Varieties of Capitalism and Technological Innovation

10,200 words

by

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August 20, 2003

Published as:
"Empirical Evidence Against Varieties of Capitalism's Theory of Technological Innovation"
in *International Organization* 58(3) (Summer 2004)

I. Introduction *(320 words)*

How can we explain cross-national differences in innovative activity across the industrialized democracies? Politics appear to play a strong causal role here, with case study after case study showing the clear influence of politics and political institutions on technological innovation.[1] However, this phenomenon is only sparsely studied by political scientists. Rather, this area has largely become the purview of small number of economists and sociologists who often ignore important political variables in their analysis. Thus great interest has recently been generated by a new "Varieties of Capitalism" (VOC) theory of innovation which holds that variance in political institutions is the primary cause of differences in national innovative behavior. In brief, the central claim of VOC's innovation theory is that the more a polity allows the market to structure its economic relationships, the more it will direct its inventive activity towards industries typified by "radical" technological change. Conversely, the more a polity chooses to coordinate economic relationships via non-market mechanisms, the more it will direct its inventive activity towards "incremental" technological change. Implicit in these predictions is an assumption that industries differ by the type of technological innovation conducted within them: that some industries are more technologically revolutionary and others more incremental. As VOC theory has yet to be proven, in this paper I will make use of new data on patents, scholarly publications, and technological diffusion to test VOC theory's central assumptions and predictions and to see whether VOC theory properly describes the empirical world of technological innovation. It will be shown that while some industries are indeed more radically innovative than others in the short-run, this cannot be confirmed in the long-run as industries age and mature technologically. I also find that VOC theory does not accurately predict innovative behavior over time and space, and that VOC's existing empirical support strongly depends upon the inclusion of a major outlier, the United States, in the set of radically innovative countries.

II. Politics, Economics, and Innovation Theory *(860 words)*

For much of the history of political economy, questions about the causes of national differences in technological innovation have remained at the periphery of the field.[2] One of the major reasons for this was the apparently random, or at least inexplicable, nature of innovation itself; even those social scientists who attempted to deal systematically with technological change (including Marx, Schumpeter, and Solow) generally regarded it, and the underlying body of scientific knowledge upon which it drew, as a "black box" proceeding according to its own internal processes largely independent of political or economic forces.[3] This attitude changed gradually during the Cold War, as vast expenditures by the US government and industry on R&D made it increasingly clear that technological innovation could be made responsive to economic and political needs, a fact further punctuated by the Soviet launch of Sputnik and later by the Japanese and German economic "miracles". In response, economists during the 1960's began to investigate whether certain supply-side or

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[1] Edwards 1996; Bauer 1995; Mokyr 1990; Beasley 1988; and Rosenberg 1985.

[2] *Technology* is defined as a physical product, or a process of handling physical materials, which is used as an aid in problem solving. More precisely, technology is a product or process which allows social agents to perform entirely new activities or to perform established activities with increased efficiency. *Innovation* is the discovery, introduction, and/or development of new technology, or the adaptation of established technology to a new use or to a new physical or social environment.

demand-side variables could explain why even developed nations followed different technological trajectories.[4] This somewhat inconclusive debate was followed in the late-1970s and 1980s by a plethora of case and country studies which tended to emphasize the importance of this or that policy, these or those historical conditions, but failed to produce any generalizable theory about the rate or direction of national innovation.

A recurring problem encountered in these debates was the contradiction between empirical observation and certain fundamental tenets of the economics of science. Specifically, Kenneth Arrow had shown that much productive knowledge takes the form of unpatentable laws of nature and advances in basic science, and is therefore a non-excludable public good available to everyone without charge.[5] And while patents and trade secrets act as temporary solutions to this appropriability problem in the area of applied knowledge, history has shown that the original inventors of technology often do not capture most of the benefits of their innovations when these inventions are transferred across borders, and that these transfers take place even in spite of considerable efforts to stop them. Theoretically speaking then, in the long-run, developed nations should not display significant variation in either per capita innovation rates or in the type of innovative activities which they pursue. Yet differences appear to abound.

One possible solution to this paradox is institutions. Institutions are perhaps the only variables which both influence the incentives for innovative behavior and which differ across nations. Indeed, political scientists and economists have long recognized the capacity of government, labor, regulatory, and legal institutions to inhibit free market exchange and thereby hamper innovation. But it was not until Paul Romer endogenized technological change that social scientists began to take seriously the ability of institutions to actively enhance aggregate economic performance through their effects on the rate and direction of technological progress.[6] To date though, beyond the broadest brushstrokes of political-economic theory, social scientists have yet to pin-point the specific mechanisms by which institutions cause countries to differ technologically.

It is into this environment which Varieties of Capitalism theory makes its foray, taking a radical new approach to explaining cross-national differences in the direction of technological progress. VOC theory is broad and foundational, it touches upon multiple aspects of political and economic life, of which innovation is but one part. At its most basic level, it is a theory of capitalism by gradation: some countries use markets more than others to coordinate economic actors and this variation is used to explain a myriad of comparative and international political-economic behavior. However, when fully articulated, we find that VOC theory does not divide the world into "free-trade vs. protectionist" or "state-owned vs. privatized" systems of political economy as is traditionally done. To do this would be to focus attention on the state, which VOC scholars wish to avoid. Rather, they view the firm as the locus of trade and production in the capitalist economy, and therefore take the firm, not the state, as their primary unit of analysis. Nor is the firm a lone or independent actor in VOC's analysis; successful operation of the firm depends heavily upon its relationships with labor, investors, and other

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[3] For an alternative view of Marx, see Bimber 1994.
[4] Summarized in Mowrey and Rosenberg 1979.
[5] Arrow 1962.

firms. It is these crucial relationships that, in turn, explain patterns of economic activity and policymaking. Therefore the central claims of VOC theory focus on how a given political-economy's institutional structure determines the conduct of these crucial relationships and how economic actors organize to solve the classic coordination problems which afflict such relations.[7] At one end of this relationship spectrum lie the "Liberal Market Economies" (LME's), such as the United States, in which firms tend to coordinate their relations and activities in the manner described by Oliver Williamson: through internal corporate hierarchies and external competitive market arrangements.[8] At the other end of the spectrum sit the "Coordinated Market Economies" (CME's), such as Germany, where firms tend to coordinate via non-market relationships, with greater dependency on relational and incomplete contracting, exchanges of private information within enduring networks, and a high degree of actor collaboration (as opposed to competition or confrontation). As we shall see in the next section, these distinctions have important implications for explaining and predicting national differences in innovation.

III. Varieties of Capitalism's Theory of Technological Innovation *(810 words)*

According to VOC theory, technological innovation comes in two types, radical and incremental, each of which forms the basis for a different mode of production. While an exact definition is elusive, VOC scholars describe radical innovation as that which "...entails substantial shifts in product lines, the development of entirely new goods, or major changes to the production processes."[9] They argue that radical innovation is therefore vital to production in high-technology sectors which require rapid and significant product changes (biotechnology, semiconductors, software) or in the manufacture of complex systems-based products (telecommunications, defense, airlines). Incremental innovation, on the other hand, is that which is "marked by continuous but small-scale improvements to existing product lines and production processes."[10] Unlike production based on radical innovation where speed and flexibility are crucial, production based on incremental innovation prioritizes the maintenance of high quality in established goods. This involves constant improvements in manufacturing processes to bring down costs and prices, but only occasional minor improvements in the product line. Incremental innovation is therefore essential for competitiveness in capital goods production (machine tools, factory equipment, consumer durables, engines).

VOC theory further predicts that LME's and CME's will tend to exert greater effort towards, and be successful in, different types of technological innovation. VOC theory interprets innovation as just another productive activity, therefore innovation should be sensitive to the firm's crucial relationships described above and the institutions which structure them. This does not mean that a given political-economic structure will result in only one kind of innovation, but that different institutions will create different types of comparative advantage for innovators. For example, incremental innovation requires a workforce that is skilled enough to

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6 Romer 1990.
7 I am concerned here with those aspects of VOC theory discussed in Hall and Soskice p. 1-44.
8 Williamson 1975, 1985.
9 Hall & Soskice 2001, 38-39.
10 Hall & Soskice 2001, 39.

come up with it, secure enough to risk suggesting it, and have enough autonomy to see innovation as a part of their job. This in turn requires that firms provide workers with secure environments, autonomy in the workplace, opportunities to influence firm decisions, education and training beyond just task-specific skills (preferably industry-specific technical skills), and close inter-firm collaboration which encourages clients and suppliers to suggest innovations as well. These are exactly the kinds of apparatus provided by CME institutions. In fact, CME's are *defined* by the very institutions which provide a comparative advantage for incremental innovation. These institutions include highly coordinated industrial-relations systems; corporate structures characterized by works councils and consensus-style decision-making; a dense network of inter-corporate linkages (such as interlocking corporate directorates and cross-shareholding); systems of corporate governance that insulate against hostile takeovers and reduce sensitivity to current profits; and appropriate laws for relationship-based, incomplete contracting between firms. VOC scholars argue that this combination of institutions results in long employment tenures, corporate strategies based on product differentiation rather than intense product competition, and formal training systems for employees which focus on high-skills and a mix of company-specific and industry-specific skills; in other words, the very factors which combine to foster incremental innovation.

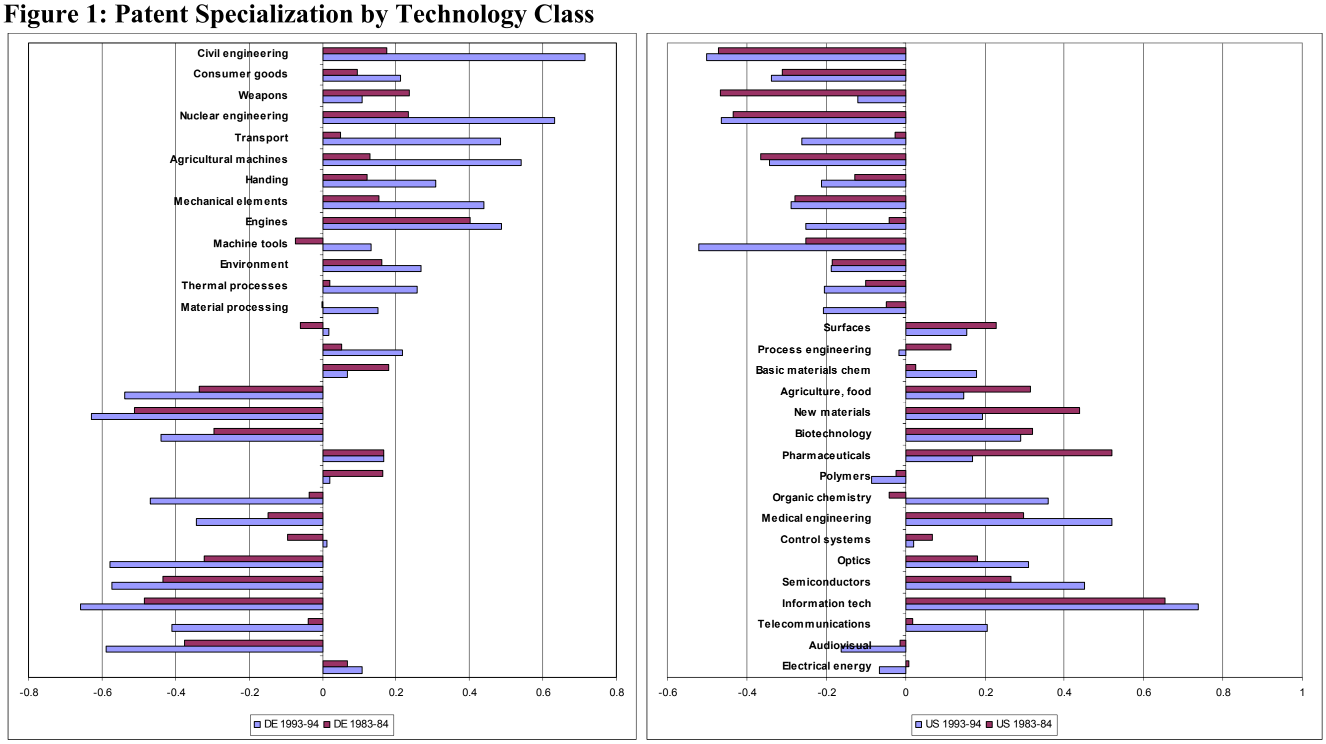
On the other hand, VOC scholars argue that these same CME institutions which provide comparative advantages for incremental innovation also serve as obstacles to radical innovation. For instance, worker representation in the corporate leadership combines with consensus-style decision-making to make radical change and reorganization difficult. Also, long employment tenures make acquisition of new skills and re-balancing one's labor mix difficult. And dense inter-corporate networks make the diffusion of disruptive innovations slow and arduous, and technological acquisition by M&A or takeovers hard. All of these act against, or reduce the potential rewards of, radical innovation.

In LME's, the situation is reversed. LME's are defined by institutions which provide a comparative advantage for radical innovation, while creating obstacles to incremental innovation. LME's have flexible labor markets with few restrictions on layoffs, which means that companies can drastically change their product lines and still acquire the proper labor mix. LME's also support extensive equity markets with dispersed shareholders providing innovators of all sizes with relatively unfettered access to capital. Also, inter-firm relations in LME's allow for a variety of aggressive asset exchanges with few restrictions on mergers and acquisition, buyouts, personnel poaching, licensing, etc., which permits firms to easily acquire scientific expertise and new technology. Concentration of power at the top of LME-based firms augments these institutions, allowing management to quickly force major change on complex organizations. All of these factors combine to create large incentives for, and an environment accommodative to, radical innovation. Conversely, LME's capacity for incremental innovation is limited due to financial arrangements which emphasize current profitability, corporate structures that concentrate unilateral control at the top and eliminate workforce security, and anti-trust and contract laws which discourage inter-firm collaboration in incremental innovation. Meanwhile, fluid labor markets and short job tenures motivate workers to pursue selfish career goals and to acquire mobile general skills rather than firm-specific or industry-specific skills. Hence, in VOC's analysis, neither workers nor firms in LME's tend to have the incentives or the resources for sustained incremental innovation.

IV. Testing the Varieties of Capitalism Claims *(500 words)*

The purpose of the remainder of this article is not to evaluate the accuracy of the LME-CME classification system or test a specific causal mechanism involved in VOC's theory of innovation. Rather, the question asked here is whether the international patterns of innovation which VOC theory predicts actually exist. The VOC causal story outlined above is both theoretically appealing and dovetails with some widely held stereotypes about national differences in innovation; however, little empirical data has yet been produced to support its central claim. The evidence offered by Hall & Soskice consists of four years of patent data from the European Patent Office (EPO) which shows that Germany and the US concentrate their patents according to the LME vs. CME model discussed above. Specifically, Hall & Soskice examine patenting activity by Germany and the US in 30 technology classes during 1983-84 and 1993-94 (Figure 1). Overall, they found that Germany's patent specialization was almost equal and opposite that of the US in both time periods.[11] More specifically, the Germans were found to be more active innovators in industries which Hall & Soskice characterize as dominated by incremental innovation (such as mechanical engineering, product handling, transport, consumer durables, and machine tools); meanwhile, firms in the US innovated disproportionately in industries which the authors perceive as more radically innovative (including medical engineering, biotechnology, semiconductors, and telecommunications).

Figure 1: Patent Specialization by Technology Class



Note: Higher scores indicate greater specialization in innovation in that particular type of technology. *Source*: Charts reproduced here with data obtained through the cooperation of Thomas Cusack, David Soskice, and Peter Hall. See also Hall & Soskice 2001, pp 42-43.

[11] Hall and Soskice's methodology will be discussed in greater detail below.

We can identify several possible problems with this approach. First, VOC theory implicitly assumes that some industries are inherently characterized by radical innovation, others by incremental innovation, and that these industries have been correctly identified. Second, in supporting their claims, Hall & Soskice use only 4 years worth of patent data from only 2 countries, one of which, the United States, is an outlier by almost any measure. Third, Hall & Soskice use only simple patent counts as their measure of innovation, hence frivolous patents are counted the same as highly innovative ones; nor do they use any non-patent measures of innovation.

In the following sections, I will address these issues in turn. In some instances, I will use Hall & Soskice's own data and methods to test the generality of their claims. In others, I will take advantage of a new dataset compiled at the National Bureau of Economic Research (NBER) of over 2.9 million utility patents granted by the US Patent & Trademark Office (USPTO) to applicants from the United States and 162 other countries during 1963-1999, and the 16 million citations made to these patents between 1975 and 1999.[12] This new dataset will allow us to go beyond Hall & Soskice's empirical investigation and to consider some thirty-six years of patenting activity for *all* of the LME and CME countries and to weight a majority of these patents by forward citations in an attempt to control for the quality of the innovations being patented. Later, data from the Institute for Scientific Information (ISI) on scholarly and professional journal publications, also weighted by forward citations, will be considered as an additional measure of innovation.

a. Independent Variable: LME vs. CME *(390 words)*

According to VOC theory, the primary independent variable for predicting innovation characteristics is the type of national political-economic institutional structure (LME or CME) within which innovators operate. The LME's include Australia, Canada, Great Britain, Ireland, New Zealand, and the United States. The CME's include Austria, Belgium, Denmark, Finland, Germany, Japan, Netherlands, Norway, Sweden, and Switzerland. In between these two ideal types, and of less importance to VOC scholars, sit a handful of hybrids denoted as "Mediterranean Market Economies" (MME's) which have mixed CME and LME characteristics. These countries include France, Greece, Italy, Portugal, Spain, and Turkey.[13] For the remainder of this article, references to the set of "LME", "CME", or "MME" countries should be understood to mean only those states listed above, as these are the only ones explicitly mentioned in the VOC claims tested here. Later, in the multivariate regressions, "LMEx" will be used to refer to the set of all LME countries except the US.

Some critics might question the "LME-ness" or "CME-ness" of certain states classified above, for example the Oceanic countries during much of the Cold War. However, I employ the existing VOC classifications for several reasons. First, in VOC theory, it is not the amount of protectionism or regulatory burden that defines an LME or CME and determines its innovative profile, but whether markets or hierarchies form the context within which economic actors organize, conduct their relationships, and solve coordination

[12] Hall, Jaffe, and Trajtenberg, 2001; database available at www.nber.org/patents.

[13] Countries such as Luxemborg and Iceland are eliminated from the VOC typology due to their small size, while others, such as Mexico, are disqualified because they are developing nations.

problems. Therefore when accepting the VOC country classifications, I privilege the relational aspects of the LME-CME distinction as discussed by Hall & Soskice, rather than protectionist or state-interventionist behavior, since the former are the most relevant and active mechanisms in VOC's theory of innovation. Second, recall that the LME-CME dichotomy is not definitive but rather "constitute[s] ideal types at the poles of a spectrum".[14] All states have some degree of tariff and non-tariff barriers to trade, and no nation is free from regulation. Therefore there are shades of LME and CME in every economy, and these change over time, hence when accepting particular classifications, I pay attention not to absolute qualities but to relative ones. Finally, all classification systems have debatable aspects, and their acceptance is often based more on their usefulness rather than their exactitude. Part of the goal of this article is to test VOC theory as stated, which includes the usefulness of their typology.

b. Dependent Variable: Innovation *(940 words)*

The most frequently used measure of innovation is patents. The debate over the proper use of patent data has proceeded vigorously and with increasing sophistication over the past several decades. The current consensus holds that patent data are acceptable measures of innovation when used in the aggregate (e.g. as a rough measure of national levels of innovation across long periods of time), but are not appropriate when used as a measure of micro-level innovation (to compare the innovativeness of individual firms or specific industries from year to year). And while this debate is ongoing and is better recounted elsewhere, this section will address some of the more pressing issues surrounding patent measures and their use in testing VOC theory.[15]

Strictly speaking, a patent is a temporary legal monopoly granted by the government to an inventor for the commercial use of her invention, where the invention can take the form of a process, machine, article of manufacture, or compositions of matters, or any new useful improvement thereof. (USPTO)[16] A patent is a specific property right which is granted only after formal examination of the invention has revealed it to be nontrivial (i.e. it would not appear obvious to a skilled user of the relevant technology), useful (i.e. it has potential commercial value), and novel (i.e. it is significantly different than existing technology). As such, patents have characteristics which make them a potentially useful tool for the quantification of inventive activity. First, patents are by definition related to innovation, each representing a "quantum of invention" that has passed the scrutiny of a trained specialist and gained the support of investors and researchers who must dedicate time, effort, and often significant resources for its physical development and subsequent legal protection. Second, patent data are widely available, and are perhaps the only observable result of inventive activity which covers almost every field of invention in most developed countries over long periods of time. Third, the granting of patents is based on relatively objective and slowly changing standards. Finally, the United

[14] Hall & Soskice 2001, 8.
[15] For a review of the debate see Griliches 1990; Trajtenberg 1990; Archibugi and Pianta 1996; Harhoff, Narin, Scherer, and Vopel 1999; Eaton and Kortum 1999; Jaffe, Trajtenberg, and Fogarty 2000; Hall, Jaffe and Trajtenberg 2000, 2001.
[16] Designs and plant life can also be patented, however most econometric analysis of patent data is confined to utility patents granted for inventions such as those listed above. For a fuller description of patents and patent laws, classifications, and the application process see http://www.uspto.gov/main/patents.htm.

States Patent and Trademark Office and the European Patent Office provide researchers with centralized patenting institutions for the two largest markets for new technology. In practical terms, this allows researchers to get around the issue of national differences in patenting laws as well as providing two separate and fairly independent data pools.

Given these qualities, patents have been used as a basis for the economic analysis of innovative activity for over thirty-five years. Current use began with the pioneering work of Frederic Scherer and Jacob Schmookler who used patent statistics to investigate the demand-side determinants of innovation.[17] However, the labor intensive nature of patent analysis, which used to involve the manual location and coding of thousands of patent documents, severely limited the extent (or at least the appeal) of their use in political and economic research. These limitations were eased somewhat during the 1970s when the advent of machine-readable patent data sparked a wave of econometric analysis.[18] In the late 1980s, the use of patent data was further facilitated by computerization, which increased the practical size of patent datasets into millions of observations. Most recently, Hall, Jaffe, & Trajtenberg at the NBER have compiled a statistical database of several million patents complete with geographic, industry, and citation information, which I will use later to test the VOC claims.[19]

However, patents do have significant drawbacks which somewhat restrict, but by no means eliminate, their usage as an index of innovation. First, there is the classification problem, in that it is difficult to assign a particular industry to a patent, especially since the industry of invention may not be the industry of eventual production or the industry of use or benefit. I address this issue, where possible, by using two different patent datasets with assorted systems and levels of patent classification. Second, it is not yet clear what fraction of the universe of innovation is represented by patents, since not all inventions are patentable and not all patentable inventions are patented. This problem is exacerbated when attempting comparative research since different industries and different countries may exhibit significant variance in their propensity to patent. I address these concerns by using publications data in addition to patents. And although patents and publications both may be imprecise measures of innovation, as long as this measurement error is random and uncorrelated with the explanatory variables, then regressions using this data should produce unbiased estimates of the coefficients (and generally with inflated standard errors).

Finally, some critics point out that patents vary widely in their technical and economic significance: most are for minor inventions, while a few represent extremely valuable and far-reaching innovations. Moreover, it has been found that simple patent counts do *not* provide a good measure of the radical-ness, importance, or "size" of an innovation. Simple patents counts correlate well with innovation inputs such as R&D outlays, but they are too noisy to serve as anything but a very rough measure of innovation output.[20] Therefore I use patent counts which have been weighted by forward citations. Forward citations on patents have been found to be a good indicator of the importance or value of an innovation, just as scholarly journal articles are often

[17] Scherer 1965; Schmookler 1966.
[18] Summaries of which can be found in Griliches 1984; Pakes 1986; and Griliches, Hall, and Pakes 1987.
[19] Hall, Jaffe, and Trajtenberg 2001.

valuated by the number of times they are cited. The idea here is that minor or incremental innovations receive few if any citations, and revolutionary innovations receive tens or hundreds. Empirical support for this interpretation has arisen in various quarters: citation weighted patents have been found to correlate well with market value of the corporate patent holder, the likelihood of patent renewal and litigation, inventor perception of value, and other measures of innovation outputs.[21]

c. Testing the VOC Industry Assumption *(1155 words)*

Armed with a better understanding of patents, we can now use them to test some of the more controversial claims made by VOC scholars. One such controversy resides in their implicit assumption about the innovative characteristics of particular industries. VOC theory assumes that some industries are inherently and statically more radically innovative, and other industries inherently and statically more incrementally innovative. However, this assumption is contradicted by a vast empirical literature which shows that the innovative characteristics of any given industry are not static but dynamic, and depend not so much on industry type but on the industry's technological maturity.[22] More specifically, studies have found that most industries are typified by two successive waves of innovation: first a flurry of radical product innovations which eventually converge on a dominant product design, followed by a flurry of process innovations in manufacturing the product at lower cost. In each wave, earlier innovations tend to be more revolutionary than subsequent ones which build upon them. For example, during the first thirty years of automobile production, more than 100 US firms produced competing models of automobiles with tremendous variance in features and operability. During this period innovation focused on radical product changes: introduction of enclosed bodies, wheel-based steering, electrical systems, gasoline-based fuel and engine systems, etc. These innovations tended to be revolutionary and dramatically affected the look and performance of successive versions of the automobile, such that cars from this period bear little resemblance to the cars of today. However, as the market converged on a dominant design for automobiles, product innovations became gradually more incremental, and the focus of radical innovation shifted to production processes. This type of innovation dynamic has been observed in almost every industry which produces assembled products.

If the innovative character of industry changes over time, then Hall & Soskice's use of snapshots of patent activity in particular industries may not properly test VOC theory. That is, for the two brief time periods covered by Hall & Soskice's patent data, we must ask whether the researchers correctly identify which industries were more radically or incrementally innovative. In order to answer this question I rely on the ability of forward citations to serve as a measure of "degree" or "value" of an innovation. For my empirical evidence, I make use of the newly compiled NBER patent dataset described above. Using the USPTO patent classifications, the NBER scholars have grouped their data into six industry categories, each consisting of 4-7 sub-categories

[20] Griliches 1984.
[21] Trajtenberg 1990; Hall, Jaffe, and Trajtenberg 2000; Lanjouw and Shankerman 1997, 1999; Jaffe, Trajtenberg, and Fogarty 2000.
[22] Summarized in Utterback 1994.

(for a total of 36 subcategories), which will allow us to compare the average patent citation rates across different industries.

Fig 2: Patents & Forward Citations by Industry, 1963-99

Industry Category	# patents	Mean (fwd. cites per patent)	Standard Dev. (fwd. cites per patent)	Min. (fwd. cites per patent)	Max. (fwd. cites per patent)
IT/Telecom	290337	6.44	10.6	0	779
Drugs/Med	204199	5.99	11.2	0	631
Electric	499741	4.75	6.70	0	251
Chemicals	606934	4.62	7.14	0	401
Others	641333	4.46	5.90	0	286
Mechanical	681378	4.17	5.71	0	411
Total	2923922	4.78	7.35	0	779

Source: NBER 2001.

Figure 2 shows the means of the forward citations per patent by industry category. The industries generally rank as assumed by VOC theory: computers & telecommunications patents receive on average the most forward citations, followed by drugs & medical, electronic, chemical, others, and finally mechanical. T-tests reveal that the differences between these means are significant beyond the 99% confidence level. Even if we sharpen the level of analysis by further subdividing the industry categories into their smaller sub-categories, we again find that patent citations behave more or less as assumed by VOC theory.[23]

Of course, analyzing the data in this manner introduces a potential truncation problem: older patents have had more time to be cited than younger patents. This problem is exacerbated in the NBER dataset since it only includes citations data from 1975 onwards.[24] Therefore, patents granted before 1975 will suffer from further truncation in that a 1969 patent will contain the citations received from patents granted during 1975-1999, but not from patents granted in 1969-74. We can control for the overall truncation problem by excluding pre-1975 patents from consideration and by using multivariate regression analysis with a control for patent age.[25] The results of these regressions are reported in Figure 3. First, we find in all of the regressions that the coefficient for patent age is significant and generally positive; note also that the age coefficient increases in strength when pre-1975 patents are omitted from the dataset, and consistently hugs 0.3 in all regressions conducted using the 1975-1999 patent data (see also Figs. 5-7 below). This is suggestive of the truncation effects described above. We can interpret this coefficient as indicating the number of additional citations received per patent for each year of its existence. The age coefficient does turn negative in Model 5, where only the very oldest patents are used. This suggests that patented innovations may have a "lifespan" of usefulness, generating much subsequent innovation while young, then slowly fading into obsolescence as either new innovations come to replace them or their capacity to serve as the foundation for new innovations is exhausted. Second, we find in Models 1 & 2 that, even when controlling for patent age (and with the added understanding that classification errors may exist), the industry coefficients generally line up as assumed by VOC theory: computers & telecommunications patents receive the most forward citations, followed by drugs & medical,

[23] Exceptions include patents in the drugs, biotechnology, food, and organic compounds sub-categories which appear to be relatively poorly cited despite the fact that these are amongst VOC's "radically innovative" industries; in the "incremental" sub-categories, patents related to gas, power systems, resins, and coatings appear to be more highly cited than VOC theory might assume. These might be partially explained by classification problems or by differences in the legal or technical need to cite in these industries.

[24] Due to the fact that citations data were not computerized prior to 1975.

Figure 3: OLS Testing of VOC's Industry-Innovation Assumption (Dep. Variable = citations received per patent)

	1	2	3	4	5	6
Data Used:	**1963-1999**	**1975-1999**	**1975-1999 (excluding US)**	**1975-1999**	**1975-1980**	**1990-1995**
IT/Telecm	2.48 (0.02)*	3.43 (0.02)*	2.70 (0.02)*	3.52 (0.02)*	3.39 (0.06)*	5.17 (0.03)*
Drugs/Med	2.07 (0.02)*	2.29 (0.02)*	0.93 (0.03)*	2.29 (0.02)*	2.83 (0.06)*	3.02 (0.04)*
Electric	0.42 (0.01)*	0.95 (0.02)*	0.92 (0.02)*	1.07 (0.02)*	0.59 (0.04)*	1.42 (0.03)*
Chemicals	0.16 (0.01)*	0.14 (0.02)*	0.18 (0.02)*	0.24 (0.02)*	0.02 (0.04)	0.15 (0.03)*
Mechancl	-0.31 (0.01)*	-0.22 (0.02)*	0.13 (0.02)*	-0.08 (0.02)*	-0.61 (0.04)*	0.016 (0.03)*
Other						
US				1.05 (0.01)*		
patent age (yrs.)	0.08 (0.000)*	0.31 (0.001)*	0.29 (0.001)*	0.31 (0.001)*	-0.04 (0.008)*	0.65 (0.005)*
_cons	3.07 (0.01)*	1.03 (0.01)*	0.82 (0.01)*	-0.40 (0.01)*	-7.29 (0.17)*	-0.42 (0.04)*
R2	0.02	0.10	0.10	0.10	0.02	0.08
Obs	2923922	2139314	939037	2139314	384270	585758

Note: Analysis is by ordinary least squares (OLS), Huber-White estimates of standard errors reported in parentheses. *p< .001. *Source*: NBER 2001.

electronic, chemical, others, and finally mechanical. The coefficients here can be interpreted as the additional number of citations received per patent for patents granted to innovations in a particular industry (relative to the omitted category "Other"[26]). The mean citations received per patent in the 1975-1999 dataset is 4.9 (with a standard deviation of 7.8), therefore the size of the innovative differences between industries suggested by the coefficients is significant, but not immense.

Since my findings in subsequent sections indicate that VOC's evidence is sensitive to the US outlier, I run two regressions to consider its effects on the industry rankings. In Model 3, I omit the US data entirely, which drastically reduces the coefficient for the IT/Telecom and Drugs/Medical categories, and increases the coefficients for the Chemicals and Mechanical categories. When I instead use a US dummy (Model 4), the coefficients change significantly for only Chemicals and Mechanical patenting. The first thing to note in both these regressions is that the rankings do not change in the areas of most concern to VOC theory: chemicals, mechanical, and "other" patents receive fewer citations than those in VOC's radically innovative sectors. Second, these regressions tell us that US is in fact a powerful outlier which affects the nature of global innovation, especially in frontier sectors.

Given the time dynamics of innovation, it is also important to confirm that the findings above are not an artifact of averaging across a long time period. Models 5 & 6 address this concern, revealing that VOC's industry assumption generally holds even when I limit the dataset to either the very earliest or very latest five years of patenting activity. In these regressions, computers & telecommunications patents consistently received the most citations, again followed by drugs & medical and electronics patents; there is however some shuffling amongst the remaining categories, especially mechanical patents which may suggest a recent small surge in

[25] All regressions reported here use a patent age based on grant year. Regressions performed using a patent age based on application year produced similar results.

innovation there. But these minor shifts do not create any major problems for the VOC assumptions. Also, though not shown here, if we again further subdivide the six categories above into their 36 subcategories, we find that patent citations behave more or less as they do at the category level.[27] Finally, given the non-constant variance in forward citations across industries (and later, countries), I correct for heteroscedasticity using Huber-White estimators of standard errors in all regressions, but find no significant differences from the results generated by the traditional estimator. In sum, patent data generally support the VOC assumption about industry innovation characteristics.

d. Testing VOC's Predictions About National Innovative Character: Simple Patent Counts *(670 words)*

Having confirmed the industry-based innovation assumption above, we can now reconsider the evidence offered by Hall & Soskice (Figure 1). Again, this chart is based on EPO patent data for the United States and Germany in thirty industries during two separate two-year periods. For each industry in each time period, Hall & Soskice calculated a patent specialization index (I) which simply subtracts a country's fraction of its total patents in a particular field from the world's fraction of total global patents in the same field.[28] Hence a positive index score means greater specialization in innovation in that particular type of technology. The chart shows that the US specializes its patenting in industries typified by radical innovation, while Germany's patent specialization is in industries typified by incremental innovation. The question then is whether this finding holds true across time and space, or have Hall & Soskice inadvertently selected outlying countries or years? In order to test this possibility, I use the same EPO dataset and computational formula used by Hall & Soskice, but instead calculate the patent specialization indices across a much longer time-span (1978-1995) and compare the innovative activities of the entire set of LME and CME countries.

The results of this exercise are summarized below in Figure 4. Note that rather than requiring an exact quantitative match, I apply a more lenient qualitative standard for VOC theory to pass, only testing which country (or set of countries) has a higher patent specialization index in each of the thirty industries. Using Hall & Soskice's data and methodology, I was able to closely reproduce their findings for Germany and the US in 1983-84 and 1993-94. However, when I extend the time period to 1978-1995, German and US patenting fails to meet VOC predictions in polymers, new materials, and nuclear engineering. Even more discrepancies arise when we expand the dataset to compare patent specialization by the set of all LME countries versus the set of all CME countries. For example, in the 1983-84 period, the set of LME's had higher patent specialization indices than the set of CME's in three industries which Hall & Soskice describe as incremental (mechanical elements, basic materials, polymers), while CME patenting had higher specialization scores in two radical industries (new materials, audiovisual tech.). But the most striking disparity occurs when we exclude the United States from the

[26] "Other" includes innovations in miscellaneous areas such as house fixtures, furniture, pipes & joints, jewelry, cutlery, recepticals, undertaking, and amusement devices.

[27] With the same exceptions at the subcategory level as those found with the citations averages. See fn 17 above.

[28] For example, in biotechnology: $I_{US\ biotech} = US_{biotech}/US_{total} - World_{biotech}/World_{total}$.

Figure 4: Violations of VOC Theory for Innovation in 30 Technology Classes (shaded squares indicate violations)[29]

	US v. Germany			LME's v. CME's			LME's (ex-US) v. CME's		
	1983-84	1993-94	1978-95	1983-84	1993-94	1978-95	1983-84	1993-94	1978-95
Agricultural Machines							■	■	■
Agriculture, Food									
Audiovisual Tech.				■	■	■	■	■	■
Basic Materials, Chem.				■			■		
Biotechnology									
Civil Engineering							■	■	■
Consumer Goods							■	■	■
Control Systems									
Electrical Energy									
Engines							■	■	■
Environment									
Handling							■		
Information Tech.							■		■
Machine Tools									
Materials Processing									
Mechanical Elements				■			■	■	■
Medical Engineering									
New Materials			■	■	■	■		■	■
Nuclear Engineering			■		■	■		■	
Optics					■	■	■	■	■
Organic Chemistry									
Pharmaceuticals									
Polymers			■	■	■	■		■	
Process Engineering					■				
Semiconductor							■	■	■
Surfaces					■			■	■
Telecom.							■		
Thermal Processes									
Transport							■		■
Weapons					■		■		■
Total Violations	**0**	**0**	**3**	**5**	**8**	**5**	**14**	**12**	**13**

Source: EPO (Hall & Soskice, 2001)

set of LME countries; under these conditions we find that VOC theory has only marginally more predictive power than random chance.

The NBER patent data presents us with a second dataset with which to test the patent specialization indices devised by Hall & Soskice. Such a test adds value in that the NBER dataset not only spans over twice

[29] Patent specialization indices (I) for the set of LME's, CME's, and LME's (excluding-US) are calculated by treating each set of nations as a single "country". A violation (shaded square) in one of these columns indicates that the difference in aggregate patent specialization indices was *opposite* that found by Hall and Soskice (2001) in their German vs. US comparison.

the time-period (1963-1999) as the EPO data used by Hall & Soskice, but consists of USPTO patents and is therefore a completely independent dataset. The NBER data also uses a completely independent classification scheme which allows us to control for some of the potential classification problems and idiosyncrasies discussed above. Yet, despite these differences, our results are generally the same as those found using Hall & Soskice's EPO data. I omit a graphic depiction of the results and instead explain the major findings. Of the 18 categories of innovation which I was able to map from Hall & Soskice to the NBER data, VOC's predictions were born out relatively well (approximately 70-80% of the time, depending on the time period) when applied to the US and Germany.[30] However, when we expand the dataset to test all LME countries versus all CME countries, we find that VOC theory loses a considerable amount of its predictive power, with a 72% success rate in 1983-84, but only 50% in 1993-94, and 56% over the entire 1963-1999 period. Omitting the US from the set of LME's results in further deterioration, with VOC's success rate ranging from 44-56%. Thus, after analyzing two different datasets and competing classification methods, it appears that the success of VOC theory strongly depends upon the inclusion of the United States as an LME.

e. Testing VOC's Predictions About National Innovative Character: Patent Citations *(1245 words)*

So far we have used simple patents counts in our comparisons of LME's vs. CME's, yet we know from the discussion above that forward citations of patents are an even better gauge of radical vs. incremental innovation. Therefore, in this section, I will use the forward citations data in the NBER patent dataset to test the VOC country claims directly, retaining the same techniques which I used above in testing the VOC assumptions about industries. As my dependent variable in all of the following regressions I again use citations-received per patent as a proxy for the radical vs. incremental nature of innovation. VOC theory suggests that country dummies or country-type dummies (LME, CME) are the primary independent variables of interest, as well as controls for industry-type (again we use industry category or sub-category), and of course a control for patent age should be included to address the truncation problem. Since the US outlier proved important in the simple statistical analysis above, I address it in two ways in the regressions. In some regressions a US dummy is introduced, in others the US is simply omitted from the class of LME's (creating a new dummy: LMEx). For data, we use the NBER patent dataset for all countries' patenting activity during the period 1975-1999.

We begin with regressions using controls only for patent age and country-type, the results of which (Figure 5) reinforce what we found previously: that LME's are more radically innovative than CME's (Model 1

[30] Agricultural machines (a particularly difficult category to define in NBER terms) is the only category which persistently defies the VOC predictions in all time periods; while patenting in optics, pharmaceuticals, transport, organic chemistry, weapons, electrical energy, and nuclear engineering (narrowly measured) each contradicted VOC theory in different time periods.

v. Model 2), but that this finding depends entirely upon the inclusion of the United States as an LME (Model 3). This effect is apparent even when the CME dummy is run together with that for LME's or LMEx's (Models 4 & 5). In each of these regressions, the coefficients can be interpreted as the additional number of citations received

Figure 5: OLS Testing of VOC Innovation Theory, by Nation Type (1975-1999)

	1	2	3	4	5	6	7
LME	0.95 (0.011)*			1.71 (0.02)*		0.65 (0.03)*	
CME		-0.59 (0.011)*		0.93 (0.02)*	-0.67 (0.01)*	0.93 (0.02)*	0.93 (0.02)*
LMEx			-0.74 (0.022)*		-0.95 (0.02)*		0.65 (0.03)*
patent age (yrs.)	0.28 (0.001)*	0.28 (0.001)*	0.29 (0.001)*	0.28 (0.001)*	0.28 (0.001)*	0.28 (0.001)*	0.28 (0.001)*
US						1.16 (0.02)*	1.81 (0.02)*
_cons	1.51 (0.01)*	2.26 (0.01)*	2.09 (0.009)*	0.76 (0.02)*	2.33 (0.01)*	0.76 (0.02)*	0.76 (0.02)*
R2	0.076	0.074	0.073	0.077	0.074	0.08	0.078
Obs	2139314	2139314	2139314	2139314	2139314	2139314	2139314

Note: Analysis is by ordinary least squares (OLS), Huber-White estimates of standard errors reported in parentheses. *p< .001. *Source*: NBER 2001.

per patent for patents granted to innovations in a particular set of nations (LME's, CME's, or LMEx's) relative to the rest of the world. Note how sharply the LME coefficient drops when we introduce a US dummy variable (Model 6) and, perhaps more interesting, that the LMEx's appear to be *less* radically innovative than the CME's (Models 7). Of equal importance is the small size of the coefficients and the differences between them. These indicate, for example in Model 4, that *even when we do not control for the US-outlier*, the innovative difference between LME's and CME's is smaller than a single citation per patent. Although this may be a statistically significant amount, it is far smaller than the innovative difference between the most vs. least innovative industries found above and does not suggest a large innovation gap.

Figure 6: OLS Testing of VOC Innovation Theory, by Nation Type & Industry (1975-1999)

	1	2	3	4	5	6	7
LME	0.94 (0.01)*			1.66 (0.02)*		0.66 (0.03)*	
CME		-0.59 (0.01)*		0.89 (0.02)*	-0.66 (0.01)*	0.89 (0.02)*	0.89 (0.02)*
LME (excluding-US)			-0.68 (0.02)*		-0.90 (0.02)*		0.66 (0.03)*
US						1.10 (0.02)*	1.76 (0.02)*
patent age (yrs.)	0.31 (0.001)*	0.31 (0.001)*	0.31 (0.001)*	0.31 (0.001)*	0.31 (0.001)*	0.31 (0.001)*	0.31 (0.001)*
IT/Telecom	3.53 (0.02)*	3.50 (0.02)*	3.42 (0.02)*	3.49 (0.02)*	3.49 (0.02)*	3.48 (0.02)*	3.48 (0.02)*
Drugs/Med	2.28 (0.02)*	2.28 (0.02)*	2.29 (0.02)*	2.29 (0.02)	2.29 (0.02)*	2.29 (0.02)*	2.29 (0.02)*
Electrical	1.07 (0.02)*	1.02 (0.02)*	0.94 (0.02)*	1.06 (0.02)*	1.02 (0.02)*	1.05 (0.02)*	1.05 (0.02)*
Chemicals	0.24 (0.02)*	0.21 (0.02)*	0.13 (0.02)*	0.22 (0.02)*	0.20 (0.02)*	0.22 (0.02)*	0.22 (0.02)*
Mechanical	-0.09 (0.02)*	-0.14 (0.02)*	-0.22 (0.02)*	-0.11 (0.02)*	-0.13 (0.02)*	-0.11 (0.02)*	-0.11 (0.02)*
Other							
_cons	0.41 (0.02)*	1.28 (0.01)*	1.07 (0.01)*	-0.29 (0.02)*	1.25 (0.01)*	-0.29 (0.02)*	-0.29 (0.02)*
R2	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Obs	2139314	2139314	2139314	2139314	2139314	2139314	2139314

Note: Analysis is by ordinary least squares (OLS), Huber-White estimates of standard errors reported in parentheses. *p< .001. *Source*: NBER 2001.

VOC theory also includes industry-type as a factor in determining innovative behavior. Hence a second set of regressions are run (Figure 6), identical to those reported in Figure 5 but with the addition of controls for industry. Yet we find no significant differences when the industry controls are added to the regression models. Again, the LME countries appear at first to be more radically innovative than the CME's (Model 1 vs. Model 2), but not when the United States is excluded from the group of LME's (Model 3). Note also that the industry coefficients in this regression match those found when we previously tested the VOC industry-innovation assumption above (Figure 3). In order to test this finding more directly we add a US-dummy, which again severely affects the coefficient of the LME dummy (Models 6 & 7). Regressions run at a finer level of analysis using industry subcategories (not shown) produce similar results.[31]

Given the broad nature of VOC theory and the complex array of causal mechanisms it hypothesizes, a fixed effects model is perhaps the best, most efficient way to conduct a statistical test of its central predictions. While the NBER dataset affords us enough degrees of freedom to use countries dummies for all 162 nations, computer memory does not. I therefore run a final set of regressions in which I include dummies for 23 of the world's highest patenting countries.[32] These countries include the aforementioned LME and CME states in addition to France, Italy, Spain, Israel, Taiwan, Singapore, and South Korea. Using only country dummies, controlling for age, and correcting for heteroscedasticity, we find that the relative strengths of the coefficients for the remaining dummies do not quite line up along the lines predicted by VOC theory (Figure 7). Here the coefficients can be interpreted as the additional number of citations received per patent for patents granted to innovations in a particular nation relative to those granted to the rest of the world (ROW). Though not astronomical, the size of the coefficients do indicate significant innovative differences between states, and that these innovative differences are comparable to those across different industries. All of the coefficients are positive, indicating that patents from the rest of the world generally receive fewer forward citations than patents from our chosen countries. Patents from the US receive the most forward citations, those from Spain, Austria, and New Zealand consistently receive the least. Interestingly, Australia and New Zealand appear to deserve a place amongst the CME's, while Japan seems to be one of the most radical innovators (Model 1). And while we are not immediately concerned with Hall & Soskice's hybrid MME's, the three which appear in the regressions (France, Italy, Spain) have major differences between them and do not appear to form a cohesive group. Also, the high placement of Israel (arguably a pre-1970s CME, increasingly MME thereafter) and Taiwan (arguably an MME), not mentioned in VOC theory, further suggest that there may be more to radical innovation than the variables captured by Hall & Soskice. Adding controls for industry do not have a significant impact on the rankings, except for some minor shuffling (Model 2).

[31] An alternate interpretation of VOC theory suggests that in place of LME/CME/LMEx controls, we might include interaction terms (LME*industry, CME*industry, and LMEx*industry). I experimented with such interaction terms but produced the same general results as those reported above.
[32] As before, all pre-1975 patents are eliminated to control for truncation effects.

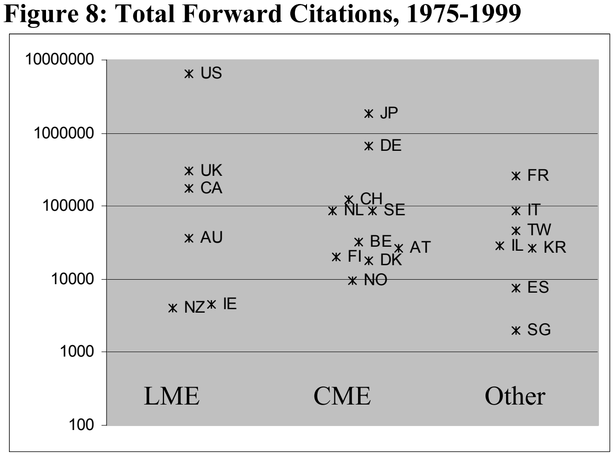
Figure 7: OLS Testing of VOC Innovation Theory, by Country & Industry (1975-1999)

				LME's						
	patent age (yrs.)	**US**	**Ireland**	**Canada**	**UK**	**Australia**	**New Zealnd**			
1	0.29 (0.001)**	2.74 (0.03)**	2.23 (0.22)**	1.74 (0.05)**	1.55 (0.04)**	1.14 (0.06)**	0.55 (0.13)**			
2	0.32 (0.001)**	2.59 (0.03)**	1.93 (0.22)**	1.76 (0.04)**	1.35 (0.04)**	1.21 (0.06)**	0.68 (0.13)**			
				CME's						
	Japan	**Nethrlds**	**Belgium**	**Denmark**	**Sweden**	**Finland**	**Germany**	**Switz**	**Norway**	**Austria**
1	2.52 (0.04)**	1.34 (0.05)**	1.27 (0.07)**	1.07 (0.09)**	1.07 (0.05)**	1.05 (0.07)**	0.92 (0.04)**	0.77 (0.05)**	0.61 (0.10)**	0.42 (0.06)**
2	2.24 (0.04)**	1.09 (0.05)**	1.28 (0.07)**	0.98 (0.09)**	1.02 (0.05)**	1.01 (0.07)**	1.00 (0.04)**	0.81 (0.05)**	0.69 (0.10)**	0.64 (0.06)**
				Others						
	Israel	**Singapore**	**Taiwan**	**S. Korea**	**France**	**Italy**	**Spain**	**ROW**		
1	2.25 (0.09)**	1.90 (0.17)**	1.34 (0.04)**	1.21 (0.04)**	1.06 (0.04)**	0.69 (0.07)**	0.07 (0.08)			
2	1.79 (0.09)*8	1.54 (0.17)**	1.56 (0.04)**	0.78 (0.04)**	0.86 (0.04)**	0.72 (0.05)**	0.18 (0.08)*			
				Industries						
	IT/Telecm	**Drugs/Med**	**Electrical**	**Chemical**	**Mechancl**	**Other**	**_cons**	**R2**	**Obs**	
1							-0.25 (0.03)**	0.08	2139314	
2	3.36 (0.02)**	2.33 (0.03)**	0.98 (0.01)**	0.23 (0.01)**	-0.14 (0.01)**		-1.14 (0.04)**	0.10	2139314	

Note: Analysis is by ordinary least squares (OLS), Huber-White estimates of standard errors reported in parentheses. **p< .001, *p< .05. *Source:* NBER 2001.

Finally, if we believe that both quality *and* quantity of patents matter, that Ireland with its relative trickle of few but highly cited patents should not necessarily be considered more radically innovative than Germany with its slightly less cited ocean of patents, then we must instead look at total citations received over time. This data is charted below in Figure 8. Here we have merely multiplied the mean citations received per patent by the total number of patents for each country. This will allow us to capture both the number and value of patents in one measure. The plots are split horizontally into three groups (LME's, CME's, and other countries) for comparison. Again we see the US outlier, but no strong general differences in total citations between the different VOC country types.

Figure 8: Total Forward Citations, 1975-1999



In sum, the VOC theory does not appear to explain innovation as measured by patenting activity. Rather, the success of VOC theory in predicting innovation appears to depend upon the inclusion of the United States, a major outlier, in the set of liberal market economies. We find this fact repeated regardless of the source of the patent data, the type of industry classification system used, or whether simple patents or forward citations are used. However, one caveat which bears repeating is that this finding depends an assumption of random error in using patents as a measure of innovation.

Social scientists cannot yet completely describe the correlation between patents (an innovation output) and total innovation, nor do we fully understand how propensity to patent varies across industry, across country, and over time. We therefore briefly consider the non-patent evidence for differences in national innovation in the next section.

V. Additional Evidence *(825 words)*

Patent statistics are by no means the only innovation data which paint a picture contradictory to the VOC claims, scholarly journal articles are another useful measure of innovation which reinforces the cross-national findings discussed above. Scholarly publications data offer advantages similar to those of patents, with each journal article representing a quantum of research innovation which must pass independent review and which tends to be cited in proportion to its innovative impact. More importantly, scholarly publications data are completely independent of patents: they are generally produced by a different set of innovators, affected by different incentives, and judged according to different institutional standards (McMillan & Hamilton 2000). Of course, journal articles also suffer many of the same shortcomings as patents, including difficulties in classification, problems with valuation, and uncertainty regarding to what degree journals represent the universe of innovation.[33] These difficulties are further complicated by changing journal sets, the lack of a single standardized referee process, and the relative importance of prestige and popularity in the publication process. However, just as with patents, information sciences scholars have found legitimate and rigorous applications for publications data in measuring innovative output. While this debate is better summarized elsewhere, the current consensus is that there is reasonable basis for using journal articles as a window on innovative activity in the aggregate.[34]

VOC theory does not make specific predictions regarding scholarly publications patterns, and indeed its authors may never have intended it to. Nonetheless, we might infer from VOC theory the following hypothesis: that scholarly publications by LME researchers should show specialization in fields associated with revolutionary scientific advances, while CME's should show specialization in fields associated with incremental scientific advances. Although it is not quite clear what a "radically" versus "incrementally" innovative field might be, one could simply map the typology used by Hall & Soskice for industrial sectors over to academic sectors. For example, CME's should excel in publishing in the engineering and technology journals, LME's in biology, medicine, and physics. A second hypothesis might surmise that researchers in the CME's should excel in professional journals and applied sciences publications where incremental research is more prominent, while LME researchers should publish heavily in the more academic or theoretical sciences journals where the research tends toward the revolutionary. A third, and less controversial, hypothesis would be that LME publications should simply have higher forward citation averages than CME publications.

[33] the innovative "representativeness" of journal articles is more of a problem in the social sciences, and less so in the physical sciences, see Hicks 1999.
[34] Glanzel and Moed 2002, Bourke and Butler 1996, Garfield 1972.

Figure 9: Specialization in Scholarly Publications (publications per field as a % of total)

1986	Clincl Med	Bio-Med	Bio	Chem	Physics	Earth Space	Eng-Tech	Math	Psych.	Soc. Sci.	Health	Prof.	*Total*
World	29.8%	15.0	7.9	12.5	12.2	4.4	6.7	1.8	2.7	3.7	0.9	2.7	*100%*
LME	31.6%	14.6	9.1	7.7	9.1	4.9	6.4	1.8	3.9	5.1	1.4	4.4	*100%*
CME	34.2%	15.1	6.8	14.2	12.9	3.0	8.0	1.7	1.4	1.8	0.3	0.6	*100%*
LME (ex-US)	32.7%	13.8	12.2	8.6	7.9	5.3	6.3	1.7	3.1	4.8	1.0	2.6	*100%*
1999	**Clincl Med**	**Bio-Med**	**Bio**	**Chem**	**Physics**	**Earth Space**	**Eng-Tech**	**Math**	**Psych.**	**Soc. Sci.**	**Health**	**Prof.**	***Total***
World	29.0%	15.0	7.0	12.5	15.0	5.4	6.8	2.0	2.0	2.7	0.9	1.8	*100%*
LME	32.1%	16.0	7.3	8.0	10.0	6.2	5.9	1.8	3.3	4.2	1.5	3.3	*100%*
CME	32.7%	15.0	6.5	13.5	17.0	4.0	6.2	1.5	1.2	1.3	0.4	0.5	*100%*
LME (ex-US)	32.0%	14.4	10.0	8.5	9.4	6.4	6.1	1.7	3.0	4.4	1.6	2.2	*100%*

Source: National Science Board 2002.

Yet, none of the patterns hypothesized above can be found in the cross-national publications data. Consider the ISI's simple journal publication data compiled in Figure 9. Compare the world publication rates by field with those of the LME's and CME's. As a group, the LME's tend to consistently specialize in clinical medicine, biology, earth-space, psychology, social science, health, and professional journals; CME's tend to

Figure 10: Relative Prominence of Scientific Literature by Country/Economy and Field (1999)

	All fields	Biolgy	Bio-med	Chem	Clincl Med	Earth Space	Eng-Tech	Math	Physics	Soc. Sci.	Psych	Health	Prof.
United States	1.35	1.16	1.40	1.50	1.27	1.31	1.20	1.24	1.47	1.28	1.12	1.14	1.16
United Kingdom	1.04	1.25	0.98	1.14	1.00	1.03	0.99	1.23	1.07	1.07	1.16	0.90	0.64
Canada	0.99	1.05	0.91	1.30	1.11	0.89	0.89	0.92	0.99	0.84	1.07	0.87	0.89
Australia	0.87	1.04	0.78	1.05	0.91	0.88	1.05	1.02	0.90	0.65	0.80	0.88	0.84
Ireland	0.82	0.99	0.57	0.98	0.87	0.67	0.85	1.02	0.93	0.56	0.76	0.67	0.47
New Zealand	0.76	0.89	0.57	1.00	0.86	0.71	0.99	0.65	1.07	0.78	1.06	0.97	0.73
LME	**1.235**	**1.136**	**1.264**	**1.381**	**1.188**	**1.190**	**1.123**	**1.193**	**1.340**	**1.167**	**1.104**	**1.055**	**1.069**
LME (ex-US)	**0.986**	**1.104**	**0.918**	**1.160**	**1.007**	**0.944**	**0.966**	**1.082**	**1.027**	**0.932**	**1.066**	**0.889**	**0.729**
Switz.	1.37	1.41	1.40	1.45	1.08	1.16	1.77	1.07	1.36	0.66	0.59	0.48	0.86
Netherlds	1.12	1.19	0.89	1.41	1.08	1.14	1.24	0.94	1.26	0.87	1.03	1.13	0.86
Sweden	1.07	1.30	0.87	1.33	0.99	0.78	1.11	1.02	1.10	0.86	0.78	0.93	0.53
Denmark	1.04	1.21	0.77	1.20	0.94	0.85	1.34	1.36	1.35	0.55	0.63	0.70	1.17
Finland	1.02	1.17	0.86	0.94	1.03	0.63	0.95	0.92	1.01	0.72	0.89	1.38	0.73
Germany	1.01	1.08	1.00	1.07	0.83	1.11	1.06	1.08	1.27	0.42	0.72	0.48	0.31
Belgium	0.95	1.14	0.80	1.06	0.92	0.75	1.01	1.04	0.96	0.72	0.86	0.34	0.81
Austria	0.91	1.04	0.83	0.96	0.81	0.64	1.01	0.64	1.15	0.45	0.65	0.83	0.51
Japan	0.83	0.79	0.78	0.99	0.76	0.83	1.00	0.72	0.87	0.41	0.43	0.53	0.62
Norway	0.82	1.18	0.67	0.80	0.82	0.86	1.04	1.23	0.84	0.76	0.82	0.71	0.58
CME	**0.968**	**1.041**	**0.899**	**1.078**	**0.871**	**0.968**	**1.070**	**0.968**	**1.069**	**0.613**	**0.762**	**0.854**	**0.612**

Note: Each number represents the country's share of cited literature adjusted for its share of published literature. A score of 1.00 would indicate that the country's share of cited literature is equal to the country's world share of scientific literature. A score greater (less) than 1.00 would indicate that the country is cited relatively more (less) than is indicated by the country's share of scientific literature. Example: $I_{US\ biology} = (\#\ US_{biology,\ cited} / \#\ World_{biology,\ cited}) / (\#\ US_{biology,\ published} / \#\ World_{biology,\ published})$. *Source:* National Science Board 2002, Appendix Tables 5-43, 5-52.

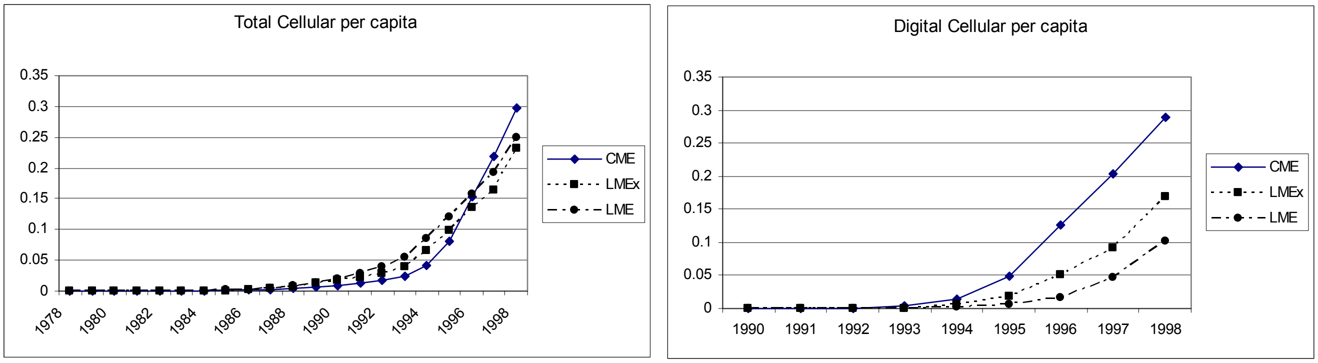
consistently specialize in clinical medicine, chemistry, and physics. Over time the CME's have increased their specialization in biomedical research, physics, and earth-space, but weakened in clinical medicine, chemistry, and engineering & technology; while the LME's have increased their specialization in biomedical, physics, and earth-space. Using forward citation indices (Figure 10 above) we find the LME's beating CME's in all fields. When we exclude the US from the set of LME's, the LME's appear to have higher citations than the CME's in all fields except earth & space, engineering, and physics. Relatively speaking, LME's are strongest in chemistry, physics, biomedical research, and math. CME's are strongest in chemistry, engineering, physics, and biology. None of these findings is what we might expect from VOC theory.

****[Following 2 paragraphs omitted from published draft]****

We should also take a *prima facie* look at technological diffusion in LME's and CME's.[35] Such a line of inquiry might not necessarily be endorsed by VOC theorists, but it is worth brief consideration. The motivation here is twofold. First, innovation and diffusion are interdependent, and can often be mistaken for one another empirically. Hence, it is possible that any original observations which might underlie the VOC innovation claims could have been misidentified by researchers. Second, and more importantly, VOC theory itself motivates a look at diffusion, since the incentives described by Hall & Soskice as affecting innovation can just as easily be construed as affecting diffusion. We therefore map the VOC innovation claims into a diffusion context and hypothesize that: more radical technologies should diffuse faster in the LME's, while the follow-on (or "second-generation") incremental improvements to these technologies should diffuse more quickly in the CME's.

Testing our diffusion claims is relatively straightforward. Again, the purpose here is not to perform a definitive test, but rather to see if there is any initial empirical support for an application of VOC theory to an important phenomena that is related to, but distinct from, innovation. Fortunately, the measurement of technological diffusion is both less controversial and easier to perform than is innovation; unfortunately, there is no single measure for technological diffusion or centralized source of diffusion data, therefore it must be measured and coded on a case by case basis. Since this investigation is to be brief and probative, priority is therefore given to finding datasets that are reliable, complete, and which cover the countries and years of interest. The International Telecommunications Union provides such data on the diffusion of a handful of telecommunications and computer technologies. These diffusion data fail to tell a consistent story. In some instances, the LME's do seem to be better at diffusing radical innovations, while the CME's appear to be better at diffusing incremental innovations. For example, the LME's rapidly diffused first-generation (analog) cellular phone technology, but the CME's were quicker to spread second-generation (digital) cellular, and this relationship holds even when the US is excluded from the LME data (Figure 11). However, such a relationship is not consistent across technologies or across time, even within the same sector. For instance, the diffusion of television technology of all sorts (initial, cable, satellite) followed the same pattern as the patent data: the LME's appear to lead the CME's in diffusion, but omitting the US from the dataset reverses this relationship. And if one considers the Internet to be an incremental innovation on computers, then the relationship further falls apart: CME's consistently trail the LME's (with or without the US) in the diffusion of both technologies. Of course, further research needs to be done in order to control for greater variation in sector and time period, however these initial findings are somewhat inauspicious.

Figure 11: Diffusion of Cellular Technology



****[Preceding 2 paragraphs omitted from published draft]****

Finally, despite problems in measuring pre-1960s innovation and diffusion, history provides researchers with some natural experiments which deserve further investigation. For example, Japan, during its first brush with democracy (1910s-1930s), was distinctively "LME-ish" but does not appear to have followed a significantly different innovation pattern than did post-war CME Japan. During this earlier period, Japan had a strong and confrontational labor movement upon which business did not hesitate to inflict frequent and severe dislocations for the sake of technological advance. Moreover, the dependence of pre-war Japan on external trade and finance exposed even the powerful *zaibatsu* to the vicissitudes of international markets and created many LME-type incentives for economic actors. Yet the Japanese appear to have been consistent incremental innovators during this time. On the other hand, the Germans of this time period rivaled the United States in technological advance, producing wave after wave of radical innovation in multiple fields including the gas-powered automobile, the Zepplin, the Haber-Bosch process, blood-typing, aspirin, and organic chemicals to name but a few. Yet, the Germans had many of the same CME-type institutions and incentives as we find there today, including a national welfare system, national health care, and large business cartels negotiating with each other, and sometimes with workers, in a fairly CME-like manner. These stylized facts, while not conclusive, do suggest areas for deeper research and further testing of VOC claims, both as a theory of innovation and as general theory of political economy.

VI. Implications *(810 words)*

In sum, we have found that the predictions made by Varieties of Capitalism theory regarding national differences in technological innovation are not supported by the empirical data, and that the existing evidence depends heavily on the inclusion of a major outlier, the United States, in the class of liberal-market economies. My empirical investigation included simple patent counts, patents weighted by forward citations, and scholarly

[35] *Diffusion* is defined here as the process by which an innovation is propagated over time amongst members of a social system.

publications (both simple counts and weighted). I investigated data covering all of the VOC countries over the course of several decades, little of which revealed the patterns predicted by VOC scholars.

These findings carry significant repercussions for both VOC and innovation theory. First, insofar as patents and scholarly publications are good indices of innovation, VOC theory clearly fails to provide an accurate picture of the innovation process, and hence the trade and production patterns which follow. Whether this is a problem with the LME-CME classification system or VOC's assumptions and causal mechanisms is not clear from the evidence presented here. However, I would suggest that while the firm may be the key actor in capitalist economies, and the primary producer of goods and services, it is difficult to ignore the role of the state in innovation as strongly as VOC's theory and classification system do. Throughout the world, much useful innovation is the result of state-sponsored and state-managed R&D, often originating in concerns with national security. Another stream of innovative R&D in many countries comes from the public university system, or private universities benefiting from significant state-support. In still other states, innovation takes the form of incremental improvements on imported technologies, where the government has had a heavy hand in deciding which technologies will get imported. Often, the government also plays a key role as a market maker for, and main diffuser of, new innovations. However, VOC's innovation theory omits these causal mechanisms entirely. This does not mean that VOC scholars are wrong to bring the firm onto the center-stage of political economy, but rather that in trying to get away from a hackneyed focus on government protectionism and state-ownership, they may have overcompensated. Future theorists must find a synthesis between the corporate-centered relationships emphasized by VOC and the state-centered mechanisms employed in traditional political economy.

Second, the statistical analyses above consistently point to the United States as an important factor in explaining global patterns of innovation. Furthermore, the fixed effects regressions reported in Figure 7 reveal that many of the world's most innovative countries are those which also tend to have the strongest military and economic ties with the US, including Japan, Canada, the UK, Israel, and Taiwan. Together, these observations suggest that in order to better understand the political economy of comparative rates of innovation, future research should perhaps focus less on domestic institutions and more on international relations. This is not to argue that domestic institutions are insignificant, but rather that the scope and depth of a country's relationship with the lead innovator may also carry significant weight in determining its technological profile. There is theoretical grounds for this supposition in that while the basic laws of science may be public goods, the tacit knowledge required to apply these laws to proper use and development of new technology is relatively excludable. Therefore factors such as foreign direct investment, educational exchanges, military assistance, and international flows of science and engineering labor between the lead innovator and other countries should be explored for their effects on innovation and the agglomeration patterns which interest both VOC and trade theorists.

Of course, we should recognize that the research reported above, while suggestive, does not necessarily shut the door on a Varieties of Capitalism approach to technological innovation. Innovation is a notoriously difficult phenomenon to measure quantitatively, and existing measures carry with them considerable noise, hence further progress needs to be made on method as well as theory. Nor does our critique here necessarily apply to other aspects of VOC theory. VOC is a broad approach to social behavior, consisting of myriad hypotheses regarding almost the whole spectrum of political economy including corporate governance, monetary policy, welfare programs and labor reform. These hypotheses are not necessarily interdependent and need to be considered and tested each on its own merits. Finally, as social scientists increasingly turn to institutions and international relationships in order to explain various phenomena related to cross-national variance in innovation, VOC scholars should be applauded for inserting political science into an area of research from which it has been all but absent.[36] While economists and sociologists have produced some excellent studies of the role of these variables in international technological performance, the comparative advantage which political scientists bring to the field in terms of methods and theory make this an area deserving far greater attention by students of politics. Varieties of Capitalism scholars have therefore provided a valuable and useful starting point for such an endeavor.

[36] Notable exceptions include Edquist 1997; Samuels 1994; Lundvall 1992; Nelson 1993.

XI. Sources *(1040 words)*

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