New Results and a Model of Scale Effects on Growth

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Abstract

A consensus in the growth literature is that scale effects of R&D are non-existent across mature industrialized economies. However, the scrutiny across emerging economies is lacklustre at best. The empirical studies of scale effects also leave the issues of unbalanced regression (non-standard distribution) largely unaddressed. In this paper, we conduct separate but parallel empirical scrutiny of scale effects across the panels of industrialized and emerging countries, clearly addressing these econometric issues, and employing a more realistic measure of the scale of R&D activities than has been applied hitherto. We provide parallel but novel estimates of significant scale effects across emerging countries, and their absence across developed countries. We then propose an endogenous growth model and show that scale effects exist during growth transitions but not at the vicinity of the long-run equilibrium, which reconciles our results. Thus, we shed light on a long-debated and important issue. Estimates of our model's predictions reveal that the long-run growth rates of per capita real GDP and TFP are driven by the growth rates of technological innovation and aggregate employment, except that only the former matters for the TFP growth across emerging countries.

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1 Introduction

The scale effects, predicted by the first generation of the R&D-based endogenous growth models (Romer, 1990b, Aghion and Howitt, 1992), posit a proportional relationship of growth rates of knowledge (technology) and real per capita GDP to the scale of research and development (R&D) activity. However, the lack of empirical support for scale effects across developed countries is established as a stylized fact. Jones (1995b) eloquently summarizes it by stating that the increasing trend of either R&D labor or real R&D expenditure bears no relation to TFP (total factor productivity) growth.[1]

The theoretical and empirical conundrum of scale effects led theorists to develop two classes of second generation R&D-based endogenous growth models: (i) semi-endogenous growth models (e.g., Jones, 1995a; Kortum, 1997; Segerstrom, 1998), and (ii) fully-endogenous "Schumpeterian" growth models (henceforth Schumpeterian; e.g., Young, 1998; Dinopoulos and Thompson, 1998; Howitt, 1999). In semi-endogenous growth models technology is assumed to exhibit decreasing returns to knowledge stock, which weakens scale effects as the

[1] A robust conclusion of the literature, as noted by Young (1998), is that the measurement of the effect of the scale on growth requires production factors, which are used intensively in the innovation process. The reason the scale of the economy is directly linked to innovation activity is the non-rivalrous nature of the latter, which allows technologies to be widespread in the economy (see Romer, 1990a, 1990b), as opposed to changes in other (general) factors of production which mainly affect certain sectors.

economy advances and accumulates knowledge. Fully endogenous growth models, on the other hand, maintain constant returns to R&D, implying that as the economy grows products proliferate, and that reduces the effectiveness of R&D in improving technology. [2]

Following the advent of second generation growth models, the empirical scrutiny of scale effects has taken a back seat, as most research is focused on developed economies where scale effects are clearly absent. Specifically, the empirical literature has since focused primarily on comparing the two classes of second generation R&D-based growth models, by testing either technology production functions or model predictions.[3] We argue that the lack of scale effects is hardly surprising when economies operate close to their long-run equilibrium, and provide novel empirical results that are consistent with the observation that developed economies operate close to their long run equilibrium (by virtue of the insignificance of scale effects), while emerging countries are in growth transitions (by virtue of the significance of scale effects). We obtain these results through separate but parallel estimates of the scale effects across developed (DE) and emerging (EME) country panels. Over the last three decades or so, EME countries have made significant headway in their R&D activities. Both the scales

[2]Put differently, in fully endogenous growth models the increased R&D expenditures lead to the development of varieties as the economy grows and, as a result, constantly lead to essentially the same technology. As demonstrated by Laincz and Peretto (2006), these models eliminate the scale effect because they focus on the scale of the firm (product line), as opposed to the scale of the economy. Dinopoulos and Syropoulos (2007) provide an alternative approach by modelling the difficulty of conducting R&D, and thus scale-invariant long-run innovation by rent-protecting activities. Şener (2008) combines the latter with diminishing returns to R&D. Other studies examine scale effects from the perspective of an integrated world economy with trade (see Jones, 2005 and Ramondo et al., 2016).

[3]e.g., see among others, Zachariadis (2003); Laincz and Peretto (2006); Ha & Howit (2007).

of R&D and of patenting activities have gone up significantly across EME countries, and, as is well known, they have also outperformed DE countries in terms of growth rates (see Luintel and Khan, 2017). Nonetheless, there is little doubt that EME countries are in growth transitions and are yet to mature. In this context, a parallel scrutiny of scale effects across DE and EME countries would be interesting from the perspectives of both the first- and the second-generation growth models. This is because if DE countries operate close to their long-run equilibrium, as is widely concurred, and if scale effects are indeed the phenomena associated with growth transitions, then one would expect to find evidence of scale effects across EME countries but not across DE countries. This is exactly what we find, which underpins both the first- and the second-generation of growth models.

We address two important and closely related issues: (i) the measurement of the scale of R&D, and (ii) valid estimation of scale parameters, while testing for the scale effects. Most extant empirical assessments of scale effects employ either the labor input (Z) of the R&D sector or the total R&D expenditure (R) to proxy the scale of R&D, and compare their time series properties with those of the growth rates of technology (TFP) and/or the per capita real GDP (e.g., Jones, 1995a), a comparison of trends between variables measured in levels versus growth rates. The variables measured in growth rates are unequivocally stationary, $I(0)$, whereas those measured in levels are non-stationary, $I(1)$, (see Section 2), hence they exhibit very different data patterns (trends), which led Jones (op. cit.) to conclude that scale effects are "counterfactual". Though revealing, these data patterns do leave scope for valid estimation and testing of scale parameters. The true scale of R&D activities comprises of the labor employed (Z) and the real capital expenditure incurred (E) in the R&D sector. A focus on Z alone, as the scale variable, suffers from the problem of omitting a relevant variable (measure of R&D scale), namely, E, and vice versa. The use of R as the scale measure captures both R&D labor and capital expenditures as a single aggregate measure, however, the downsides of employing the aggregate measure are (i) it does not allow for the potentially different effects (roles) of Z and E – as two distinct components of the scale of R&D – on the growth rates of per capita real GDP and/or technology, and (ii) any attempt to estimate the scale parameters in a bivariate setting – by employing either R or Z as the scale measure – is likely to suffer from the problem of unbalanced regression (non-standard distribution) and spurious parameter estimates. This is because the theory of scale effects associates $I(0)$ dependent variables measured in growth rates with $I(1)$ covariates measured in levels (scales of R&D), which gives rise to the problem of an unbalanced regression (relevant tests in Section 2). To our knowledge, this issue has not been formally addressed while testing the scale effects. We address this issue by incorporating both Z and E as covariates in estimating the scale effects.

Our trivariate approach not only captures the scale of R&D accurately but also resolves the issue of unbalanced regression and provides valid estimates of scale parameters, so long as the two scale variables (covariates) are mutually cointegrated, and this is what we find. Thus, our estimates of the scale effects are based on a more realistic measure of the scales of R&D than has been utilized hitherto, and on an estimation strategy that addresses the issue of non-standard distribution. Our results – obtained by separately analyzing a panel of 19 DE countries for the period 1965–2016, and a panel of 26 EME countries for the period 1988–2016 – reveal that the average cross-country scale effects are insignificant (non-existent) in the DE panel, whereas they are strictly positive and significant under both measures of the scale in the EME panel. Our results from the DE panel are consistent with the core findings in the literature that scale effects are missing in these economies as they operate close to their long-run equilibrium. Likewise, the significance of scale effects across EME economies is also consistent with the view that these countries are in growth transitions.

To the best of our knowledge there has been no formal analysis of the dynamics of scale effects in an endogenous growth setting. In light of the strikingly different results across developed and emerging country panels, we propose an endogenous growth model by incorporating R&D labor and capital in a distinct manner, and analyze the dynamics of scale effects, which reconciles our empirical results. Our model draws from Acemoglu (1998) and augments it by Jones' (1995a) technology production function.[4] The evolution of technology, that enhances the production of final goods, is determined by the R&D activity of a perfectly competitive research sector, which employs scientists and engineers (i.e., the R&D labor), who seed the innovation of new discoveries. When a research firm innovates, it patents its discovery and becomes a monopolist of the new technology. Then, the monopolist translates the technology into a tangible form by embedding it in a device for a profit using R&D capital.[5] Research firms without the patent can conduct research in enhancing the technology and sell the outcome of their research to the firm possessing the patent.[6]

[4]Our augmented technology production function differs from the one used by Ha and Howitt (2007) for comparing and testing second generation growth models.

[5]Unlike Aghion and Akcigit (2017), we do not assume that new discoveries make old discoveries obsolete. Instead, we follow Acemoglu (1998) and assume that real R&D capital depreciates fully after use. In this framework, R&D capital stock and real R&D capital expenditure coincide.

[6]For instance, consider a technological discovery which facilitates the fast and effective processing of

Unlike much of the literature, we consider R&D capital and labor as distinct inputs of the production processes and incorporate them in the model via different channels. R&D labor is focused on innovation, leading to the development of incremental technologies, while R&D capital facilitates the embodiment of these technologies in the production function of final goods producing firms. We show that scale effects are a function of an economy's position along its path to long-run equilibrium, and that they are non-monotonically related to the shares of new technologies, which are proportional to the growth rate of technology. We characterize developed economies as those having relatively small shares of new technologies due to their large accumulated knowledge stocks (the denominator of the share). Emerging economies, on the other hand, are characterized as having relatively large shares of new technologies due to their small accumulated knowledge stocks. Small shares of new technologies across DE countries imply small scale effects, whereas large shares across EME countries imply large scale effects, unless the latter are at the very early stage of development with little or no accumulated R&D capital stock.

Our model shows that when the economy converges to its balanced growth path (BGP),

speech recognition and another technological discovery that identifies whether a Wi-Fi network is shared with neighbors. All sector research firms have access to these technologies and can make further improvements to them, i.e., to maximize their effectiveness/quality. However, only the firm that initially discovered the technology and was granted a patent, can build and sell a device that incorporates the technology (e.g., to internet service providers in the case of the Wi-Fi identifier). All the other research firms can only sell their output to the firm that owns the patent. Note that while the number of Wi-Fi identifier devices produced enable the firm to control accessibility, and thus increase the speed of connection and operational efficiency, without the technology embedded in each device, the devices on their own are of no use.

the rate of economic growth is driven by the growth rates of aggregate employment and technological innovations. EME countries, being at a further distance from their BGP relative to DE economies, take longer to converge. We empirically evaluate the model's long-run growth predictions, approximating technological innovations by the flow of patent filings (a widely used measure in the literature), and find that the results are consistent with the predictions.

The rest of the paper is organized as follows. Section 2 presents empirical estimates of scale effects, Section 3 presents the endogenous growth model, and Section 4 tests the long-run predictions of the model. Section 5 concludes.

2 Estimates of Scale Effects

In this section, we discuss our sample and data, lay out our econometric model and estimation method, and report the parallel results of scale effects obtained from DE and EME country panels. We have an unbalanced panel of DE countries, which consists of 19 OECD countries with data on almost all relevant variables spanning for the period of 1965–2016. The exceptions are (i) the data on TFP which cover the period of 1965–2014, and (ii) the employment data for Austria and Denmark which span 1969–2016.[7] The DE panel has a minimum of 950 to a maximum of 988 country years of data points spanning at least 50 years. Our EME country panel is also unbalanced, consisting of 26 countries with data

[7]Throughout our analysis, we employ the TFP measure obtained from the Penn Tables, which is a widely used measure. Although this TFP measure is derived using a production function which somewhat differs from the one used in our theoretical model (see the following section), we argue that it is a good proxy, especially for the long-run analysis.

points covering a minimum of 609 to a maximum of 719 country years, spanning a maximum of 29 (1988–2016) to a minimum of 23 (1994–2016) years. Of the 26 sample EME countries, three (Belarus, Cuba, and Pakistan) do not have data on TFP. Table A1 of Appendix A lists data sources and sample countries.

Summary statistics of some of the key R&D variables pertaining to both country panels are reported in Table A2 of Appendix A. There is considerable heterogeneity in the growth rates of real per capita income, domestic patent filings, R&D and research intensities, and research productivity both within and across these country panels. Our panel of EME countries shows an average annual growth rate of 2.69% during the sample period. China records the highest average annual growth rate of 8.19% and the Russian Federation the lowest (0.006%). Likewise, the average annual growth rate is 2.05% across the DE panel: Ireland records the highest (3.80%) and Switzerland the lowest (1.16%). The average number of annual domestic patent filings is 26,594 in the DE panel which is 2.6 folds higher than in the EME panel (10,232). China is dominant in patent filings across the EME countries, and the USA is dominant across the DE countries. However, Chinese average annual domestic patent filings are 61% higher than those of the USA. Our empirical results, reported below, are robust to the exclusions of big and/or small countries from the panel. The sample average R&D intensity is 0.75% across EME countries, which is much lower than that of DE countries (1.69%). Singapore shows the highest R&D intensity of 1.90% across the EMEs, and Sweden across the DEs (2.54%). The average research intensity across EME countries is about two-thirds of the DE level. The average research productivity in DE countries is a lot higher (over 4 folds) than in EME countries. The USA shows quite a low proportion of

R&D capital expenditure relative to its total R&D expenditure, which may reflect its mature R&D sector.

The theory of scale effects posits a proportional relationship of growth rates of knowledge (technology – TFP) and real per capita GDP (x) to the level (scale) of R&D activity. Specifically, we estimate the average cross-country-time scale effects across EME and DE countries, as measured by the average cross-country and time semi-elasticities $\varepsilon_{M,Z} = \frac{1}{nT}\sum_i^n \sum_t^T \varepsilon_{M,Zi,t}$ and $\varepsilon_{M,E} = \frac{1}{nT}\sum_i^n \sum_t^T \varepsilon_{M,E_{i,t}}$ for $M \in \{x\ ;\ TFP\}$. To this end, we specify an auxiliary regression of the following form:

$$g_{M,i,t} = \rho_i + \gamma_t + \varepsilon_{M,Z} \ln Z_{i,t} + \varepsilon_{M,E} \ln E_{i,t} + \sum_{j=-2}^{2} \eta_j \Delta \ln Z_{i,t-j} + \sum_{j=-2}^{2} \mu_j \Delta \ln E_{i,t-j} + e_{i,t}, \tag{1}$$

where $g_{M,i,t}$ is the growth rate of M, for country i at time t. Equation (1) is a fixed effects linear-log model in the Dynamic OLS (DOLS, Stock and Watson, 1993) framework, where ρ_i captures the country-specific fixed effects and γ_t captures the time effects. The scale effects relationship is between the dependent variable, $g_{M,i,t}$, measured in growth rates, and the covariates, $Z_{i,t}$ and $E_{i,t}$, measured in log levels. Panel unit root tests confirm that growth rates of per capita real GDP, $g_{x,i,t}$, and total factor productivity, $g_{TFP,i,t}$, are $I(0)$, while scale variables, $lnZ_{i,t}$ and $lnE_{i,t}$, are $I(1)$.[8] This very presence of stationary $I(0)$ dependent

[8] We implement a Fisher-type Phillip-Perron panel unit root test (Maddala and Wu, 1999), by setting a fixed lag length of 3, that allows for heterogenous unit root processes across panel units. The tests confirm that $lnZ_{i,t}$ and $lnE_{i,t}$ are $I(1)$, whereas, $g_{x,i,t}$, and $g_{TFP,i,t}$, are $I(0)$. Specifically, under the null of unit root, the p-values for $lnZ_{i,t}$ and $lnE_{i,t}$, are 0.590 and 0.903 respectively, across the EME panel and 0.823 and 0.267 across the DE panel. Likewise, the respective p-values for $g_{x,i,t}$, and $g_{TFP,i,t}$, are 0.000 for both

variable and non-stationary $I(1)$ covariates may give rise to the problem of an unbalanced regression while testing the scale effects.

Any estimation of scale effects through bivariate regressions which employs a single proxy of the scale of R&D – whether lnZ or lnE or lnR as they all are $I(1)$ – suffers from the problem of an unbalanced regression and non-standard distribution because the regression residuals will be non-stationary. However, our specification is a trivariate one, and so long as the two $I(1)$ covariates, lnZ and lnE, are mutually cointegrated, they provide a sensible specification for the $I(0)$ dependent variable by making the estimating equation balanced.[9] Our specification, therefore, has two clear advantages: (i) it provides valid estimates of scale parameters as lnZ and lnE are cointegrated, and (ii) the inclusion of both lnZ and lnE captures the scale of R&D activities distinctly and more accurately.

The DOLS is a powerful and efficient estimator of a cointegrating relationship when the regression model contains a mixture of stationary and non-stationary variables. This approach augments the estimating equation by the suitably differenced leads and lags of non-stationary regressors, which eliminate endogeneity. Stock and Watson (1993) allow for covariates with different orders of integration – e.g., $I(0)$, $I(1)$, and $I(2)$ – in the regression

panels.

[9] Kao's Engle-Granger residual based panel test of cointegration decisively rejects the null of non-cointegration between lnZ and lnE across both panels. Under the null of no cointegration, the test statistics are -2.70 (0.004) and -1.625 (0.052), respectively for the EME and the DE panels; figures within parentheses are p-values. We allow for individual intercept and set a fixed lag length of 3 while calculating these test statistics; allowing for the automatic lag length selection improves the precision of both test statics (p-values of 0.000).

equation; however, they always maintain the dependent variable as $I(1)$. Our dependent variable is stationary, therefore, our trivariate specification, which incorporates two mutually cointegrated regressors, is important for a valid estimation and inference of scale effects.

Table 1 reports the estimates of scale parameters for the EME and DE country panels. Results from the EME panel show significant scale effects of R&D, as both lnZ and lnE appear positive and significant in explaining $g_{x,i,t}$, and $g_{TFP,i,t}$. The estimated scale parameter of lnZ is significant at 1% in explaining $g_{x,i,t}$ while the scale parameter of $lnE_{i,t}$ is significant at 10% or better. Likewise, lnE appears significant at 1% in explaining $g_{TFP,i,t}$ but lnZ is significant at 10% or better. The Levin, Lin and Chu (2002) t-tests (t_{llc}) reject the non-stationarity of the error correction term at a very high level of precision, confirming the estimated scale effect relationships for the EME panel are indeed cointegrated. In sharp contrast, equivalent estimates of scale effects for the DE panel appear completely insignificant.[10]

This difference in scale effects results between the EME and DE country panels is consistent with the view that scale effects are unlikely to exist amongst mature economies that are on or close to their BGP but may exist when economies are progressing through growth

[10]Truncating the DE sample to 1988–2016 and making it exactly match the sample period of the EME panel also shows no support for the scale effects across the DE panel. Further, significant scale effects found for the EME panel remain largely robust to the exclusion of large countries like China and India. Specifically, excluding China from the EME panel maintains the significant scale effects of lnE on $g_{x,i,t}$ and $g_{TFP,i,t}$ while the parameter estimates of lnZ turns somewhat imprecise (insignificant at 10%). The exclusion of India does not alter the significant scale effects on $g_{x,i,t}$ but the parameter estimates of lnZ turns imprecise for $g_{TFP,i,t}$.

Table 1: Panel DOLS Estimates of Scale Effects

	26 Emerging Countries (1988–2016)		19 OECD Countries (1965–2016)	
Regressors	Dependent variables			
	g_x	g_{TFP}	g_x	g_{TFP}
$\ln Z$	0.045	0.024	0.013	-0.002
	(0.018)	(0.014)	(0.009)	(0.007)
	{0.012}	{0.095}	{0.139}	{0.827}
$\ln E$	0.016	0.027	-4e-4	-0.004
	(0.009)	(0.011)	(0.005)	(0.003)
	{0.089}	{0.011}	{0.939}	{0.297}
Panel Cointegration Tests of Scale Effects Relationships				
t_{llc}	{0.000}	{0.000}	N/A	N/A
N [OBS]	26 [501]	23 [446]	19 [890]	19 [893]

Notes: Numbers in parentheses are standard errors and those within curly braces are p-values of Wald tests under the null that the estimated coefficient is zero, which are $\chi^2(1)$. t_{llc} {p-value reported} are the Levin, Lin, and Chu (ibid.) t-test of the the null of unit root in the panel error correction term (i.e., the null of non-cointegration of the estimated relationships). Since all parameter estimates of OECD panels are statistically insignificant, it makes no sense to conduct cointegration tests hence "N/A". The second order leads and lags are used for augmentations, and constant and linear trend are maintained as individual deterministic components. Belarus, Cuba, and Pakistan do not have data on g_{TFP}. N [OBS] denotes the number countries [data points] used in each estimation after accounting for the leads and the lags. Numbers beyond three decimal places are reported as 3.5e-4=0.00035.

transitions, as may be the case for the emerging countries. Our findings vis-à-vis the industrialized countries are consistent with those of Jones (1995a, 1995b), despite our different empirical approach.

Interestingly, the estimated scale parameters show large scale effects of R&D on economic and productivity growth rates of emerging countries. Dependent variables are measured as proportions (i.e., 5% as 0.05) and covariates are measured in log levels, hence the reported parameters are semi-elasticities. To give some perspective on the magnitudes of the scale effects using the estimated scale parameters, a 1% increase in Chinese R&D labor would increase the Chinese growth rate of per capita real GDP by 0.55% (point elasticity).[11] Likewise, a 1% increase in real R&D capital expenditure would increase the Chinese growth rate of per capita real GDP by 0.20%. Chinese average annual productivity growth has been 1.91% during the sample period. The scale effect parameter estimates imply point elasticity of Chinese TFP of above unity with respect to both Z and E. Likewise, other emerging countries appear to benefit by increasing the scale of their R&D activities: countries experiencing lower growth rates are set to benefit more by expanding their R&D sectors.

[11]Note that $\frac{\partial g_{x,i,t}}{\partial lnZ_{i,t}} = \frac{\partial g_{x,i,t}}{\partial Z_{i,t}/Z_{i,t}} = \varepsilon_{x,Z}$, which can be rewritten as $\frac{\partial g_{x,i,t}}{\partial Z_{i,t}} = \frac{\varepsilon_{x,Z}}{Z_{i,t}}$. Using the latter, the elasticity of $g_{x,i,t}$ with respect to $Z_{i,t}$ is written as $\frac{\partial g_{x,i,t}}{\partial Z_{i,t}} \frac{Z_{i,t}}{g_{x,i,t}} = \frac{\varepsilon_{x,Z}}{Z_{i,t}} \frac{Z_{i,t}}{g_{x,i,t}} = \frac{\varepsilon_{x,Z}}{g_{x,i,t}}$. Then, using the cross-time average growth rate for country i, the elasticity for country i is written as $\frac{\varepsilon_{x,Z}}{\bar{g}_{x,i}}$. Thus, the growth rate elasticity with respect to R&D labor for China is $0.045/0.082 \approx 0.55$.

3 Endogenous Growth Model

We propose an endogenous growth model that reconciles these two diametrically different sets of results – the significant scale effects across emerging country panels and the insignificant scale effects across developed country panels – which allows us to analyze the dynamics of scale effects. The structure of our model is similar to that of Acemoglu (1998), while the evolution of technology is modelled along the lines of Jones (1995a,b). There is a continuum of infinitely-lived individuals, with identical intertemporally additive preferences defined over consumption. The marginal utility of consumption is assumed to be constant, which implies that the rate of time preference $r > 0$ is also the interest rate.

3.1 Production of Final Goods

Aggregate output, Y, is produced by perfectly competitive firms, defined on the unit interval such that $Y = \int_0^1 y(i)di$, where $y(i)$ denotes the output produced by firm i. The price of the final output is the numeraire. Output for firm i is produced using neutral technology $A(i)$, labor $n(i)$, and, general capital $k(i)$, such that $y(i) = A(i)n(i)^{\beta}k(i)^{1-\beta}$, where $0 < \beta < 1$. The general capital is the physical capital owned by consumers who rent it out to firms. The aggregate supply of workers and general capital are given by $N \equiv \int_0^1 n(i)di$ and $K \equiv \int_0^1 k(i)di$, respectively. The evolution of neutral technology is driven by R&D-induced intangible technology, Q, which takes on a tangible form through the use of R&D capital that enables the technology to be used in the production process. Put differently, Q acquires material form once it is embedded into a device using firm-specific R&D capital, $e(i)$. The function that maps Q into tangible technology devices is $F(i) = Qe(i)^{\lambda}$, where

$0 < \lambda < 1$. The firm that utilizes technology Q must incur the firm-invariant cost of R&D capital, denoted by χ, per unit of R&D capital. It follows that the change of firm-specific neutral technology $A(i)$ is given by $\dot{A}(i) = \lambda^{-(1-\phi_A)} A(i)^{\phi_A} F(i)$, where $0 < \phi_A < 1$ and $\dot{A}(i)$ is the derivative of $A(i)$ with respect to time. For the sake of notational simplicity, we omit time as an argument unless it is necessary. The profit function for firm i is, $\pi(i) = A(i)n(i)^{\beta}k(i)^{1-\beta} - \chi e(i) - wn\,(i) - r_K k(i)$, where w and r_K are the wage rate and the rental price for general capital, respectively, while the level of neutral technology is given by:

$$A(i) = \frac{1}{\lambda}\left[(1-\phi_A)\int_0^t Q(\tau)e(i,\tau)^{\lambda} d\tau\right]^{\frac{1}{1-\phi_A}}. \qquad (2)$$

The firm chooses quantities of $n(i)$, $k(i)$ and $e(i)$ in order to maximize profit. Firms are identical, therefore, in equilibrium, they end up making the same choices, hence the optimality conditions reduce to: $w = \beta A(K/N)^{1-\beta}$; $\chi = \lambda^{\phi_A} A^{\phi_A} Q E^{-(1-\lambda)} N^{\beta} K^{1-\beta}$; and, $r_K = (1-\beta)A(K/N)^{-\beta}$; where $N \equiv n$, $E \equiv \int_0^1 e(i) = e(i)$, and $Y \equiv y(i)$. Due to the risk-neutrality of consumers, who are also the owners of physical capital, $r_K = r + \delta$, where δ is the depreciation rate of general capital.[12]

3.2 Research & Development Sector

We assume a research sector with free entry that is populated by perfectly competitive firms. A research firm j contributes $q(j)$ to the development of technology $Q = \int_0^1 q(j)dj$

[12]This condition further implies that in equilibrium general capital per capita depends on the level of technology that is, $K/N = (1-\beta)A^{1/\beta}/(r+\delta)$.

by carrying out R&D using researchers, $z(j)$.[13] The profit from R&D activity is given by $\pi^D(j) = \rho(j)V(j) - Bq(j)z(j)$, where $\rho(j) \equiv \varphi(Q,Z)Cz(j)$ is the flow rate of innovation with $\varphi(Q,Z) = \nu^{-(1-\phi_Q)}Q^{\phi_Q}Z^{\nu-1}$, $Z = \int_0^1 z(j)dj$, C is a productivity factor defined below, $0 < \phi_Q < 1$, $0 < \nu < 1$, $V(j)$ is the value of innovation, and $Bq(j)$ is the firm's cost per researcher with $B > 0$. Research firms take $\varphi(Q,Z)$ as given, i.e., they perceive themselves to be too small to affect the aggregate invention probability.[14] The productivity factor $C(t) = \sigma e^{g_C t}$, where σ is a scale factor which coincides with the Poisson rate at which a new idea arrives at a research firm and $g_C > 0$ is the sectoral growth rate of productivity due to new ideas.[15] In other words, while new ideas at the sectoral level grow over time, at every instant a new idea is randomly allocated to a single research firm and although access to C is not exclusive to the allocated firm, the latter acquires a monopoly right over the particular vintage by receiving a patent. Once the technology is upgraded, the patent holding research firm is the only firm that can sell the upgraded technology to the final goods firms, charging a profit maximizing rent for the R&D capital needed to translate technology into tangible form.

[13]Researchers may also be included in aggregate labor N and receive a premium for their research work, in addition to general salary, w. None of the results will be affected by this assumption.

[14]This assumption is equivalent to Acemoglu's (1998) assumption that small firms ignore their impact on the invention probability of other firms working to improve the same machine.

[15]Without compromising our findings, we have assumed that the growth rate of productivity $C(t)$ is time invariant. Alternatively, we could have assumed that $C(t) = \sigma e^{\int_0^t g_C(s)ds}$, where $g_C(t)$ captures the fact that the magnitude of the impact of each new idea on productivity varies over time. Whether g_C is time invariant or not however does not have any effect on our results. Hence, we simplify the model by assuming that g_C is constant.

While the patent prevents the rest of the research firms from accessing the market of final goods, they can sell their research output to the firm that possesses the patent for $\rho(i)V(i)$. The firm that owns the patent has an incentive to purchase the research output of other firms in order to motivate them to work on improving technology further since the latter improves its own productivity via $\varphi(Q, Z)$. The ownership value of the leading vintage of technology input is given by:

$$rV(j) = \pi^m(j) - \int_0^1 \rho(i)V(i)di + \dot{V}(j), \tag{3}$$

where $\pi^m(j)$ is the instantaneous profit of the monopolist that owns the leading vintage and $\dot{V}$ is the derivative of V with respect to time, which captures changes in the valuation of the leading vintage. The profit function $\pi^m(j)$ is written as $\pi^m = \chi(E)E - QE$; where $\chi(E)$ is the inverse demand for R&D capital derived from the problem of the firm producing final output. As in Acemoglu (1998), the profit-maximizing price, χ, turns out to be a constant mark-up over marginal cost, that is, $\chi = Q/\lambda$.[16]

3.3 The Balanced Growth Path and Transition Dynamics

In this section, we characterize the Balanced Growth Path (BGP) and the transition dynamics to it. Using the production function of final output, the growth rate of per capita output, $x = Y/N$, can be written as $g_x = g_A + (1 - \beta)g_{\bar{K}}$, where $g_{\bar{K}}$ denotes the growth rate of per capita general capital. The optimal condition for general capital implies that $g_{\bar{K}} = (1/\beta)g_A$,

[16] The fact that $\rho(i)V(i)$ is subtracted from the right hand side of (3) is also consistent with Acemoglu's (1998) assumption that this term captures the rate that firm j loses its monopoly position.

which means that $g_x = (1/\beta)g_A$. Since C is common across all research firms, in equilibrium, $z(j) \equiv Z$, $V(j) = V$, $q(j) \equiv Q$ and thus $\rho(j) = \rho$, while the optimal condition for a research firm becomes $\varphi(Q, Z)CV = BQ$ for all j. It follows that Q evolves according to $\dot{Q} \equiv \rho$ which implies that,

$$Q = \frac{1}{\nu}\left[(1-\phi_Q)\int_0^t C(\tau)Z(\tau)^{\nu}d\tau\right]^{\frac{1}{1-\phi_Q}}. \tag{4}$$

Along the BGP all variables grow at a constant rate, i.e., $\dot{g}_A = \dot{g}_Q = \dot{g}_x = \dot{g}_N = \dot{g}_E = \dot{g}_Z = \dot{g}_V = 0$. As shown in Appendix B, at the BGP the growth rates of all endogenous variables are driven by the growth rates of the exogenous arrival of new ideas, g_C, and aggregate employment, g_N, that is,

$$g_J = \gamma_{J,C}g_C + \gamma_{J,N}g_N, \tag{5}$$

for $J = Z, Q, E, A, x$, where $\gamma_{J,C}$ and $\gamma_{J,N}$ are functions of structural parameters.[17] For $g_C > 0$ and $g_N > 0$, the existence of a BGP requires that,

$$0 < \nu < \overline{\nu} \equiv \frac{(1-\phi_Q)[\beta(1-\phi_A)-\lambda]}{1-\beta(1-\phi_A)},$$

with the necessary condition $\lambda < \beta(1-\phi_A)$. If parameter values do not satisfy these inequalities, the non-negativity conditions for Q, A, E as well as g_C and g_N, along the BGP, are violated.[18] Thus, the solution of our model shows that the long-run growth is not only

[17]The solutions for $\gamma_{J,C}$ and $\gamma_{J,N}$ by way of structural parameters are provided in Appendix B.

[18]If $\nu > \overline{\nu}$ then, $\gamma_{A,C} < 0$ and $\gamma_{A,N} < 0$ and as a consequence $g_A < 0$, which is infeasible since $Q > 0$, $A > 0$ and $E > 0$ imply that $g_A = \lambda^{-(1-\phi_A)}A^{-(1-\phi_A)}QE^{\lambda} > 0$. If $\nu = \overline{\nu}$ then, $g_N = -\frac{1-\beta(1-\phi_A)}{\beta(1-\phi_A)(1-\phi_Q)}g_C$

driven by a measure of population growth as a typical semi-endogenous model would suggest, but also by innovations by virtue of the monopoly rents.

Figure 1 displays the transition dynamics towards the BGP, which are summarized by two lines in the (g_A, g_Q) space: a vertical line for g_Q, as per the BGP equation B2 (Appendix B), and an upward sloping line for g_A, as per the equation B1 (Appendix B). The economy tends to converge to the unique BGP where the two lines intersect and the growth rates of A and Q are driven only by g_C and g_N.[19]

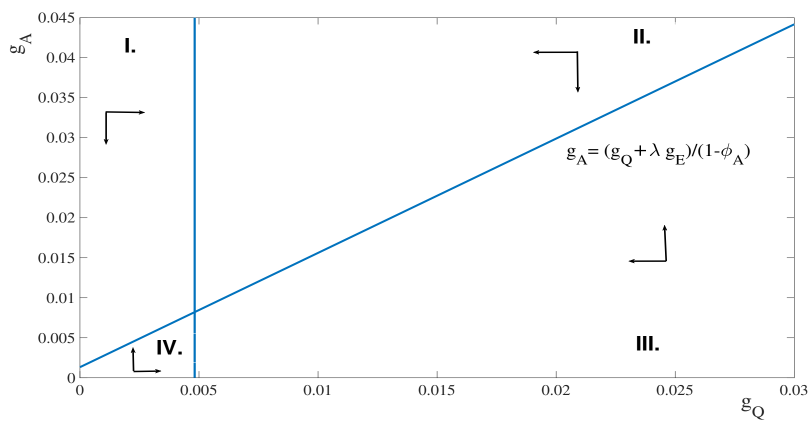

Figure 1: Transition Dynamics Toward the BGP

which contradicts the fact that both g_C and g_N are strictly positive. If $\nu < \overline{\nu}$ then, $\gamma_{A,C} > 0$ and $\gamma_{A,N} > 0$ and thus $g_A > 0$.

[19]Differentiating the growth rate of A with respect to time, using equation 1, allows us to obtain an equation that describes the evolution of g_A that is, $\dot{g_A}/g_A = g_Q + \lambda g_E - (1-\phi_A)g_A$. It follows that when $g_A < (g_Q + \lambda g_E)/(1-\phi_A)$ then $\dot{g_A}/g_A > 0$, whereas when $g_A > (g_Q + \lambda g_E)/(1-\phi_A)$ then $\dot{g_A}/g_A < 0$. Likewise, differentiating the growth rate of Q with respect to time, using equation 3, allows us to obtain an equation that describes the evolution of g_Q that is, $\dot{g_Q}/g_Q = g_C + \nu g_Z - (1-\phi_Q)g_Q$. It follows that when $g_Q < (g_C + \nu g_Z)/(1-\phi_Q)$ then $\dot{g_Q}/g_Q > 0$, whereas when $g_Q > (g_C + \nu g_Z)/(1-\phi_Q)$ then $\dot{g_Q}/g_Q < 0$. Therefore, g_A and g_Q always tend to converge towards their BGP, which explains the arrows of Figure 1.

To examine the dynamics of scale effects, we consider the semi-elasticities: $\partial g_J/\partial \ln E$ and $\partial g_J/\partial \ln Z$ for $J = Q$, A, x. These semi-elasticities, denoted by $\varepsilon_{J,E}$ and $\varepsilon_{J,Z}$, can be written as:

$$\varepsilon_{A,E}(t) = \frac{\lambda\theta_A(t)\left[1-\theta_A(t)\right]}{1-\phi_A}, \quad \varepsilon_{A,Z}(t) = \frac{\nu\theta_Q(t)\theta_A(t)\left[1-\theta_A(t)\right]}{(1-\phi_A)(1-\phi_Q)}, \quad \varepsilon_{Q,Z}(t) = \frac{\nu\theta_Q(t)\left[1-\theta_Q(t)\right]}{1-\phi_Q}$$

$$\varepsilon_{x,E}(t) = \frac{\varepsilon_{A,E}(t)}{\beta}, \quad \varepsilon_{x,Z}(t) = \frac{\varepsilon_{A,Z}(t)}{\beta},$$

where $\theta_A(t)$ and $\theta_Q(t)$ are the following technology shares:

$$\theta_A(t) = \frac{Q(t)E(t)^{\lambda}}{\int_0^t Q(\tau)E(\tau)^{\lambda}d\tau} \equiv (1-\phi_A)g_A(t), \text{ and } \theta_Q(t) = \frac{C(t)Z(t)^{\nu}}{\int_0^t C(\tau)Z(\tau)^{\nu}d\tau} \equiv (1-\phi_Q)g_Q(t).$$

As shown above, the growth rates of technology are proportional to the technology share parameters, θ_Q and θ_A, which reflect the economy's state of development, measured by the technology shares. We take that emerging economies, which are at the early stages of development, exhibit high technology shares, while developed economies, which operate close to their BGP, exhibit low technology shares. This is because emerging (developed) economies have small (large) accumulated stocks of technology, therefore incremental technology forms a large (small) share of their accumulated stocks. Since g_A and g_Q are proportional to technology shares, the technological growth rates of emerging economies are relatively high while those of the developed economies are relatively low. It follows that emerging economies at the initial stages of development exhibit high growth rates of technology which lie at the top corners of Figure 1, denoted by areas I and II or at a point along the 45° line. However, when EMEs gradually develop by accumulating technology, their rates of growth of technology slow down as they converge towards their BGP values at the intersection of the two lines of Figure 1.

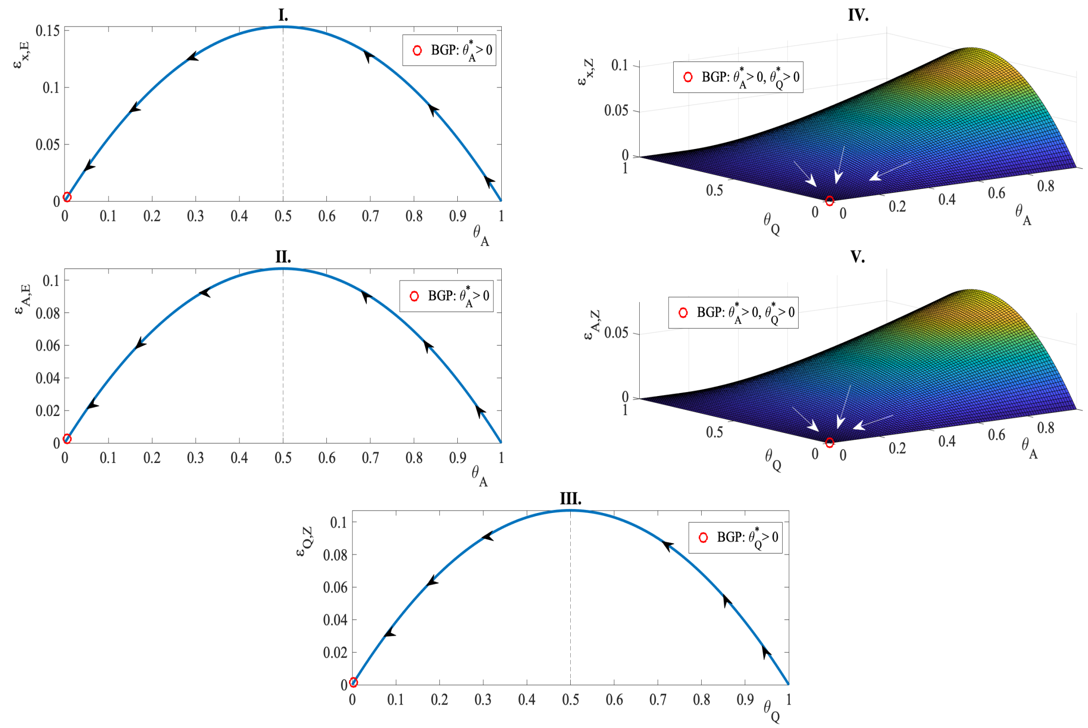

Figure 2: Transition of Scale Effects Toward the BGP

Figure 2 is a visual display that relates the transition dynamics of scale effects with the technology shares. Specifically, it highlights the BGP semi-elasticities versus the technology shares obtained from a calibration exercise where $\lambda = \phi_A = \phi_Q = \nu = 0.1$, $\beta = 0.75$ and $g_C = g_N = 1\%$. The implied BGP scale effect from this calibration is $\varepsilon_{x,E} = 0.34\%$, as measured by R&D capital, and $\varepsilon_{x,Z} = 3.9079e - 05$, as measured by R&D labor.[20] To make

[20]This calibration is chosen for expositional purposes only. It further implies that $\varepsilon_{A,E} = 0.18\%$, $\varepsilon_{A,Z} = 2.9309e - 05$, $\varepsilon_{Q,E} = 0.25\%$, and $\varepsilon_{Q,Z} = 0.18\%$.

the BGP values of θ_Q and θ_A visually distinct we denote them by θ_Q^* and θ_A^*.

As is evident from Figure 2, economies that are either at the very early stages of development where technology growth rates are high (on the lower right corners of Figures 2.I–2.III and on the lower right corners of Figures 2.IV and 2.V) or operating close to their BGP, where technology growth rates are low (on the lower left corners of Figures 2.I–2.III and on the lower front corners of Figures 2.IV and 2.V), exhibit small scale effects, measured both by R&D capital and researchers. That is, technology growth rates at the very early stages of economic development are large, and so logarithmic increments of Z and E have negligible effects on the former. On the other hand, for economies operating very close to their BGP, scale effects cease to exist due to decreasing returns to technology. Intuitively, economies which are about to converge to their BGP have large accumulated stocks of knowledge, hence any new incremental knowledge induced from either Z or E exerts a trivial effect on overall knowledge stocks.[21]

Thus, our model shows that once the emerging countries pass through their initial stages of development and begin their transition towards their long-run equilibrium, they initially experience amplified scale effects. As they approach closer and closer to their BGPs, the scale effects gradually subside. Hence, scale effects are seen during growth transitions but not at the BGP or at its vicinity, which reconciles our empirical results of significant scale effects across EME countries but their insignificance across DE countries, unless EME countries are

[21] In terms of the mathematical expressions of the elasticities, at early stages of economic development since θ_Q and θ_A are close to unity, $\theta_Q(1-\theta_Q)$ and $\theta_A(1-\theta_A)$ are close to zero. Likewise, for economies operating in the neighborhood of their BGP, $\theta_Q(1-\theta_Q)$ and $\theta_A(1-\theta_A)$ are close to zero because θ_Q and θ_A are close to zero.

at the very early stages of their development.

4 Evaluating the Model's Long-Run Growth Predictions

Our theoretical model predicts that g_z, g_E, g_A and g_x are all driven by g_C and g_N at the BGP (equation (5)). We empirically evaluate these predictions by transforming the long-run growth relationships into log level relationships and employing suitable cointegration tests.[22] To this end, let $g_{J,t} \in G_J(g_J)$, $g_{C,t} \in G_C(g_C)$, $g_{N,t} \in G_N(g_N)$ for $J = Z, E, TFP, x$, where G_J, G_C and G_N are the neighborhoods of the corresponding BGP's and TFP is our proxy for technology (A). Since the logarithmic first differences approximate growth rates, the BGP relationships of equation (5) can be expressed in terms of the variables in log levels as $lnJ_t - lnJ_{t-1} = \gamma_{J,C}[lnC_t - lnC_{t-1}] + \gamma_{J,N}[lnN_t - lnN_{t-1}]$, which can be rearranged as $lnJ_t - \gamma_{J,C}lnC_t - \gamma_{J,N}lnN_t = lnJ_{t-1} - \gamma_{J,C}lnC_{t-1} - \gamma_{J,N}lnN_{t-1}$. At the BGP, the latter can be extended further to $lnJ_t - \gamma_{J,C}lnC_t - \gamma_{J,N}lnN_t = lnJ_{t-1} - \gamma_{J,C}lnC_{t-1} - \gamma_{J,N}lnN_{t-1} = lnJ_{t+1} - \gamma_{J,C}lnC_{t+1} - \gamma_{J,N}lnN_{t+1} = lnJ_{t+2} - \gamma_{J,C}lnC_{t+2} - \gamma_{J,N}lnN_{t+2} = ... = lnJ_{t+n} - \gamma_{J,C}lnC_{t+n} - \gamma_{J,N}lnN_{t+n} = ...$. Hence, the BGP relationships imply cointegrating relationships between lnJ_t, lnC_t and lnN_t with the cointegrating vector of $(1, -\gamma_{J,C}, -\gamma_{J,N})$, which can be shown as:

$$lnJ_t = \gamma_{J,C}lnC_t + \gamma_{J,N}lnN_t \tag{6}$$

[22] In our empirical evaluations, we avoid using sample averages of growth rates as they are likely to be away from the BGP values.

If variables in (6) form valid cointegrating (long-run) relationships then this evidence would be consistent with the BGP relationships of (5).

For a robust inference on the BGP relationships, we employ two estimators of cointegrating relationships, namely, DOLS and the FMOLS (Fully Modified OLS; Phillips and Hansen, 1990, and Phillips and Moon, 1999), supplemented by the Levin, Lin, and Chu (ibid.) t-test (t_{llc}), on the estimated error correction term. Unlike the scale effects specifications in (1), which contain variables in logarithmic first differences and levels in the estimating equation, (6) contains all variables in log levels, which are $I(1)$, hence the use of FMOLS is valid.[23] Since the exogenous productivity variable, C, is directly unobservable, we proxy it by the flow of domestic patent filings of sample countries which is a widely used measure of new-to-the-world ideas.[24] Note that in our model, whenever a new idea is invented, that increases C, and is patented by the inventor. Hence, there is a natural link between patent flows and the variable C.

The cointegration estimates, which proxy the BGP relationships, as predicted by our model, are reported in Table 2. Panel A reports the results for the EME panel, and Panel B for the DE panel. It is evident that the levels of per capita real GDP, R&D employment,

[23]The Fisher-type Phillip-Perron (PP) panel unit root test (Maddala and Wu (ibid.)) confirm that $lnGDP$, lnZ, lnE, $lnTFP$, and lnN are all I(1) across both panels but the null of unit root is rejected for lnC at the conventional significance levels of 10% or better. However, t_{llc} test decisively shows it to be $I(1)$; hence, on balance, we treat lnC as $I(1)$. The latter result is also widely reported in the literature.

[24]We recognize that patents, despite their wide usage, are a noisy measure of innovations as they greatly differ in their "universality" and "size" (Eaton et al., 1998), as well as in values (Battke et al., 2016). Nevertheless, patent flows are the only consistent proxy of innovations that are around and in wide usage.

Table 2: Estimates of Long-run (BGP) Relationships

	Panel A: 26 Emerging Countries							
	DOLS				FMOLS			
Regressors	Dependent variables							
	$lnGDP$	lnZ	lnE	$lnTFP$	$lnGDP$	lnZ	lnE	$lnTFP$
$\ln C$	0.092	0.303	0.443	0.023	0.211	0.308	0.483	0.066
	(0.011)	(0.022)	(0.028)	(0.011)	(0.022)	(0.033)	(0.036)	(0.012)
	{0.000}	{0.000}	{0.000}	{0.042}	{0.000}	{0.000}	{0.000]}	{0.000}
$\ln N$	0.784	2.164	2.042	-0.011	0.618	2.108	1.986	-0.094
	(0.034)	(0.145)	(0.163)	(0.039)	(0.121)	(0.189)	(0.212)	(0.072)
	{0.000}	{0.000}	{0.000}	{0.775}	{0.000}	{0.000}	{0.000}	{0.188}
	Panel cointegration tests							
t_{llc}	{0.000}	{0.046}	{0.023}	{0.001}	{0.002}	{0.047}	{0.049}	{0.000}
N [OBS]	26 [584]	26 [575]	26 [561]	23 [522]	26 [679]	26 [659]	26 [632]	23 [568]

	Panel B: 19 OECD Countries							
	$lnGDP$	lnZ	lnE	$lnTFP$	$lnGDP$	lnZ	lnE	$lnTFP$
$\ln C$	0.200	0.289	0.273	0.076	0.194	0.462	0.313	0.052
	(0.019)	(0.055)	(0.046)	(0.011)	(0.027)	(0.065)	(0.068)	(0.018)
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.004}
$\ln N$	1.144	2.887	2.377	0.383	1.324	2.826	2.443	0.462
	(0.064)	(0.134)	(0.117)	(0.033)	(0.084)	(0.196)	(0.208)	(0.054)
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
	Panel cointegration tests							
t_{llcf}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
N [OBS]	19 [883]	19 [885]	19 [885]	19 [885]	19 [957]	19 [961]	19 [961]	19 [923]

Variable mnemonics are: $lnGDP$= real GDP per capita; lnZ = scientists and engineers employed in the R&D sector; lnE = capital expenditure in the R&D sector; $lnTFP$ = total factor productivity; lnC = flow of exogenous technological innovations proxied by the patent filings of sample countries; and, lnN = total employment. All variables are measured in natural logarithms. Numbers in parentheses are standard errors and those within curly braces are p-values of Wald tests under the null that the estimated coefficient is zero, which are $\chi^2(1)$. Country fixed effects are maintained in all estimations. Belarus, Cuba, and Pakistan do not have data on TFP. N [OBS] denotes the number countries [data points] of each estimation. t_{llc} denotes the Levin, Lin and Chu (ibid.) test of the null of non-cointegration (i.e., the non-stationarity of the error correction tem), p-values reported.

and R&D capital expenditure are cointegrated with the flow of new ideas (innovations) and the level of total employment across emerging countries. Their cointegrating parameters are positive and significant at very high levels of precision (1% or better), and the t_{llc} tests reject the null of non-cointegration (i.e., the non-stationarity of the error correction term). However, TFP only appears cointegrated with the flow of innovations, as the cointegrating parameter of lnN appears statistically insignificant. The reported t_{llc} test for TFP only captures the significant parameret of lnC. These results are robust across both estimators: DOLS and FMOLS. They imply that, in the long run, growth rates of per capita real GDP (g_x), R&D employment (g_Z), and R&D capital expenditure (g_E) are driven by both the growth rates of exogenous technology (g_C) and total employment (g_N) across emerging countries. These results are consistent with the long-run predictions of our model. However, the growth rate of TFP is driven by (g_C) alone, a purely Schumpeterian outcome.

The results of Panel B show significant cointegrating relationships of the levels of per capita real GDP, total factor productivity, R&D employment, and R&D capital expenditure with the flow of innovations and the level of total employment across developed countries. All estimated cointegrating parameters are positive and highly significant, and the t_{llc} test unequivocally rejects the null of non-cointegration across all estimates.

Specifically, the results of Table 2 suggest that a 1% increase in the flow of innovation, C, induces an increase of per capita real GDP by 0.09% (0.21%) for emerging countries in the long run, and by 0.20% (0.19%) for OECD countries based on the DOLS (FMOLS) estimates. Likewise, a 1% increase in the aggregate employment, N, induces an increase of per capita real GDP by 0.78% (0.62%) for emerging countries and 1.14% (1.32%) for OECD countries.

5 Conclusion

This paper provides new theoretical and empirical insights on the long-debated issue of R&D scale effects on the growth rates of technology and output. By conducting separate but parallel estimates of scale effects across both the developed and the emerging country panels, we report significant scale effects across emerging countries, and their complete insignificance across developed countries. Importantly, our results are based on a more realistic measure of the scale of R&D activities than has been applied hitherto, as well as on an empirical method that addresses the issues of unbalanced and spurious regressions. Specifically, R&D activities are captured by the joint use of R&D labor and R&D capital expenditure of each sample country, which gives the true scale of R&D. We elucidate that the theoretical prediction of scale effects implies a test equation that is statistically unbalanced, relating stationary regressands to non-stationary covariates and hence the potential problem of spurious regressions. We apply an appropriate estimator which addresses these estimation issues.

To analyze the dynamics of scale effects as a function of a country's position on its transition path to a long run equilibrium, we propose an extension of Acemoglu's (1998) endogenous growth model with a production technology in the lines of Jones (1995a, b). We show that during the course of transition to long-run equilibrium, scale effects of both R&D labor and R&D capital tend to be large and prominent, but as a country approaches its long-run equilibrium, scale effects deplete.

Our model predicts, among other things, that the long-run growth rates are driven by both the rate of growth of technological innovations and aggregate employment. Empirical scrutiny of the long-run growth implications of our model reveals that the long-run growth rates of per capita real GDP, R&D labor, and R&D capital are driven by the growth rates of technological innovation and aggregate employment for both emerging and developed countries; as is the case for the growth rate of TFP across developed countries. However, the long-run growth rate of TFP across emerging countries is driven only by the growth rate of technological innovation, which we argue might be due to these countries being further from their long-run equilibrium. This paper establishes, both theoretically and empirically, that scale effects exist across emerging countries because they are in growth transitions but not across mature economies which operate close to their long-run equilibrium.

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Appendix A: Data Sources and Descriptive Statistics

Table A1: Data Sources and Sample Countries

Resident patent applications at national patent office – OECD and EME countries: Word Intellectual Property Organization (WIPO), Statistics Database: https://www3.wipo.int/ipstats/ https://www.wipo.int/ipstats/en/#resources
Employment at the R&D sector (Research scientists and engineers employed at the R&D Sector) – OECD countries: Main Science and Technology Indicators (MSTI database): https://www.oecd.org/sti/msti.htm EME countries: UNESCO – http://data.uis.unesco.org/
Total R&D expenditure – OECD countries: Total R&D expenditure on research and development in constant 2010 PPP$ in million. Source OECD MSTI. MSTI: https://www.oecd.org/sti/msti.htm EME countries: Total R&D expenditure on research and development (GERD series) in national currency, UNESCO – http://data.uis.unesco.org/ R&D expenditure in 2011 PPP$ – our own calculation by using GDP deflator and PPP series from the World Bank.
R&D capital expenditure – OECD countries: Total R&D capital expenditure in constant PPP$ (2010) in million. Gross domestic expenditure on R&D by sector of performance and type of expenditure (OECD R&D database): https://www.oecd.org/sti/inno/researchand developmentstatisticsrds.htm EME countries: UNESCO (http://data.uis.unesco.org/) by "type of cost series". R&D Capital expenditure in 2011 PPP$, million, is our own calculation by using GDP deflator and PPP data series from the World Bank.
Total factor productivity (TFP) – OECD and EME countries: Penn world table version 9. TFP index 2011 = 1. Series code rtfpna. https://www.rug.nl/ggdc/productivity/pwt/pwt-releases/pwt9.0
GDP and GDP deflator – OECD countries: Gross domestic products in constant 2010 PPP$, million. From World Bank WDI dataset for all countries except Switzerland, for the latter is from OECD Economic Outlook 105. World Bank WDI – https://databank.worldbank.org/source/world-development-indicators OECD Economic Outlook: OECD (2019), "OECD Economic Outlook No. 105 (Edition 2019/1)", OECD Economic Outlook: Statistics and Projections (database), https://doi.org/10.1787/b8fe9e35-en GDP deflator series are also from the same sources as GDP except for Canada, New Zealand and Switzerland. Deflator series for these three countries are obtained from OECD Economic Outlook No. 105 (Edition 2019/1). EME countries: GDP in 2011 PPP$, millions. Our own calculation based on: GDP in national currency (series code: NY.GDP.MKTP.CN); GDP deflator (series code: NY.GDP.DEFL.ZS); PPP$ (Series code PA.NUS.PPP) World Bank WDI – https://databank.worldbank.org/source/world-development-indicators.

Notes: Data on GDP, GDP per capita, total R&D expenditure, and R&D capital expenditure across sample countries are converted into constant (2010) PPP US dollars. TFP is measured as index: 2011 = 1 for emerging countries and 2010 = 1 for developed countries at the source. R&D labor is the full-time equivalent of research scientists and engineers employed in the R&D sector.

Table A1: Continued....

Purchasing power parity, national currency per USD – OECD and EME countries: World Bank WDI – https://databank.worldbank.org/source/world-development-indicators.
Employment – OECD countries: Total employment in million from OECD Economic Outlook Nos. 79 and 105. OECD Economic Outlook: OECD (2019), "OECD Economic Outlook No. 105 (Edition 2019/1)", OECD Economic Outlook: Statistics and Projections (database), https://doi.org/10.1787/b8fe9e35-en EME countries: World Bank data series, "Employment to population ratio, 15+, total (%)" (series code:SL.EMP.TOTL.SP.ZS). We employ total population data to convert ratios to absolute numbers. World Bank WDI – https://databank.worldbank.org/source/world-development-indicators
Population: – OECD and EME countries: World Bank WDI – https://databank.worldbank.org/source/world-development-indicators
Sample Countries:
Twenty-six countries of emerging (EME) Panel Argentina, Belarus, Brazil, China, Colombia, Croatia, Cuba, Czechoslovakia, Hong Kong, Hungary, India, Latvia, Malaysia, Mexico, Morocco, Pakistan, Poland, Russian Federation, Singapore, Slovakia, Slovenia, South Africa, Thailand, Tunisia, Turkey, and Uruguay.
Nineteen countries of developed (DE or OECD) Panel: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and United States.

Notes: Total employment is the labor force employed (in millions). All data accessed in March 2019.

Table A2: Descriptive Statistics (Sample Mean)*

	g_x	Patents	R&D Exp.	R&D int.	Z	Res. int.	Res. prod.	R&D–KEXP%
				EME Panel				
Max	8.192^{E1}	208.556^{E1}	129505.5^{E1}	1.898^{E4}	976.787^{E1}	1.037^{E4}	16.672^{E1}	21.98^{E7}
Min	0.006^{E2}	0.031^{E3}	154.204^{E3}	0.207^{E5}	1.193^{E3}	0.034^{E5}	0.420^{E6}	5.050^{E2}
Mean	2.694	10.232	10517.04	0.750	83.185	0.348	3.982	14.113
Obs.	693	714	636	627	676	676	674	636
				OECD Panel				
Max	3.798^{1}	129.229^{3}	248977.00^{3}	2.541^{5}	823.183^{3}	0.868^{6}	47.657^{7}	17.923^{4}
Min	1.161^{2}	0.223^{4}	1440.287^{4}	0.609^{4}	7.310^{1}	0.296^{4}	2.963^{4}	0.221^{3}
Mean	2.054	26.594	28607.35	1.688	117.912	0.558	17.662	10.518
Obs.	963	988	988	982	988	980	988	988

*Reported sample means are calculated over the available data length for each country and each variable. g_x is the average annual growth rate of real per capita GDP (%); Patents refer to annual national filings in '000'; R&D Exp. (expenditures) are in millions 2010 PPP$ (2011 PPP$) for OECD (EME) countries; R&D int. (intensity) refers to total R&D expenditure as percentage of GDP; Z refers to researchers, scientists and engineers in R&D Sector in '000'; Research int. (intensity) refers R&D researchers as percentage of the total employment; Research prod. (productivity) refers to resident patent applications per 100 researchers; and $R\&D-KEXP\%$ refers to R&D capital expenditure as a percentage of total R&D expenditure. Superscripts: $E1$=China; $E2$ = Russain Federation; $E3$ = Uruguay; $E4$ = Singapore; $E5$ = Colombia; $E6$ = Pakistan; $E7$ = Poland; refer to the countries resuming either the maximum or the minimum values of the corresponding measures in the emerging country panel. Likewise, subscripts: 1 = Ireland; 2 = Switzerland; 3 = USA; 4 = Portugal; 5 = Sweden; 6 = Finland; 7 = Japan; denote countries in the developed country panel.

Appendix B: Growth Rates along the BGP

Since $\dot{Q} \equiv \rho \equiv \varphi(Q,Z)CZ$, the optimal condition of the R&D firm reduces to $\dot{Q}V = BQZ$ or $g_Q = BZ/V$. Differentiating the latter with respect to time and taking into account the fact that along the BGP $\dot{g_Q} = 0$, then $g_V = g_Z$. Along the BGP equilibrium equation (3) reduces to $rV = \pi^m - \rho V + \dot{V}$, which can be rewritten as

$$g_Z = r + \rho - \frac{\pi^m}{V} \tag{B1}$$

Differentiating equations 2 and 4 with respect to time we obtain:

$$g_A = \frac{1}{1-\phi_A}\left(g_Q + \lambda g_E\right), \tag{B2}$$

$$g_Q = \frac{1}{1-\phi_Q}\left(g_C + \nu g_Z\right), \tag{B3}$$

Dividing the monopolist profit function by V that is, $\frac{\pi^m}{V} = \frac{1-\lambda}{\lambda}\frac{EQ}{V}$ and then differentiating it with respect to time, it reduces to

$$\dot{\left(\frac{\pi^m}{V}\right)} = \frac{1-\lambda}{\lambda}\frac{EQ}{V}\left(g_E + g_Q - g_Z\right). \tag{B4}$$

Using $\rho = \dot{Q}$ and $\ddot{Q} = g_Q \dot{Q}$, differentiating B1 with respect to time and using B4 we obtain,

$$g_Q^2 = \frac{1-\lambda}{\lambda}\left(g_E + g_Q - g_Z\right)\frac{E}{V} \tag{B5}$$

Since the growth rates are constant along the BGP, it must be the case that $g_E = g_V$ and since $g_V = g_Z$, it follows that $g_E = g_Z$. From the optimal condition of the monopolist, $\chi = Q/\lambda$, it follows that $g_\chi = g_Q$. The latter along with the growth rate of χ using the inverse demand for E imply

$$g_A = \frac{\beta\left[(1-\lambda)g_Z - g_N\right]}{1-\beta(1-\phi_A)} \tag{B6}$$

B6, B2 and B3 imply

$$g_Z = \frac{1-\beta(1-\phi_A)}{\psi} g_C + \frac{\beta(1-\phi_A)(1-\phi_Q)}{\psi} g_N, \tag{B7}$$

where $\psi = \beta(1-\phi_A)(1-\phi_Q+\nu) - \lambda(1-\phi_Q) - \nu$. For $g_C > 0$ and $g_N > 0$, a sufficient condition for $g_Z > 0$ is $\psi > 0$ or $0 < \nu < \overline{\nu}$, which also implies the necessary condition $\beta(1-\phi_A) > \lambda$. Using B7 in B3, then the latter and B2 imply

$$g_Q = \frac{\beta(1-\phi_A) - \lambda}{\psi} g_C + \frac{\nu\beta(1-\phi_A)}{\psi} g_N, \tag{B9}$$

and

$$g_A = \frac{\beta(1-\lambda)}{\psi} g_C + \frac{\beta[\nu + \lambda(1-\phi_A)]}{\psi} g_N, \tag{B10}$$

with $g_x = g_A/\beta$.