their sources are listed below:

Data	**Sources**
GDP, GDP per capita, Labor force, Gross Fixed Capital Formation	World Bank (World Development Indicators)
Resident Patent applications field at the national patent offices	World Intellectual Property Organization
R&DEXP, Research scientists and engineers	UNESCO and OECD
Bilateral total and machinery imports	UN COMTRADE database
Bilateral FDI inflows	OECD
TFP	Penn World Table 8