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Building BRICS: 2-Stage DEA analysis of R&D Efficiency*

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Abstract

Should inputs such as bank finance affect innovation in BRICS vs. developed countries similarly? Arguably these elasticities may depend on a country's economic progress (Gerschenkron, 1962; Liu and White, 2001). Applying a combination of DEA and Tobit to a sample of 22 countries, we show how innovation (measured patents, scientific publications and high-tech sectoral output) responds favourably to private-sector R&D. No significant differences are recorded for BRICS countries. Differences emerge between BRICS and non-BRICS for the elasticity of innovative efficiency to banking inputs.

Keywords: BRICS countries, National Innovation System (NIS), innovation, DEA

JEL: O30, O57, P52

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Introduction

Brazil, India, Russia, China, and South Africa (BRICS countries) with average growth rates of 5.9 percent during the period 2000-2009 well outstripped the 2.6 percent world growth rate average. Their ascent is even more striking when pitted against the 1.6 percent for wealthy OECD counties for the period. But there is a paradox: Despite their growth, none of the BRICS make it into the top 25 of the 2012 Global Competitiveness Report competitiveness listing. [1]

The lack of consensus as to the most appropriate National Innovation System metric (see Sharif, 2006) is problematic. [2] Additionally, Furman and Hayes (2004) have argued that standard, reduced form methodologies (cross-section and time-series) are handicapped by endogeneity concerns. These caveats hint at the potential usefulness of other, more agnostic approaches like DEA where the latter can shed light on heterogeneous country-specific effects where drivers like bank finance or private R&D can operate differently for countries at various economic/ technological stages development stages (See Gerschenkron, 1962; Hu and Mathews, 2005; Liu and White, 2001). [3]

Accordingly, our research question is as follows: When the BRICS are viewed collectively, can we say that the drivers of R&D outputs (e.g. banks, private-sector finance) behave in the same way as efficiency drivers in developed countries?

Our study is methodologically inspired by Wang and Huang (2007) who similarly apply DEA. Specifically, we combine DEA (innovation efficiency) with a second stage analysis which calculates the elasticity of derived innovation efficiency to private R&D and other measures. We distinguish ourselves from Wang and Huang by testing, for the first time, for returns to scale and regressing directly on this computed innovation efficiency score. Uniquely, in the second stage, we apply a rich set of covariates, the selection of which is based on theory and stylized facts.

Our findings reveal that our computed efficiency measure responds positively to private-sector R&D. Although the elasticity of innovation to private-sector R&D is lower for BRICS countries (in line with arguments that innovation in 'latecomer countries' free-rides on existing knowledge), these differences are reassuringly not significant for BRICS countries. Differences arise however,

[1] This disconnect is especially pronounced for China which ranked at 26 in terms of competitiveness; in stark contrast to its number 1 and 2 positions for growth and GDP respectively.
[2] Specifically, the Global Competitiveness Index (GCI), based on expert opinion and calculation, assumes that the 'home keys' comprising these 12 pillars have been correctly identified.
[3] Hu and Mathews (2005) give some compelling reasons why 'latecomer countries', *aka* BRICS, should be expected to rely more on imitative technologies and hence on world technology stocks in lieu of their own private R&D efforts. This would have implications for the elasticity of innovation to R&D spending.

for the innovation/banking nexus where the generally negative relationship is positive for BRICS countries.

Our paper is organized as follows. We present an overview of other studies isolating which identify co-determinants of a country's innovation/growth. We then describe our 2-stage DEA methodology in some detail as there are some novel aspects. The section following this reports our innovation efficiency calculations. This is followed by a section where we regress key determinants of innovation efficiency on innovation scores for Western vs. BRICS countries. The final section concludes with implications of our findings.

Measuring a Country's Innovative Capacity and Efficiency

1.1 History and Context of DEA

There is a well established empirical literature dating from the mid 1990's documenting how well various countries deliver innovation outputs based on input into the innovation process. There are broadly three ways of deriving these performance metrics, namely by deriving composite (innovation) indicators, by using econometric modeling and lastly through the application of Data Envelopment Analysis (DEA). Arguably, the ubiquitous EU Community Innovation Survey (CIS) and annual surveys compiling data for the European Innovation Scoreboard (EIS) have placed this issue of calibrating how well countries perform in the thick of a lively debate.

Studies which apply composite indicators have the advantage, when carefully performed, of revealing many facets of a country's innovation capability and what a country does with this capability (efficiency). A major drawback is that these studies can be self-referential. Specifically, the 'summing up' of indicators covering a country's innovation inputs, outputs, procedures and organization thereof, can eclipse the interconnectivities between key drivers of the innovation process, most obviously the link between innovation inputs and innovation outputs. Under this system, somewhat paradoxically, economies with 'high innovation inputs and low innovation outputs' could be awarded a score equal to or even higher than those with 'low innovation inputs and high innovation outputs'.

The Modelling/Econometric Approach is in many ways vastly superior to the simple composite indicators approach, combining as it does a mixture of theoretical analysis, mathematical modeling and econometric estimation. This approach has been successfully applied in several comparative studies of innovation (Furman et al., 2002; Hu and Mathews, 2005; 2008). One obvious advantage of this approach is that it is less *ad hoc*, being supported both by economic theory and empirical analysis. However, it does suffer the drawback of confining itself to one single outcome variable. For instance, 'International Patents Granted' is traditionally used on its own as a measure of innovation capacity.

In contrast to the composite indicator approach, DEA focuses on the input-output nexus (efficiency). A country's innovation system encompasses a myriad of activities which support innovation from ICT infrastructure to banking. Each country, in turn, is regarded as an independent DMU (Decision Making Unit) whose relative efficiencies can be calculated. Since the seminal Farrell (1957) study advancing the idea of technical, price (allocative), productive (production frontier) and overall (economic) efficiency), subsequent studies have successfully applied and built on this technique. Frontier estimation techniques can, in turn, be subdivided into DEA and Stochastic Frontier Analysis (SFA) using mathematical programming and econometrics respectively, the former being equipped to deal with multiple innovation outputs and therefore less restrictive (Coelli, 1995; Lovell, 1993).[4] Several recent studies apply DEA to compare and contrast the innovation efficiency of different countries and/or regions (Nasierowski and Arcelus, 2003; Guan et al. 2006; Cullmann et al., 2010; Wang and Huang, 2007).

To sum up, DEA gives a composite snapshot of a country's innovation efficiency. Nevertheless, the efficiency score merely reflects the general capability of the NIS, and not the underpinning drivers of this efficiency.

1.2 Two-Stage DEA: combining the DEA and Modelling/Econometric approach

It is possible to synthesize the DEA and the Modelling/Econometric approach in order to draw on the strengths of both approaches. This hybrid approach, 'Two-Stage DEA' generates efficiency scores using DEA but subsequently determines the drivers of these efficiency scores using a standard parametric technique like Tobit analysis. In this sense, 'Two-Stage DEA' derives the efficiency scores in a semi-parametric framework. Removing these scores from their 'black box', the second-stage parametric makes clear the contribution of innovation inputs like R&D spending in explaining cross-country (-regional) innovation efficiency differences. Although the technique has been successfully applied in other contexts (e.g. See Guan et al., 2006), it is not yet widely applied in innovation research.[5]

Although the two-stage DEA method has been widely used in many papers, there are some problems with how this methodology has been applied in the past. Simar and Wilson (2007) point out that

[4] SFA encounters problems constructing aggregate outputs, particularly in the absence of reliable price data.
[5] The exception being the recent paper by Cullmann et al (2010) who apply the technique to investigate knowledge production within the OECD. Wang and Huang (2007) apply a similar technique to analyze the R&D efficiency of 30 countries intensively engaged in R&D activities. However, the dependent variable in the stage of Tobit regression is the 'observed input slacks', not the efficiency scores where they focus on higher education enrollment, PC density and English proficiency as drivers of efficiency differences.

most of the existing studies lack transparency. A clear description of the underlying DGP (Data Generation Process) for the first stage efficiency scores is frequently not given making regressions hard to interpret. Moreover, when using finite samples, steps need to be taken to ensure that first stage efficiency scores do not cause serial correlation in the second stage. Specifically, Simar and Wilson (2007, 2011) bootstrap standard errors when deriving efficiency scores to support the consistency and asymptotic properties of their second stage estimations.

2 Methodology

2.1 Choice of input/output indicators and countries (Data Measurement Units)

Since it was pioneered by Charnes et al (1978), DEA has been used to measure the efficiency of the so called Data Measurement Units (DMUs), whether these are countries, industries or other entities whose relative efficiency can be calculated. Our paper concentrates on the R&D efficiency of the BRICS nations. Accordingly, it is appropriate to treat R&D related activities as a productive sector within each national economy and to use DEA to calculate the comparative efficiency of these activities across the units under observation. Specifically, inputs into this system comprise human and financial resources while the outputs comprise WIPO patents granted, scientific publications, and the output of high-tech industries. The data covering these indicators, spanning the period 2000 to 2008, is collected from a variety of sources. These data sources comprise the World Bank's Open Database (DataBank), the database of UNESCO Institute for Statistics and data hosted on the World Intellectual Property Organization (WIPO) website. A full variables listing can be viewed in Appendix 2.

The next step is to choose the units for comparison. Clearly the 5 BRICS countries must be included but we also need widen the net to include other countries. In so doing, we can approximate a technology frontier which maps well to the true world technology frontier.[6] Accordingly, we include all G7 member states (world's largest developed economies), 8 European countries with a proven innovation track-record (Finland, Sweden, Denmark, Switzerland, Netherlands, Austria and Belgium). Finally, we include South Korea (exemplary catch-up economy) and Australia as two representative nations from the Asia Pacific region.

[6] Estimations based on more limited numbers of units generate biased efficiency scores which in turn cause problems for subsequent efforts to rank countries based on their relative efficiencies.

2.2 Optimization model for the efficiency measurement

We apply the linear programming technique pioneered by Charnes et al (1978, 1985) which is flexible enough to deal with either constant or variable returns to scale (i.e. CRS vs. VRS). Accordingly, we first describe how the technique works before testing for returns to scale using the DEA efficiency estimates and the bootstrapping process proposed by Simar and Wilson (2002).

When deciding on an appropriate optimization model, we opt for a system (Output-Oriented) which allows us to fix the inputs (used to derive relative efficiency) and track the variation in outputs (patents, scientific publications, and hi-tech exports) on the basis of these fixed inputs.[7] Moreover, we need to decide whether our estimation model assumes constant or variable returns to scale.[8] Accordingly we first test for returns to scale using the DEA efficiency estimates and the bootstrapping process proposed by Simar and Wilson (2002). The efficiency scores for CRS can be calculated with the following linear programming.

$$\max_{\phi\lambda,} \phi, \text{ subject to } x_0 \geq X_{m\times n} \bullet \lambda_{n\times 1}, Y_{s\times n} \bullet \lambda_{n\times 1} \geq \phi y_0 \qquad (1)$$

Here, *X* is the input matrix, while *Y* the output matrix; *m* and *s* refer to the number of input indicators and output indicators respectively; and *n* is the number of the DMUs (countries in this paper). φ is the efficiency score to be calculated for each DMU, and λ the corresponding solution vector for the optimization. To calculate the efficiency scores for VRS, an additional constraint equation is needed.

$$\sum^{n}_{j=1} \lambda_j = 1 \qquad (2)$$

To move from CRS to VRS, the assumption of convexity is relaxed and the distance functions are calculated relative to a VRS rather than a CRS technology. The scale effect is calculated as the residual.

Applying the Simar and Wilson (2002) test for constant returns to scale (H_0), we set the bootstrap to 1,000 iterations to generate the bootstrapped estimators. These estimators in turn, can be compared to the observed values for our 22 country units. The programme used is the standard *FEAR* in *R* package (see Wilson, 2010 for a good description of this procedure). If the critical value of the bootstrapped estimator is less than the value of the observed estimator, we can reject the null hypothesis of constant returns to scale. Table 1 shows that values of 2 observed estimators exceed

[7] The other option would be to apply the Intput-Oriented measure where outputs are fixed and inputs are allowed to vary (See Farrell, 1957). The Output- and Input-Orientated measurement provide comparable measures for technical efficiency where when constant returns to scale exist (Färe and Knox Lovell, 1978). Reassuringly, whichever option is decided upon is fairly irrelevant for the scores obtained (Coelli, 1996).

[8] In Wang and Huang (2007), an input-oriented model of variable Returns to scale (VRS) is chosen directly.

the critical values (10 percent significance levels) for all 9 years, leading us to 'accept' the null hypothesis of constant returns to scale.

(Table 1 here: Returns to Scale)

Accordingly, we proceed to first estimate the efficiency scores and ranking for the returns to innovation inputs for our 22 country units from 2000 to 2008. There is an obvious problem with our initial estimates. Conventional DEA represents the efficiency of each individual country, not relative to the true world technology frontier, but an approximated frontier based on the 22 (in our case) country units. To improve the robustness of these efficiency scores and the corresponding ranking, we propose using the Simar and Wilson (2007; 2011) approach of replicating the data generation process (DGP) of the original observed sample of 22 country units and estimating a new frontier based on bootstrapped estimates to help eliminate this bias that would otherwise arise. Rankings based on the robust estimates are reported in Table 2.[9]

(Table 2 here: Country Rankings)

Several points become clear from viewing the rankings. Firstly, the BRICS countries separate into China and India topping the rankings in recent years with South Africa and Brazil, faring less well. Secondly, the G7 countries are ranked relatively similarly. Thirdly, some small countries like Sweden (SE) and Switzerland (CH) and the Netherlands (NL) are also strongly ranked. Finally, there is relative internal stability in the rankings with countries which are well placed in 2008, generally performing well over the preceding years. Some movement can be seen in the ascent of India and China, however to top the list in recent years.

Of course, emerging economies like India and China which are rich in plentiful cheap labour derive their efficiency from other sources other to those obtained by the Netherlands (also high-performing but skills-rich). Rankings skim over the possible causes for this heterogeneity. It is therefore useful to look at these rankings in greater depth in order to ascertain what the theory has to say about possible causes.

3 Drivers of relative efficiency in the BRICS countries

3.1 Why efficiency differences?

It is clear from Table 2 that our estimations show wide variation in the innovative performance of the 17 selected Western economies. For example, a priori, we would expect the technologically similar economies of the US and the Netherlands to perform roughly similarly in terms of innovative efficiency. However, this is not the case. Efficiency scores of 0.77 and 0.2 are noted for the Netherlands and the US respectively, showing that the US trails behind the Netherlands. This

[9] The corresponding efficiency rankings are reported in Appendix 1

apparent paradox suggests that technological similarity is not the only criteria underpinning innovative performance. Other socio-economic factors also play a role including scale economies, resource endowments, the economic development country's stage etc. Let us first turn to natural resource endowments. Both Brazil (one of the BRICS members) and Australia both rich in mineral and other wealth perform relatively badly in terms of innovation efficiency. Clearly ample mineral wealth does not in itself assure strong innovative performance. Another major dimension in which we can view relative performance is in terms of trade openness. Do more open economies perform better? Some of the better performing economies in our estimations are also classified as more open in terms of trade. Specifically, we include in this group the Netherlands, Sweden, South Korea, Belgium, Switzerland and China all of whom demonstrate high foreign trade ratios. Yet a further context, in which we can observe the relative efficiencies of country units, is in terms of GDP wealth. Do wealthier countries perform better in terms of delivering higher innovation efficiency? The answer here appears more nuanced and better fits a picture of nonlinear returns from increasing wealth whereby countries with comparatively low GDP deliver relatively high innovation efficiency (China and India) but so also countries ranking among the richest in the world (US and Norway).

There are some stylized facts which we can glean from existing studies allowing us to interpret some of these patterns. First to the role of market size and hence trade liberalisation. Acemoglu and Linn (2004) argue that greater product market size acts as a spur to innovation. This happens if higher profits from higher product market sales are ploughed into innovation. Desmet and Parente (2010) support trade openness as a way of increasing market size and thereby strengthening innovation. Roper and Love (2010) also attribute positive returns to innovation from trade liberalization but due to improved knowledge diffusion.

What role does a country's natural resource base have on innovation? Papyrakis and Gerlagh (2005) argue that higher earnings in the natural resources sector crowd out innovation: innovation based workers are drawn away from innovation towards the primary natural resources sector. This may partially explain the 'Resources Curse'. Bas and Kunc (2009) concur with this view and allude to Chile's copper mining industry. A country's development stage is also key to innovation, though the effect is nuanced. Latecomer nations are at a technological disadvantage compared to first movers. However, there are advantages for emerging economies. While lead countries have to maintain their lead through cutting-edge innovation, latecomer countries only need focus on technology transfer and innovation diffusion (Hu and Mathews, 2005; Mathews, 2001). Moreover, developing countries with their ageing populations are at a further disadvantage: if the young are more creative than the old, it follows that we should expect higher returns to innovation in countries with young populations.

3.2 Data

We have seen some potential determinants of a country's innovative capacity. Accordingly, we set about capturing some of these determinants using proxy variables designed to map as closely as possible to drivers such as market size. Our variables are taken alternately from the World Bank listing of cross-country indicators and the UNESCO Institute for Statistics. The extraction gives us annual data from 2000 to 2008.[10] Since coverage is for only 9 years, there is no need to apply the panel unit root test (Hsiao, 2003, p.298). However, care needs to be taken before applying these raw data. With 25 indicators and only 22 cross-sections, there would be a clear problem applying a random effects model. Moreover, many of these indicators are potentially correlated, which would lead to serial correlation and inconsistent estimates. To deal with this, we apply Principal Components Analysis (PCA) as an initial data reduction exercise (e.g. See Jolliffe, 1982). This is to reduce the potential for multicollinearity in subsequent regressions. We first check the bivariate correlations between these factors before embarking on the PCA. Table 3 reports the results of this data reduction exercise with strong commonalities registered in factors such as ICT infrastructure and Business Constraints & 'red tape'.

(Table 3 here: Table for PCA)

3.3 Censored Panel Data Analysis / Panel Tobit Regression

Having searched for commonalities in our data and extracted relevant factors, we are ready to progress to our analysis using a more parsimonious set of variables. Given that our response variable efficiency score is bounded between 0 and 1, an appropriate econometric framework is the standard panel Tobit which allows for time invariant fixed effects (country fixed effects in our case). Specifically, our panel Tobit can be written as;

$$y_{it}^{*} = x_{it}'\beta + \varepsilon_{it} = x_{it}'\beta + \mu_i + \nu_{it} \qquad (3)$$

Where μ_i represents the country fixed effect and v_{ii} a disturbance term. The estimates, which are derived by maximum likelihood, are reported in Table 4.

(Table 4 here: Determinants of Innovation Efficiency)

Our coefficient estimates for the stepwise regression are broadly stable across the estimations with little evidence of sign switching. We now look to the variables themselves. Regression 1 gives the results for the most basic model. Firstly and foremost, private R&D spending is a major determinant of a country's innovative efficiency. (Including a BRICS*R&D interactive effect to check for differential effects for the BRICS-5 does not change this result). Here we see that ageing populations have

[10]The full list of indicators is reported in Appendix 2

reduced innovation efficiency as evidenced by the negatively signed coefficient. These economies may lack the ability to deliver innovation outputs efficiently if such economies are deficient in ideas and lacking in vigorous, young workers. Reassuringly, exports are associated with higher innovation returns as is private R&D spend. Findings for bank finance and the market value of listed companies are less clear-cut. The banking measure is inversely related to innovation efficiency, possibly a consequence of the nuanced relationship between banking and economic growth at various stages in a country's economic development. Bank-based economies perform routinely worse in terms of innovation returns as seen in the negatively signed coefficient for 'bank finance'. There is a lack of consensus on the overall contribution of bank finance to growth. Levine and Zervos (1998) argue that bank is complementary to market based forms (see market capitalization variable), while Gerschenkron (1962) argues that banks help smooth market frictions at the early stages of a country's development (subject to certain conditions). Some economists posit a U-shaped relationship with a role for bank-based credit early on in a country's economic development and again at more advanced development stages (e.g. Germany which has a bank-based system). The general opinion is that banks, while useful in economic development, are not a linchpin of growth. Stulz (2004) in his excellent review of the literature concludes that 'financial structure is not a distinguishing characteristic of success (innovation and growth)'[11]. Finally, the market capitalization variable carries a negative, albeit insignificant coefficient. The mixed results for this variable over the three model specifications may be attributable to the variable 'caplst' itself which may fail to capture investment in secondary capital markets (analogous to the US NASDAQ where the more innovative SMEs are listed) and therefore may underreport the extent to which capital market investment facilitates innovation.

Regression 2 represents the most exhaustive listing of variables. The relatively inflated t-values (compare regression 1 and 3) however, hint at collinearity. In the Wealth and Trade category, wealthier and larger economies perform best. Collective spending on private-sector R&D manifests a consistently positive sign and high t-value. Moreover, there is good news for economies which have invested in ICT capability evidenced by the returns to such investments, although the relationship is admittedly weak and not evident in all model specifications. Turning to the role of the composite variable, Business Constraints & 'red tape', which captures the impact of taxation and the costs for business, we see an unsurprisingly negative effect of the latter on innovation returns suggesting that Government should be careful not to choke off innovation potential by imposing excessive taxation.

Given the suspected collinearity in the highly saturated regression 2, our preferred models are the more parsimonious models 1 and 3. Here the magnitudes of the t-values are broadly in line.

[11] Chapter 4 in Financial Structure and Economic Growth' by René Stulz (editors: Demirgüç-Kunt and Ross Levine 2004)

Regression 3 looks more closely at the issue of a country's Governance and tests for higher returns to innovation for banking at early stages of a country's economic development. Governance carries an economic cost if excessive regulation encourages a 'Big Brother' mentality, stifling innovation for wealthier economies. However, in smaller doses (interaction effect for Governance*BRICS), governance is marginally significant and positive. To test for differential returns to banking at early- and late-stage economic development, we include a BRICS*banking interaction dummy in model 3 which carries the expected positive sign. This indicates that bank investment promotes a country's innovativeness when the country is relatively underdeveloped but can thereafter dampen growth.

4 Concluding remarks

Having applied a two-stage semi-parametric DEA method to calculate efficiency scores for the national innovation systems of China, other BRICS countries and 17 additional countries, what can be said about the key findings? Firstly, there are vast differences in the innovation efficiency of the BRICS countries. China, India and Russia demonstrate relatively high efficiency scores and accordingly a high ranking. On the other hand, Brazil and South Africa perform badly, ranking almost at the bottom among the 22 selected countries. It is not by accident that the two countries best endowed with natural resources (Brazil and South Africa) come last in the efficiency rankings. This may suggest that their strongly performing natural resource sector crowds out innovation in other sectors.

Our findings reveal that our computed efficiency measure responds favourably to private-sector R&D. Although the elasticity of innovation to private-sector R&D is lower for BRICS countries (in line with arguments that innovation in 'latecomer countries' free-rides on existing knowledge), these differences are reassuringly not significant for BRICS countries. Differences arise however, for the innovation/banking nexus where the generally negative relationship is positive for BRICS countries.

Our finding of an equivalence of private sector R&D for BRICS vs. developed countries (despite a smaller coefficient for BRICS) is reassuring for policy-makers who are seeking to put pay to the stereotypical view that 'latecomer countries' such as China are largely reliant on imitative rather than truly creative technology. Steve Lohr (November 2011) writing in the New York Times nicely summarizes this perception. However, other evidence (e.g. by Guan et al. 2009) challenge this stereotype. However, the positive role for R&D revealed in our findings must be interpreted with some care because we do not isolate the effects of State R&D.[12]

Summing up, we can point to the helpfulness of banks in promoting innovation efficiency in the BRICS. This positive result ties well with theories of banking intermediation which envision a role for

[12] Despite the underperforming role of State R&D (insignificant for China in regressions by Hu and Mathews, 2005), State R&D may help to co-determine innovation efficiencies in 'latecomer countries' seeking to catch-up).

banks and soft budget constraints with financial markets. Overall, our findings highlight no major differences in the impact of enterprise R&D on efficiency for BRICS vs. more developed countries.

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Table 1: Observed and bootstrap estimators for testing returns to scale

	$\hat{S}_{1n}^{crs}$	$\hat{S}_{1nb}^{crs*}$ (5%)	$\hat{S}_{1nb}^{crs*}$ (10%)	$\hat{S}_{2n}^{crs}$	$\hat{S}_{2nb}^{crs*}$ (5%)	$\hat{S}_{2nb}^{crs*}$ (10%)
2000	0.6959	0.6225	0.6464	0.6624	0.6010	0.6205
2001	0.6989	0.6408	0.6582	0.6678	0.6208	0.6387
2002	0.7214	0.6695	0.6924	0.6973	0.6518	0.6732
2003	0.6743	0.6091	0.6321	0.6418	0.5843	0.6083
2004	0.6725	0.6165	0.6408	0.6369	0.5903	0.6117
2005	0.6845	0.6341	0.6579	0.6526	0.6058	0.6329
2006	0.7076	0.6497	0.6736	0.6795	0.6278	0.6511
2007	0.6842	0.6301	0.6489	0.6548	0.6028	0.6263
2008	0.7080	0.6481	0.6718	0.6758	0.6241	0.6415

Notes: (1)the percentage of 5% (or 10%) in the first row means only 5% (or 10%) of all the bootstrap estimated values are less than the value in the corresponding column, which can be regarded as the critical value for nominal size of 5% (or 10%). (2)The calculations are conducted by coding with the software package FEAR in R environment (Wilson, 2010)

Table 2: Bias-corrected Ranking

	2000	2001	2002	2003	2004	2005	2006	2007	2008
CN	6	3	4	2	2	2	2	2	1
NL	1	1	1	1	1	1	1	1	2
IN	12	9	9	6	5	6	5	5	3
CH	7	4	2	4	4	5	6	6	4
SE	3	2	5	3	3	3	4	4	5
BE	8	7	3	7	6	9	9	8	6
RU	5	8	8	9	10	7	8	9	8
UK	2	6	7	8	7	8	7	7	9
FI	11	12	13	12	14	12	12	12	10
DE	13	11	11	11	11	10	10	10	11
AT	9	10	10	10	9	11	11	11	12
IT	14	13	14	13	12	14	13	13	13
FR	15	16	15	16	15	15	15	15	14
CA	10	14	16	15	17	16	16	14	15
NO	20	20	19	20	21	20	18	19	16
JP	18	18	17	17	16	17	17	17	17
DK	16	15	12	14	13	13	14	16	18
ZA	19	19	20	18	18	18	19	18	19
US	17	17	18	19	19	19	20	20	20
BR	22	21	21	21	20	21	21	21	21
AU	21	22	22	22	22	22	22	22	22
KR	4	5	6	5	8	4	3	3	7

Key:

G7
BRICS
OTHER

Notes:

(1) Statistical size of the confidence intervals α set to be 5%, and the number of bootstrapping replications set to 999

(2) Country abbreviations: , Brazil- BR, Russia Federation- RU, India- IN, China- CN, South Africa- ZA, United States- US, Japan- JP, Germany- DE, United Kingdom- UK, France- FR, Canada- CA, Italy- IT, Finland- FI, Sweden- SE, Denmark- DK, Switzerland- CH, Netherlands- NL, Norway- NO, Austria- AT, Belgium- BE, Australia- AU, Korea- KR.

(3) Data sorted for 2008 rankings

Table 3: Factor Loadings (Principal Components)

Description	Label	Loadings	Cumulative proportion
ICT infrastructure	commp1	0.6210ITNET+0.5610MOBL+0.5476TEL	0.745
Bank finance	credp1	0.7071CDBBAN+0.7071CDTPRV	0.959
Involvement of firms in R&D	frdp1	0.5527ENTRRE+0.6044ENTRPGERD+0.5738ENTRPFGERD	0.784
Business Constraints & ‘red tape‘	mkp2	0.8414PRCOST-0.1360BSCOST-0.5230TAXRATE	0.807
Governance	govp1	0.42CORRUP+0.42GOVEFF+0.39POLSTAB+0.41REGULA+0.41LAW+0.39VOACCT	0.924

Table 4: Determinants of Innovation Efficiency

	y: Bias-corrected innovation efficiency scores (Panel Tobit: 0 to 1)					
	(1)		(2)		(3)	
	Estimate	(t value)	Estimate	(t value)	Estimate	(t value)
R&D Investment & Infrastructure						
firm R&D (frdp1)	0,0029	(3,575) ***	0,0050	(17,934) ***	0,0056	(2,104) **
BRICS_Firm R&D (bfrd)					-0,0029	(-1,09)
ICT infrastructure (commp1)			0,0012	(2,835) **		
Demographic factors						
Ageing population (age)	-0,0097	(-2,607)**	-0,0299	(-13,893) ***	-0,0619	(-2,614) **
Wealth and Trade						
Relative gdp p.c (rgdppc)			0,0211	(3,817) ***		
Trade to gdp (trtgdp)	0,0011	(1,772)*	0,0015	(7,474) ***	0,0099	(3,859) ***
BRICS_Trade_to_gdp (trtgdp)					-0,0090	(-3,507) ***
GDP share in World GDP (porgdp)			0,0053	(2,635) **		
Business Environment						
Bank finance (credp1)	-0,0010	(-3,895) ***	-0,0012	(-18,671) ***	-0,0038	(-3,738) ***
BRICS_bank finance (bbf)					0,0027	(2,598) **
Business Constraints & 'red tape' (mkp2)			-0,0036	(-4,896) ***		
market value of listed companies (caplst)	-0,0004	(-1,361)	-0,0004	(-5,246) ***		
BRICS_market value (bcap)						
Governance (gov)			0,0024	(0,345)		
BRICS_Governance (bgov)						
Skills						
Tertiary school enrollment (teenrl)			-0,0015	(-4,616) ***		
Other						
natural resources income (nrtgdp)			-0,0003	(-0,303)		
(Intercept)	0,3944	(6,019)***	0,2266	(5,100) ***	0,4111	(4,579) ***
log $\sum \mu$	-1.7937	(-24.152) ***	-1,6480	(-60,357) ***	-1.8236	(-25.112) ***
log $\sum \nu$			-2,8730	(-48,488) ***		
Log likelihood (DOF)	74.21	(7)	260.56	(15)	80.11	(10)

Notes:
Where *** , ** and * means significant to the 0.01, 0.05 and 0.10 level respectively
Numbers in the parentheses are the standard errors for corresponding estimations

Appendix 1

Bias-corrected Efficiency Scores

		2000	2001	2002	2003	2004	2005	2006	2007	2008
BRICS	BR	0.150	0.184	0.194	0.157	0.171	0.178	0.181	0.157	0.173
	RU	0.545	0.496	0.584	0.484	0.448	0.541	0.530	0.427	0.544
	IN	0.335	0.496	0.583	0.538	0.552	0.565	0.612	0.621	0.759
	CN	0.517	0.599	0.693	0.698	0.725	0.737	0.754	0.741	0.803
	ZA	0.242	0.269	0.252	0.213	0.210	0.213	0.213	0.197	0.208
G7	US	0.271	0.285	0.290	0.193	0.190	0.193	0.210	0.186	0.200
	JP	0.269	0.273	0.302	0.230	0.228	0.235	0.252	0.216	0.225
	DE	0.297	0.377	0.443	0.345	0.385	0.377	0.406	0.331	0.364
	UK	0.689	0.506	0.638	0.486	0.539	0.539	0.589	0.497	0.449
	FR	0.287	0.318	0.343	0.251	0.240	0.246	0.271	0.242	0.279
	CA	0.366	0.333	0.319	0.269	0.225	0.237	0.256	0.251	0.278
	IT	0.291	0.342	0.344	0.303	0.300	0.295	0.296	0.266	0.281

Appendix 1 (Ctd.)

		2000	2001	2002	2003	2004	2005	2006	2007	2008
OTHERS	FI	0.345	0.352	0.397	0.320	0.275	0.334	0.302	0.296	0.445
	SE	0.660	0.671	0.686	0.654	0.654	0.656	0.668	0.650	0.659
	DK	0.286	0.325	0.402	0.298	0.291	0.309	0.281	0.230	0.225
	CH	0.455	0.587	0.755	0.605	0.612	0.572	0.599	0.559	0.699
	NL	0.777	0.780	0.796	0.773	0.765	0.771	0.763	0.761	0.776
	NO	0.184	0.237	0.280	0.179	0.169	0.187	0.219	0.195	0.268
	AT	0.369	0.434	0.572	0.434	0.458	0.350	0.371	0.315	0.332
	BE	0.410	0.503	0.695	0.535	0.541	0.533	0.504	0.482	0.581
	AU	0.164	0.182	0.188	0.157	0.140	0.125	0.131	0.113	0.117
	KR	0.646	0.527	0.670	0.540	0.538	0.616	0.748	0.670	0.571
means		0.389	0.413	0.474	0.394	0.393	0.400	0.416	0.382	0.420

Notes:

The statistical size of the confidence intervals α is set to be 5%, and the number of bootstrapping replication is set to be 999.

Country abbreviations: , Brazil- BR, Russia Federation- RU, India- IN, China- CN, South Africa- ZA, United States- US, Japan- JP, Germany- DE, United Kingdom- UK, France- FR, Canada- CA, Italy- IT, Finland- FI, Sweden- SE, Denmark- DK, Switzerland- CH, Netherlands- NL, Norway- NO, Austria- AT, Belgium- BE, Australia- AU, Korea- KR.

Appendix 2: Potential Efficiency Drivers/Outcomes and their Proxies

Influencing factors	Proxy Indicators	Abbreviation
Demographic structure/ageing	Population ages 65 and above (% of total)	AGE
ICT infrastructure	Internet users (per 100 people)	ITNET
	Mobile cellular subscriptions (per 100 people)	MOBL
	Telephone lines (per 100 people)	TEL
Bank finance	Domestic credit provided by banking sector (% of GDP)	CDBBAN
	Domestic credit to private sector (% of GDP)	CDTPRV
	Market capitalization of listed companies (% of GDP)	CAPLST
Involvement of firms in R&D	Researchers (FTE) - Business enterprise %	ENTRRE
	GERD - performed by Business enterprise %	ENTRPGERD
	GERD - financed by Business enterprise %	ENTRFGERD
Education	School enrollment, tertiary (% gross)	TEENRL
	School enrollment, secondary (% gross)	SEENRL
Market Factors	Cost of business start-up procedures (% of GNI per capita)	BSCOST
	Total tax rate (% of commercial profits)	TAXRATE
	Cost to register property (% of property value)	PRCOST
Governance	Control of Corruption	CORRUP
	Government Effectiveness	GOVEFF
	Political Stability and Absence of Violence/Terrorism	POLSTAB
	Regulatory Quality	REGULA
	Rule of Law	LAW
	Voice and Accountability	VOACCT
Market Size	Proportion of GDP in the World total output (%)	PORGDP
Openness	Trade (% of GDP)	TRTGDP
Natural resource endowments	Total natural resources rents (% of GDP)	NRTGDP
Development Stage	GDP per capita to the world average	RGDPPC