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Innovation Capacities in Advanced Economies: Relative Performance of Small Open Economies

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Abstract

This paper offers an empirical examination of the determinants of a nation's ability to produce commercially viable innovations, measured as patents, across a sample of twenty three advanced economies. The approach employed is based on estimating National Innovation Capacity that focuses on the long-run ability of economies to produce and/or commercialize innovative technologies, in the spirit of Furman, Porter and Stern, (2002).

Motivated by differences in the rate of innovation between economies with different economic structures we examine the Small Open Economies chosen from this country sample to assess whether there is a significant difference between the determinants of Innovative Capacity in Small Open Economies and the other developed economies. A number of alternative specifications are estimated.

We find that advanced Small Open Economies and larger economies do not differ substantially in their determinants of patenting activities and, notwithstanding the limitations of patents as measures of innovative activity, we conclude that policy choice and variation plays a key role in determining the productivity of R&D, when measured as patenting activity.

1 Introduction

Innovative capacity lies at the heart of factors affecting future competitiveness particularly for advanced modern economies since, under a Solow-type growth framework, such economies are likely to have exhausted their ability to generate increased output from further investments in capital. According to Furman et al. (2002: 899) an economy's innovative capacity represents

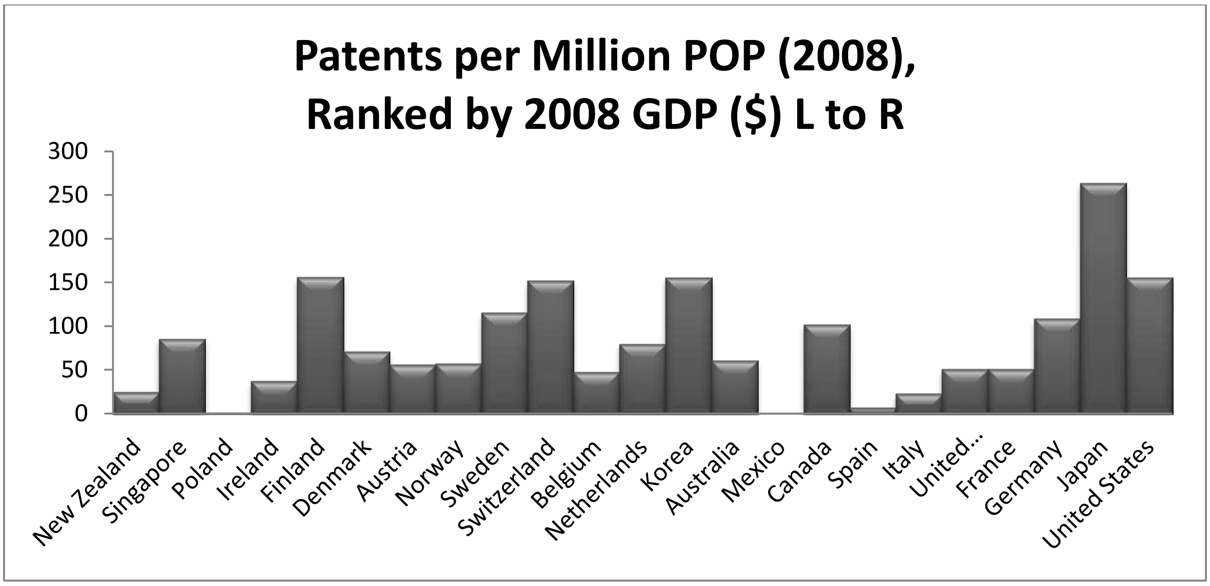
> the ability ... to produce and commercialize a flow of innovative technology over the long term.

Many studies (e.g. Gans and Stern (2003) and Gans and Hayes (2008)) have followed such an approach and have found evidence to support the contention that the intensity to which countries innovate varies based on a set of variables relating to:

- each nation's Common Innovative Infrastructure (CII);
- its Cluster Specific Environment (CSE); and
- the Quality of Linkages between both its CIE and CSE.

This approach facilitates the identification of a set of economic factors that drive patenting activity/intensity and also allows for a policy-centred focus on how best to consider the long-term choices that impinge on innovation capacity. This policy-centred focus applies as easily to business development policy, on the one hand, as to business strategy on the other, given the microeconomic basis of the cluster concept.

Empirically, the variation in the ability of countries to produce new-to-world technologies, that are patented, is striking. Some countries consistently outperform others by a large margin. For example, Canada, the US, Finland, Switzerland and Japan produce well over 100 patents per year (per million of population in 2008), while most advanced economies average approximately 60 patents per million and still others such as Spain, Portugal, New Zealand and Italy all may be considered to 'underperform' with less than 25 patents per million.



Source: IMF WEO, USPTO

This variation in patent outcomes is not explained by larger economies performing better, or smaller 'nimbler' economies generating better results. This is depicted by Figure 1 above where a country's patent output is ranked by their 2008 GDP from left to right with little or no correlation, positive or negative, between a country's GDP and patent output per million of population.

As Furman et al. (2002) point out there is a strong patenting bias in those countries which have a history of patents production such the US and Switzerland (due to path dependency and the importance of the history of resource commitments). However, other 'new' innovative countries' rate of growth in patents per million has been nothing short of phenomenal: Singapore, for example, has an average annual patent growth rate of 30% between 1981 and 2008, going from just over 1 patent per million in 1981 to 84 in 2008. Such performance begs analysis and raises the question for us in this paper as to whether smaller economies generally are supported or hindered by their relatively low scale, or low critical mass in economic terms, in achieving innovative success. The varying rates of increase in patent production is treated in detail in Furman and Hayes (2004).

As with any economic definition of success, innovative success requires elaboration and explanation. In the context of this study the selected measure of innovative 'success' is represented by patent output, which is far from problematic and will be detailed further in Section 5.1.

The issues considered in this paper focuses, firstly, on whether the mix of drivers of Innovative Capacity vary across advanced economies when categorised by their SOE status. Thus, this paper addresses possible heterogeneities that may exist in relation to different economy structures. We examine the extent to which a set of factors drive a nation's Innovative Capacity as previously found in the literature and question whether or not the mix of policy choices, in terms of the areas mentioned above, for an SOE are significantly different from other economies. That is, do SOEs perform differently in terms of their innovative output (patenting activity) compared to their advanced economy peers when using the same policy mix?

Secondly we examine whether an SOE's innovative capacity is optimised by an emphasis on certain on different, if the same basic mix of factors is found to be effective in the first instance.

This question addresses a gap in the literature and, therefore, it is necessary to assess the relative performance of SOEs. While some literature on innovative capacity examines specific SOEs, such as New Zealand in Marsh (2000), it tends to concentrate on an individual industry without adopting a broader international perspective which is the chosen perspective offered here, grounded in the National Innovative Capacity approach.

We set out the background to the National Innovative Capacity approach in Section 2 outlining its constituent parts, and potentially relevant measures. Our model for estimation is presented in Section 3, with Data described in Section 4. Empirical results for various specifications will be examined in Section 5.

2 National Innovative Capacity Framework

The National Innovative Capacity framework integrates three perspectives on the sources of innovation i.e.:

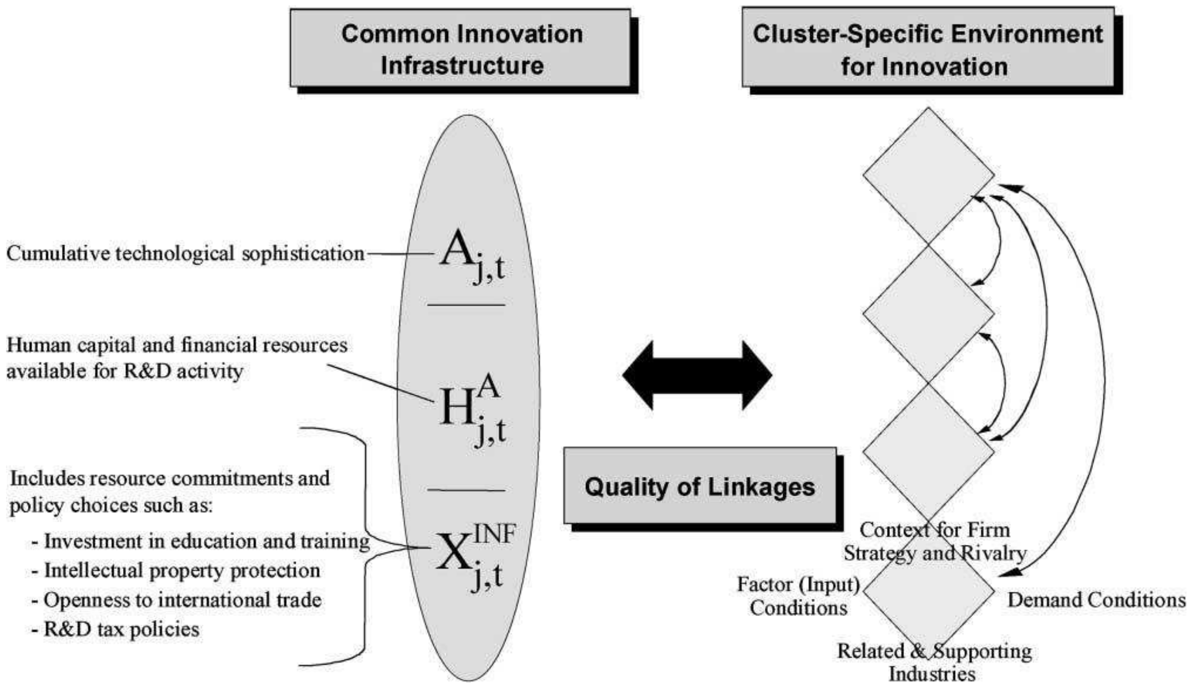
- ideas-driven growth theory as outlined in Romer (1990);
  microeconomics-based models of national competitive advantage and industrial clusters developed by Porter (1990); and
- research on national innovation systems as proposed in Nelson (1993).

Both the characteristics of the direct producers of patents are relevant in this context, as are the outcomes generated by previous investments, policies and supports for innovation-based activities.

Our view is that Innovative Capacity should be viewed differently to science and technology advances, as we are interested in economically viable applications. The discovery of a new technology (or significant facts/information) is considered to be independent of its benefit to an economy unless it can be harnessed domestically through having the structures and resources available to exploit its value before the knowledge becomes diffused and may be exploited elsewhere. With limited data availability and suitability for identification of economically viable applications of scientific advances, however, we limit ourselves to a proxy in the form of patents.

The National Innovative Capacity Framework is illustrated diagrammatically in Figure. 1.

Fig. 1: National Innovative Capacity Framework



Source: Furman et al. (2002: 906)

2.1 Common Innovative Infrastructure

This element of the framework relates to features of an economy's innovation infrastructure that confer no particular advantage on any sector or cluster yet provide support for innovation activities generally across the economy. Furman et al. (2002) appeal to endogenous growth theory to identify the two main determinants in their model of the quality of the Common Innovative Infrastructure: the aggregate level of technological sophistication or its accumulated stock of knowledge - denoted by A in Fig.1 - and the range of the talent pool of workers appropriate for the generation of new knowledge in an economy (denoted by H^A in Fig. 1). In addition to these to determinants they add other universal factors that aid innovation such as Higher Education Graduates, Property Rights Protection, the availability of R&D Tax Credits, all of which are denoted by X^{INF} in Fig. 1.

Gans and Stern (2003) offer a broader list of potentially relevant variables that may be included under the heading of X^{INF}, given below:

- Investment in basic research
- Tax policies affecting corporate R&D and investment spending
- Supply of risk capital
- Aggregate level of education in the population
- Pool of talent in science and technology

- Information and communication infrastructure
- Protection of intellectual property
- Openness to international trade and investment
- Overall sophistication of demand

2.2 Cluster Specific Environment

This aspect of the innovative capacity of an economy makes reference to microeconomic theory, specifically the fact that while wider policy-related issues facilitate innovation it is ultimately firms that create new technologies. This firm-level impact on national innovative capacity depends upon the microeconomic environment present within and across a nation's clusters (following the definition by Porter, 1990).

A variety of cluster-specific circumstances, investments, and policies impact on the extent to which a country's industrial clusters compete on the basis of technological innovation. Innovation in particular pairs of clusters may also be complementary to one another, both due to knowledge spillovers and other interrelationships (represented by lines connecting selected 'Diamonds' in Fig. 1).

This is a particularly difficult feature to include when estimating an econometric model as there are few national or international statistics pertaining directly to the extent of cluster activity that are available for the period of the analysis conducted here (for more on issues in the challenges of applying a cluster approach see Doyle and Fanning, 2007). Instead a number of proxies are identified and estimated for our purposes in this paper.

2.3 Quality of Linkages

The quality of the two previous factors is reinforced by the way in which they are linked, as depicted in Fig. 1. For instance even firms within a well developed cluster will not be able to produce economically viable new-to-world technologies unless they have access to a pool of scientists and engineers and access to basic research and, in some cases, perhaps access to advice from local universities.

3 Modelling Innovative Capacity

The basis of the model specified by Furman et al. (2002) uses the findings of prior research into the geographic impact of knowledge spillovers, the differences in access to human capital and ways that regional differences are driven by public policies. Ideas driven endogenous growth models form the base of the model that is extended to incorporate additional and more nuanced factors previously not used from industrial organisation, the composition of funding (public versus private), public policies and the degree of technological specialisation. For example, while Public R&D spending adds to the innovative process by reinforcing the Common Innovation Infrastructure, Private R&D spending and the Specialisation of a country's technological outputs also reflects the nation's cluster innovation environment.

To estimate the relationship between the production of international patents and observable contributors to national innovative capacity, we adopt the ideas production function of endogenous growth theory as a baseline (Equation 1):

$$A_{j,t} = \delta H^{A}{}_{j,t} A^{\varphi}{}_{t} \tag{1}$$

where $A_{j,t}$ is the flow of new-to-the-world technologies from country j in year t, $H^{A}{}_{j,t}$ the total level of capital and labor resources or inputs devoted to the ideas sector of the economy, and $A^{\varphi}{}_{j,t}$ is the total stock of knowledge held by an economy at a given point in time relevant to drive future ideas production.

As the national innovative capacity framework suggests that a broader set of influences determine innovative performance a production function for new-to-the-world technologies is extended from Equation 1 generating the formulation of Equation 2:

$$A_{j,t} = \delta_{j,t}(X^{INF}{}_{j,t}\ ,\ Y^{CLUS}{}_{j,t}\ ,Z^{LINK}{}_{j,t}\ )H^{A}{}_{j,t}\ A^{\varphi}{}_{j,t} \tag{2}$$

The additional variable X^{INF} refers to the level of general resource commitments and policy choices that constitute the common innovation infrastructure, Y^{CLUS} refers to the particular environment for innovation in a countries' industrial clusters, and Z^{LINK} captures the strength of linkages between the common infrastructure and the nation's various clusters. Under Equation (2), we assume that the various elements of national innovative capacity are complementary in the sense that the marginal boost to ideas production from increasing one factor is increasing in the level of all of the other factors.

The parameters associated with Equation 2 are estimated using a panel dataset of 23 OECD countries plus Singapore over 13 years. These estimates can therefore depend on cross-sectional variation, time-series variation, or both. While comparisons across countries can easily lead to problems of unobserved heterogeneity, cross-sectional variation provides the direct inter-country comparisons that can reveal the importance of specific determinants of national innovative capacity. Time-series variation may be subject to its own sources of endogeneity (e.g. shifts in a country's fundamentals may reflect idiosyncratic circumstances in its environment), yet time-series variation provides insight into how a country's choices manifest themselves in terms of observed innovative output.

Recognizing the issues surrounding panel estimations our analysis explicitly compares how estimates vary depending on the source of identification. In most of our analysis, we include either year dummies in order to account for the evolving differences across years in the overall levels of innovative output and a dummy on the US to account for differences in the definition of the dependant variable for that economy (explained further below).

The analysis is organized around a log–log specification, except for qualitative variables and variables expressed as a percentage. The estimates, thus, have a natural interpretation in terms of elasticities, are less sensitive to outliers, and are consistent with the majority of prior work in this area including Jones (1998), Furman et al. (2002), Gans and Stern (2003), Gans and Hayes (2008).

Finally, with regard to the sources of error, we assume that the observed difference from the predicted value given by Eq. (2) (i.e. the disturbance) arises from an idiosyncratic country/year-specific technology shock unrelated to the fundamental determinants of national innovative capacity. Integrating these choices and letting L denote the natural logarithm, our main specification takes the following form of Equation 3:

$$\begin{aligned} L\,A_{j,t} &= \alpha + +\delta_{INF} LX^{INF}{}_{j,t} + \delta_{CLUS} L\,Y^{CLUS}{}_{j,t} \\ &+\delta_{LINK} L\,Z^{LINK}{}_{j,t} + \lambda\,LH^{A}{}_{j,t} + \varphi L\,A^{\varphi}{}_{j,t} + \varepsilon_{j,t} \end{aligned} \qquad \textbf{(3)}$$

Conditional on a given level of R&D inputs (H^A), variation in the production of innovation (A^{φ}) reflects R&D productivity differences across countries or over time. For example, a positive coefficient on elements of δ^{INF}, δ^{CLUS} or δ^{LINK} suggests that the productivity of R&D investment is increasing in the quality of the common innovation infrastructure, the innovation environment in the nation's industrial clusters, and the quality of linkages. As $A_{j,t}$, measured by the level of international patenting, is only observed with delay, our empirical work imposes a 3-year lag between the measures of innovative capacity and the observed realization of innovative output. This follows Furman et al. (2002), but differs from Gans and Stern (2003) and Gans and Hayes (2008), who impose no lag and a two year lag respectively: including alternative lag structures does not significantly alter our results.

4 Possible Reasons for SOE Heterogeneity

A number of ideas may contribute to SOE's having a different set of factors that add to its innovative capacity; or that some factors may be of greater importance in maximising its potential for ideas production.

4.1 Scale Effects

The idea that in larger conglomerations of people new ideas and innovations will be more readily available is an old one. William Petty (1682) commenting on the reconstruction of London after the Great Fire of 1666 wrote:

> "it is more likely that one ingenious curious man may rather be found amongst 4 millions than among 400 persons."

This Scale Effect has also been incorporated in neo-classical growth theories such as Romer (1990) which forms a part of the basis for the National Innovation Capacity framework used in this paper. In Romer's (1990) model, the growth rate of an economy is proportional to the total amount of research undertaken in it. And an increase in the population of an economy will generally lead to an increase in the R&D workforce, thereby increasing the growth rate of per capita income.

So that a small open economy's ability to produce new to world technologies may be affected due to the lower probability of it's having the "ingenious curious" persons that William Petty talks about as well as lacking the critical mass of researchers to maximise growth as in Romer's theory.

In studies testing scale effects in economic growth however there is no clear evidence that larger economies grow faster. Jones (1995b) studied time series evidence and concluded against scale effects in economic growth. However on a more concentrated level Backus (1992) found scale effects were evident in the manufacturing output in the variety of models used.

4.2 Knowledge Spillovers

Studies such as Faehn (2008) emphasise the importance of knowledge spillovers for SOE's. Cohen and Levinthal (1989) point out that R&D has "two faces" in its interaction with an economy. Not only does it produce new innovations it also allows for the easier absorption and understanding of new technologies, both domestically and internationally.

Due to the lack of scale in SOE's discussed in the earlier section the importance to SOE's of absorbing all knowledge internationally in order to be able to act at the technological fromtier in producing new to world technologies means that a different policy emphasis may be required. Faehn (2008) discusses how national policy can enhance the exploitation of the international knowledge stock and find that subsiding R&D is important for domestic innovation as it is effective in generating these knowledge spillovers from abroad. Faehn (2008) also finds that eports play an important role for SOE's in encouaraging knowledge spillovers.

5 Data

5.1 Innovative Output

This analysis requires an observable country-specific indicator of the level of commercially valuable innovative output in a given year. We follow previous research and employ as the dependant variable the number of "international patents" (PATENTS), defined as "the number of patents granted to inventors from a particular country other than United States by the USPTO in a given year. For the United States, PATENTS is equal to the number of patents granted to corporate or government establishments (this excludes individual inventors)" (Furman et al. 2002: 909).

Following Eaton and Kortum (1996), Kortum and Lerner (1999), Griliches (1984) and Furman et al. (2002) we recognise a number of difficulties in relation to using patents as a measure of innovation at a national level, such as:

- Not all inventions are patentable,
- Not all inventions of economic value are patented,
- Not all patented innovations have the same quality or value to an economy,
- There are varying degrees of willingness to patent across countries and sectors.

However a large number of previous studies used patents based on the assumption that they are "the only observable manifestation of inventive activity with a well-grounded claim for universality" (Trajtenberg, 1990:183). We temper this assumption by interpreting our findings carefully, noting that our dependant variable is an imperfect proxy relating to innovations that are economically viable applications and that the true rate of innovation is unobservable.

This belief is based on the expense that is required for a non-american investor to register a patent with the USPTO acting as a barrier unless there is a strong belief that the innovation will produce a sufficient return. A patent registered by an America will be either from a firm or the government, again reducing the number of patents registered lacking economic value. Any asymmetry this may cause between US and non-US patents does not affect our results as we include a US dummy variable in all regressions, in keeping with the previous literature.

5.2 Defining Small Open Economies

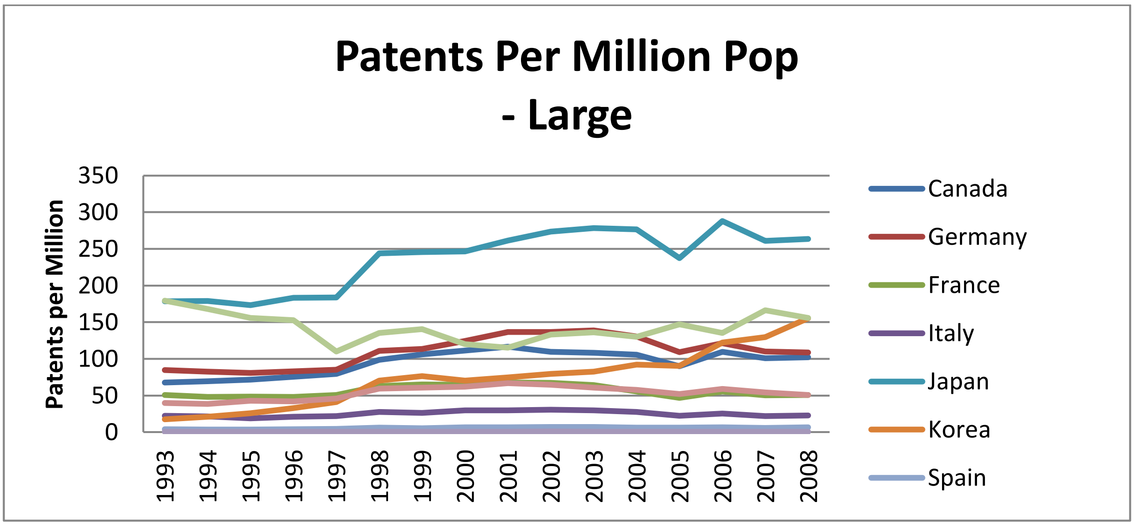
There are 30 economies in the OECD and this study also includes Singapore as a strong example of an SOE for which patenting activity has become particularly strong. However, Portugal, Turkey and Iceland, Greece were not used as observations as required data was available for the Specialisation variable (detailed below). In addition to this Luxembourg was excluded as its small size added very little to the data and as it would be given the same weighting would bias the results. Mexico and Poland were also excluded due to the extremely low level of patenting when shown relative to population as in Fig 2.

In the literature there appears to be no one method applied to define an SOE. The conceptual definition of an SOE is an economy that participates in international trade, but is small enough compared to its trading partners that its policies do not alter world prices, interest rates, or incomes. However this paper must divide the 23 countries estimated into SOEs and others and in order to do this data was collected on:

1) Import/Export Openness of the economy, calculated as exports plus imports divided by GDP taken from the Penn World Tables.
2) Size of the economy, calculated as the relative GDP weighting of each in our overall sample. The GDPs of the 31 countries were aggregated and the proportion each accounted for was calculated.

For the purposes of this paper an SOE is defined as one whose GDP makes up less than 2% of the 31 countries aggregate GDP and its exports plus imports over GDP is equal to or greater than 70%, which is within half a standard deviation of the mean of 100%.

Fig. 2: Patents per Million of Population: Large Countries and SOEs



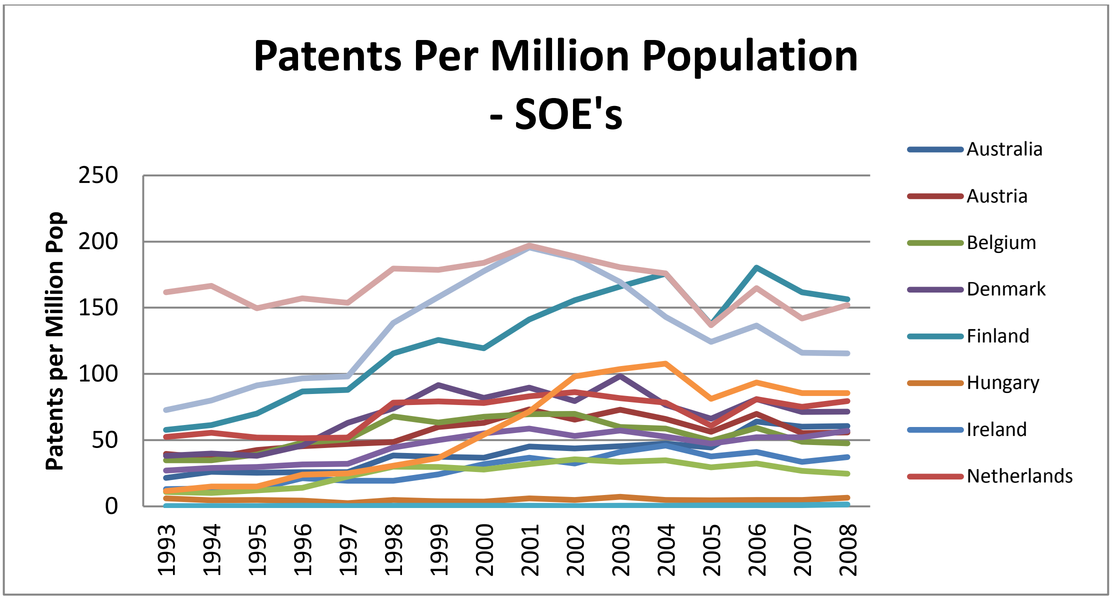


Table 1 provides a full list of the sampled countries and their status as an SOE or 'other': Turkey was not an SOE under these criteria, and Portugal and Iceland were SOEs. This process was somewhat ad hoc and some countries were border-line. Canada, for instance, is studied as an SOE by Appelbaum and Kohli (1979), but its GDP was nearly 3% of the aggregate, while its international trade openness was 87% of GDP.

Table 1: Selection of Small Open Economies and Others

SOE	Size:% of Aggregate GDP	Openness	Large	Size: % of aggregate GDP	Openness
Australia	1.36%	46%	USA	37.81%	26%
Austria	0.74%	101%	UK	5.70%	58%
Belgium	0.90%	169%	Japan	17.98%	20%
Czech Republic	0.22%	147%	Germany	7.34%	67%
Denmark	0.62%	80%	France	5.14%	56%
Finland	0.47%	76%	Italy	4.24%	56%
Hungary	0.18%	127%	Canada	2.79%	87%
Ireland	0.37%	176%	Spain	2.24%	62%
Netherlands	1.49%	130%	South Korea	2.06%	87%
New Zealand	0.20%	72%			
Norway	0.65%	77%			
Singapore	0.36%	342%			
Sweden	0.95%	89%			
Switzerland	0.96%	88%			

Source: Authors' calculations based on data from Penn World Tables.

5.3 Independent Variables

Following the previous literature this paper uses proxies for measures of Common Innovative Infrastructure, Cluster Specific Environment and the Quality of Linkages in order to estimate the determinants of National Innovative Capacity. These are detailed in Table 2 which includes variable definitions and sources. Table 3 details variable means and standard deviations.

Table 2: Variable Descriptions and Sources

Dependent Variable	**Full Variable Name**	**Definition**	**Source**
Patents $_{j,t}$	International Patents Granted by Year of Application	Non-US countries: patents granted by the USPTO. US: patents granted by the USPTO to corporations or government.	USPTO Patent Database
Independent Variables			
QUALITY OF THE COMMON INNOVATION INFRASTRUCTURE			
R&D PPL $_{j,t}$	Aggregate Personnel Employed in R&D	Full time equivalent R&D personnel in all sectors	OECD Science & Technology Indicators
R&D \$ $_{j,t}$	Aggregate Expenditure on R&D	Total R&D expenditures in Mill of US\$ (base 2000)	OECD Science & Technology Indicators
Property Rights Protection $_{j,t}$	Legal Structure and Security of Property Rights	Average survey response by executives on a 1-10 scale regarding relative strength of Legal Structure and Security of Property Rights	Economic Freedom of the World Index
ED SHARE $_{j,t}$	Share of GDP Spent on Secondary and Tertiary Education	Public spending on secondary + tertiary educ. as share of GDP	World Bank: Edstats
OPENNESS $_{j,t}$	Freedom to Trade Internationally	Average survey response by executives on a 1-10 scale regarding relative strength of freedom to trade internationally	Economic Freedom of the World Index

GDP/POP $_{j,t}$	GDP Per Capita	Gross Domestic Product per capita, constant price, chain series, US$	IMF: World Economic Outlook
GDP $_{j,t}$	GDP	Gross Domestic Product constant price, chain series, US$, Billions.	IMF: World Economic Outlook
CLUSTER-SPECIFIC INNOVATION ENVIRONMENT			
PRIVATE R&D $_{j,t}$	Percentage of R&D Funded by Private Industry	R&D expenditures funded by industry divided by total R&D expenditures	OECD Science & Technology Indicators
SPECIALISATION $_{j,t}$	E-G concentration index, excluding the US	Relative concentration of innovative output in chemical, electrical and mechanical USPTO patent classes	Computation from USPTO data using formulae from Furman *et al.* (2002) detailed below
QUALITY OF LINKAGES			
UNIV R&D $_{j,t}$	Percentage of R&D Performed by Universities	R&D expenditures of universities divided by total national R&D expenditures	OECD Science & Technology Indicators

Table 3: Variable means and standard deviations

Variable	N	Mean	Standard Deviation
Patents $_{j,t}$	293	4,607	10,081
QUALITY OF THE COMMON INNOVATION INFRASTRUCTURE			
R&D PPL $_{j,t}$	293	193,276	300,649
R&D \$ $_{j,t}$	293	24,687	49,779
Property Rights Protection $_{j,t}$	293	8.21	1.21
ED SHARE $_{j,t}$	293	3.4	0.94
OPENNESS $_{j,t}$	293	8.1	0.63
GDP/POP $_{j,t}$	293	25,619	9,480
GDP $_{j,t}$	293	1,120	2,059
CLUSTER-SPECIFIC INNOVATION ENVIRONMENT			
PRIVATE R&D $_{j,t}$	293	61	11
SPECIALISATION $_{j,t}$	293	0.53	0.64
QUALITY OF LINKAGES			
UNIV R&D $_{j,t}$	293	22	6

5.4 Specialisation

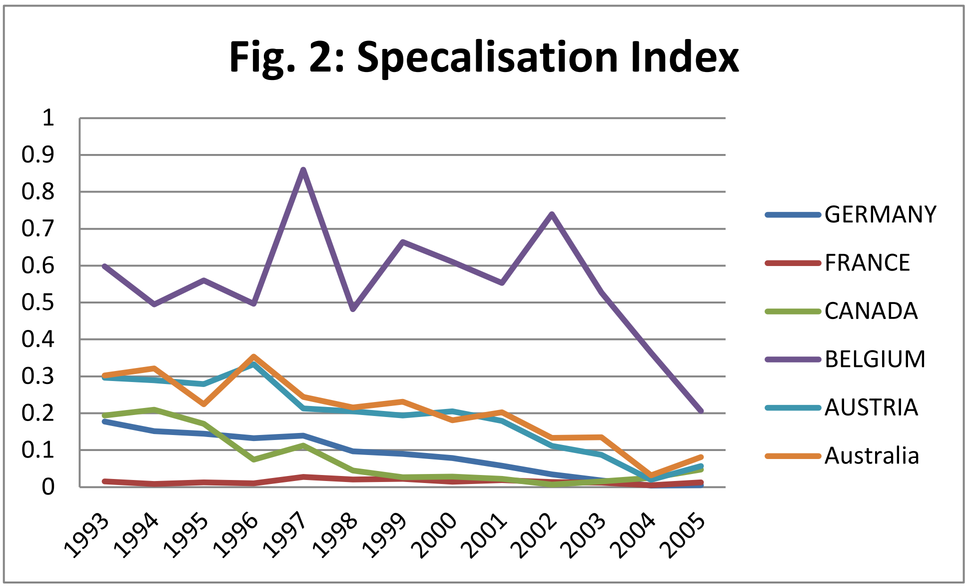
While most variables for our analysis were readily available, SPECIALISATION was estimated based on a methodology developed by Ellison and Glaeser (1997). Since individual clusters will tend to be associated with technologies from specific technological areas, this is a measure of the degree of technological focus by a country (SPECIALISATION) acts as a proxy for the intensity of innovation-based competition in a nation's clusters. SPECIALISATION is a "relative" concentration index based on the degree to which a given country's USPTO-granted patents are concentrated across three broad technology classes (chemical, electronics, and mechanical) which cover all patents. While the measure of specialization is too general to identify specific clusters and the role of the mix of clusters in shaping R&D productivity, SPECIALIZATION is designed as a noisy but unbiased measure capturing an important consequence of cluster dynamics, the relative specialization of national economies in specific technologies fields.

Specifically, traditional measures of specialization, such as the Herfindahl Index ignore two issues important for cross-country comparisons: technology classes differ in terms of their average share across all countries and some countries have only a small number of patents overall. While the Ellison and Glaeser index was developed and applied for measuring the specialization of industries across geographic regions, Furman et al (2002) applied in several other contexts, including the measurement of the degree of specialisation of research output following previous authors such as Lim (2000). In the present context, the Ellison and Glaeser formula adjusts the country observed shares for each technology class to account for the average share for that technology group across the sample; and for the total number of patents in each "country–year" observation, as shown:

$$\text{Specalisation}_{i,j,t} = \sum_j \left(\frac{\text{Patents}_{i,j,t}}{\text{Patents}_{i,j,t-1}} \right) \left(\frac{\sum_i (s_{i,j,t} - x_{i,t})^2}{1 - \sum x_{i,t}^2} - \frac{1}{\text{PATENTS}_{i,j,t}} \right)$$

where: Patents $_{i,j,t}$ = Patents of country i in year t across each technology class j,
s $_{i,j,t}$ = share of class j patents in total country patents in year t,
$x_{i,t}$ = average share of patent class j over all i in any t

Figure 2 below offers a sample of results of the Specialisation measure.



Source: Authors' calculations based on data from UPSTO data.

6 Empirical Results

This section outlines the results from our empirical analyses enabling a dissection of the drivers of national innovative capacity across our sample of 23 countries and with specific focus on the results for the sample of SOEs, as defined earlier. We first test all models presented in Section 6.2 for parameter stability. We then included slope and level dummies into our regressions to assess if there are specific differences in the way that SOE's and other economy types produce new to world technologies.

The panel regression method used is the Random Effects Method. As Baltagi (2005: 28) explained:

> The random effects model is an appropriate specification if we are drawing N individuals randomly from a large population

As this study focuses on a sample of SOEs and non-SOE economies, this is an appropriate method. In addition, each regression is tested using the Breusch and Pagan Lagrangian Multiplier test of Fixed versus Random Effects to assess the appropriateness of the method: all regressions are found to be suitable for Random Effects estimation.

6.1.1 Chow Tests for Parameter Stability: Methodology

All models estimated in Section 6.2 were tested for parameter stability using the Chow test. This test assesses if there is a difference in the structure of the relationship between the dependant variable and the independent variables, when estimated for the SOE's or larger economies.

This is done by estimating each model 3 times: Equ.1 with all country observations, Equ.2 with just SOE countries and Equ.3 for the non-SOE countries. Equ.1 assumes that the intercept as well as the slope coefficients remains the same for both economy types; that is, there is no structural difference in how the two economy types produce patents. Equ's 2 and 3 assume there is a structural difference.

To carry out the chow test we run all three regressions to find the residual sum of squares (RSS). From Equ.1 we find the restricted RSS (RSS_r) as we are forcing the coefficients to have the same value for both economy types. We now assume the other two regressions to be independent and add their RSS's to get the RSS_{ur}. If there is no structural change, then the RSSR and RSSUR should not be statistically different. Therefore, if we form the following ratio:

$$F = \frac{(RSS_r - RSS_{ur})/k}{RSS_{ur}/(n_2 + n_3 - 2k)} \sim F_{[k,(n_1+n_2-2k)]}$$

Where:

k = No. of parameters estimated
$n_2 + n_3$ = Number of observations in regression 2 and 3 respectively

We do not reject the null hypothesis of parameter stability (i.e., of no structural change) if the computed F value in an application does not exceed the critical F value found in the F tables at a given level of significance.

6.1.2 Chow Tests for Parameter Stability: Results

All models estimated and tested for parameter stability showed that there was no change in the structure of the relationship between the dependant variable and the independent variables, when estimated for SOE's or larger economies. This means that based on these findings SOEs innovation is driven by the same set of factors as other economy structures.

Section 6.2 will investigate where there are specific factors that a have statistically significantly different effect on innovative output. Full results of regressions using a full sample of countries and the SOE sample are shown in Appendix 2.

6.2 Dummy Regressions: Results

Results for regressions including an SOE slope dummy for each of the variables national innovative capacity are shown in Table 3, 4 and 5 below, along with an intercept dummy. Regression coefficients from each single regression line are shown in two columns with the independent variables in the right hand column and the equivalent dummy in the left hand column.

Regressions are grouped into three categories. Ideas Production Functions (**Table 1**), Common Innovative Infrastructure and National Innovative Capacity (**Tables 3 and 4**). **Tables 3** uses GDP, Population and GDP per capita as proxies for a countries knowledge stock while in **Table 4** the stock of patents built up by the country is used as a proxy.

Table 3: Determinants of New to World Technologies (GDP/POP as Knowledge Stock)				
Ideas Production Functions				
	Equ. 1.1		Equ. 1.3	
	Independent Variables	Equivalent Dummy	Independent Variables	Equivalent Dummy
Constant	-2.6044 (0.036)	-1.6688 (0.289)	1.2125 (0.444)	-6.1050 (0.002)
L GDP	-0.0026 (0.983)	-0.0885 (0.588)		
L GDP PER CAPITA			0.03111 (0.811)	0.01014 (0.544)
L POP	1.6762 (0.000)	-2.120 (0.000)		
L R&D PPL	0.2696 (0.002)	0.6972 (0.000)	0.4919 (0.000)	0.3668 (0.004)
R^2	0.6673		0.5954	

Table 4: Determinants of New to World Technologies (GDP/POP as Knowledge Stock)						
	Common Innovative Infrastructure				National Innovative Capacity	
	Equ. 1.4		Equ. 1.5		Equ. 1.6	
	Independent Variables	Equivalent Dummy	Independent Variables	Equivalent Dummy	Independent Variables	Equivalent Dummy
Constant	-6.3061 (0.000)	-1.1061 (.0556)	-6.0268 (0.000)	-3.9321 (0.088)	-8.2346 (0.000)	-1.7041 (0.459)
L GDP	0.0674 (0.600)	0.2552 (0.120)				
L GDP PER CAPITA			0.0504 (0.697)	0.2608 (0.102)	0.2682 (0.072)	0.0168 (0.924)
L POP	0.4300 (0.146)	-0.6694 (0.046)				
L R&D PPL	-0.05881 (0.584)	0.9280 (0.686)	-0.0779 (0.461)	0.1631 (0.437)	0.0151 (0.887)	0.0523 (0.798)
L R&D $	1.0101 (0.000)	-0.1767 (0.407)	1.1898 (0.000)	-0.3597 (0.069)	1.2692 (0.000)	-0.4024 (0.055)
ED SHARE	0.0050 (0.938)	0.0782 (0.305)	-0.0189 (0.796)	0.1050 (0.165)	-0.0016 (0.979)	0.0701 (0.338)
IP	0.1790 (0.000)	0.0378 (0.629)	0.1904 (0.000)	0.0375 (0.628)	0.1648 (0.001)	0.0679 (0.372)
Openness	0.1379 (0.069)	0.1890 (0.043)	0.1246 (0.102)	0.2028 (0.030)	0.2401 (0.003)	0.0793 (0.415)
Private R&D					-0.0293 (0.000)	0.0283 (0.003)
Specialisation					0.3730 (0.289)	-0.7489 (.0.077)
University R&D					-0.0381 (0.000)	0.0510 (0.000)
R^2	0.9380		0.9487		0.9517	

Table 5: Determinants of New to World Technologies (Patent Stock as Knowledge Stock)				
	Common Innovative Infrastructure		National Innovative Capacity	
	Equ. 3.1		**Equ. 3.2**	
	Independent Variables	**Equivalent Dummy**	**Independent Variables**	**Equivalent Dummy**
Constant	-5.7483 (0.000)	0.8037 (0.667)	-4.0317 (0.018)	-0.7616 (0.722)
L Patent Stock	0.3586 (0.001)	-0.1770 (0.089)	0.4138 (0.000)	-0.2075 (0.098)
L R&D PPL	-0.048 (0.613)	-0.2499 (0.297)	0.0461 (0.657)	-0.2405 (0.220)
L R&D $	0.6445 (0.001)	0.2499 (0.297)	0.5803 (0.015)	0.2832 (0.310)
ED SHARE	-0.0484 (0.434)	0.0921 (0.208)	-0.0689 (0.261)	0.0864 (0.233)
IP	0.1092 (0.031)	0.1089 (0.155)	0.1055 (0.038)	0.0770 (0.320)
Openness	0.0878 (0.207)	0.1376 (0.113)	0.1465 (0.042)	0.0800 (0.363)
Private R&D			-0.0210 (0.017)	0.0189 (0.058)
Specialisation			0.0859 (.808)	-0.7476 (0.084)
University R&D			-0.0333 (0.000)	0.0345 (0.005)
L GDP 1993	0.3553 (0.038)	-0.1901 (0.367)	0.1861 (0.056)	-0.0865 (0.716)
R^2	0.949		0.953	

As pointed out above, a country's Patent Stock has been shown to be a major factor in determining its current and future patent output. This analysis agrees also finds that it plays a statistically significant role with a 10% non-SOE's sample. The SOE dummy variable is significant and shows that patent stock has roughly half the effect in an SOE.

This may point to the fact that Patent stock not only captures the accumulated knowledge stock of the country but also the fact that a country with a large stock of patents may well have a more fully developed innovative infrastructure. The sample of SOE's tends to contain the lesser developed of the sample countries with notable exceptions.

The level of economic development was proxied by GDP and GDP per Capita. When these factors were examined without reference to patent stock it was found that results were neither statistically or economically significant in general but had a positive relationship with patent output. This could be explicable as it was essentially measuring whether changes in the level of economic development resulted in changes in patent output. But as the countries in this sample are all well developed it is possible that improvements in an already advanced economy had only a marginal effect.

When Patent Stock was included, rather than test for changes in the level of development from year to year only the level of development in 1993, the beginning of the sample, was used to give a different and static level of development for each country. For the whole sample of advanced economies this was significant and large with a 10% difference in a country's level of development in 1993 resulting in a 3.5% increase in patenting. For SOE's it is a less important determinant being both economically and statistically significant.

Appendix 1: Countries sampled in this paper and Furman et al. (2002), with time scale.

Furman et al. (2002), Sample countries (1973–1995)	Doyle et al. (2009), Sample Countries (1993–2005)
Australia	Australia
Austria	Austria
Canada	Belgium
Denmark	Canada
Finland	Czech Republic
France	Denmark
Germany	Finland
Italy	France
Japan	Germany
Netherlands	Hungry
New Zealand	Ireland
Norway	Italy
Spain	Japan
Sweden	Netherlands
Switzerland	New Zealand
UK	Norway
United States	Singapore
	South Korea
	Spain
	Sweden
	Switzerland
	UK
	United States

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