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Innovation Rankings: Good, Bad or Revealing?*

Yuezhou Cai[a], and Aoife Hanley

Abstract

The standard indicators used to compare cross-country innovation are in the Global Competitiveness Report (GCR). But there are problems with aggregation and response bias with these largely self-reported measures (Hollanders and van Cruysen, 2008).

We propose a theory-based metric using Data Envelopment Analysis which corrects for sample bias and considers Returns to Scale. The derived ranking compares well to components of the GCR. Moreover, in second-stage estimations, our corrected efficiency score correlates well with standard Growth Theory indicators.

Keywords: Data Envelopment Analysis, Efficiency Indicators, Global Competitiveness Report

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The Problem with International Rankings

The innovation competitiveness of different countries is deceptively difficult to measure. One problem is that 'innovation' is not a singular but multiple construct. Let us illustrate this problem by referring to the most widely cited) report dealing with global competitiveness: The Global Competitiveness Report (hereafter GCR). This lists 7 innovation competitiveness indicators under a section of its report called 'Pillar 12' focusing on innovation competitiveness where the relative performance of countries is ranked on several measures. Depending on the measures used, different countries climb up the rankings.[1] This lack of internal consistency in the innovation measures is a cause for concern, especially when summing measures. Otherwise, an equivalent weighting is given to petroleum-rich Qatar for its purchasing of oilfield equipment, (not innovation in its truest sense) and to R&D intensive Switzerland which tops the list for 'Private R&D spending' (genuine innovation). A further problem is that most measures are self-referential (Hollanders and van Cruysen, 2008).

Aim of our paper

What we propose to do in our paper is to describe a technique for deriving a complementary metric which is theory-based and empirically robust.

We estimate a model which builds on a standard Griliches knowledge production function (see Griliches et al., 1987), which distinguishes Research and Development spending from other innovation descriptors. Our subsequent ranking analysis applies Data Envelopment Analysis (henceforth DEA) but uniquely allows us to 1) calculate multiple outputs simultaneously and 2) bootstrap the standard errors in the estimations. Uniquely, we also apply data for some emerging economies (China, India, Russian Federation, Brazil and South Africa) in our estimation sample as it is generally acknowledged that these countries are interesting, because they do not generally perform well in the GCR but have high growth levels.[2]

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[1] Qatar, Singapore and the UAE top the 'Government procurement of high-tech equipment' list but Switzerland, Japan and Finland top the 'Private R&D spending' list.

[2] Differences in the competitiveness of the BRICS are highlighted in the 2013 Global Competiveness Report (2012-2013) where of all the BRICS countries, only China is viewed as competitive (see 'heat-map' P.12)

We find that our modified[3] DEA estimator is broadly in line with the 'PCT Patent Applications' question within the GCR rankings, once we have bootstrapped the standard errors from our estimations. Unlike the former, however, our method is theory based and our 'Output-based' estimator allows us to create a composite innovation construct which is also empirically sound.

Griliches Knowledge-Production Function: R&D spending is an input

Theories of innovation efficiency can be used underpin any constructed measure. We apply a simplified version of the standard Pakes-Griliches framework where, Z (country's efficiency indicator) is related back to increases in economically valuable knowledge, $\dot{K}$, research expenditures, R, and the efficiency drivers X,

$$Z = bR + \dot{b}u + e$$

where the residual, e, needs to be uncorrelated with the response variable, efficiency. When applying these generated estimates in a second-stage and recycling first-stage covariates, care should be taken to adjust for this bias (See Simar and Wilson, 2011).

Augmented DEA

Our main input into the DEA is 'Company R&D spending' is in line with the Griliches model. We model innovation outputs as WIPO patents granted, scientific publications and the output of high-tech industries. [4]

The data spanning the period 2000 to 2008, was collected from the World Bank's Open Database (DataBank), the UNESCO Institute for Statistics and the World Intellectual Property Organization (WIPO) website.

The next step was to select countries based on their strong innovation performance and their policy interest. Importantly, the estimation sample must include the strongest performing countries allowing

[3] Where the DEA considers Returns to Scale and bootstraps estimates (See Simar and Wilson, 2002)

[4] The flexibility of our method ('Output Oriented') allows for the inclusion of other inputs. Both 'Output-Oriented' and 'Input-Oriented' versions give comparable measures for technical efficiency and eventual ranking scores when CRS exist (Färe and Knox Lovell, 1978; Coelli, 1996)

us to generate an estimate for innovation efficiency approximating the world technology frontier. Accordingly, we included all G7 member states, 8 European countries with a proven innovation track-record (Finland, Sweden, Denmark, Switzerland, Netherlands, Austria and Belgium). Also included was South Korea (exemplary catch-up economy) and Australia to represent the Asia-Pacific region.

We apply a linear programming technique pioneered by Charnes et al (1985) which is sufficiently flexible to deal with either constant or variable returns to scale (i.e. CRS vs. VRS). When deciding on an appropriate optimization model, we opt for a system (Output-Oriented) model assuming fixed inputs (used to derive relative efficiency) and allowing us to track the variation in outputs (patents, scientific publications, and hi-tech exports).[5] Moreover, we need to decide whether our estimation model assumes CRS or VRS. The CRS efficiency scores are calculated as:

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

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

$\sum^{n}_{j=1}\lambda_j=1$ (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 with the scale effect as the residual.

Applying the Simar and Wilson (2002) test for CRS (H_0), we set the bootstrap to 1,000 iterations to generate the bootstrapped estimators using the *FEAR* in *R* package, rejecting the null hypothesis of CRS if the critical values of the bootstrapped estimator are lower than the observed estimator (See Wilson, 2008).

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%).

Comparisons with the GCR Ranking

Next, we estimate the efficiency scores and ranking for the returns to innovation inputs for our 22 countries (2000 to 2008) by replicating the data generation process of the original observed sample and estimating a new frontier based on bootstrapped estimates. The first 5 rankings based on our adjusted (bootstrapped) DEA estimates are reported in Table 1.

Table 1: Global Competitiveness Report measures vs. our calculated Efficiency Score

			Global Competitiveness Report measures (GCR)[1]	
	2008		2008/2009	
Rank	Our bootstrapped efficiency DEA measure		PCT patent applications	[2]Company R&D spending
1	China	0.803	Sweden	Switzerland
2	Netherlands	0.776	Switzerland	Japan
3	India	0.759	Finland	Finland
4	Switzerland	0.699	Israel	Germany
5	Sweden	0.659	Japan	Sweden

Notes: [1] See P.514 & 518 GCR. [2]Self-reported

In Table 1, both Sweden and Switzerland occupy the first 5 slots under the 2 Global Competitiveness Report Measures, regardless of the measure used. China and India enter the first 5 slots for our calculated DEA measure. There is an interesting dynamism in our calculated measure over time where Table 3 illustrates that the UK, US and Australia have lost out most in the rankings since 2000.

Table 3: Losers and Winners in Global Innovation Competitiveness

		Our bias corrected efficiency score		2000 score as % of 2008 score	
		2000	2008	2000	2008 score (scaled to 100)
Winners	India	0.335	0.759	44	100
	China	0.517	0.803	64	100
	Switzerland	0.455	0.699	65	100
Losers	US	0.271	0.200	135	100
	Australia	0.164	0.117	141	100
	UK	0.689	0.449	153	100

Our Efficiency Scores and Growth Theory

Countries do not achieve efficiency scores in a vacuum. Growth Theory points to the role of institutions (e.g. banks, education system), population size, internationalization and other variables (e.g. Aghion and Howitt, 1998). Table 4 reports some preliminary findings for our second-stage Tobit where reassuringly ‘Company R&D’ and internationalization (trtgdp) are positively related to innovativeness.[6] Banks are not seen to contribute positively, a result tying in with comments by Stulz (2004) that ‘financial structure is not a distinguishing characteristic of success (innovation and growth)’.

[6] For a more detailed discussion of the second-stage set-up and results see Cai and Hanley (2012)

Table 4: Second-Stage Estimates

y: Bias-corrected innovation efficiency scores (Panel Tobit: 0 to 1)		
	Estimate	(t value)
R&D Investment & Infrastructure		
firm R&D (frdp1)	0.0029***	(3.575)
Demographic factors		
Ageing population (age)	-0.0097**	(-2.607)
Wealth and Trade		
Trade to gdp (trtgdp)	0.0011*	(1.772)
Business Environment		
Bank finance (credp1)	-0.0010***	(-3.895)
market value of listed companies (caplst)	-0.0004	(-1.361)
(Intercept)	0.3944***	(6.019)
$\log \sum \mu$	-1.7937***	(-24.152)
Log likelihood (DOF)	74.21	

Notes: Where *** , ** and * means significant to the 0.01, 0.05 and 0.10 level respectively. Data from World Bank's Open Database (DataBank), and the UNESCO Institute for Statistics. Standard errors are bootstrapped.

Conclusion

Our bootstrapped innovation DEA derived efficiency ranking corresponds, to some extent, with Global Competitiveness Report rankings and performs reassuringly well in second-stage estimations. However, our measure raises the prominence of India and China, not surprisingly since both these countries registered the greatest change in the computed score in the period 2000 to 2008. We suggest that a similar derived DEA metric be used to complement the existing GCR measures.

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