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The determinants of national innovative capacity

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Abstract

Motivated by differences in innovation intensity across advanced economies, this paper presents an empirical examination of the determinants of country-level production of international patents. We introduce a novel framework based on the concept of *national innovative capacity*. National innovative capacity is the ability of a country to produce and commercialize a flow of innovative technology over the long term. National innovative capacity depends on the strength of a nation's common innovation infrastructure (cross-cutting factors which contribute broadly to innovativeness throughout the economy), the environment for innovation in a nation's industrial clusters, and the strength of linkages between these two. We use this framework to guide an empirical exploration into the determinants of country-level differences in innovation intensity, examining the relationship between international patenting (patenting by foreign countries in United States) and variables associated with the national innovative capacity framework. While there are important measurement issues arising from the use of patent data, the results suggest that the production function for international patents is well-characterized by a small but nuanced set of observable factors. We find that while a great deal of variation across countries is due to differences in the level of inputs devoted to innovation (R&D manpower and spending), an extremely important role is played by factors associated with differences in R&D productivity (policy choices such as the extent of IP protection and openness to international trade, the *share* of research performed by the academic sector and funded by the private sector, the degree of technological specialization, and each individual country's knowledge "stock"). Further, national innovative capacity influences downstream commercialization, such as achieving a high market share of high-technology export markets. Finally, there has been convergence among OECD countries in terms of the estimated level of innovative capacity over the past quarter century. *Journal of Economic Literature* classification: technological change (O3); technological change: choices and consequences (O33); economic growth and aggregate productivity: comparative studies (O57). © 2002 Published by Elsevier Science B.V.

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1. Introduction

While R&D activity takes place in many countries, the development and commercialization of "new-to-the-world" technologies has been concentrated historically in relatively few countries. For example, during the 1970s and the early 1980s, two countries, United States and Switzerland maintained a per capita "international" patenting rate well in excess of all other advanced economies. The variation among advanced economies in their ability to innovate at the global frontier raises an empirical puzzle: if inventors draw on technological and scientific insights from throughout the world, why does the intensity of innovation depend on location?

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This question is important for at least two reasons. First, though there is substantial agreement that technological innovation plays a central role in the process of long-run economic growth, there is debate about the underlying drivers of the innovation process itself. International variation in the intensity of innovation presents an opportunity to examine various influences on the pace of technological change. Second, understanding international differences in the intensity of innovation informs public policy. While most studies of innovation are set in a *given* public policy environment (Griliches, 1994, 1998), policy analysis requires an evaluation of how innovation varies with country-level policy differences.

This paper evaluates the sources of differences among countries in the production of visible innovative output. To do so, we introduce a novel framework based on the concept of *national innovative capacity*. National innovative capacity is the ability of a country—as both a political and economic entity—to produce and commercialize a flow of new-to-the-world technologies over the long term. National innovative capacity is not the realized level of innovative output per se but reflects more fundamental determinants of the innovation process. Differences in national innovative capacity reflect variation in both economic geography (e.g. the level of spillovers between local firms) as well as cross-country differences in innovation policy (e.g. the level of public support for basic research or legal protection for intellectual property (IP)).

The national innovative capacity framework draws on three distinct areas of prior research: ideas-driven endogenous growth theory (Romer, 1990), the cluster-based theory of national industrial competitive advantage (Porter, 1990), and research on national innovation systems (Nelson, 1993).[1] Each of these perspectives identifies country-specific factors that determine the flow of innovation. These theories share a number of common analytical elements, but differ with respect to their levels of abstraction and the factors they emphasize. Whereas endogenous growth theory operates at a high level of abstraction, focusing on the economy-wide "knowledge stock" and the size of the R&D labor pool, the other two perspectives emphasize more nuanced determinants. For example, Porter highlights the microeconomic underpinnings of innovation in national industrial clusters (including the interaction between input supply and local demand conditions, the presence and orientation of related and supporting industries, and the nature and intensity of local rivalry), while the national innovation systems literature emphasizes the role of the overall national policy environment (e.g. IP or trade policy), higher education, and country-specific institutions (e.g. the funding approaches of specific agencies).

Our framework builds on these perspectives, characterizing national innovative capacity as the result of three building blocks. First, national innovative capacity depends on the presence of a strong common innovation infrastructure: cross-cutting factors contributing to innovativeness throughout the economy. Among other things, the common innovation infrastructure includes a country's overall science and technology policy environment, the mechanisms in place for supporting basic research and higher education, and the cumulative "stock" of technological knowledge upon which new ideas are developed and commercialized. The common innovation infrastructure therefore includes several of the elements highlighted by the national innovation systems perspective and ideas-driven growth theory. Second, a country's innovative capacity depends on the more specific innovation environments present in a country's industrial clusters. As emphasized by Porter (1990), whether firms invest and compete on the basis of new-to-the-world innovation depends on the microeconomic environment in which they compete, which will vary in different fields. Third, national innovative capacity depends on the strength of the linkages between the common innovation infrastructure and specific clusters. For example, a given common innovation infrastructure results in a more productive flow of innovative output when there are mechanisms or institutions, such as a vibrant domestic university system or established funding sources for new ventures, which encourage the commercialization of new technologies in particular clusters.

[1] While our framework is organized according to these three specific formulations, we incorporate insights from related studies in each research stream, including, among others, Jones (1995) and Kortum (1997) in the ideas-driven growth literature, Rosenberg (1963), and Carlsson and Stankiewicz (1991) on the relationship between innovation and industrial clusters and Mowery and Nelson (1999) on the linkages between industrial clusters and the national innovation system.

We use this framework to guide our empirical evaluation of the sources of cross-country differences in the production of innovative output. We do so by estimating the relationship between the production of "international" patents and observable measures of national innovative capacity. Our use of patent data to evaluate the rate of technological innovation is subject to several important (and well-known) limitations, including differences in the propensity to patent across different time periods, geographic regions, and technological areas. We attempt to address these issues by (a) using *international patents*; (b) establishing the robustness of our results to controls through the use of year and country dummies; and (c) carefully interpreting our findings in light of the potential for measurement error.[2] Also, since some elements of national innovative capacity (such as the environment for innovation in specific clusters) cannot be directly observed at the aggregate level, we employ measures reflecting more aggregate outcomes associated with the presence of these drivers.

Our results suggest that the production function for international patents is well-characterized by a small number of observable factors that describe a country's national innovative capacity. We distinguish between scale-based differences across countries (arising from differences in population or the level of inputs devoted to innovation) and productivity-based differences (i.e. differences in innovative output per unit of effort expended on the innovation process). While scale-related measures, such as total population, the size of the R&D workforce, or R&D spending have important explanatory power, more nuanced factors separately impact country-level R&D productivity. We find robust and quantitatively important evidence that R&D productivity varies with aggregate policy choices such as the extent of IP protection and openness to international trade, the shares of R&D *performed* by the academic sector and *funded* by the private sector, the degree of specialization by technology area (a proxy for cluster specialization) and each individual country's knowledge stock. We also find that the estimated level of national innovative capacity affects total factor productivity (TFP) growth and a nation's share of high-technology exports.

Our results provide evidence on the sources of differences in innovation intensity and R&D productivity across countries and over time. We find that there has been substantial *convergence* in the level of per capita national innovative capacity across the OECD since the mid-1970s. During the 1970s and early 1980s, the predicted level of per capita international patenting by United States and Switzerland substantially exceeded that of other OECD members. Since that time, several countries (most notably Japan, some Scandinavian countries, and Germany) have achieved levels of predicted per capita international patenting similar to that of United States and Switzerland. Interestingly, there are exceptions to the convergence pattern; for example, UK and France have shown little change in their measured level of national innovative capacity over the past quarter century.

The paper proceeds by motivating and developing our theoretical framework, outlining the relationship between "visible" innovative output and the elements of national innovative capacity, describing data and methods, and discussing our empirical results.

2. Theories of new-to-the-world innovation production

The national innovative capacity framework seeks to integrate three perspectives regarding the sources of innovation: ideas-driven growth theory, microeconomics-based models of national competitive advantage and industrial clusters, and research on national innovation systems. While these perspectives contain common elements, each highlights distinct drivers of the innovation process at the national level.

Ideas-driven growth theory, the most abstract conceptualization, focuses at an aggregate level, emphasizing the quantifiable relationships among a small set of factors that determine the flow of new ideas in an economy. While the centrality of technological

[2] In using international patenting data to understand the sources and consequences of innovation, this paper builds on Evenson (1984), Dosi et al. (1990), and recent work by Eaton and Kortum (1996, 1999). We extend these prior analyses by linking our results more closely to a range of theories about the determinants of national innovative capacity and by exploring a relatively long panel which allows us to incorporate both cross-sectional and time-series variation. As well, we supplement the patent analysis by examining alternative indicators of new-to-the-world innovative output, including scientific articles and export shares in "high-technology" industry segments.

innovation in economic growth has been appreciated since the seminal contributions of Solow (1956) and Ambramovitz (1956), it was only in the late 1980s that technological change was treated endogenously. The Romer (1990) growth model articulates the economic foundations for a sustainable rate of technological progress ($\dot{A}$) by introducing an ideas sector for the economy, which operates according the national ideas production function:

$$\dot{A}_t = \delta H_{\mathrm{A},t}^{\lambda} A_t^{\phi} \tag{1}$$

According to this structure, the rate of new ideas production is a function of the number of ideas workers (H_{A}) and the stock of ideas available to these researchers (A_t), making the rate of technological change endogenous in two distinct ways. First, the share of the economy devoted to the ideas sector is a function of the R&D labor market (which determines H_{A}); allocation of resources to the ideas sector depends on R&D productivity and the private economic return to new ideas. Second, the productivity of new ideas generation is sensitive to the stock of ideas discovered in the past. When $\phi > 0$, prior research increases current R&D productivity (the so-called "standing on shoulders" effect); when $\phi < 0$, prior research has discovered the ideas which are easiest to find, making new ideas discovery more difficult (the "fishing out" hypothesis). Though there is a sharp debate over the precise value of these parameters (Jones, 1995; Porter and Stern, 2001)[3] as well as the precise form and equilibrium logic of the model linking "ideas" production to economy-wide long-term productivity growth (Grossman and Helpman, 1991; Kortum, 1997; Silverberg et al., 1988), there is relatively broad agreement that these factors are, indeed, crucial in explaining the realized level of economy-wide innovation.

Whereas ideas-driven growth theory focuses almost exclusively on this important but limited set of factors, a number of authors have emphasized the importance of the microeconomic environment in mediating the relationship between competition, innovation, and realized productivity growth. Building on important studies such as Rosenberg (1963), which identifies interdependencies between aspects of the microeconomic environment and the realized rate of technological innovation and economic growth, Porter (1990) developed a framework enumerating the characteristics of the environment in a nation's industrial clusters that shape the rate of private sector innovation, and applied it in a sample of 10 countries over the post World War II period. As several researchers have emphasized, it is important to recognize the dynamics of innovation within clusters, and particularly the role of dynamic interactions between clusters and specific institutions—from universities to public institutes—within given geographic areas (Porter, 1990, 1998; Niosi, 1991; Carlsson and Stankiewicz, 1991; Audretsch and Stephan, 1996; Mowery and Nelson, 1999).

The Porter framework encapsulates these forces by identifying four key drivers (see Fig. 1). The first is the availability of high-quality and specialized innovation inputs. For example, while the overall availability of trained scientists and engineers (emphasized in ideas-driven growth theory) is important for economy-wide innovation potential, cluster-specific R&D productivity also depends on the availability of R&D personnel who are specialized in cluster-related disciplines. A second determinant is the extent to which the local competitive context is both intense and rewards successful innovators. This depends on general innovation incentives such as IP protection as well as cluster-specific incentives such as regulations affecting particular products, consistent pressure from intense local rivalry, and openness to international competition in the cluster (Sakakibara and Porter, 2000). A third determinant of cluster-level innovation is the nature of domestic demand for cluster producers and services. Innovation is stimulated by local demand for advanced goods and the presence of a sophisticated, quality-sensitive local customer base. Demanding customers encourage domestic firms to offer best-in-the-world technologies, and raise the incentives to pursue innovations that are globally novel. The final element in this framework is the availability,

[3] In Romer's model of sustainable long-term growth from new ideas, $\phi = \lambda = 1$, implying that a given percentage increase in the stock of ideas results in a proportional increase in the productivity of the ideas sector. Under this assumption, the growth rate in ideas is a function of the level of effort devoted to ideas production ($\dot{A}/A = \delta H_{\mathrm{A}}$), ensuring a sustainable rate of productivity growth. In contrast, Jones (1995) suggests that ϕ and λ may be less than 1, with the potential consequence of eliminating the possibility of sustainable long-term growth. However, in a companion paper, we suggest that, at least for explaining the dynamic process of producing visible innovation (i.e. patents), the hypothesis that $\phi = 1$ cannot be rejected (Porter and Stern, 2001).

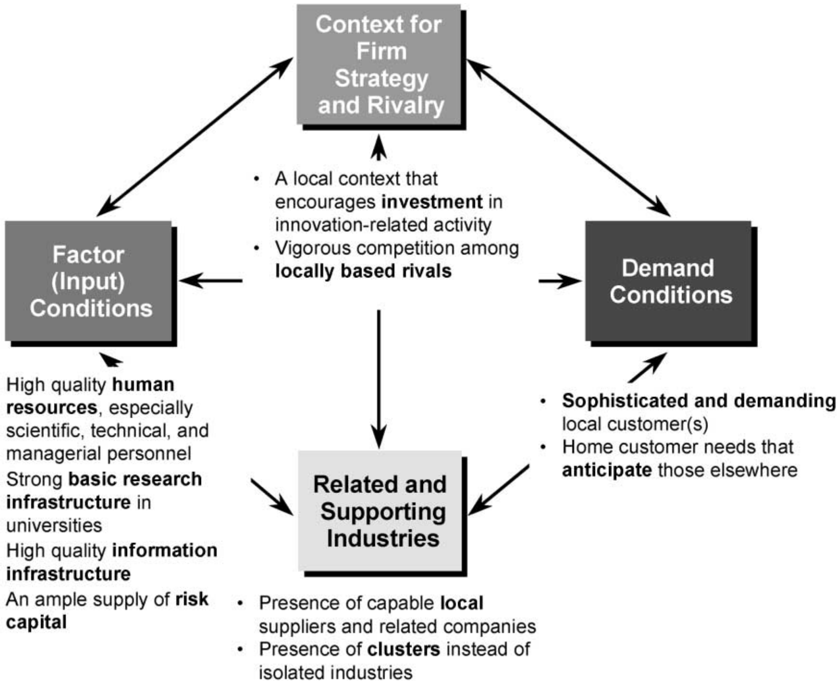

Fig. 1. The innovation orientation of national industry clusters.

density and interconnectedness of vertically and horizontally related industries. These generate positive externalities both from knowledge spillovers, transactional efficiencies, and cluster-level scale economies, which are enhanced when clusters are concentrated geographically. Overall, this framework suggests that the level of realized innovation in an economy depends upon the degree to which private R&D is fueled by innovation-based domestic competition.

The national innovation systems approach focuses on a textured description of the organization and patterns of activity that contribute to innovative behavior in specific countries, and identifies those institutions and actors who play a decisive role in particular industries, emphasizing the diversity in national approaches to innovation (see Nelson, 1993, for the most comprehensive account in this literature, as well as Dosi, 1988, and Edquist, 1997).[4] While both the ideas-driven growth models and theories of national industrial competitive advantage incorporate the role of public policies in shaping the rate of innovation (at least to some degree), the national innovation systems literature emphasizes the active role played by government policy and specific institutions. Particular institutional and policy choices highlighted by this literature include the nature of the university system (Nelson and Rosenberg, 1994), the extent of intellectual policy protection (Merges and Nelson, 1990), the historical evolution of the organization of industrial R&D (Mowery, 1984) and the division of labor between private industry, universities and government in R&D performance and funding (Mowery and Rosenberg, 1998).[5] Fig. 2 highlights some of the key components and linkages

[4] This perspective is first articulated in the papers by Nelson (1988), Lundvall (1988) and Freeman (1988) in part five of Dosi et al. (1988).

[5] More generally, this literature builds on insights about the historical relationship between the resource endowments and geographic structure of United States and the evolution of its institutions and industries relative to that of UK and the rest of Europe (Rosenberg, 1969, 1972; Nelson and Wright, 1992; Romer, 1996). Recent research in this literature particularly emphasizes the relationship between technological change, market structure, and institutions (see, especially, Mowery and Nelson, 1999).

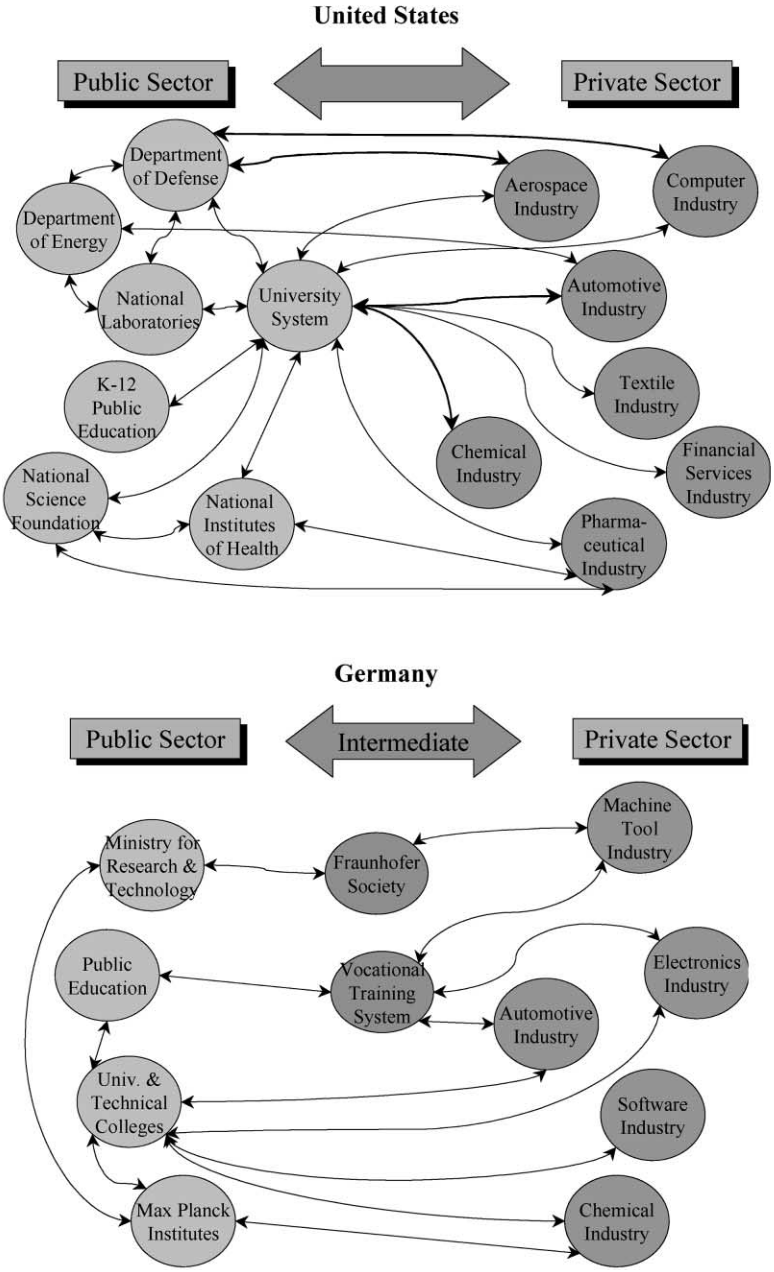

Fig. 2. A comparison of some important elements of the national innovation systems of United States and Germany.

in the national innovation systems of United States and Germany, as described in Nelson (1993).

These perspectives share a number of insights about the innovation process. For example, all three agree on the centrality of R&D manpower and the need for a deep local technology base. Without skilled scientists and engineers operating in an environment with access to cutting-edge technology, it is unlikely that a country will produce an appreciable amount of new-to-the-world innovative output.

Beyond these common elements, Porter highlights the way the flow of innovation is shaped by specialized inputs and knowledge, demand-side pressures, competitive dynamics, and externalities across related firms and industries; in contrast, the national innovation systems literature stresses the role played by a nation's scientific and innovation-oriented institutions and policies. Whereas idea-driven growth and cluster theory focus on the economic impact of geography (i.e. localized spillovers), the national innovation systems literature focuses more on the political implications of geography (i.e. the impact of national policies and institutions). While all three perspectives acknowledge the importance of both political and economic factors, prior work has not assessed how they interact in shaping the realized rate of innovation at the economy-wide level. This paper aims to contribute at this level, with an emphasis on a connection between underlying microeconomic forces and models of endogenous technical change, in part responding to the call of Patel and Pavitt (1994) for analysis that articulates "the essential properties and determinants of national systems of innovation".

3. National innovative capacity

National innovative capacity is defined as country's potential—as both an economic and political entity—to produce a stream of commercially relevant innovations. Innovative capacity depends in part on the overall technological sophistication of an economy and its labor force, but also on an array of investments and policy choices by both government and the private sector. Innovative capacity is related to but distinct from scientific and technical advances per se, which do not necessarily involve the economic application of new technology. Innovative capacity is also distinct from current national industrial competitive advantage or productivity, which results from many factors (such as the skills of the local workforce and the quality of physical infrastructure) that go beyond those important to the development and commercialization of new technologies. Differences in national innovative capacity reflect variation in both economic geography (e.g. the impact of knowledge and innovation spillovers among proximate firms) and innovation policy (e.g. the level of public support for basic research or protection for IP).

Technological opportunities are most likely to be exploited first in those countries whose environments are most conducive to the development of new-to-the-world technology. Given the sustained investment in innovative capacity in United States in the two decades after World War II, for example, it is not surprising that many of the most important scientific and technological breakthroughs of that era—including the transistor, the laser, electronic computing, and gene splicing—were developed and initially exploited by American universities and companies. Even though serendipitous technical or scientific advances may occur in countries with lower levels of innovative capacity, the development and commercialization of such advances is likely to take place in those countries with higher levels of innovative capacity. For example, while the British chemist Perkin was responsible for the initial discovery of aniline dye, the chemical sector emerged most strongly in Germany, at least in part due to Germany's stronger university–industry relationships and wider availability of capital for technology-intensive ventures (Murmann, 1998; Arora et al., 1998).

We divide determinants of national innovative capacity into three categories: the common pool of institutions, resource commitments, and policies that support innovation across the economy; the particular innovation environment in the nation's industrial clusters; and the linkages between them (see Fig. 3). The overall innovative performance of an economy results from the interplay among all three. [6]

3.1. Common innovation infrastructure

Some of the most important investments and policy choices that support innovative activity have broad impact throughout an economy—these are the common

[6] Our framework focuses on clusters (e.g. information technology) rather than individual industries (e.g. printers) as spillovers across industrial segments connect both the competitiveness and rate of innovation towards this more aggregate unit of analysis. In addition, while the current discussion focuses at the country level, we could also conduct our analysis at the regional level, with potentially important insights, as many of the most dynamic industrial clusters seem to be quite local in nature (Porter, 1990, 1998).

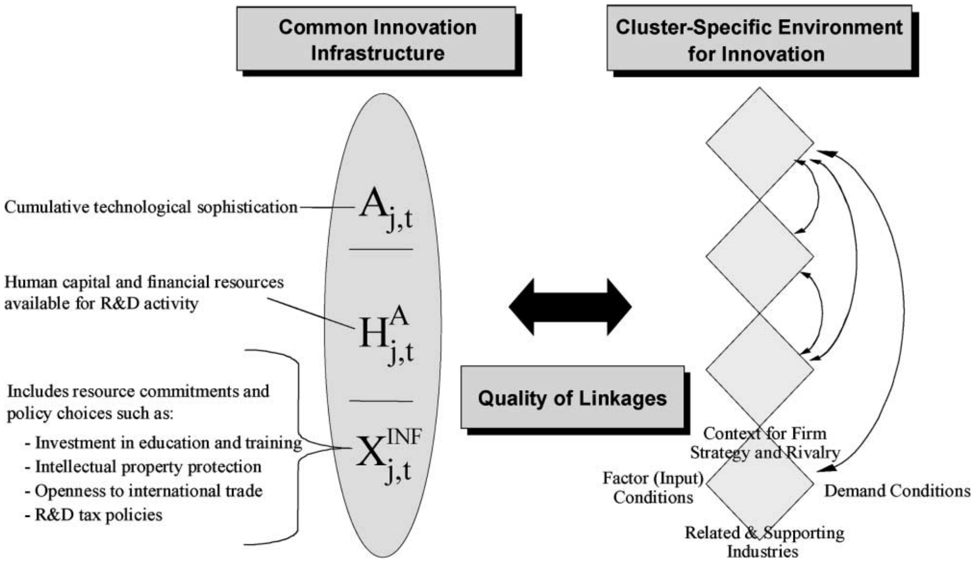

Fig. 3. National innovative capacity framework.

innovation infrastructure. The left-hand side of Fig. 3 portrays some of its elements. Endogenous growth theory highlights two important determinations of the production of ideas in an economy: an economy's aggregate level of technological sophistication (A) and the size of the available pool of scientists and engineers who may be dedicated to the production of new technologies (H_A). We expand on this conception to include other cross-cutting factors that impact innovative activity denoted by X^{INF}, including the extent to which an economy invests in higher education and public policy choices such as patent and copyright laws, the extent of R&D tax credits, the nature of antitrust laws, the rate of taxation of capital gains, and the openness of the economy to international competition.[7] It is important to note that the common innovation infrastructure incorporates both the overall scale of innovation inputs within an economy (H_A, the size of R&D employment and spending) as well as economy-wide sources of R&D productivity (A and X^{INF}).

[7] While some of these policies have stronger impact on some industries than others, e.g. intellectual property protection is especially salient for pharmaceutical innovation, these policies generally support innovation across a wide range of sectors in an economy.

3.2. The cluster-specific innovation environment

While the common innovation infrastructure sets the general context for innovation in an economy, it is ultimately firms, influenced by their microeconomic environment, that develop and commercialize innovation. Thus, national innovative capacity depends upon the microeconomic environment present in a nation's industrial clusters (as highlighted in Fig. 1 and the diamonds on the right-hand side of Fig. 3). A variety of cluster-specific circumstances, investments, and policies impact the extent to which a country's industrial clusters compete on the basis of technological innovation (Porter, 1990). 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. 3). Just as a strong cluster innovation environment can amplify the strengths of the common innovation infrastructure, a weak one can stifle them. For example, despite a strong infrastructure supporting scientific education and technical training in France, national regulatory policies towards pharmaceuticals have limited innovation in the French pharmaceutical cluster through 1970s and 1980s (Thomas, 1994).

3.3. The quality of linkages

The relationship between the common innovation infrastructure and industrial clusters is reciprocal: for a given cluster innovation environment, innovative output will tend to increase with the strength of the common innovation infrastructure (and vice versa). For example, while stringent local environmental regulations and well-developed supporting industries may encourage innovation-oriented competition in the environmental technologies cluster in Sweden, the ability of the Swedish cluster to generate and commercialize environmental innovations also depends in part on the overall availability of trained scientists and engineers, access to basic research, and overall policies which reward the development and commercialization of new technologies in the economy. The strength of linkages influences the extent to which the potential for innovation induced by the common innovation infrastructure is translated into specific innovative outputs in a nation's industrial clusters, thus shaping the realized rate of national R&D productivity. Linkages can be facilitated by various types of institutions, ranging from universities to cluster trade associations to informal alumni networks. In the absence of strong linking mechanisms, upstream scientific and technical activity may spill over to other countries more quickly than opportunities can be exploited by domestic industries. Germany took advantage of British discoveries in chemistry, for example, while three Japanese firms successfully commercialized VCR technology initially developed in United States (Rosenbloom and Cusumano, 1987). While the roles played by some particular linking mechanisms have been studied (from the Fraunhofer Institutes in Germany to MITI in Japan to the use of Cooperative Research and Development Associations (CRADAs) in United States), there have been few attempts to evaluate the impact of such institutions on international R&D productivity.

4. Modeling national innovative capacity

The national innovative capacity framework incorporates a wide set of both the economic and policy influences of national boundaries in explaining cross-country differences in the intensity of innovation. We therefore integrate prior research that focuses on the impact of geography on knowledge spillovers and differential access to human capital,[8] as well as the work that emphasizes how regional differences may be driven by differential public policies and institutions (Nelson, 1993; Ziegler, 1997). Our framework embodies the predictions of ideas-driven growth models while also including more nuanced factors, which have not been incorporated into formal models but may be important contributors to innovative output (such as those related to industrial organization, the composition of funding, and public policy). Finally, the framework highlights the potential importance of the *composition* of research funding and performance and the degree of technological specialization by a country's R&D sector. For example, while public R&D spending adds to the innovative process by reinforcing the common innovation infrastructure, private R&D spending and the specialization 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 (recall (1)). The national innovative capacity framework suggests that a broader set of influences determine innovative performance; hence, our framework suggests a production function for new-to-the-world technologies slightly more general than the Romer formulation:

$$\dot{A}_{j,t} = \delta_{j,t}(X^{\mathrm{INF}}_{j,t}, Y^{\mathrm{CLUS}}_{j,t}, Z^{\mathrm{LINK}}_{j,t}) H^{\mathrm{A}\lambda}_{j,t} A^{\phi}_{j,t} \tag{2}$$

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

[8] In addition to Porter (1990), see Jaffe et al. (1993), Krugman (1991), Saxenian (1994), Zucker, Darby and Brewer (1998), Audretsch and Stephan (1996), Glaeser et al. (1992), Bostic et al. (1996), Park (1995), Coe and Helpman (1995), and Keller (2000).

To these are added X^{INF}, which refers to the level of cross-cutting resource commitments and policy choices that constitute the common innovation infrastructure, Y^{CLUS}, which refers to the particular environments for innovation in a countries' industrial clusters, and Z^{LINK}, which captures the strength of linkages between the common infrastructure and the nation's industrial clusters. Under Eq. (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.

Deriving an empirical model from Eq. (2) requires addressing three issues: the source of statistical identification, the precise specification of the innovation output production function, and the source of the econometric error. Our choices with respect to each of these issues reflects our overarching goal of letting the data speak for itself as much as possible.

First, the parameters associated with Eq. (2) are estimated using a panel dataset of 17 OECD countries over 20 years. These estimates can therefore depend on cross-sectional variation, time-series variation, or both. Choosing among the two potential sources of identification depends on the production relationships to be highlighted in our analysis. 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 benefits (and pitfalls) associated with each identification strategy, our analysis explicitly compares how estimates vary depending on the source of identification. In most (but not all) of our analysis, we include either year dummies or a time trend in order to account for the evolving differences across years in the overall level of innovative output. Much of our analysis also includes either country dummies or measures which control for aggregate differences in technological sophistication (e.g. as reflected in GDP PER CAPITA).[9] The analysis is organized around a log–log specification, except for qualitative variables or 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 (Jones, 1998). 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:

$$\begin{aligned}\mathrm{L}\,\dot{A}_{j,t} = {} & \delta_{\mathrm{YEAR}}\mathrm{YEAR}_t + \delta_{\mathrm{COUNTRY}} C_j \\ & + \delta_{\mathrm{INF}}\mathrm{L}\,X^{\mathrm{INF}}_{j,t} + \delta_{\mathrm{CLUS}}\mathrm{L}\,Y^{\mathrm{CLUS}}_{j,t} \\ & + \delta_{\mathrm{LINK}}\mathrm{L}\,Z^{\mathrm{LINK}}_{j,t} + \lambda\,\mathrm{L}\,H^{\mathrm{A}}_{j,t} \\ & + \phi\mathrm{L}\,A_{j,t} + \varepsilon_{j,t}\end{aligned} \tag{3}$$

Conditional on a given level of R&D inputs (H^{A}), variation in the production of innovation ($\dot{A}$) reflects R&D productivity differences across countries or 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 $\dot{A}_{j,t}$, 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.

5. The data

Implementing Eq. (3) requires that each of the concepts underlying national innovative capacity be tied

[9] By controlling for year and country effects in most of our analysis, we address some of the principal endogeneity and autocorrelation concerns. However, we have extensively checked that the results reported in Section 5 are robust to various forms of autocorrelation (results available on request) and have investigated the potential for endogeneity more fully in related work (Porter and Stern, 2001).

to observable measures. We employ a novel dataset of patenting activity and its determinants in a sample of 17 OECD countries from 1973 to 1996. Our results, then, describe the relationship between measured innovative inputs and outputs in highly industrialized economies. Table 1 defines and provides sources for all variables; Table 2 reports the means and standard deviations, and Appendix A lists all included countries and reports pairwise correlations. We draw on several sources in constructing these data, including United States patent and trademark office (USPTO), CHI research, the OECD basic science and technology statistics, NSF science and engineering indicators, the World Bank, the Penn world tables, and the IMS world competitiveness report. [10]

5.1. The measurement of visible innovative output

Our analysis requires a consistent country-specific indicator of the level of commercially valuable innovative output in a given year. We employ a variable based on the number of "international patents" (PATENTS), which is 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 United States, PATENTS is equal to the number of patents granted to corporate or government establishments (this excludes individual inventors); to ensure that this asymmetry between US and non-US patents does not affect our results we include a US dummy variable in our regressions. [11]

The pitfalls associated with equating patenting with the level of innovative activity are widely recognized (Schmookler, 1966; Pavitt, 1982, 1988; Griliches, 1984, 1990; Trajtenberg, 1990). As Griliches (1990, p. 1669) points out, "not all inventions are patentable, not all inventions are patented, and the inventions that are patented differ greatly in 'quality', in the magnitude of inventive output associated with them". We address these limitations, in part, by constructing PATENTS to include only commercially significant innovations at the world's technical frontier and by carefully testing the measure for robustness. First, since obtaining a "foreign" patent is a costly undertaking that is only worthwhile for organizations anticipating a return in excess of these substantial costs. Second, USPTO-granted "international" patenting (PATENTS) constitutes a measure of technologically and economically significant innovations at the world's commercial technology frontier that should be consistent across countries. [12] Third, we are careful to accommodate the potential for differences in the propensity to apply for patent protection across countries and over time (as highlighted by Scherer, 1983) by evaluating robustness of our results to year- and country-specific fixed effects.

Even with these checks, we recognize that that the "true" rate of technological innovation is unobservable and PATENTS is but an imperfect proxy for the level of new-to-the-world innovation. With this in mind, we explore the precision of the statistical relationship between PATENTS and our measured drivers of national innovative capacity (i.e. how well do the small number of factors employed in our analysis explain this "noisy" measure of the innovation process?) and our interpretations take into account likely sources of bias arising from specific variables (i.e. are there reasons that our findings are driven by the PATENTS measure rather the level of innovation per se?). Ultimately, our approach is based on the assessment that patenting rates constitute "the only observable manifestation of inventive activity with a well-grounded claim for universality" (Trajtenberg, 1990, p. 183), a judgment reflected in prior work employing international patent data (Evenson, 1984; Dosi et al., 1990; Cockburn and Henderson, 1994; Eaton and Kortum, 1996, 1999; Kortum, 1997; Vertova, 1999).

Across the sample, the average number of PATENTS produced by a country in a given year is 3986 (with S.D. of 8220). PATENTS has increased over time, reaching a peak in the final year of the

[10] To ensure comparability across countries and time, we subjected each measure to extensive analysis and cross-checking, including confirming that OECD data were consistent with comparable data provided by individual national statistical agencies. When appropriate, we interpolated missing values for individual variables. For example, most countries report educational expenditure data only once every other year; our analysis employs the average of the years just preceding and following a missing year. Financial variables are in PPP-adjusted 1985 $US.

[11] We have also analyzed our results using the number of US patents filed in at least one other international jurisdiction, and there are no qualitative differences in any of our results (results available from the authors).

[12] See Eaton and Kortum (1996, 1999) for a thorough discussion of the economics of international patenting.

Table 1
Variables and definitions[a]

Variable		Full variable name	Definition	Source
Innovative output				
	$\text{PATENTS}_{j,t+3}$	International patents	Patents granted in United States to the establishments in country j in year $(t+3)$; for United States, the number of patents issued to US investors associated with an institution such as a company, governmental body, & university	CHI US patent database
	$\text{PATENTS/MILLION POP}_{j,t+3}$	International patents per million persons	PATENTS divided by million persons in the population	CHI US patent database
Quality of the common innovation infrastructure				
A	$\text{GDP PER CAPITA}_{j,t}$	GDP per capita	Gross domestic product in thousands of PPP-adjusted 1985 US$	World Bank
A	$\text{PATENT STOCK}_{j,t}$	Stock of international patents	Cumulative PATENTS from 1973 until $(t-1)$	CHI US patent database
H^{A}	$\text{POP}_{j,t}$	Population	Population (millions of persons)	OECD science and technology indicators
H^{A}	$\text{FTE S\&E}_{j,t}$	Aggregate employed S&T personnel	Full-time equivalent scientists and engineers in all sectors	OECD science and technology indicators
H^{A}	$\text{R\&D \$}_{j,t}$	Aggregate R&D expenditures	R&D expenditures in all sectors in millions of PPP-adjusted 1985 US$	OECD science and technology indicators
X^{INF}	$\text{OPENNESS}_{j,t}$	Openness to international trade and investment	Average survey response by executives on a 1–10 scale regarding relative openness of economy to international trade and investment	IMD World Competitiveness Report
X^{INF}	$\text{IP}_{j,t}$	Strength of protection for IP	Average survey response by executives on a 1–10 scale regarding relative strength of IP	IMD world competitiveness report
X^{INF}	$\text{ED SHARE}_{j,t}$	Share of GDP spent on higher education	Public spending on secondary and tertiary education divided by GDP	World Bank
X^{INF}	$\text{ANTITRUST}_{j,t}$	Stringency of antitrust policies	Average survey response by executives on a 1–10 scale regarding relative strength of national antitrust policies	IMD world competitiveness report

Table 1 (*Continued*)

Variable		Full variable name	Definition	Source
Cluster-specific innovation environment				
Y^{CLUS}	PRIVATE R&D FUNDING$_{j,t}$	Percentage of R&D funded by private industry	R&D expenditures funded by industry divided by total R&D expenditures	OECD science and technology indicators
Y^{CLUS}	SPECIALIZATION$_{j,t}$	E–G concentration index	Relative concentration of innovative output in chemical, electrical, and mechanical USPTO patent classes	Author computation from USPTO data
Quality of linkages				
Z^{LINK}	UNIV R&D PERFORMANCE$_{j,t}$	Percentage of R&D performed by universities	R&D expenditures performed by universities divided by total R&D expenditures	OECD science and technology indicators
Z^{LINK}	VC$_{j,t}$	Strength of venture capital markets	Average survey response by executives on a 1–10 scale regarding relative strength of venture capital availability	IMD world competitiveness report
Contributing and related outcome factors				
	JOURNALS$_{j,t}$	Publications in academic journals	Number of publications in international academic journals, using 1981 journal set	CHI database of Science Citation Index
	GDP$_{j,t}$	Gross domestic product	Gross domestic product in billions of PPP-adjusted 1985 US$	Penn World Tables
	LABOR$_{j,t}$	Labor force	Number of full-time equivalent persons employed in the labor force	Penn World Tables
	CAPITAL$_{j,t}$	Capital	Non-residential capital stock in billions of PPP-adjusted 1985 US$	Penn World Tables
	MARKET SHARE$_{j,t}$	Market share	Share of exports in high-technology industries (among countries in our sample)	National Science Foundation

[a] The natural logarithm of a variable, X, is denoted LX.

Table 2
Mean and S.D.

Variable		N	Mean	S.D.
Innovative output				
	PATENTS	378	3986.23	8219.89
	PATENTS/MILLION POP	378	3.73	1.02
Quality of the common innovation infrastructure				
A	GDP/POP	357	18.66	5.10
A	PATENT STOCK	357	38016.59	98252.46
H^{A}	POP	357	42.4	57.1
H^{A}	FTE S&E	353	226344.60	407124.50
H^{A}	R&D $	355	12859.86	27930.46
X^{INF}	ED SHARE	351	3.08	1.20
X^{INF}	IP	162	6.87	0.97
X^{INF}	OPENNESS	216	7.00	1.10
X^{INF}	ANTITRUST	162	5.75	1.09
Cluster-specific innovation environment				
Y^{CLUS}	PRIVATE R&D FUNDING	355	48.60	12.88
Y^{CLUS}	SPECIALIZATION	357	0.02	0.03
The quality of linkages				
Z^{LINK}	UNIV R&D PERFORMANCE	355	21.50	6.20
Z^{LINK}	VENTURE CAPITAL	214	5.45	1.32
Contributing and related outcome factors				
	JOURNALS	378	17446.39	28621.21
	GDP	357	772.44	1161.64
	LABOR	321	18.10	25.60
	CAPITAL	306	550.00	795.00
	TFP	304	1.42	0.21
	MARKET SHARE	357	5.88%	6.85%

sample (when the average level of PATENTS is equal to 5444). Fig. 4 reports two country-level measures of differences in the intensity of innovation across countries. The first panel explores the most aggregate relationship, PATENTS PER CAPITA (in terms of population, in millions), while the second panel provides a first glance of R&D productivity, the level of PATENTS per unit of effort *devoted* to innovation, as measured by the number of full-time equivalent scientists and engineers (PATENTS PER FTE S&E).[13] While the latter corresponds more closely to a traditional productivity measure, the former provides a greater sense of total innovation output relative to total inputs which *could* be devoted to innovation.

Three facts stand out. First, countries differ markedly in their production of international patents per capita and per unit of effort devoted to innovation. Second, at the beginning of the sample, the only country with a per capita patenting rate similar to that of United States is Switzerland, and the only additional country with a similar level of PATENTS PER FTE S&E is Sweden.[14] Third, there is noticeable narrowing over time in the gap between countries. This *convergence* is most apparent for Japan, but also is evident for most (though not all) other OECD countries.

We also explore several alternative output measures to PATENTS that are less comparable across countries and likely to be less closely linked to the

[13] Several alternative measures of productivity could be constructed (e.g. PATENTS per unit of R&D expenditure) and are available upon request.

[14] Recall that US patenting level is determined by the number of patents issued to US inventors associated with an institution such as a company, governmental body, or university.

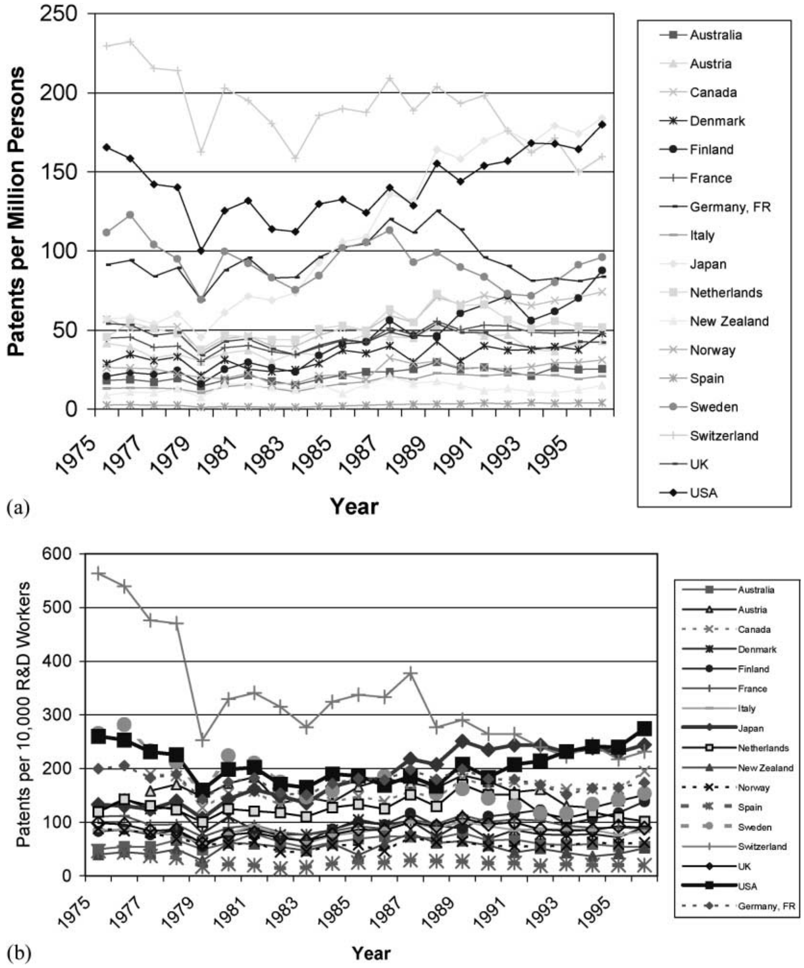

Fig. 4. (a) International patents per million persons; and (b) International patents per 10,000 FTE S&E.

level of new-to-the-world innovative output. The level of publication in scientific journals (JOURNALS), although a product of inventive effort, is more an upstream indicator of scientific exploration than of commercially significant innovation. We examine two more downstream measures of the impact of national innovative capacity: the realized market share of a country in "high-technology" industries (MARKET SHARE) and a measure of TFP, defined as the level of GDP controlling for the levels of CAPITAL and LABOR. Both MARKET SHARE and TFP should depend on national innovative capacity over the long-run. In the near term, however, both measures will be affected by other determinants of overall competitiveness, including microeconomic factors and macroeconomic factors that affect impact competitiveness but are only indirectly related to the rate of innovation. [15]

[15] Several measures of technological output are neither available nor usefully comparable across countries or time. For example, the level of technology licensing revenues realized by a country captures activity in some technology areas, but in practice is not nearly broad-based enough to have a well-founded claim for comparability. While measures such as copyrights and trademarks are direct indicators of innovative output in certain industries (e.g. software), the lack of comparability of these data across countries and time limits their usefulness for our analysis.

5.2. Measuring national innovative capacity

To estimate a model consistent with our framework, we require measures of a nation's common innovation infrastructure, the innovation environment in its industrial clusters, and the nature of the linkages between these elements. For the common innovation infrastructure, a number of relatively direct measures are available; however, direct measures of the cluster innovation environment and the quality of linkages are not available for international data. We address this challenge by employing intermediate measures or proxies that capture important economic outcomes associated with strength in these areas.

The common innovation infrastructure consists broadly of a country's knowledge stock, the overall level of human and capital resources devoted to innovative activity, and other broad-based policies and resource commitments supporting innovation. Our analysis explores two distinct measures for knowledge stock at a given point in time ($A_{j,t}$): GDP PER CAPITA and the sum of PATENTS from the start of the sample until the year of observation (PATENT STOCK).[16] Although both measure the overall state of a country's technological development, they differ in important ways. GDP PER CAPITA captures the ability of a country to translate its knowledge stock into a realized state of economic development (and so yields an aggregate control for a country's technological sophistication). In contrast, PATENT STOCK constitutes a more direct measure of the country-specific pool of new-to-the-world technology.

We measure the level of capital and labor resources devoted to the ideas-producing sector using each country's number of full-time-equivalent scientists and engineers (FTE S&E) and gross expenditures on R&D (R&D $). While individual R&D and engineering efforts will tend to be specialized in particular technical and scientific areas, the outputs of R&D impact a variety of economic sectors via direct application or as a basis for future efforts (Rosenberg, 1963; Glaeser et al., 1992). Hence, we classify the overall supply of innovation-oriented labor and capital as key elements of the common innovation infrastructure. We also include population (POP) in H^{A}, since the total size of a country indicates the scale of resources (workers) potentially available for innovative activity.

There is evidence for convergence in the level of resources devoted to R&D activity (Fig. 5). FTE S&E per capita has generally increased among OECD countries and growth has been higher for those countries whose initial levels were lower. Growth in FTE S&E per capita over the sample period has been particularly high in Japan and the Scandinavian countries, while UK and United States actually experienced small declines in FTE S&E per capita. R&D $ also displays a similar though less pronounced pattern of convergence.

The common innovation infrastructure also encompasses national policies and other resource commitments that broadly affect innovation incentives and R&D productivity throughout the economy. We include the fraction of GDP spent on secondary and tertiary education (ED SHARE) as a measure of the intensity of human capital investment. A high level of ED SHARE creates a base of highly skilled personnel upon which firms and other institutions across the economy can draw, both for formal R&D activities as well as other innovation-related activities. We also measure some policy choices that particularly affect the environment for innovative activity including the relative strength of IP protection, the relative stringency of country's antitrust policies (ANTITRUST), and the relative openness of a country to international trade and competition (OPENNESS). Controlling for resources, we expect the level of each of these three policy variables (measured on a 1–10 Likert scale)[17] to be positively related to the productivity of international patenting.[18] Given that these variables are drawn from an imperfect survey instrument, however, each captures the underlying concept only with inevitable noise.

[16] See Porter and Stern (2001) for a derivation and thorough discussion of differences between these two measures.

[17] IP, OPENNESS, and ANTITRUST are average (1–10) Likert score variables from the IMD World Competitiveness Report, an annual survey in which leading executives rank their perceptions of countries' circumstances along a variety of dimensions relevant to international competitiveness. These variables become available in the late 1980s (between 1986 and 1989 depending on the variable). The analysis corrects for missing values by including a dummy variable which is equal to one in years where these measures are unavailable.

[18] Note, as well, that each of these policy measures may increase the level of resources devoted towards innovation; however, our analysis focuses on the productivity effects of these policies.

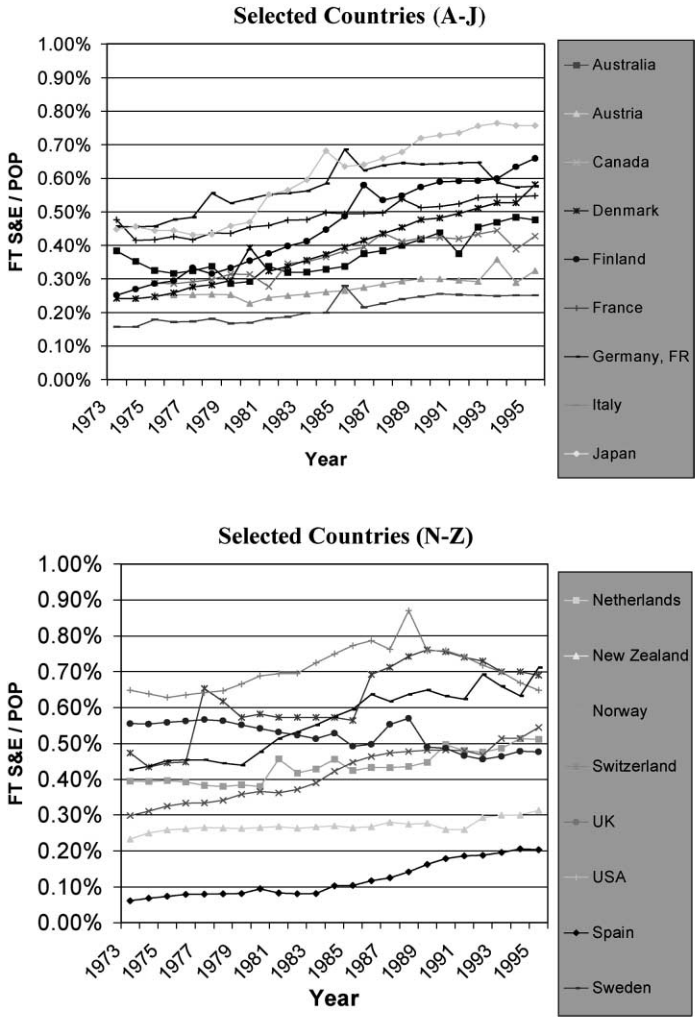

Fig. 5. FTE S&E as a percentage of population selected countries (A–J) and (N–Z).

While the common innovation infrastructure is quite amenable to measurement, the environment for innovation in a nation's industrial clusters is difficult to measure because of the subtlety of the concepts involved as well as the lack of systematic international data. Indeed, the aggregate framework offered here clearly cannot provide a test of the nuanced and distinct implications of the national industrial cluster framework. For example, providing evidence that innovation is driven by the interactions among complementary industry segments versus rivalry within industrial segments requires a level of detail which cannot be addressed in the current context.[19] Instead, we use the detailed qualitative and quantitative insights arising from prior research on industrial clusters to develop intermediate measures that are consistent with the outcomes of innovation-oriented cluster-level dynamics.

First, we employ the intensity of privately financed R&D activity in an economy to measure the collective importance of innovation-based competition across clusters. Conditional on the overall level of R&D

[19] See, however, Porter and Stern (2001).

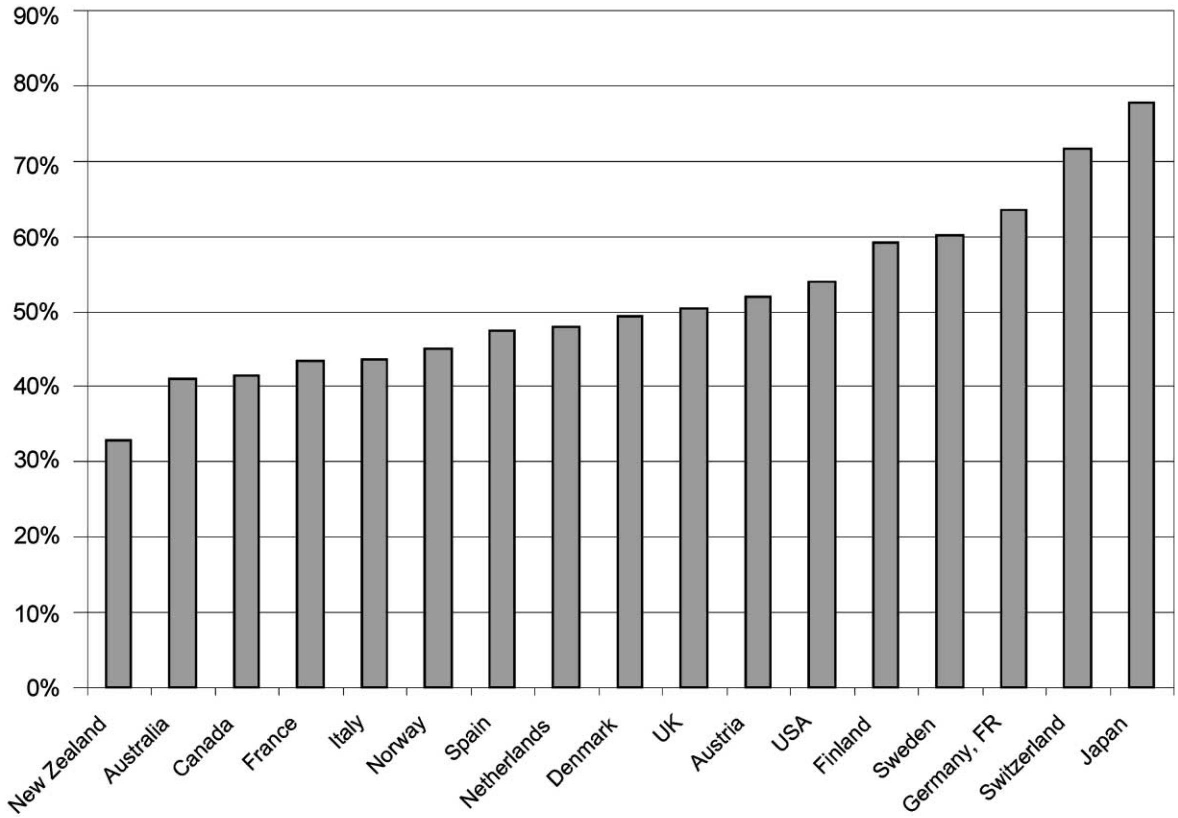

Fig. 6. Percent of R&D expenditure funded by industry.

investment in an economy, the fraction of total R&D spending conducted by the private sector (PRIVATE R&D FUNDING) provides a useful summary indicator of the vitality of the environment for innovation in national industrial clusters that is comparable across countries and available for an international sample. [20] This measure does not, of course, explicitly portray the subtle implications of industrial clusters, but does reflect a broader theme arising from that perspective: the productivity of innovative investment will depend on whether private firms within the economy are choosing to direct resources towards that end. Fig. 6 demonstrates the variance in this measure. In 1990, for example, companies financed between 40 and 60% of R&D in most countries (Japan and Switzerland are outliers with over 70%). Interestingly, the traditionally social market economy of Finland is near the top of the range of this measure; the high private sector role in R&D is directly related to Finland's globally competitive and innovation-driven telecommunications cluster.

Second, since individual clusters will tend to be associated with technologies from specific technological areas, we calculate a measure of the degree of technological focus by a country (SPECIALIZATION) as a proxy for the intensity of innovation-based competition in a nation's clusters. SPECIALIZATION is a "relative" concentration index based on the degree to which a given country's USPTO-granted patents are concentrated across the three (relatively broad) technology classes (chemical, electronics, and

[20] Other measures, such as the average private R&D-sales ratio, may be more ideal for this purpose, but comparable cross-country data are not available. Also, we do not include higher-order terms since we are focusing on the first-order impact of these measures in their observed range rather than calculating their predicted impact outside of the observed range or solving for the "optimal" level of such measures.

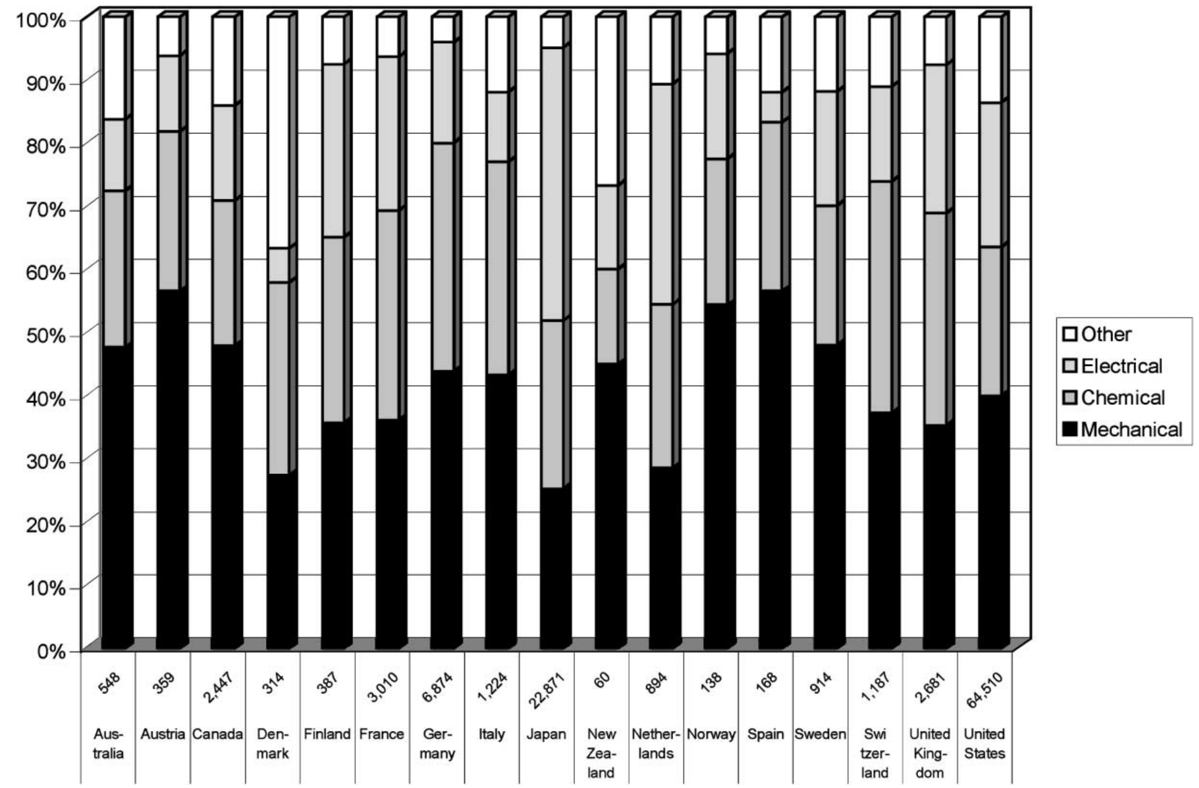

Fig. 7. Composition of USPTO patent grants by technological class, 1995.

mechanical). While our measure of specialization is too coarse 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. Fig. 7 demonstrates that countries differ in the shares of their patents associated with each area. We use this classification system to develop a measure of specialization appropriate for our context. Specifically, traditional measures of specialization, such as the Herfindahl (which in this context would be equal to $\sum_{i=\mathrm{ELEC,CHEM,MECH}}(\mathrm{PATENTS}_{i,t}/\mathrm{TOTAL\ PATENTS}_t)^2 = \sum_i s_{i,t}^2$), ignore two issues important for cross-country comparisons: (a) technology classes differ in terms of their average share across all countries (e.g. the mechanical class has the highest average share); and (b) some countries have only a small number of patents overall.[21] We overcome these concerns by using a methodology developed by Ellison and Glaeser (1997; hereafter, E–G). While the E–G index was developed and applied for measuring the specialization of industries across geographic regions (Ellison and Glaeser, 1997), it has been applied in several other contexts, including the measurement of the degree of specialization of research output (Lim, 2000). In the present context, the E–G formula adjusts the country observed shares for each technology class to account for (a) the average share for that technology group (across the sample); and (b) for the total number of patents in each "country–year" observation.

[21] When a country has only a very small number of patents in a given year, it is possible to overstate the degree of specialization. In the extreme, if a country only produces a single patent, its patent "portfolio" will necessarily be confined to only a single technology class.

Allowing x_i to be the average share of patent class i across all country–years, the E–G index is

$$\text{SPECIALIZATION}_{i,j,t} = \left(\frac{\text{PATENTS}_{i,j,t}}{\text{PATENTS}_{i,j,t}-1}\right)\left(\frac{\sum_i (s_{i,j,t}-x_i)^2}{1-\sum_i x_i^2} - \frac{1}{\text{PATENTS}_{i,j,t}}\right)$$

Essentially, this measure captures the degree to which PATENTS are specialized in country i in year t across each technology class j (note that its mean is just above 0, reflecting the fact that the "average" country, by construction, has an average level of concentration). For example, consistent with Japan's strength in the electronics cluster (see Fig. 7), its patenting is concentrated in electronics and its SPECIALIZATION measure (in 1995) is equal to 0.125, more than 3 S.D. above the mean.[22] Like PRIVATE R&D FUNDING, SPECIALIZATION is a noisy but potentially useful and unbiased measure of the underlying strength and environment for innovation in a nation's industrial clusters.

The final element of our framework, the strength of linkages between industrial clusters and the common innovation infrastructure and vice versa, is similarly difficult to quantify directly. The mechanisms for scientific and technological transfer vary both across countries and over time. Our analysis considers two mechanisms that qualitative research suggests are relatively consistent contributors to the strength of linkages: the importance of the university sector in R&D performance, measured by the share of total R&D accounted for by universities (UNIV R&D PERFORMANCE), and the availability of venture-backed (VC) financing. University research tends to be more accessible to researchers in industry than government laboratory research, and universities provide a forum for the exchange of ideas between different R&D communities. The unique role that universities play in training future industrial researchers suggests another way in which common resources for innovation (i.e. S&E graduate students) are mobilized in a nation's industrial clusters. VC (measured as a 1–10 Likert scale variable by the IMD Competitiveness Report, 1989–1999) captures the degree to which risk capital is available to translate scientific and technological outputs into domestic opportunities for further innovation and commercialization.

6. Empirical results

Our empirical results are presented in three parts. First, we present the paper's primary results, which evaluate the determinants of the production of new-to-the-world technologies. Second, we explore the downstream consequences of national innovative capacity through its impact on TFP and high-technology MARKET SHARE. The final section discusses the patterns in national innovative capacity implied by the estimates over the sample period.

6.1. Determinants of the production of new-to-the-world technologies

Tables 3–7 present a broad range of results regarding the relationship between innovative output (PATENTS_{t+3})[23] and the drivers of national innovative capacity ($A_{j,t}$, $H^{\text{A}}_{j,t}$, $X^{\text{INF}}_{j,t}$, $Y^{\text{CLUS}}_{j,t}$, $Z^{\text{LINK}}_{j,t}$) that highlight the main relationships in the data as well as the source of variation underlying particular findings. Overall, we find a robust and relatively precise relationship between PATENTS and measures associated with each component of national innovative capacity: the common innovation infrastructure, the cluster-specific innovation environment, and the linkages between these two areas.

Table 3 evaluates a series of pairwise relationships between PATENTS and several measures of country size and the total level of R&D inputs: POP, GDP, FTE S&E, and R&D \$. Since these measures are highly correlated with each other (see Appendix A), it is useful to establish the unconditional relationship between each and PATENTS. Individually, each measure explains between two-thirds and 90% of the overall variation in PATENTS. The coefficients range from 0.98

[22] The data used in these calculations are from Technological Assessment and Forecast Reports (USPTO, 2000a,b,c), which also define the patent classes included in the chemical, electrical, and mechanical categories.

[23] Recall that we evaluate the relationship of PATENTS in year $t+3$ to the level of the contributors to innovative capacity in year t and that our main results are robust to changes in this lag structure.

Table 3
Simple regressions on scale-dependent measures

	Dependent variable = ln(PATENTS)$_{j,t+3}$				
	Population only (3.1)	FTE S&E only (3.2)	R&D expenditures only (3.3)	GDP only (3.4)	L PATENT STOCK and YEAR (3.5)
L POP	1.159 (0.042)				
L FTE S&E		1.168 (0.022)			
L R&D $			0.982 (0.027)		
L GDP				1.297 (0.033)	
L PATENT STOCK					0.971 (0.011)
YEAR					−0.100 (0.003)
R^2	0.682	0.892	0.892	0.811	0.958

to 1.30, suggesting only a modest departure from constant returns-to-scale. These results demonstrate that a large fraction of the variance in PATENTS can be explained by single measures of a country's size or effort devoted to R&D. However, these models provide little intuition regarding the forces that drive national innovative output. The question remains whether more nuanced factors have a separate and quantitatively important impact on national innovative output distinct from these scale-dependent measures.

Table 4 begins with a specification similar to the formal model of the national ideas production function suggested by Romer (1990) and Jones (1995). In the first regression (4.1), we see that PATENTS is increasing in two variables suggested by endogenous growth theory, L GDP and L FTE S&E. Interpreting the coefficients as elasticities, (4.1) implies that, ceteris paribus, a 10% increase in GDP is associated with slightly more than a 10% rise in international patent output. As suggested by proponents of endogenous growth, a country's existing level of technological sophistication and the level of inputs devoted to R&D play key roles in determining innovative output. After controlling for the level of GDP and FTE S&E, POP has a negative coefficient; the lower the implied level of GDP PER CAPITA, the lower the flow of new-to-the-world innovation.

We include the remainder of the measures of H^{A} and X^{INF} in (4.2). This specification (along with (4.3) and (4.4)) also includes year-specific fixed effects to control for variation arising from changes in the rate of patent grants per year. With the exception of ANTITRUST, each of the measures of the common innovation infrastructure affects international patenting significantly, with the expected sign, and with an economically important magnitude (note also that these regressors have only a modest impact on the coefficients associated with L GDP). Perhaps more interestingly, the sum of the coefficients on L R&D $ and L FTE S&E in (4.2) is quite similar to the single coefficient on L FTE S&E in (4.1). In other words, the total impact of R&D inputs (in terms of aggregate labor and capital) devoted to innovation is similar whether we focus on a single variable (e.g. FTE S&E in (4.1)) or include both measures (e.g. FTE S&E and R&D $ in (4.2)).

After controlling for L R&D $ and L FTE S&E (R&D inputs), the remaining coefficients can be interpreted as economy-wide factors affecting national R&D productivity. The elements of X^{INF} are expressed as Likert scale measures (IP, OPENNESS, and ANTITRUST) and as shares of GDP (ED SHARE). Given the relative crudeness and limited availability of these measures, it is striking that these variables enter significantly, suggesting that policy variation has an important role to play in determining R&D productivity.[24] The coefficients associated with the Likert scale measures will measure the predicted percentage change in PATENTS which would result from a one unit change in that variable (e.g. from a value of 3–4). For example, the coefficients on IP (0.22) and OPENNESS (0.10) imply that a one-point increase in these Likert

[24] Indeed, given the noisy nature of the Likert variables and the fact that poorly designed antitrust policies can stifle rather than stimulate innovation (e.g. by expropriating the returns from successful R&D efforts), it is perhaps not surprising that the model does not identify a separate impact for the ANTITRUST variable.

Table 4
Determinants of the production of new-to-the-world technologies (GDP/POP as knowledge stock)

		Dependent variable = ln(PATENTS)$_{j,t+3}$			
		Ideas production function (4.1)	Common innovation infrastructure (4.2)	National innovative capacity: including all variables (4.3)	National innovative capacity: preferred model (4.4)
Quality of the common innovation infrastructure					
A	L GDP	1.034 (0.131)	1.067 (0.122)		
A	L GDP PER CAPITA			0.876 (0.102)	0.903 (0.098)
H_{A}	L POP	−1.337 (0.086)	−1.217 (0.087)		
H_{A}	L FTE S&E	1.407 (0.072)	0.988 (0.070)	0.891 (0.045)	0.899 (0.044)
H^{A}	L R&D $		0.343 (0.047)	0.259 (0.044)	0.251 (0.043)
X^{INF}	ED SHARE		0.101 (0.017)	0.153 (0.016)	0.152 (0.015)
X^{INF}	IP		0.246 (0.056)	0.208 (0.050)	0.196 (0.044)
X^{INF}	OPENNESS		0.085 (0.033)	0.066 (0.031)	0.068 (0.029)
X^{INF}	ANTITRUST		−0.061 (0.050)	−0.036 (0.045)	
Cluster-specific innovation environment					
Y^{CLUS}	PRIVATE R&D FUNDING			0.014 (0.002)	0.014 (0.002)
Y^{CLUS}	SPECIALIZATION			2.605 (0.673)	2.705 (0.659)
Quality of the linkages					
Z^{LINK}	UNIV R&D PERFORMANCE			0.007 (0.003)	0.008 (0.003)
Z^{LINK}	VENTURE CAPITAL			0.016 (0.021)	
Controls					
Year fixed effects			Significant	Significant	Significant
US dummy			−0.239 (0.092)	0.053 (0.089)	0.060 (0.087)
Constant		−11.213 (0.394)			
R^2		0.9400	0.9684	0.9752	0.9752
Adjusted R^2		0.9394	0.9655	0.9727	0.9728
Observations		353	347	347	347

Table 5
Determinants of the production of new-to-the-world technologies (using patent stock as knowledge stock)

		Dependent variable = ln(PATENTS)$_{j,t+3}$		
		Baseline ideas production function (with year FTE) (5.1)	Common innovation infrastructure (5.2)	National innovative capacity: preferred model (5.3)
Quality of the common innovation infrastructure				
A	L PATENT STOCK	1.174 (0.072)	0.605 (0.040)	0.478 (0.039)
H^{A}	L FTE S&E	0.431 (0.062)	0.388 (0.050)	0.544 (0.051)
H^{A}	L R&D $		0.011 (0.040)	0.069 (0.037)
X^{INF}	ED SHARE		0.034 (0.014)	0.073 (0.014)
X^{INF}	IP		0.104 (0.044)	0.080 (0.033)
X^{INF}	OPENNESS		−0.011 (0.027)	−0.001 (0.023)
X^{INF}	ANTITRUST		−0.010 (0.027)	
Cluster-specific innovation environment				
Y^{CLUS}	PRIVATE R&D FUNDING			0.009 (0.002)
Y^{CLUS}	SPECIALIZATION			3.220 (0.555)
Quality of the linkages				
Z^{LINK}	UNIV R&D PERFORMANCE			0.006 (0.003)
Controls				
Country fixed effects		Significant		
Year fixed effects		Significant		
YEAR			−0.099 (0.007)	−0.081 (0.007)
L GDP 1967			0.375 (0.085)	0.443 (0.083)
US dummy			−0.221 (0.081)	−0.010 (0.076)
R^2		0.9960	0.9771	0.9819
Observations		353	347	347

measures (roughly equal to 1 S.D. shift) is associated with a 22 and 10% increase in PATENTS, respectively. Similarly, a 1% point increase in ED SHARE (approximately 1 S.D.) is associated with an 11% increase in the level of PATENTS.

We then turn to two specifications including measures drawing upon insights emphasizing the importance of the cluster-specific innovation environment (Y_{CLUS}) and the quality of linkages between the common infrastructure and clusters (Z_{LINK}).[25] These additions neither affect the significance nor the appreciably alter the coefficients of the measures included in previous models. However, consistent with a perspective that innovation-based competition in a country's industrial clusters raises the marginal productivity of R&D resources, SPECIALIZATION and PRIVATE R&D FUNDING enter positively and significantly. A 1 S.D. increase in SPECIALIZATION (0.03) is associated with an 8% increase in the rate of international patenting by a country, while a 1% point increase in the fraction of R&D *funded* by the private sector is associated with a 1.4% increase in PATENTS. This implies that, for our sample, relatively higher levels of technological specialization and industry R&D funding are associated with higher levels of R&D productivity. While these findings in no way imply a dispositive hypothesis test of the role that clusters and linkages play in determining innovation, they suggest that outcomes associated with the operation of these mechanisms does play an important role in shaping national R&D productivity.

The first of our indicators of the quality of linkages between industrial clusters and the common innovation infrastructure, the fraction of R&D *performed* by

[25] Note that the coefficients in (4.2) on L GDP and L POP are of roughly equal magnitude though opposite in sign, and so we simply employ GDP PER CAPITA in most of the remainder of our analysis.

Table 6
Exploring the sources of dispersion in international patenting[a]

		Stage 1 (6.1a)	Stage 2 (6.1b)
		Dependent variable $= \ln(\text{PATENTS})_{j,t+3}$	Dependent variable: Stage 1 residuals $\varepsilon_{(\text{stage 1})} = \ln(\text{PATENTS})_{j,t+3} - E[\ln(\text{PATENTS})_{j,t+3}]$
Stage 1: factors related to the scale of innovative efforts			
A	L GDP PER CAPITA	1.420 (0.091)	
H^{A}	L FTE S&E	0.854 (0.050)	
H^{A}	L R&D $	0.352 (0.051)	
Year fixed effects		Significant	
US dummy		−0.198 (0.080)	
Constant		−9.084 (0.428)	
Stage 2: policy and other non-scale dependent factors			
X^{INF}	ED SHARE		0.116 (0.015)
X^{INF}	IP		0.100 (0.040)
X^{INF}	OPENNESS		0.072 (0.029)
Y^{CLUS}	PRIVATE R&D FUNDING		0.005 (0.001)
Y^{CLUS}	SPECIALIZATION		3.459 (0.639)
Z^{LINK}	UNIV R&D PERFORMANCE		0.002 (0.003)
Constant			−0.711 (0.108)
R^2		0.96	0.27
Adjusted R^2		0.96	0.25
Observations		353	347

	Stage 3 (6.2)	Stage 4 (6.3)	Stage 5 (6.4)
Stage 1			
Dependent variable $= \ln(\text{PATENTS})_{j,t+3}$	L FTE S&E	L GDP/POP	L GDP/POP
	L R&D $	ED SHARE	L FTE S&E
		IP	L R&D $
		OPENNESS	ED SHARE
		PRIVATE R&D FUNDING	IP
		SPECIALIZATION	OPENNESS
		UNIV R&D PERF	
R^2	0.93	0.58	0.97
Adjusted R^2	0.92	0.55	0.97
Observations	353	349	347
Stage 2			
Dependent variable: Stage 1 residuals	L GDP/POP	L FTE S&E	PRIVATE R&D FUNDING
$\varepsilon_{(\text{stage 1})} = \ln(\text{PATENTS})_{j,t+3} - E[\ln(\text{PATENTS})_{j,t+3}]$			
	ED SHARE	L R&D $	SPECIALIZATION
	IP		UNIV R&D PERFORMANCE
	OPENNESS		
	PRIVATE R&D FUNDING		
	SPECIALIZATION		
	UNIV R&D PERFORMANCE		
R^2	0.47	0.43	0.14
Adjusted R^2	0.45	0.43	0.13
Observations	353	347	347

[a] All models include a constant term and all Stage 1 equations include a US dummy and year fixed effects. Equations with IP and OPENNESS also include dummy variables for years in which data for these variables exist.

Table 7
Exploring robustness

		Dependent variable = ln(PATENTS)$_{j,t+3}$				
		(5.3) with scale effects (7.1)	(4.4) with year and country fixed effects (7.2)	(4.4) using only post-1980 observations (7.3)	(4.4) using only European countries (7.4)	(4.4) including journal articles (7.5)
Quality of the common innovation infrastructure						
A	L GDP	0.370 (0.163)				
A	L GDP PER CAPITA		0.511 (0.221)	0.702 (0.115)	0.762 (0.111)	0.706 (0.095)
A	L PATENT STOCK	0.498 (0.039)				
A	L JOURNALS					0.568 (0.073)
H^{A}	L POP	−0.520 (0.162)				
H^{A}	L FTE S&E	0.629 (0.068)	0.477 (0.089)	0.887 (0.059)	0.890 (0.049)	0.421 (0.075)
H^{A}	L R&D $	0.065 (0.038)	0.129 (0.041)	0.280 (0.058)	0.307 (0.048)	0.264 (0.042)
X^{INF}	ED SHARE	0.076 (0.013)	0.039 (0.021)	0.155 (0.019)	0.207 (0.028)	0.089 (0.017)
X^{INF}	IP	0.084 (0.033)	−0.020 (0.025)	0.214 (0.044)	0.216 (0.051)	0.194 (0.040)
X^{INF}	OPENNESS	−0.002 (0.023)	−0.052 (0.017)	0.068 (0.028)	0.034 (0.037)	0.045 (0.027)
Cluster-specific innovation environment						
Y^{CLUS}	PRIVATE R&D FUNDING	0.009 (0.002)	0.003 (0.003)	0.016 (0.002)	0.014 (0.002)	0.021 (0.002)
Y^{CLUS}	SPECIALIZATION	2.500 (0.625)	3.501 (0.726)	1.954 (0.804)	2.937 (1.106)	3.962 (0.643)
Quality of the linkages						
Z^{LINK}	UNIV R&D PERFORMANCE	0.003 (0.002)	−0.002 (0.004)	0.010 (0.004)	0.014 (0.004)	0.009 (0.003)
Controls						
Country fixed effects			Significant			
Year fixed effects			Significant	Significant	Significant	Significant
YEAR		−0.092 (0.007)				
L GDP 1967		−0.100 (0.172)				
US dummy		0.090 (0.080)		0.057 (0.103)		−0.043 (0.084)
Constant		1.084 (0.887)				
R^2		0.9826	0.9944	0.9762	0.9608	0.9791
Adjusted R^2		0.9817	0.9936	0.9737	0.9561	0.9770
Observations		347	347	238	267	323

universities enters into (4.3) with a positive sign and coefficient significant at the 5% level. This implies that countries with a higher share of their R&D performance in the educational sector (as opposed to the private sector or in intramural government programs) have been able to achieve significantly higher patenting productivity. In light of the results for PRIVATE R&D FUNDING, this finding provides evidence that, controlling for the level of R&D inputs, the *composition* of spending affects the level of realized international patenting. The second indicator of Z^{LINK}, VENTURE CAPITAL, enters positively into the equation, but is not significant. This may reflect the relatively low level of variation of VC across the world outside United States and the existence of non-VC sources of risk capital in many OECD countries.

Consistent with prior studies (Jones, 1995), the coefficients of the year dummies decline over time, suggesting that average global R&D productivity has declined since the mid-1970s. In other words, while PATENTS has been increasing over time as a result of increased investments in innovation and improvements in the policy environment, countries have also tended to experience a "raising the bar" effect in which ever-more R&D resources must be devoted in order to yield a constant flow of visible innovative output. We present our preferred model of national innovative capacity in (4.4), including only those contributors to national innovative capacity that enter significantly in prior models (i.e. excluding ANTITRUST and VENTURE CAPITAL). Each of the included regressors has a quantitatively important impact, consistent with our perspective that relatively nuanced influences on national innovative capacity have an important impact on the level of international patenting. In Table 5, we present regressions that employ the alternative measure of $A_{j,t}$, PATENT STOCK, rather than population-adjusted GDP.[26] Whereas population-adjusted GDP is a comprehensive, composite indicator of a country's technological sophistication, PATENT STOCK provides a more direct measure of the knowledge stock upon which a country draws for technological innovation. This table also employs alternative structures to control for year and country effects; (5.1) includes dummies for every country and year, while (5.2) and (5.3) rely on GDP 1967 to control for the "baseline" knowledge stock.[27] By exploring differences in the measure of the knowledge stock as well as by varying the means of identification, Table 5 highlights the robustness of the results to alternative assumptions about the nature of heterogeneity among countries and the specification for the country-specific level of technological knowledge. Though there are differences in the magnitude of some variables and the significance of others, the results are similar to those obtained in Table 4. Perhaps the most important difference is that the coefficient on FTE S&E is much smaller in the equations of Table 5, suggesting greater concavity of PATENTS to FTE S&E. In other words, the impact of changes in FTE S&E on PATENTS is lower after controlling for the realized level of prior international patenting. In addition, the coefficient on R&D $ is insignificant (though of similar magnitude to Table 4), implying that PATENT STOCK incorporates much of the statistical information embedded in R&D $. Finally, OPENNESS becomes negative and insignificant, perhaps because of the small number of observations for this variable. Nonetheless, the basic elements of our framework remain significant, suggesting that (a) the level of R&D inputs is a critical determinant of the level of realized innovation; and (b) more nuanced measures of the national environment for innovation play an important role in determining R&D productivity.

We evaluate the relative role of these different forces in explaining the overall dispersion of innovation in Table 6. As discussed earlier, even a single measure of the size of the economy or the level of R&D inputs can explain a substantial share of the overall variation in PATENTS. Therefore, even

[26] By including PATENT STOCK in the specification which includes FTE S&E and controls for year and country effects, (5.1) serves as an empirical test of a key parametric restriction associated with ideas-driven growth models. In particular, in order for ideas production to be a sustainable source of equilibrium long-term growth, $\phi = 1$ (a hypothesis which cannot be rejected in (5.1)). Such parametric restrictions for ideas-driven growth models are explored much more extensively (and derived formally) in Porter and Stern (2001).

[27] This contrasts with our use of year-specific fixed effects from Table 4. Note that because the Likert variables are not observed until the late 1980s, we include separate dummy variables to denote whether such variables are included in the regression.

though coefficients identify the statistical and quantitative impact of the measures of national innovative capacity, it is useful to evaluate the degree to which these additional measures explain the overall variation in PATENTS. To do so, we undertake a series of two-stage regression procedures. In the first stage, we regress a year dummies and some (but not the full set) of measures associated with national innovative capacity. For example, in (6.1), the first-stage regression includes year dummies, GDP PER CAPITA, FTE S&E and R&D $ (i.e. the elements of A and H^{A}). In the second stage, we then regress the *residuals* from the first stage on the remaining measures (i.e. in (6.1), ED SHARE, IP, OPENNESS, PRIVATE R&D FUNDING, SPECIALIZATION, and UNIV R&D PERFORMANCE). The R^2 of this regression provides a conservative indication of the relative importance of measures included in the second stage. Specifically, the second stage indicates the share of the variance in PATENTS unexplained by variables in the first stage that *can* be explained by measures in the second stage.

Our results are informative. Even after first controlling for factors associated with the endogenous growth literature (A and H^{A}), over one-quarter of the remaining variance can be explained by relatively noisy measures associated with the national innovative systems and national industrial clusters literatures (X^{INF}, Y^{CLUS} and Z^{CLUS}). Similarly, our analysis suggests that differences in innovation across countries are linked not only to the level of R&D inputs but to differences in the drivers of R&D productivity. Specifically, when we include *only* R&D inputs in the first stage, nearly 50% of the idiosyncratic variance can be tied to measures associated with R&D productivity in the second-stage regression. In contrast, when we first include the R&D productivity measures in the first stage and include *only* the R&D input measures in the second stage, a smaller share of the remaining variance (43%) is explained. Finally, even if we include all of the elements of the common innovation infrastructure in the first stage, the compositional variables (PRIVATE R&D FUNDING, SPECIALIZATION, and UNIV R&D PERFORMANCE) explain over 14% of the remaining variance in the second-stage regression, a share consistent with the amount that can be explained by the policy variables (IP and OPENNESS) when they are included exclusively in the second stage.

6.2. Robustness checks

Table 7 explores the robustness of the primary model to alternative specifications and sample subgroups. Equation (7.1) demonstrates robustness to the inclusion of scale-dependent measures (GDP and POP) alongside PATENT STOCK. Both GDP and PATENT STOCK are positive and significant. Despite being strongly correlated, each has a separate, quantitatively important impact on PATENTS. Also, as in (4.1) and (4.2), the negative coefficient on L POP suggests that, after controlling for the level of prosperity and technological sophistication, increases in population (implying a decrease in GDP PER CAPITA) are associated with less new-to-the-world innovation. Together with our earlier results, we interpret this to suggest that both PATENT STOCK and population-adjusted GDP provide useful measures of a nation's national innovation infrastructure. Indeed, to the extent that PATENT STOCK itself provides an index of the knowledge stock of an economy, the separate impact of GDP suggests the role of economy-wide demand influences in the rate of new-to-the-world innovation. High per capita income allows buyers to demand more advanced products and services, encouraging the development of new-to-the-world technologies.

To establish the precise role of cross-sectional variation in our results, equation (7.2) includes country-specific fixed effects. Most of the results are robust to this modification: GDP PER CAPITA, R&D expenditure, FTE R&D, and higher education spending remain significant and of the expected sign in explaining patent output. It is interesting to note that the magnitude of the coefficient on FTE S&E increases, suggesting that the level of innovative output is sensitive to *changes* in the level of the scientific workforce within a given country. SPECIALIZATION also remains significant (and its coefficient increases nearly 40%). However, the R&D composition variables become insignificant and OPENNESS enters negative and significant. The estimates of these regressors are sensitive to the inclusion of country-specific fixed effects because UNIV R&D PERFORMANCE, PRIVATE R&D FUNDING change only slowly over time and OPENNESS is observed for only a short time period (1989–1993).

We examine the robustness of our results to various sample subgroups in (7.3) and (7.4). Restricting the sample to post-1970s data in (7.3), we highlight a period of relatively higher macroeconomic stability in which the reliability of the data is most likely improved. All of the results remain significant, although the coefficients in this equation suggest that aggregate national prosperity (GDP PER CAPITA) is somewhat less important as a driver of R&D productivity in the last 15 years of our sample, while the importance of private sector funding (PRIVATE R&D FUNDING) and university R&D performance (UNIV R&D PERFORMANCE) has increased. In other words, in the second half of our sample period, more nuanced drivers of national innovative capacity take on increased relative importance in determining the flow of PATENTS. To explore regional differences in our data, we restrict attention to European countries in (7.4). The impact of GDP PER CAPITA on innovative output is somewhat lower in these countries, while the relative influence of ED SHARE is somewhat higher. Similar to earlier results, OPENNESS loses its significance in this sub-sample, suggesting that variation among European countries is not sufficient to establish this result.

We explore the impact of academic publication on international patenting productivity by adding JOURNALS to our preferred specification in (7.5). Although this specification is obviously subject to endogeneity (and we leave separating out the separate exogenous drivers of each to future work), the results suggest that while JOURNALS is significant and positively correlated with PATENTS, its inclusion does not substantially change our earlier qualitative conclusions, except for reducing OPENNESS to insignificance (consistent with some of our other robustness checks), and somewhat reducing the coefficients on FTE S&E and ED SHARE. In other words, the empirical relationship between international patenting and key drivers of commercially-oriented innovative output is relatively unaffected, at least in the short- to medium-term, by the level of abstract scientific knowledge produced by a country.

6.3. The impact of national innovative capacity on downstream competitiveness measures

Our analysis so far has focused exclusively on the sensitivity of PATENTS to measures of the strength of national innovative capacity. We extend our analysis to consider more downstream consequences of innovative capacity, and find that the elements of national innovative capacity play an important role in shaping both the level of TFP and MARKET SHARE.

Table 8 begins with an overall assessment of the sensitivity of TFP to cumulative ideas production (PATENT STOCK). Specifically, (8.1) evaluates the sensitivity of GDP to PATENT STOCK, conditional on the level of LABOR and CAPITAL. The coefficient on PATENT STOCK can be interpreted as a contributor to the level of TFP.[28] As discussed more fully in Porter and Stern (2001), this relationship is critical for establishing the role of “ideas production” in long-run economic growth. Theoretical growth models assume that there is a strong R&D productivity advantage associated with technological sophistication that translates into a proportional advantage in the realized level of TFP. Equation (8.1) implies that while the PATENT STOCK has a significant effect on TFP, this effect is *much* smaller than proportionality (which would require that the coefficient be equal to unity). This modest relationship suggests that national innovative capacity plays a significant role in shaping the medium-term level of productivity, but raises the possibility that the linkage between national innovative output and productivity growth may be more subtle than commonly assumed.

We examine whether MARKET SHARE can be explained using the national innovative capacity framework in equations of (8.2)–(8.4). First, (8.2) shows that (lagged) PATENT STOCK, GDP, POP and a time trend explain nearly 80% of the variance in MARKET SHARE across countries. This demonstrates that countries that accumulate advanced knowledge stocks later achieve high shares in

[28] Alternatively, we could have simply imposed factor shares on LABOR and CAPITAL and computed TFP directly; while we experimented with this formulation, the less restrictive specification in (9.1) is more consistent with the exploratory nature of the exercise in this paper (but see Porter and Stern, 2001, for further details).

Table 8
Exploring relationship to TFP and international trade

		Sensitivity of TFP to ideas production (8.1)	Sensitivity of market share to patent stock (8.2)	Sensitivity of market share to predicted national innovative capacity (8.3)	Sensitivity of market share to elements of national innovative capacity (including JOURNALS) (8.4)
Dependent variable		$\ln(\text{GDP})_{j,t+3}$	Market $\text{share}_{j,t+3}$	Market $\text{share}_{j,t+3}$	Market $\text{share}_{j,t+3}$
Measures of national innovative capacity					
PREDICTED PATENTS_{t+3}				0.610 (0.085)	
L PATENT STOCK		0.113 (0.015)	0.487 (0.061)		
Quality of the common innovation infrastructure					
A	L GDP		0.979 (0.260)	0.593 (0.326)	0.833 (0.358)
A	L JOURNALS				0.210 (0.182)
H^{A}	L POP		−0.463 (0.200)	−0.249 (0.233)	−0.283 (0.252)
H^{A}	L FTE S&E				0.558 (0.259)
X^{INF}	L R&D $				−0.242 (0.105)
X^{INF}	ED SHARE				0.109 (0.042)
X^{INF}	IP				0.071 (0.090)
X^{INF}	OPENNESS				0.306 (0.065)
Cluster-specific innovation environment					
Y^{CLUS}	PRIVATE R&D FUNDING				0.036 (0.005)
Y^{CLUS}	SPECIALIZATION				3.904 (1.778)
Quality of the linkages					
Z^{LINK}	UNIV R&D PERFORMANCE				0.031 (0.008)
Controls					
L LABOR		0.643 (0.040)			
L CAPITAL		0.215 (0.051)			
YEAR		−0.001 (0.003)	−0.084 (0.008)	−0.028 (0.008)	−0.039 (0.017)
US dummy		0.029 (0.055)			
Constant		−10.922 (0.717)	−5.481 (0.854)	−8.275 (0.706)	−13.598 (1.960)
R^2		0.9771	0.7979	0.7914	0.8379
Adjusted R^2		0.9767	0.7956	0.7890	0.8305
Observations		304	357	347	323

worldwide high-technology markets. Equation (8.3) replaces PATENT STOCK with the predicted level of PATENTS, where the weights are derived from (4.4). Not surprisingly, given how closely we characterize PATENTS in (4.4), these results are quite similar to those in (8.2). Finally, in (8.4), we include the measures incorporated into our preferred model of national innovative capacity (4.4), along with JOURNALS. This exercise fits the MARKET SHARE data similarly well and each element of national innovative capacity remains significant, with the exception of IP, which is not estimated precisely. Notably, JOURNALS is also insignificant in the regression, suggesting that scientific output per se does not play an independent short-term role in affecting national shares of world technology exports.

6.4. Trends in national innovative capacity

Our framework allows us to analyze whether differences in the intensity of innovation and R&D productivity reported earlier (see Fig. 4) can be understood in terms of the sources of national innovative capacity. Since, at the most aggregate level, we are interested in the potential production of innovative output relative to national population, we measure innovative capacity by calculating the level of expected PATENTS (using the coefficients from our preferred model (4.4)) and dividing by the level of population (in millions).[29] In effect, we are computing the predicted value for a country's level of international patenting per capita based on its fundamental resource and policy commitments, thereby providing a useful benchmark to compare the relative ability of countries to produce innovations at the international frontier.

The result of this exercise is presented in Fig. 8. Consistent with the historical PATENTS PER CAPITA data, United States and Switzerland are in the top tier throughout the sample period. As a result of sustained investments in fundamentals, such as increases in FTE S&E and R&D $, improvement in IP protection and openness, and a high share of R&D performed in industry, Japan, Germany, and Sweden joined this top group over the course of the 1980s. A second set of countries, including the remaining Scandinavian countries, France, and UK, comprise a "middle tier", while a third group, including Italy, New Zealand and Spain, lags behind the rest of the OECD over the full-time period.[30]

The most striking finding of this analysis is the *convergence* in measured innovative capacity among OECD countries over the past quarter century. Not only has the top tier expanded to include Japan, Germany, and Sweden, but some middle tier countries, such as Denmark and Finland, have achieved substantial gains in innovative capacity. Moreover, convergence seems to be built on the fundamentals of innovative capacity, rather than transient changes. This is exemplified by the case of Germany, in which the components of innovative capacity grew strongly throughout the 1980s. Despite a drop-off resulting from reunification with the east beginning in 1990, Germany has maintained a relatively high level of innovative capacity throughout 1990s.

In general, there has been a slow but steady narrowing of the gap between the leaders in the OECD and nations with historically lower levels of innovative capacity. It is important to note, however, that some major countries, most notably France and UK have seen erosion in their relative innovative capacity over the past quarter century by investing less in common innovation infrastructure, providing less supportive cluster environments, and/or losing relative position in linkage mechanisms. While this approach does not provide a forecast of the ability of a country to commercialize new technologies in the short-term, our results do suggest that both Japan and Scandinavia have already established themselves as important innovation centers and that the nations that produce new-to-the-world

[29] We have also completed this exercise dividing through by FTE S&E rather than POP. The results are quite similar (and are available upon request).

[30] It is important to bear in mind that these results are in part affected by the industrial composition of national economies in terms of patenting propensity across industries. Our choice of PATENTS implies that innovation in countries whose clusters are concentrated in industries with low patent intensities (such as Italy in textiles) will be understated relative to those with clusters in patent-intensive industries (such Switzerland in pharmaceuticals). However, it is useful to note that the analysis does control for differences captured in the scale of R&D effort per se, through the FTE S&E and R&D $ measures.

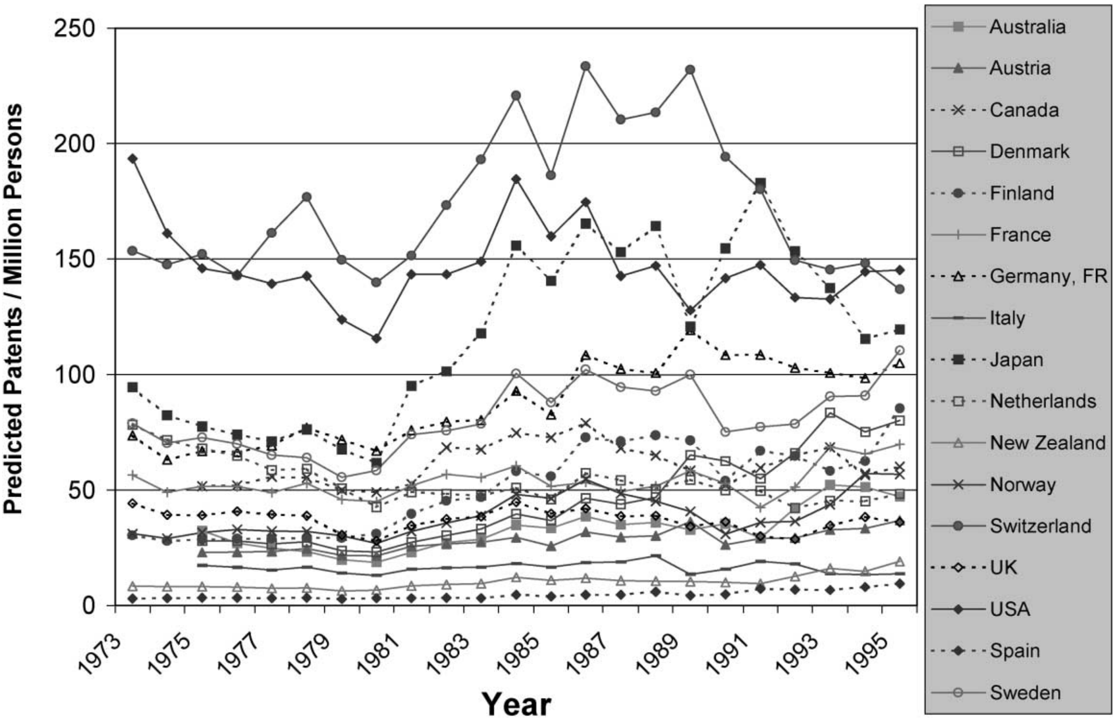

Fig. 8. Trends in national innovative capacity.

innovation are likely to become more diverse over time.[31]

7. Concluding thoughts

This paper introduces the concept of *national innovative capacity* to integrate previous perspectives on the sources of differences in the intensity of innovation and R&D productivity across countries and provides an empirical framework to distinguish among alternative causes of these differences. Our results suggest that the empirical determinants of international patenting activity are: (a) amenable to systematic empirical analysis motivated by our framework and (b) more nuanced than the limited factors highlighted by ideas-driven growth theory. We find that a set of additional factors also plays an important role in realized R&D productivity. Further theoretical and empirical research in growth theory may benefit from incorporating the role of industrial organization and the national policy environment (e.g. the role of the university system or incentives provided for innovation).

Country-level R&D intensity and productivity seem to be amenable to quantitative analysis (though with some caveats), a finding that should be of particular interest to researchers in the tradition of the national innovation systems literature. In particular, future research can usefully distinguish between those phenomena that are reflected in observable measures of innovative output (such as the patenting activities we examine here) and those with more subtle effects that may not be subject to direct observation (such as institutions or mechanisms encouraging non-patented process innovations). At the very least, our results suggest that quantitative research can play a larger role in distinguishing among alternative perspectives in this field.

Our results suggest that public policy plays an important role in shaping a country's national innovative capacity. Beyond simply increasing the level of

[31] This part draws on Porter and Stern (1999).

R&D resources available to the economy, other policy choices shape human capital investment, innovation incentives, cluster circumstances, and the quality of linkages. Each of the countries that have increased their estimated level of innovative capacity over the last quarter century—Japan, Sweden, Finland, Germany—have implemented policies that encourage human capital investment in science and engineering (e.g. by establishing and investing resources in technical universities) as well as greater competition on the basis of innovation (e.g. through the adoption of R&D tax credits and the gradual opening of markets to international competition).

Finally, our results suggest that United States, the dominant supplier of new technologies to the rest of the world since World War II, had been less proactive in its investment in innovative capacity in the early 1990s than it was in the late 1980s. With the conclusion of the Cold War, the traditional American rationale for investing in its national innovation infrastructure became less clear, and US policy had become less focused. In light of continuously increasing investments by an increasingly diverse set of countries, convergence in innovative capacity across the OECD should not be surprising. This convergence suggests that the commercial exploitation of emerging technological opportunities (from biotechnology to robotics to Internet technologies) may well be less geographically concentrated than was the case during the post World War II era.

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Appendix A

Sample countries (1973–1995)

Australia	France	Netherlands	UK
Austria	Germany[a]	Norway	United States
Canada	Italy	Spain	
Denmark	Japan	Sweden	
Finland	New Zealand	Switzerland	

[a] Prior to 1990, data for the Federal Republic of Germany include only the federal states of West Germany; beginning in 1991, data for Germany incorporate the new federal states of the former German Democratic Republic.

Pairwise correlations

	PATENTS$_{t-3}$	POP	GDP	GDP PER CAPITA	PATENT STOCK	FTE S&E	R&D $	PRIVATE R&D FUNDING	UNIV R&D PERFORMANCE
POPULATION	0.940*								
GDP	0.973*	0.984*							
GDP PER CAPITA	0.110*	−0.063	0.044						
PATENT STOCK	0.920*	0.832*	0.906*	0.164*					
FTE S&E	0.981*	0.974*	0.988*	0.051	0.897*				
R&D $	0.928*	0.844*	0.920*	0.175*	0.974*	0.903*			
PRIVATE R&D FUNDING	0.226*	0.188*	0.216*	0.589*	0.218*	0.193*	0.252*		
UNIV R&D PERFORMANCE	−0.377*	−0.488*	−0.444*	0.110*	−0.331*	−0.437*	−0.337*	−0.216*	
SPECIALIZATION	0.052	0.015	0.027	−0.138*	0.004	0.0216	0.091	0.140*	0.003

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