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Does culture still matter?: The effects of individualism on national innovation rates

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ABSTRACT

Does a society's culture affect its rate of inventive activity? This article analyzes several independent datasets of culture and innovation from 62 countries spanning more than two decades. It finds that most measures of individualism have a strong, significant, and positive effect on innovation, even when controlling for major policy variables. However, the data also suggest that a certain type of collectivism (i.e. patriotism and nationalism) can also foster innovation at the national level. Meanwhile, other types of collectivism (i.e. familism and localism) not only harm innovation rates, but may hurt progress in science worse than technology.

1. Executive summary

Is there a linkage between a society's cultural values and its ability to innovate? Since entrepreneurs often use technological innovation as their basis upon which to build new businesses and industries, the question of whether national culture promotes innovation should be of critical importance. However, there is a paucity of culture–innovation research that focuses on the national level. This gap needs to be filled. After all, an entrepreneurial firm's organizational culture may not match, or might be overwhelmed by, the culture of the society within which it innovates or whose workers it employs. Furthermore, evidence that a nation's culture affects innovation may carry important implications for business strategists concerned with locating R&D facilities internationally. Also, if national culture matters, then simply budgeting more money for R&D, industrial infrastructure, and the promotion of entrepreneurship may not be sufficient to increase the national innovation rate of a country whose underlying cultural values are antithetical to innovative activity.

Some scholars suggest that cultures which emphasize individualism should foster high rates of technological innovation. However, few cross-national studies of individualism and innovation exist to confirm this suspicion. Those that do exist have relied on limited quantitative data or non-generalizeable case studies. In fact, cross-national statistical analysis of culture and innovation has not progressed much beyond Shane's (1992, 1993) seminal articles in this journal. Meanwhile, several countries without individualist cultures (e.g. Taiwan, South Korea, Finland, India) have built up globally competitive high-technology industries. Fortunately, in the past two decades, significant improvements have been made in the amount and richness of quantitative data on culture and innovation. Given this recent progress in empirical measures, this article asks whether Shane's initial observations regarding individualism can be confirmed. Furthermore, do the improved data allow us to generate new findings about the culture–innovation relationship?

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Specifically, this study adds value with analysis of new data that has four significant improvements over data available in prior years. First, instead of a single empirical measure of culture or innovation, we use several datasets developed during the past decade to triangulate on both the independent and dependent variables. We employ two rival measures of innovation: technology patents (from the NBER patent database) and science-engineering publications (from the Thomson-ISI National Science Indicators database). We also use several rival cultural measures drawn from three independent datasets (Hofstede, Schwartz, and GLOBE). Second, instead of using simple patent or publication counts to measure innovation, we weight patents and publications by their forward citations in order to control for quality (e.g. such that the patent for the transistor is not treated as equal to the patent for the paper-clip). These measures allow us to probe the culture–innovation relationship with greater certainty than was possible in prior statistical research. Third, additional data allow us to broaden the scope of the investigation beyond that possible in the early 1990s, almost doubling the number of countries under analysis. Also, since brief time spans can miss correlations that might appear over the long-run, we analyze innovation data over two decades, instead of only two or four individual years as was done previously. Finally, in some regressions, we go beyond Shane and control for institutional, policy, and resource variables which are theorized by many innovation scholars to affect innovation, and thereby might constitute sources of omitted variable bias in Shane's studies.

Our results are surprising. On one hand, we mostly confirm that high-levels of cultural individualism correlate with national innovation rates. These results imply that individualism generally helps (and collectivism generally hurts) rates of technology patenting and scientific research publication, even when controlling for wealth, military spending, trade openness, fuel exports, and education and R&D spending. However, the new data do not support a wholesale endorsement (condemnation) of individualism (collectivism) as is predicted by much of the conventional wisdom. Rather, the regressions suggest fundamental changes in the way scholars and business should approach the relationship between culture and innovation. Specifically, they suggest that a culture of individualism in the market which demands new technologies may be more important for national innovation rates than individualism in the market which supplies innovators and entrepreneurs. This might serve as an empirical warning to culture–innovation theorists: they may be missing an important causal mechanism by focusing primarily on the cultural aspects of the supply, while often ignoring those of demand. Furthermore, the data also suggest that a certain type of collectivism (i.e. patriotism and nationalism) can foster innovation at the national level, while other types of collectivism (i.e. familism and localism) not only harm national innovation rates, but may hurt progress in science worse than in technology. These findings imply that businesses and innovation scholars should avoid stereotyping all collectivist cultures as anti-innovation. They also suggest that researchers and businesses investigating the effects of different incentive structures should consider the importance of cultural fit. Reward systems that foster innovation in one cultural context may fail to do so in another. Of course statistical analysis of culture and innovation can only take us so far; but these findings provide a basis upon which social scientists using surveys, interviews, case studies, and ethnographic techniques can build and test more precise theories.

2. Introduction

Innovation scholars spanning several academic disciplines have theorized that national culture affects innovation by influencing the preferences, expectations, and incentives of individuals across a society. Since entrepreneurs often use technological innovation as their basis upon which to build new businesses and industries, this question of whether national culture promotes innovation should be of critical importance. National culture, however, has received comparatively light treatment in this journal despite frequent assertions by prominent economists and innovation scholars that differences in technological capabilities "can be explained satisfactorily only when cultural factors are considered." (Saha, 1998: 499; also Landes, 1998; Harrison and Huntington, 2000) The research that does consider culture has concluded that it matters for innovation rates at the level of the individual (McGrath et al., 1992) and the firm (O'Regan et al., 2006; Irani et al., 2004; Stock and McDermott, 2001). However, at the national level, only a few empirical investigations have been made into whether culture influences innovation rates (Suzuki et al., 2002; Lee et al., 2000; Senker, 1996; Shane, 1992, 1993).

This gap in the literature needs filling. After all, a firm's organizational culture may not match, or might be overwhelmed by, the culture of the society within which it innovates or whose workers it employs. Furthermore, evidence of a nation-level culture–innovation relationship may carry important implications for scholars and business strategists concerned with the international placement or performance of R&D facilities. And if national culture matters, then simply spending more money on research, development, and industrial infrastructure may not efficiently increase the national innovation rate of a country whose underlying cultural values are antithetical to innovative activity. Thus science and technology policy scholars should also be concerned with the potential effects of culture on innovation. Finally, while non-cultural explanations might account for the innovation rate of a particular country at a specific point in time, none has been able to explain national innovation rates across multiple countries over a long period of time (i.e., they are not generalizeable). Hence the grand debates over endogenous economic growth and national competitiveness in high-technology may also ultimately depend on the results of culture–innovation research.

Some scholars have posited that societies which rank high on individualism are highly inventive. Innovation theorists and historians alike have documented the importance of entrepreneurial individuals to scientific progress and technological change. Case studies have also shown that, in both research and business, successful innovation often requires that these individuals act against the wisdom of their peers and even the general public. Yet to date, few scholars have gone beyond single case studies to offer evidence to support this assumption at the aggregate level or across time and space. The star scientist, the renegade entrepreneur, and other upstart individualists (and societal tolerance for them) have long been the stereotypical vehicles of progress on the "technological frontier" (Spar, 2003). But does this conventional wisdom apply at the national level?

This article therefore asks a simple empirical question: can statistical data confirm prior observations that a national culture of individualism helps innovation in the long-run? In an attempt to answer this question, we analyze several independent quantitative datasets of both culture and innovation from 62 countries spanning more than two decades. On the one hand, we find that high-levels of cultural individualism do strongly correlate with long-run national innovation rates. However, the data also suggest that a certain type of collectivism (i.e. patriotism and nationalism) can also foster innovation at the national level. Meanwhile, other types of collectivism (i.e. a cultural emphasis on loyalty to family, friends, and one's immediate social circle) not only harm national innovation rates, but may hurt progress in science worse than in technology. Finally, the data suggest that a culture of individualism in the market which demands new technologies may be more important for national innovation rates than is individualism in the market that supplies innovators.

While previous investigations of a culture–innovation relationship have produced intriguing results, this study adds value with several significant improvements. First, of the few studies that have tested the effects of national culture on innovation, most examined only one or two countries and only during brief time spans. However, two-country comparisons are vulnerable to selection bias, while studies of brief time spans can miss correlations that might appear over the long-run. To improve upon this, we analyze innovation data for dozens of countries over two decades. Second, prior statistical research which tested culture–innovation hypotheses (e.g. Shane, 1992, 1993) suffered from data limitations which this study overcomes. For example, often the only data available to previous scholars was a single dataset or measure of culture or innovation. To improve upon this, we use several datasets developed during the past decade to triangulate on both the independent and dependent variables. We employ two rival measures of innovation (technology patents and science–engineering patents) and several rival cultural measures. Finally, instead of using simple patent or publication counts to measure innovation, we weight patents and publications by their forward citations in order to control for quality (e.g. such that the patent for the paper-clip is not treated as equal to the patent for the transistor) and control for population (and hence the number of innovators). These finer measures will allow us to probe the culture–innovation relationship with greater certainty than was possible in prior statistical research.

3. Literature review

A precise definition of culture is elusive and remains the subject of intense scholarly debate. Thankfully, the purposes of this article require only a useful working definition as a basis upon which to proceed. That is, imitating Tabellini (2005), we seek not to argue over competing definitions of culture. Rather, our aim here is to test whether specific indicators of national culture correlate strongly and robustly with national innovation rates.

We conceptualize culture as reflecting a country's “central tendencies” in terms of values, beliefs, and preferences (Hofstede, 1991). We choose this interpretation because it generally matches the definitions of culture used by culture and innovation scholars across several fields, including the social scientists who constructed the empirical datasets used below.[2] Certainly, individuals and firms will differ in the degree to which they reflect or deviate from their nation's central cultural tendencies. But in the aggregate and over the long-run, these random differences should cancel each other out, allowing the systematic central tendencies of culture to emerge and have causal impact on a nation's economic activities, such as innovation. While these central tendencies can change, most culture research suggests that they do so slowly over generations, if at all, a reflection of their durability (Guiso et al., 2006).

While there is no consensus over which are the “right” cultural values to promote long-run national innovation rates, some of the historical and research literature theorize that individualism is a strong candidate. An emphasis on creative, unconventional individuals and societies that tolerate, or even foster them, can be found in innovation scholarship by philosophers (Steiner, 1995), theorists (Tiessen, 1997), and empirical researchers (Mueller and Thomas, 2001). More widely known proponents of individualism–innovation theory include economic historian Temin (1997), who credits Protestantism and its “celebration of the individual” for the technological lead acquired by several northwestern European countries during the industrial revolution. Similarly, Mokyr (2002) argues that since innovation is an act of revolt, a culture of individualism should aid it, while a culture of hierarchy, tradition, respect for status-quo and authority should obstruct it. He further suggests that an anti-technology bias is created in societies which foster conformist values, hew to tradition, and discourage rebellious behavior. Florida (2002) argues that technological innovative cities and countries depend on a “creative class” of innovators who are drawn to locales which indulge individualistic behavior, typified by diversity, tolerance, and open-mindedness. Hence collectivism and conformity are anathema to innovation.

Some of the most highly cited articles in this journal, or any journal for that matter, that test the culture–innovation linkage at the national level are Shane (1992, 1993). Using basic patent statistics and Geert Hofstede's four cultural measures, Shane (1992, 1993) analyzed data on 33 countries during four years. In both articles, he determined that societies which rank high on individualism are highly inventive, even when controlling for wealth. Although Shane's work was groundbreaking for its time, the quantitative datasets available during the early 1990s on both culture and innovation were limited. Also, several societies that rank low on individualism (e.g. Taiwan, South Korea, Finland, India) have since become globally competitive high-technology innovators. Shane himself recognized the preliminary nature of his work and the need to improve the quantity and quality of the underlying data. Fortunately, in the nearly two decades since then, much work has been done. Significant improvements have been made in the amount and richness of quantitative data on culture and innovation. This new empirical data prompts us to ask:

[2] For example, at the broadest level, culture has been defined as a “collective programming of the mind which distinguishes the members of one human group from another” (Hofstede and Bond, 1988:13; Shane, 1993, also similar to the definition used by Temin, 1997). Going into finer detail, House et al. (2004:15) describe culture as “shared motives, values, beliefs, identities, and interpretations or meanings of significant events that result from common experiences of members of collectives that are transmitted across generations.” This closely matches the definitions employed by Schwartz (2006); Guiso et al. (2006); Landes (1998); Grief (1994), the researchers writing in Harrison and Huntington (2000) and many business and innovation scholars.

do Shane's findings regarding individualism still stand? Furthermore, do the improved data allow us to generate new findings about the culture–innovation relationship? This article will attempt to answer these questions.

Although this article will not test specific causal mechanisms, a brief review of them here is useful. The causal mechanisms linking individualism with innovation are diverse. For example, like individualistic firms, individualistic societies may have a competitive edge in innovation because not only do they provide a more tolerant environment for would-be innovators to operate in, they also offer more social incentives for individuals to do so. Also, an emphasis on personal freedom allows individuals to think and act creatively, to discover for themselves what works and what does not. This has positive implications for actors across all stages of the innovation process, including scientists, entrepreneurs, investors, and even consumers. Furthermore, an individualist culture arguably promotes the circulation of information across different levels of society, and may motivate elites to place more trust in their informed subordinates (Hayek, 1945; Tiebout, 1956), better fostering Surowiecki's (2004) "wisdom of crowds". Finally, individualistic societies believe in the efficacy of the individual effort and are therefore more likely to single out innovators for financial compensation. For example, Suzuki et al. (2002) note that the accumulation of personal wealth, which they term an individualistic factor, is a powerful motivator for Silicon Valley entrepreneurs.

In contrast, collectivist societies tend to impede communication upwards through the social hierarchy, over-centralize authority, rely on rules and procedures over trust, and resist the radical social changes that often accompany innovation. For example, the imperial Chinese state, having reached the pinnacle of preindustrial development centuries before Western Europe, failed to innovate further and embark on the Industrial Revolution until it was too late to contain the incursions of Western powers. David Landes attributes this failure to the predominant values of traditional Chinese society, which included an absence of individual freedom, disapproval of self-enrichment, and the oppressive weight of custom and consensus over personal decision-making (Landes, 2006).

Finally, different scholars theorize different levels of cultural causality. Some scholars argue that culture is a "master variable" which determines social behavior, political–economic institutions, and even the fundamentals of government policy (Landes, 1998). Others argue that culture acts alongside other important causal variables, such as wealth, natural resources, education levels, and major government policies. Scholars also differ in the degree to which they believe culture changes over time (Harrison and Huntington, 2000). Models based on each of these competing assumptions will be tested below.

4. Methodology

Given the preliminary nature of prior observations, the vast improvements in data, and the appearance of technologically competitive societies that are *not* culturally individualist, the purpose of the remainder of this article is to ask a simple empirical question: is there evidence to substantiate prior observations of a general relationship between cultural individualism and innovation at the national level? Note that we do not test for the presence of a specific causal mechanism. This is because innovation scholars collectively, and sometimes individually, describe multiple causal mechanisms by which culture should affect innovation. Statistical data alone are not sufficient to test these mechanisms. Therefore we test only for the presence of a general correlation. Nonetheless, this exercise adds value because, no matter which mechanism is in operation (i.e. enhanced incentives for personal gain, increased scientific and economic freedom, greater diversity), or even if the specific mechanism(s) remains unidentified, the regression models employed below should reveal a correlation between individualism and innovation if a causal relationship actually exists. The new data also allow us to generate new hypotheses regarding the effects of culture on national innovation rates.

In the subsequent regressions, we conduct cross-sectional statistical analysis of innovation rates across 62 countries during the 1975–1995 period.[3] Although time-series cross-sectional regressions would be ideal here, the presence of rarely changing independent variables over time creates multicollinearity issues, especially when used with country fixed effects. Therefore we stick with ordinary least squares (OLS), with Huber–White estimates of the standard errors. Since there are significant changes in some of the control variables during these two decades, we later split the into five-year sub-periods and test each separately.

4.1. Data

In selecting our data, we triangulate datasets in order to increase our confidence in the statistical analysis. That is, we use competing and independent measures of the same phenomena, for both the primary independent and dependent variables. Triangulation allows researchers to better measure phenomena that are difficult to quantify, such as culture and innovation. Although any single dataset may suffer from measurement error, if competing and independent data produce similar results, then we can have greater confidence in these results.

4.1.1. Independent variable: individualism–collectivism

For cultural measures of individualism, we triangulate by using data generated by three separate and independent research projects: Hofstede (2001); Schwartz (2006), and GLOBE (House et al., 2004). Hofstede gathered data from 117,000 surveys from over 88,000 employees from 72 countries (reduced to 40 countries that had more than 50 responses each) in 20 languages at IBM between 1967 and 1969 and again between 1971 and 1973. This database was later expanded with 10 additional countries and

[3] Poisson regression is not used because the data neither follows, nor satisfies the assumptions for, a Poisson distribution.

three regions (i.e. Arab countries and East and West Africa). Hofstede then aggregated national means of different sets of individual questions to generate four cultural measures (later expanded to five) for each country. Of these measures, Hofstede's *Individualism* (HIDV) is defined as "a loosely knit social framework in which people are supposed to take care of themselves and of their immediate families only" (Hofstede, 1983). Low scores on the HIDV measure indicate collectivism, which Hofstede describes as being "characterized by a tight social framework in which people distinguish between in-groups and out-groups, they expect their in-group to look after them, and in exchange for that they feel they owe absolute loyalty to it" (Hofstede, 1983).

Schwartz created three indices which measure individualism, both centering on autonomy. Schwartz's *Intellectual Autonomy* (SINT) measures the degree to which a society "…encourages individuals to pursue their own ideas and intellectual directions independently" (Schwartz, 2006: 140). He argues that cultures which emphasize SINT place high value on broadmindedness, curiosity, and creativity. Schwartz's *Affective Autonomy* (SAUT) measures the degree to which a society "…encourages individuals to pursue affectively positive experience for themselves…pleasure, excitement, variation" (Schwartz, 2006: 140). Schartz's *Embeddedness* (SEMB) indicates the degree to which individuals find meaning via "identifying with the group…restraining actions that might disrupt in-group solidarity or the traditional order" (Schwartz, 2006: 140). Schwartz used two instruments to generate his indices. One instrument was a survey of his own design administered in 1988–2000 to over 75,000 schoolteachers (k-12) and college students from 67 nations. The second instrument used data gathered as part of the European Social Survey 2002–2003 from representative national samples in 20 countries with 52 distinct cultural groups.

The GLOBE study produced two cultural measures useful for our tests, both centering on the opposite of individualism: collectivism. These scholars split "collectivism" into two dimensions. An *In-Group Collectivism* dimension (GIGC) measures pride in, and loyalty to, small groups such as family, organization, circle of close friends, etc. We interpret this as familism or localism. An *institutional collectivism* scale (GIC) measures collectivism across the society as a whole. Specifically, it is "the degree to which organizational and societal institutional practices encourage and reward collective distribution of resources and collective action." (House et al., 2004: 12). This might interpreted more broadly as patriotism or nationalism. Certainly culture scholars might quibble with our specific interpretations, but it is uncontroversial to say that GIGC measures loyalty to smaller and more local collectives, while GIC measures loyalty to larger, broader, and society-wide collectives. For both indices, low scores reflect a more individualistic emphasis and high scores reflect a more collectivistic emphasis. The GLOBE's researchers based their cultural measures on questionnaire responses from 17,000 mangers from 951 organizations operating in 62 societies throughout the world. These surveys were then supplemented with interviews, focus groups, and content analysis of printed media, all during the 1993–2003 period. Summary statistics of these cultural measures are shown in Table 1, while the correlation matrix can be found in Table 2.

4.1.1.1. Dependent variable: innovation. In order to triangulate on the dependent variable, we use two independent measures of innovation: citations-weighted technology patents (per capita) and citations-weighted scientific publications (per capita). Patents are the most commonly used quantitative measure of national innovation because, by definition, they are related to innovation. Each patent represents an individual "quantum" of invention that has passed the muster of trained specialists and won the support of investors and researchers who dedicate their time, effort, and resources to research and to acquiring legal protection. The use of patents to measure innovative activity was pioneered in the 1960s by Scherer (1965) and Schmookler (1966) who used patent statistics to investigate the demand-side determinants of innovation.

Certainly patents are not a perfect quantitative measure of innovation. One weakness with this approach is that raw patents counts do not take into account the quality or impact of the innovation patented. Most patents are for minor innovations, and only a very few could be considered revolutionary innovations. Furthermore, while raw patents counts have been found empirically to correlate well with innovation inputs (e.g. R&D spending), they are too noisy to serve as anything but a very rough measure of innovation output (Griliches, 1984). To remedy these deficiencies, we will weight patents by their forward citations. The idea here is that minor innovations receive few, if any, citations while more important patents receive tens or hundreds. Weighting patent

Table 1
Sample summary statistics, 1990–1995.

	Obs	Mean	Std. dev.	Min	Max
Patents*	103	4.47	3.07	−2.35	10.97
S&E Publictns*	135	−6.27	2.19	−10.5	−1.54
GDP*	132	7.92	1.52	4.62	10.7
Milspend**	103	4.71	8.33	0	61.3
Tradeopen**	127	75.5	44.7	7	253
Fuel exports***	87	16.7	27.7	0	97
Eductn spending**	102	4.29	1.81	0.86	8.98
R&D spending**	22	1.63	0.79	0.33	2.91
HIDV	62	41.7	23.8	6	91
SAUT	67	3.53	0.56	2.20	4.50
SEMB	67	3.77	0.37	3.05	4.59
GIC	53	4.26	0.42	3.41	5.26
GIGC	53	5.21	0.69	3.46	6.37

*Natural log of per capita figure. **per GDP ***as % of merchandise exports.
HIDV = Hofstede's individualism; SAUT = Schwartz's affective autonomy; SEMB = Schwartz's embeddedness; GIC = Globe's institutional collectivism; GIGC = Globe's in-group collectivism.

Table 2
Correlations of culture measures.

	HIDV	SAUT	SEMB	GIC	GIGC
HIDV	1				
SAUT	0.67	1			
SEMB	−0.55	−0.88	1		
GIC	0.25	0.27	−0.10	1	
GIGC	−0.80	−0.70	0.54	−0.47	1

HIDV = Hofstede's individualism; SAUT = Schwartz's affective autonomy; SEMB = Schwartz's embeddedness; GIC = Globe's institutional collectivism; GIGC = Globe's in-group collectivism.

citations in this manner to measure innovation rates has solid empirical support. Citation-weighted patents have been found to correlate well with inventor perceptions of value, the likelihood of patent renewal and litigation, the market value of the corporate patent holder, and other measures of innovation outputs (Trajtenberg, 1990; Lanjouw and Schankerman, 1999; Hall et al., 2000; Jaffe et al., 2000).

A second weakness is that it is often unclear what fraction of a nation's innovation is actually patented, or to what degree selection bias exists in any given set of patent data. This problem is exacerbated by variance between different countries in their propensity to patent. However, national aggregates of citation-weighted patents have been found to correlate highly with other measures that are associated with innovation, such as exports of capital goods, capital formation, GDP growth, manufacturing growth, productivity, and Nobel Prize winners (Amsden and Mourshed, 1997). Thus, even though patents may not capture the entire universe of a country's inventive activity, they do appear to capture a representative sample of it when weighted by forward citations and used in large aggregates.

In order to increase confidence in our results, and to accommodate different perspectives on the phenomenon and measurement of innovation, we corroborate the regressions of citation-weighted patent data (per capita) with similar regressions of scientific publications weighted by forward citations (per capita). Science–engineering research publications offer measurement advantages similar to those of patents, with each journal article representing a discrete "byte" 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 almost entirely independent of patents. They are generally affected by different incentives, produced by a different set of innovators, and judged according to different institutional standards (Bourke and Butler, 1996; McMillan and Hamilton, 2000; Glanzel and Moed, 2002).

The patent data comes from a subset of the National Bureau of Economic Research (NBER) Patents Database and includes data on over 1.7 million utility patents granted by the U.S. Patent & Trademark Office (USPTO) to applicants from the United States and 146 other countries during 1974–1995, and the 9.7 million citations made to these patents during the same time period.[4] The scientific publications data comes from a subset of the Thomson-ISI National Science Indicators database and includes data on over 9.4 million articles published in scientific journals by researchers in over 170 countries during 1981–1995, and the 164.2 million citations made to these articles during the 1981–2002 period.

4.1.1.2. Additional control variables. In order to test the weaker versions of the individualism hypothesis, we also include controls for those variables specified by theorists as possibly countering or masking the effects of culture on innovation. For example, almost universally, these researchers assume that the level of a country's economic development will affect innovation rates. The idea here is that innovators with more economic resources per capita are better able to transform inputs into new technology. Hence we control for GDP per capita (World Bank *World Development Indicators*). Additional control variables will be discussed below in the context of particular hypothesis tests. These will include military spending, trade openness, natural resources, education spending, and R&D spending.

The regressions are based on log–log specification, except for the culture measures and the policy variables (which are expressed in percentages). The estimates are therefore less sensitive to outliers and can be interpreted in terms of elasticities; log–log models are also consistent with much of the prior work in this type of research (Furman et al., 2002; Jones, 1998). This results in a primary regression model along the following lines:

$$\begin{aligned}\mathrm{Ln}(\mathrm{Innovation}_{t=0\text{ thru }1}) = {} & B_0 + B_1{}^*(\mathrm{Individualism}_{t=0}) + B_2{}^*\mathrm{Ln}(\mathrm{Level\ of\ Econ.\ Development}_{t=0}) \\ & + B_3{}^*(\mathrm{Policy\ Variables}_{t=0}) + B_4{}^*(\mathrm{Natural\ Resource\ Endowment}_{=0})\end{aligned}$$

where patenting activity in period t = 0 through t = 1 is a function of the independent variables at time t = 0. The model is identical when publications are used as the measure of innovation.

This model will doubtless arouse some criticism for its narrow approach. Economists, sociologists, and policy-analysts often take a more encompassing view when performing statistical analysis of innovation at the national level, and include a myriad of

[4] Although data availability for some independent variables may limit the number of countries considered in each regression, the remaining countries consistently account for at least 98% of the USPTO patent dataset.

institutions, policy variables, and financial controls alongside the primary independent variables of interest. Given the large potential number of causal lines feeding into national innovation rates, this temptation is understandable. Why not control for, say, those factors identified by Furman et al. (2002) as contributing to national innovative capacity? The answer is that the strong form of the individualism hypothesis holds that such policies are either endogenous to culture, or are overwhelmed by its causal effects. Furthermore, even if culture has an additive effect to institutions, these mid-level institutions and policies are exactly those which "national innovation systems" scholars have been unable to generalize as causal explanations after two decades of research (Sharif, 2006; Balzat, 2006). As for broader institutions, statistical tests of the effects on national innovation rates of different varieties of capitalism, levels of democracy, political decentralization, and free-markets have produced small or insignificant coefficients for each of these institutions, thus these broader institutions may not be determinative causal forces either (for example, see Akkermans et al., 2009; Taylor, 2004, 2009).

5. Results

The regressions results are surprising. On one hand, we mostly confirm prior observations that high-levels of cultural individualism correlate with national innovation rates. These results imply that individualism generally helps (and collectivism generally hurts) rates of technology patenting and scientific research publication, even when controlling for wealth, military spending, trade openness, fuel exports, and education and R&D spending. However, the data also generate evidence for a novel type of collectivism-innovation relationship. Specifically, the data also suggest that a certain form of collectivism (i.e. patriotism, nationalism) can foster innovation at the national level, while other types of collectivism (i.e. familism and localism) not only harm national innovation rates, but may hurt progress in science worse than in technology. Finally, the data suggest that a culture of individualism in the market which demands new technologies may be more important for national innovation rates than individualism in the market which supplies innovators and entrepreneurs.

We conducted three sets of tests based upon different assumptions commonly held by culture–innovation theorists. The first assumption holds that cultural is a "master variable", a causal force affecting innovation which either determines or overwhelms all other causal factors. The second assumption instead holds that culture has an additive causal effect on national innovation rates, one that acts alongside other important economic conditions. Both of these schools of thought generally assume that culture is static. Therefore the third set of regressions assumes is that culture changes quickly, over the course of years rather than generations. Regardless of which assumption we operated under, the data tended to support similar findings.

Assumption #1. Culture as a "master variable".

Many culture theorists and historians assume that cultural is a "master variable", a causal force affecting innovation which either determines or overwhelms all other causal factors. If this holds true, then an individualism–innovation correlation should be observable in simple bivariate regressions. The results of such regressions (Table 3) confirm that individualism generally helps (and collectivism hurts) innovation in both science and technology, regardless of the cultural measure used.

Interpreting the quantitative meaning of the coefficients for the culture variables is not intuitive, therefore we also report the standardized beta coefficients (in italics) which allow us to interpret their effects in terms of standard deviations. Note that the

Table 3
Culture as a master variable, 1975–1995.

DV=	Pats	Pats	Pats	Pats	Pats	Pubs	Pubs	Pubs	Pubs	Pubs
HIDV	0.09 *0.72* [0.01]***					0.07 *0.80* [0.006]***				
SAUT		3.58 *0.59* [0.59]***					2.89 *0.72* [0.35]**			
SEMB			−5.76 *−0.66* [0.57]***					−4.45 *−0.75* [0.41]***		
GIC				2.91 *0.41* [0.68]***					2.04 *0.38* [0.65]**	
GIGC					−3.25 *−0.77* [0.36]***					−2.50 *−0.78* [0.19]***
Constant	−12.8 [0.59]***	−22.0 [2.06]***	12.4 [2.14]***	−21.3 [2.88]***	7.84 [1.86]***	−7.30 [0.37]***	−14.5 [1.25]***	12.5 [1.54]***	−13.0 [2.78]***	8.68 [0.97]***
Obs	56	59	59	47	47	58	62	62	49	49
R2	0.52	0.35	0.44	0.17	0.59	0.64	0.51	0.57	0.14	0.60

Note: Analysis is by ordinary least squares (OLS), Huber-White estimates of standard errors reported in brackets. S*tandardized beta coefficients in italics*. All independent variables are 1974 values, all dependent variables are logged, per capita values for the 1975–1995 period. HIDV = Hofstede's individualism; SAUT = Schwartz's affective autonomy; SEMB = Schwartz's embeddedness; GIC = Globe's institutional collectivism; GIGC = Globe's in-group collectivism. † $p<.10$, *$p<0.05$, **$p<0.01$, ***$p<0.001$.

coefficients are similar across the different measures of individualism, with a one standard deviation increase in individualism having a 0.3 to 0.8 standard deviation effect on patenting, and an almost identical range of effects on science publications. This is a fairly large effect. For example, a unit increase in Schwartz's *affective autonomy* (mean 3.56, standard deviation 2.24) correlates with a 358% increase in citation-weighted patents per capita and a 289% increase in citations-weighted publications per capita! Therefore, if we accept the assumption that culture is a master variable, then individualism appears to have a strong positive effect on national innovation rates.

Of course, the "culture as a master variable" condition is a strong assumption. While we take no position on its validity (because our data does not allow us to test it), we note the R^2's are relatively high for simple bivariate regressions. The R^2's indicate that individualism explains between one-third and two-thirds of the variation in patents or publications, lending some quantitative support to the "master variable" case. The exception here is GLOBE's *institutional collectivism* which explains merely 14%–17% of the variation in innovation.

A third interesting finding, and one which repeats itself in the regressions below, is that of a positive effect of GLOBE's *institutional collectivism* on innovation rates, which contrasts with a negative effective of GLOBE's *in-group collectivism*. At first, this would seem counterintuitive. However, if we stick with our interpretation of the former form of collectivism as patriotism or nationalism, then we can better understand its positive effect on innovation. Recall that innovators must endure high-levels of risk and uncertainty, as must societies confronting the costs and distributive effects of scientific research and technological change (Acemoglu, 2009). Cultures which emphasize GLOBE's *institutional collectivism* might produce a social environment in which both innovators and those bearing the costs of change are more willing to endure these difficulties for the benefit of their society. We find further empirical support for such an argument within the case study data on Japan's rapid innovation rate during the 20th century (Tiessen, 1997; Suzuki et al., 2002; Dore, 1973). Meanwhile, *in-group collectivism* emphasizes loyalty to family, friends, and one's immediate social circle. Cultures which emphasize these kinds of loyalties might foster opposition to technological change or science funding which threatens local interests. Preliminary case study evidence for this type of relationship can be found within the research on Italy's relatively poor technology-based economic development, especially in its southern Mezzogiorno region (Putnam, 1993).

Assumption #2. Culture as an additive variable.

Next, we relax the assumption that culture is a master variable, and instead assume it to have an additive causal effect on national innovation rates, one that acts alongside other important economic conditions. Put another way, we must test the proposition that the findings produced by the simple bivariate regressions above are not merely an artifact of omitted variable bias (e.g. economic development, natural resources, or a major policy variable). We therefore control for these types of variables to see if the effects of culture remain strong and significant.

The three additional variables controlled for are those specifically cited by scholars as important causal factors for innovation, and are arguably not necessarily endogenous to culture. First, openness to trade (defined as exports plus imports as a share of GDP) is generally considered by economists to provide competitive motivation for long-run innovation (Daniels, 1997; Grossman and Helpman, 1991, 1995).[5] Second, military spending is also considered by innovation scholars to be a major source of technological progress, and is included in the regressions as a percentage of gross national product (McNeill, 1982; Smith, 1985; Ruttan, 2006).[6] Some might argue that culture determines levels of violence, and hence military spending. Yet, critical cases reveal that even societies dominated by strict non-violent cultural norms (e.g. some Buddhist and Christian denominations) have practiced armed conflict not unlike societies typified by norms relatively more accepting of violence (Tambiah, 1992; Popovski et al., 2009). Therefore, for those who consider military spending to be not, or only weakly, determined by culture, we include it as a control. Third, natural resources are considered an obstacle to innovation, "cursing" otherwise innovative countries into a cycle of dependence on exports of energy, metals, raw materials, and agricultural products (Ross, 1999; Sachs and Warner, 1995; Gelb, 1988). We therefore experiment with three alternate measures of natural resource base (as a percent of total, alternately: fuel exports, arable land, or metal/ore exports) in our regressions (World Bank, 2002).

Again, we observe similar results: individualism appears to have a significant positive effect on technological innovation and scientific progress (Table 4). Although each culture variable has a smaller coefficient here than in the bivariate regressions, they generally remain strong and significant with no sign changes (only the *embeddeness* measure drops completely out of significance). They also retain the same relative influence on patenting versus publication.

Specifically, in these regressions, we found that a one standard deviation increase in Hofstede's *individualism* translates into a 95% increase in both technology patenting and scientific publications.[7] Almost equally strong is the negative effect of *in-group collectivism* (i.e. familism, localism) on both patenting and publications. *Affective autonomy* has between one-third and one-half the effect of *individualism*, but can be considered significant for patents only if we allow a 90% confidence level. Here, a one standard deviation increase in *affective autonomy* results in 41% increase in technology patenting and a 49% increase in scientific publications.

[5] Data source for the regressions is World Bank (2002).
[6] Data source for the regressions is USACDA (1975-1996).
[7] One standard deviation in HIDV = 23.8. Since the dependent variable is logged, and the coefficient on HIDV is 0.4, this translates into a 95.2% increase in citations-weighted patents per capita for a one s.d. increase in HIDV.

Table 4
Culture as an additive variable, 1975–1995.

DV=	Pats	Pats	Pats	Pats	Pats	Pubs	Pubs	Pubs	Pubs	Pubs
HIDV	0.04					0.04				
	0.30					*0.42*				
	[0.01]**					[0.006]***				
SAUT		0.74					0.87			
		0.13					*0.23*			
		[0.43]†					[0.40]*			
SEMB			−0.48					−1.04		
			−0.06					*−0.18*		
			[0.97]					[0.67]		
GIC				1.31					0.73	
				0.20					*0.14*	
				[0.37]**					[0.39]†	
GIGC					−1.16					−0.96
					−0.28					*−0.30*
					[0.35]**					[0.17]***
GDP/capita	1.42	1.78	2.00	1.71	1.41	0.91	1.14	1.20	1.37	1.08
	[0.20]***	[0.19]***	[0.28]***	[0.16]***	[0.20]***	[0.10]***	[0.17]***	[0.20]***	[0.14]***	[0.16]***
Milspend	0.04	0.08	0.07	0.06	0.06	0.07	0.10	0.11	0.10	0.09
	[0.04]	[0.02]***	[0.03]**	[0.02]**	[0.02]**	[0.02]***	[0.02]***	[0.02]***	[0.02]***	[0.02]***
Trade open	0.007	0.003	0.003	−0.001	0.006	0.004	0.001	0.001	−0.002	0.002
	[0.003]**	[0.003]	[0.003]	[0.003]	[0.002]*	[0.001]**	[0.002]	[0.002]	[0.002]	[0.002]
Fuel exports	−0.01	−0.003	−0.004	−0.02	−0.02	−0.005	−0.004	−0.003	−0.01	−0.008
	[0.01]	[0.004]	[0.005]	[0.01]	[0.01]*	[0.005]	[0.007]	[0.007]	[0.008]	[0.005]
Constant	−22.6	−26.6	−25.6	−28.7	−15.0	−13.9	−16.9	−10.5	−18.8	−8.60
	[1.26]***	[1.12]***	[5.71]***	[1.75]***	[3.20]***	[0.69]***	[0.89]***	[3.99]**	[1.85]***	[2.24]***
Obs	48	43	43	41	41	50	44	44	41	41
R2	0.86	0.88	0.87	0.88	0.89	0.91	0.90	0.89	0.86	0.89

Note: Analysis is by ordinary least squares (OLS), Huber-White estimates of standard errors reported in brackets. S*tandardized beta coefficients in italics*. All independent variables are 1974 values, all dependent variables are logged, per capita values for the 1975–1995 period. HIDV = Hofstede's individualism; SAUT = Schwartz's affective autonomy; SEMB = Schwartz's embeddedness; GIC = Globe's institutional collectivism; GIGC = Globe's in-group collectivism. GDP/capita is logged; Milspend = military spending as % of GDP; trade open = (exports + imports)/GDP. Fuel exprts = Fuel exports as % of merchandise exports.
†p<0.10, *p<0.05, **p<0.01, ***p<0.001.

Interestingly, *institutional collectivism* (i.e. patriotism and nationalism) has a stronger positive effect on technology patenting than on scientific publication; in contrast, *affective autonomy* appears to benefit science more than technology. Thus it may be that nationalism is comparatively better at fostering technological change, while individualism is better suited to aid scientific inquiry.

In this article, we are not explicitly interested in the coefficients for the other control variables in their own right, but some aspects are worth nothing. First, the coefficients for level of economic development are strong, significant, and relatively robust across all models. Second, military spending does correlate with small increases in both patenting and publications (6%–11% per unit increase in military spending as percentage of GDP). Meanwhile, the effect of openness to trade is always small and generally insignificant for both technology and science. Similarly, natural resource abundance appears to have little effect on innovation rates. The coefficients for fuel exports and metal exports (not shown) were small and insignificant for every regression model which included them, while arable land (not shown) had only a minor positive effect (1%–2% per unit increase in arable land as a percentage of total) on scientific publications in two regression models. More importantly, the coefficients for the culture variables are robust across models with different measures of natural resources.

Next we added controls for education and R&D spending (Tables 5 and 6). For education, we triangulated by alternately including controls for undergraduates in science and engineering (per capita and logged total), literacy (as percent of population), and government expenditure on education (as percent of total and percent of GNP) (World Bank, 2002). The R&D spending data (gross domestic expenditure on R&D per GDP) comes from the OECD *Science and Technology Indicators* (OECD, 1986).

Even when controlling for education and R&D spending, cultural individualism continues to favor scientific progress and technological innovation, and often with similar coefficients as those produced by previous regression models. There is some shifting in the balance between science and technology however. For example, *affective autonomy* favors technology patenting more strongly in 1990–1995, but favors science-engineering publishing in the previous time period. Different measures of education also produce minor changes to the given tables.[8] However these shifts are likely the result of sample-bias. Indeed, due to data constraints, the inclusion of additional controls for education and R&D data requires us to restrict ourselves to two sub-periods 1985–1990 and 1990–1995, and only OECD countries, resulting in fewer observations (n = 12–17). We must therefore interpret these regressions with caution, though we might justifiably permit a lower confidence level (90%) for statistical significance. Nonetheless, these two sub-period sets of regressions generally corroborate the findings from the previous regressions.

[8] Replacing education spending with a control for S&E undergraduates brings *institutional collectivism* into significance at the 10% level with a positive coefficient of 1.45 (DV = patents). This also brings *in-group collectivism* into significance at the 5% level with a negative coefficient of −0.71 (DV = publications).

Table 5
Culture as an additive variable, 1990–1995.

DV=	Pats	Pats	Pats	Pats	Pats	Pubs	Pubs	Pubs	Pubs	Pubs
HIDV	0.05					0.02				
	[0.01]**					[0.004]**				
SAUT		1.78					1.25			
		[0.74]*					[0.21]***			
SEMB			−0.41					−0.95		
			[1.37]					[0.75]		
GIC				0.84					1.21	
				[1.63]					[0.38]*	
GIGC					0.57					−0.71
					[1.18]					[0.28]*
GDP/capita	1.46	0.78	1.19	1.70	2.14	0.84	0.41	0.54	1.67	0.55
	[0.97]	[1.39]	[1.42]	[1.53]	[1.68]	[0.31]*	[0.30]	[0.49]	[0.50]*	[0.48]
Milspend	−0.05	0.05	−0.03	0.07	0.15	−0.09	−0.04	−0.02	0.12	−0.12
	[0.26]	[0.33]	[0.35]	[0.29]	[0.43]	[0.10]	[0.06]	[0.12]	[0.12]	[0.09]
Trade open	−0.002	−0.01	−0.004	0.00	0.002	−0.002	−0.007	−0.005	0.002	−0.001
	[0.005]	[0.01]	[0.009]	[0.01]	[0.01]	[0.002]	[0.002]**	[0.004]	[0.004]	[0.004]
Fuel exports	−0.02	−0.01	−0.01	0.03	0.06	−0.002	0.005	0.00	0.04	0.01
	[0.02]	[0.02]	[0.02]	[0.04]	[0.06]	[0.005]	[0.004]	[0.01]	[0.01]*	[0.01]
Eduspend	0.14	0.39	0.36	0.27	0.44	0.05	0.17	0.20	−0.279	−0.04
	[0.24]	[0.33]	[0.34]	[0.61]	[0.43]	[0.07]	[0.05]**	[0.10]†	[0.12]	[0.09]
RDspend	0.51	1.20	1.19	1.08	1.17	0.29	0.59	0.62	0.16	0.37
	[0.66]	[0.79]	[0.68]	[0.67]	[0.57]†	[0.21]	[0.15]**	[0.19]*	[0.21]	[0.13]*
Constant	−10.6	−9.94	−5.60	−12.4	−20.4	−12.9	−13.2	−6.53	−24.0	−6.43
	[9.90]	[14.0]	[14.2]	[15.5]	[22.3]	[2.81]**	[3.08]**	[5.74]	[5.74]**	[6.66]
Obs	17	17	17	14	14	17	17	17	14	14
R2	0.93	0.86	0.81	0.85	0.86	0.94	0.95	0.88	0.96	0.96

Note: Analysis is by ordinary least squares (OLS), Huber-White estimates of standard errors reported in brackets. S*tandardized beta coefficients in italics*. All independent variables are 1989 values, all dependent variables are logged, per capita values for the 1990–1995 period. HIDV = Hofstede's individualism; SAUT = Schwartz's affective autonomy; SEMB = Schwartz's embeddedness; GIC = Globe's institutional collectivism; GIGC = Globe's in-group collectivism. GDP/capita is logged; Milspend = military spending as % of GDP; Trade open = (exports + imports)/GDP.
†p<0.10, *p<0.05, **p<0.01, ***p<0.001.

Table 6
Culture as an additive variable, 1985–1990.

DV=	Pats	Pats	Pats	Pats	Pats	Pubs	Pubs	Pubs	Pubs	Pubs
HIDV	0.04					0.02				
	[0.006]***					[0.01]†				
SAUT		0.91					1.21			
		[0.33]*					[0.16]***			
SEMB			−0.88					−0.95		
			[0.61]					[1.06]		
GIC				−0.15					0.79	
				[0.49]					[0.35]†	
GIGC					−0.30					−1.04
					[0.82]					[0.36]*
GDP/capita	0.21	−0.15	−0.19	−0.10	−0.49	0.82	0.52	0.51	1.25	0.10
	[0.33]	[0.46]	[0.56]	[1.14]	[1.76]	[0.46]*	[0.28]	[0.39]	[0.76]	[0.89]
Milspend	−0.77	−0.73	−0.73	−0.91	−0.95	−0.20	−0.15	−0.15	−0.09	−0.27
	[0.11]***	[0.21]**	[0.24]*	[0.39]†	[0.49]	[0.21]	[0.20]	[0.26]	[0.25]	[0.24]
Trade open	−0.001	−0.009	−0.007	−0.01	−0.009	−0.002	−0.01	−0.007	−0.003	−0.004
	[0.002]	[0.004]*	[0.006]	[0.01]	[0.01]	[0.003]	[0.002]**	[0.004]	[0.007]	[0.01]
Fuel Exports	−0.001	0.008	0.006	0.02	0.01	0.006	0.01	0.01	0.03	0.01
	[0.005]	[0.006]	[0.01	[0.03]	[0.04]	[0.01]	[0.005]*	[0.01]	[0.02]	[0.02]
Eduspend	0.12	0.37	0.45	0.44	0.37	0.07	0.21	0.31	0.01	−0.002
	[0.06]	[0.11]*	[0.11]**	[0.27]	[0.29]	[0.16]	[0.08]*	[0.11]*	[0.18]	[0.16]
RDspend	2.01	2.47	2.57	2.64	2.71	0.61	0.86	0.99	0.52	0.72
	[0.25]***	[0.41]**	[0.49]**	[0.78]*	[0.95]*	[0.46]	[0.34]*	[0.42]*	[0.45]	[0.48]
Constant	3.11	3.88	10.2	7.27	12.4	−13.4	−14.3	−6.96	−19.3	−0.67
	[2.88]	[4.42]	[6.10]	[9.72]	[20.8]	[4.40]**	[3.05]**	[6.02]	[6.73]	[9.95]
Obs	15	15	15	12	12	15	15	15	12	12
R2	0.99	0.95	0.93	0.94	0.94	0.91	0.94	0.87	0.93	0.95

Note: Analysis is by ordinary least squares (OLS), Huber–White estimates of standard errors reported in brackets. S*tandardized beta coefficients in italics*. All independent variables are 1984 values, all dependent variables are logged, per capita values for the 1985–1990 period. HIDV = Hofstede's individualism; SAUT = Schwartz's affective autonomy; SEMB = Schwartz's embeddedness; GIC = Globe's institutional collectivism; GIGC = Globe's in-group collectivism. GDP/capita is logged; Milspend = military spending as % of GDP; Trade open = (exports + imports)/GDP.
†p<0.10, *p<0.05, **p<0.01, ***p<0.001.

Table 7
Culture as changing variable.

DV=	Pats (75–80)	Pats (75–80)	Pubs (80–85)	Pubs (80–85)	Pats (90–95)	Pubs (90–95)	Pats (90–95)	Pubs (90–95)
HIDV	0.10 [0.01]***	0.03 [0.01]**	0.08 [0.01]***	0.06 [0.01]***				
SAUT					4.21 [0.57]***	2.89 [0.32]***		
SEMB							−6.29 [0.67]***	−4.70 [0.38]***
GDP/capita		1.68 [0.19]***		0.60 [0.18]**				
Trade open		0.007 [0.005]		0.007 [0.005]				
Fuel exports		−0.008 [0.008]		−0.005 [0.006]				
Constant	1.68 [0.55]**	−9.73 [1.39]***	−9.30 [0.35]***	−13.5 [1.23]***	−9.81 [2.04]***	−15.5 [1.12]***	28.7 [2.49]***	−12.4 [1.41]***
Obs	55	49	61	51	59	66	59	66
R2	0.59	0.90	0.68	0.82	0.44	0.53	0.46	0.61

Note: Analysis is by ordinary least squares (OLS), Huber-White estimates of standard errors reported in brackets. *Standardized beta coefficients in italics*. All dependent variables are logged, per capita values for the time period listed; all independent variables are values for the prior year. HIDV = Hofstede's individualism; SAUT = Schwartz's affective autonomy; SEMB = Schwartz's embeddedness; GIC = Globe's institutional collectivism; GIGC = Globe's in-group collectivism. GDP/capita is logged; Milspend = military spending as % of GDP; Trade open = (exports + imports)/GDP.
†$p<0.10$ *$p<0.05$, **$p<0.01$, ***$p<0.001$.

Again, our goal is to test the influence of cultural factors, therefore we are not directly concerned with the results of R&D or education. But we do note that the coefficients for R&D spending indicate a much stronger effect on technology patenting than on science-engineering publications. The results for education are inconclusive and not robust, possibly a result of differing education policies and philosophies across countries. Space limitations force us to leave these as subjects for future research.

Assumption #3. Culture as a changing variable.

The previous tests assume that culture changes very slowly (e.g. over the course of several human generations), if at all. From a methodological perspective, this assumption implies that the values captured by GLOBE, Schwartz, and Hofstede are unchanging and therefore valid measures over time. However, if culture changes relatively quickly, then there might be a temporal mismatch between the dependent variable and the culture measures in the regressions above. If this were the case, then we would want to test Hofstede's measure (gathered between 1967–1969 and again between 1971–1973) against innovation during the earliest sub-period (1975–1980 for patents, 1980–1985 for publications); test Schwartz's measures (gathered 1988–2000) against innovation during the latest sub-period (1990–1995); and discard the GLOBE measures which were gathered so recently (1994–2004) that the NBER patent and Thomson-ISI publication datasets cannot be tested against them.

The results of the multivariate Schwartz sub-period tests can already be found in Table 5 (columns 2, 3, 7, and 8), the bivariates in Table 7 (columns 5–8). Again, these tests consistently show a positive effect of *affective autonomy* on both patenting and publications. As before, *embeddedness* has a negative significant effect on patents and publishing in the simple bivariate regressions (Table 7), but drops out of significance when other control variables are included. Hofstede's *individualism* is also positive and significant, with coefficients similar to those found in previous regressions. Any missing cells in Table 7 are due to the lack of reliable data during the 1975–1980 time period for education spending, R&D spending, or military spending; furthermore the Thomson-ISI publications dataset starts in 1980, therefore the earliest sub-period available for to test this data is 1980–1985. These gaps admittedly handicap these regressions results in that we cannot make perfect apples-to-apples comparisons with those reported earlier; however the data gaps do not invalidate the findings.

5.1. What about intellectual autonomy?

Another surprising finding was that *intellectual autonomy* was strongly positive and significant only in the bivariate regressions, with standardized beta coefficients of 0.6 for patenting and 0.7 for publications. However, in all other regression models, the coefficients for *intellectual autonomy* were small and insignificant. This unexpected result might be better understood if we shift from explanations emphasizing a supply-side role for culture, to those focusing on the demand-side.

Innovation scholars generally assume, as we have thus far, that cultural forces such as individualism affect national innovation rates via two supply-side mechanisms. First, culture affects the number of practicing innovators (i.e. prompting more or less people to innovate). Second, culture affects the degree of social tolerance and reward for these innovators. However, these findings suggest the possibility of that culture might affect innovation rates via the demand-side.

Demand-side individualism might affect innovation via a number of causal mechanisms. It may take the form of von Hippel's (1988) user-based innovation, in which consumers themselves are the sources of innovation as they seek to customize new technologies to their own particular situations. It may alternatively be driven by producers harnessing technological advances to cater to mass individualistic demand for goods that are unique and customizable. In this case, every individual acts as a "market of one" in terms of both products and pricing (Pine et al., 1993; Smith, 1956). In many cultures, this demand for individualized goods is present across economic sectors, finding expression in the ever-increasing number of customization options available for goods as diverse as automobiles and operating systems (Varian et al., 2004).

Regardless, the general weakness and insignificance of the coefficients for *intellectual autonomy* should serve as an empirical warning to culture–innovation researchers. It may be that we are missing an important causal mechanism by focusing only on the cultural aspects of the supply of innovators and entrepreneurs, while generally ignoring the cultural aspects of the demand for innovation within a society. Although the datasets used here do not allow us to investigate these mechanisms further, we offer this finding as empirical grounds for deeper investigation. Future research might compare consumer product innovation across different national markets over time, perhaps even examining innovation in product lines within the same multinational corporation as it seeks to satisfy demand across different cultural consumer markets. Alternatively, one could test for the "user-based" versus "market of one" mechanisms by comparing innovation across products which are classically user-based (e.g. scientific instruments, software) versus manufacturer based (e.g. construction equipment; plastics).

6. Conclusions and implications

In this paper, we were able to verify prior, preliminary observations that cultural individualism aids national innovation rates. As predicted by both theory and conventionalism wisdom, individualism was generally found to have a statistically significant, strong, and positive effect on both scientific progress and technological innovation (as measured by citation-weighted research publications and patents). These effects remained robust to the inclusion of controls for economic development, military expenditures, openness to trade, natural resource endowments, education, and R&D spending. This general finding regarding individualism was corroborated by findings on *in-group collectivism*. This measure of localism or familism consistently had a significant, strong, and negative impact on science and technology, which was likewise robust across different time periods and regression models.

However, several findings also suggested that the conventional wisdom regarding individualism and collectivism needs some parsing. First, *institutional collectivism*, which we interpret as patriotism or nationalism, was found to be almost as strong as individualism in its positive effects on innovation rates. This suggests that collectivism may actually foster innovation when it encourages society-wide efforts to develop scientific and technological solutions to national problems. However, collectivism may be detrimental to innovation when it results in local loyalties that encourage popular resistance to such national efforts. This implies that businesses and innovation scholars should avoid stereotyping all collectivist cultures as anti-innovation. Instead, what people living in these cultures define as their most relevant "collective" may be a more significant indicator of innovative capacity than a simple social tendency toward group versus individualistic behavior. The very same risks and costs of innovation which might be valued as a worthwhile sacrifice for one's country or company can be simultaneously interpreted as a threat to one's family or locality.

Second, the conventional wisdom holds that individualistic culture should favor the creative minds of the eccentric entrepreneur or the star scientist, but the regressions above suggest that the effects of *intellectual autonomy* were generally small and insignificant. However, measures of *affective autonomy,* which emphasize values of personal gratification, were significant and positive. Therefore cultural individualism in the markets demanding new technologies (i.e. the consumer) may be as important to innovation rates as the individualism of those innovators who supply them. This finding also implies that researchers and businesses investigating the effects of different incentive and reward structures should consider the importance of cultural fit. For example, reward systems that foster innovation in cultures which rank highly on *affective autonomy* may not function as well in cultures which emphasize *institutional collectivism*.

Of course, we must be candid about the limitations to this study. Statistical analysis can show correlation but not causation; regressions do not allow researchers to test or observe directly the causal mechanisms at work. Therefore we have avoided assertions about specific causal mechanisms, which await testing via other methodological approaches. Similarly, statistical analysis is a poor tool for revealing omitted causal variables or other forms of specification error which might be obscuring linkages between culture and technological innovation. In this regard, we have tried to strike a balance by including those control variables strongly supported by prior research, but avoiding "kitchen-sink" regressions or data-mining. Finally, statistical findings are only as good as the data on which they are based. Here there are two potential problems specific to culture–innovation research. First, even widely respected innovation data are currently limited to the 1970s–1990s and are therefore restricted to a relatively small, and perhaps unrepresentative, period in time. Hence we can make no claims about other time periods using this data. Second, one might question the accuracy of quantitative indices of innovation or culture, both infamously difficult phenomena to measure objectively. We have attempted to correct for such measurement error by using multiple, competing datasets and measures. Yet, we would argue that, in the end, regardless of what is being measured in these cultural datasets, they show a relatively robust and consistent correlation with rates of technology patenting and scientific research publications. Therefore even if one doubts the accuracy of quantitative culture indices, they appear to be capturing some variable that correlates with national innovation rates.

Finally, these findings suggest two avenues for future theory and research. First, while this article has focused on individualism, other culture–innovation hypotheses remain to be tested. For example, many scholars argue that Confucianism explains why several East Asian societies have been able to rapidly catch up to the technological frontier during the last century, often surpassing countries that were theoretically better equipped to do so. In testing the effects of different forms of collectivism above, we have accomplished part of this investigation; but collectivism is just one aspect of the Confucian hypothesis. Future research should investigate its other aspects.

A second line of research might consider whether the effectiveness of different political–economic institutions (e.g. democracy, federalism, varieties of capitalism) in national innovation rates is conditional on different cultural values. That is, while political–economic institutions alone have generally been shown not to have generalizeable effects on national innovation rates (Breznitz, 2007), it may be that the effectiveness of institutions is conditional on the cultural environment within which they are set. Such a research program might provide a novel test of the "one size fits all" institutional approach to constructing a technologically competitive economy.

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