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How does Culture Shape Innovative Capability? Insights from a Global Study

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Abstract

Theory predicts a country's cultural norms and values can influence its innovative capability- its research and development, technological output, and scientific output. The extent of this influence is however unknown. Theoretical predictions of three leading schools of cultural values literature are therefore tested across all countries of the world for which there is sufficient data, using ordinary least squares, negative binomial, quantile, and count data quantile regressions. Findings provide insights into channels through which cultural values act differently to enable or constrain innovative capability. Almost all tight norms and values seem to constrain research and development. In-group collectivism seems to constrain all three components of innovative capability. Whereas future orientation and power distance relate negatively to research and development, they relate positively to technological output, yet only future orientation is positively related to both technological and scientific output. Findings suggest a failure to consider causal influences of a country's culture on its innovative capability may be costly in the face of potentially existential threats not only to firms but also countries at this time.

Keywords: Technological innovation; technological output; scientific output; R&D; culture; cultural norms; cultural values; innovative capability

Introduction

Firms and countries across the world now face a host of potentially existential threats. Growth in globalisation was already slowing before a post-2015 increase in political anti-globalisation sentiment that was associated with a rejection of trade openness and free movement of people (Dent, 2020; Fidler, 2017; Langlois, 2021; Wilson, 2017). Subsequent shocks to firms and countries of trade wars (Burggraf, Fendel, & Huynh, 2020; Joppke, 2020; Meng & Zeng, 2020) have been exacerbated by Covid pandemic disruptions (Altig et al., 2020; Kuckertz et al., 2020). Geopolitical tensions associated with trade wars have also intensified since the outbreak of the Russia-Ukraine war (Behnassi & El Haiba, 2022; Bounghou & Yatić, 2022; Johannesson & Clowes, 2022). These tensions seem to be increasing global supply chain insecurities (Uy, 2022), accelerating a trend of costly supply chain reconfiguration (Wan, Orzes, Sartor, Di Mauro, & Nassimbeni, 2019; Wan, Orzes, Sartor, & Nassimbeni, 2019). Efforts to mitigate climate change have also been set back by increasing acceptance of fossil fuel use in response to energy supply constraints caused by the war (Pereira, Bašić, Bogunovic, & Barcelo, 2022).

A country's ability to mitigate consequences of serious threats and problems depends primarily on its ability to generate problem solving knowledge, as well as to assimilate it from other contexts. This knowledge increases a country's capacity to apply problem solving technological or process innovations. Recent literature highlights increasing effectiveness of technological innovations in problem solving (Gong & Ribiere, 2021; Raimo, De Turi, Albergo, & Vitolla, 2022; Sestino, Prete, Piper, & Guido, 2020; Spanò, Massaro, & Iacuzzi, 2021). Romer's (1990) primary theoretical rationale associated with endogenous growth theory suggests that knowledge of how to combine resources and solve problems can act as 'recipes' that can be shared with others. These recipes can have scalable

benefits. They can be shared at relatively low cost because they are non-rivalrous- costs of sharing can be very low, and their value can increase the more they are shared.

A country's ability to generate and assimilate these recipes for problem solving may depend on its national innovative capability. National innovative capability has been defined and operationalised for empirical testing by Castellacci and Natera (2013) as a country's innovative inputs (R&D expenditure), technological output (patent production), and scientific output (production of scientific and technical journal articles). Accordingly, a country's ability to mitigate serious problems or threats depends on its innovative capability, which also incorporates its ability to productively absorb and appropriate knowledge, its absorptive capacity (Cohen & Levinthal, 1990). Knowing what contributes to innovative capability may be increasingly important if technological advances are exacerbating cross-country differences in threat and disaster mitigation capabilities.

A faster growing country may have more resources to allocate to problem solving. Solow's (1957) growth theory predicts that developing countries obtain higher returns to capital, and will therefore grow faster than, and will therefore economically converge with, more developed countries. Rapidly advancing technological knowledge may nevertheless increase global inequality between countries over time, a possibility suggested by endogenous growth theory (Aghion & Howitt, 1992; Grossman & Helpman, 1991; Romer, 1990, 1994). In line with this possibility, evidence suggests technological capabilities of many developing countries are diverging from those of both the United States and China, with implications for growth, development, and poverty alleviation (You, Dal Bianco, & Amankwah-Amoah, 2020). In spite of research highlighting the importance of innovative capability (Castellacci & Natera, 2013), literature to date seems to have largely failed to account for the extent to which a country's innovative capability is constrained or enabled by its unique configuration of cultural norms and values.

Culture functions primarily to solve societal problems (Hofstede, 2001). A society's cultural norms (Gelfand et al., 2011) and values (Hofstede, 2001) emerge over time to act as an informal problem-solving mechanism. Cultural tightness versus looseness (CLT) studies demonstrate societies develop tighter cultures to improve collective responses to disasters such as wars, famines, and pandemics (Gelfand, Nishii, & Raver, 2006; Gelfand et al., 2011; Uz, 2015). CLT refers to differences between societies in "strength of social norms and tolerance of deviant behaviour" (Gelfand et al., 2011, p. 1101). Culture has been defined as "collective programming of the mind that distinguishes the members of one group or category of people from others" (Hofstede, 2011, p. 3) and by the Global Leadership and Organizational Behavior Effectiveness (GLOBE) studies as "shared motives, values, beliefs, identities, and interpretations or meanings of significant events" (House, Hanges, Javidan, Dorfman, & Gupta, 2004, p. 15). Knowing how a country's culture affects its innovative capability may allow it to exploit advantages and mitigate disadvantages posed by its unique configuration of norms and values.

Tighter cultures may confer an advantage in imitation-type but looser cultures in innovation-type activities in adoption of innovations (Lee, Trimi, & Kim, 2013). These differences might have important implications. For example, although containment of the COVID-19 pandemic was more effective in countries with tighter cultures (Cao, Li, & Liu, 2020), it is yet unclear if this is due to differences in innovative capability associated with tightness. Ambidexterity- the ability to undertake both explorative and exploitative innovation (Tushman & O'Reilly, 1996) is required to fully take advantage of innovative opportunities, to exploit efficiency and improvements in knowledge or incremental innovation, as well as exploration associated with more radical innovation (Andriopoulos & Lewis, 2009).

Accordingly, we suggest that country-level ambidexterity may also be required to fully exploit implementation or imitation-type as well as inventive-type innovation activities. Although many studies have tested effects of national culture norms and values on certain specific indicators of innovative activity (Dwyer, Mesak, & Hsu, 2005; Griffith, Hu, & Ryans, 2000; Kaasa & Vadi, 2010; Kostis, Kafka, & Petrakis, 2018; Lee et al., 2013; Png, Tan, & Wee, 2001; Rothwell & Wissema, 1986; Uzuegbunam & Geringer, 2021; Van Everdingen & Waarts, 2003), many of these indicators are aspects of innovative capability, and it remains unclear the extent to which these norms and values affect total innovative capability itself. It is currently unclear if norms and values work through imitation-type or inventive-type channels to either constrain or enable R&D, technological output, and scientific output as cornerstone components of a country's innovative capability. It is also unclear if these channels act synergistically or antagonistically in their net relationships with innovative capability.

Both a country's innovative capability (Castellacci & Natera, 2013) and its societal culture (Hofstede, 1980) are expected to evolve over time to solve societal problems, as formal and informal societal-level mechanisms, respectively. Although societal values are slowly changing, their differences between countries remain relatively stable over time (Beugelsdijk, Maseland, & van Hoorn, 2013), whereas innovative capability may evolve or co-evolve (see Castellacci & Natera, 2013) more rapidly. The problem-solving potentials of culture and innovative capability may therefore be asynchronous. Given lack of knowledge of such alignment we seek to empirically test the extent to which tight cultural norms and values matter in the development of a country's innovative capability.

To do so, we use data on countries across the world from Gelfand et al. (2011) as well as Uz (2015) to test CTL theory predicting effects of tight cultural norms on innovative capability. Further data from the GLOBE studies (de Luque, Javidan, & House, 2004; Hanges & Dickson, 2004; House et al.,

2004) are then used to test the predicted operations of specific theoretical mechanisms through which cultural values may affect innovative capability. In doing so, we contribute to this literature by identifying not only the extent to which CTL theory predicts country-level relationships between tightness norms and innovative capability, but also the extent to which cultural values theory predicts specific mechanisms, or theoretical channels through which cultural values affect different components of innovative capability. We therefore seek to contribute to this literature in the following main ways.

First, we build on similar previous studies to extend empirical culture literature on relationships between culture and innovative activity. More specifically, we also extend recent work such as that of Uzuegbunam and Geringer (2021) who test effects of the Uz CLT societal norm measure together with Hofstede's cultural values indices on adoption of disruptive innovations. Here, we use both the Uz and Gelfand et al. (2011) indices, as well as the GLOBE cultural values indices which extend Hofstede's work both theoretically and empirically (Javidan, House, Dorfman, Hanges, & De Luque, 2006). Similarly, whereas Uzuegbunam and Geringer (2021) focus on effects of cultural tightness on a single aspect of innovation, we extend their work to consider three comprehensive indicators of a country's innovative capability- its R&D expenditure as well as its technological and scientific capability, thereby also extending Castellacci and Natera's (2013) work in this regard. We therefore contribute to this literature by offering comprehensive tests of the extent to which leading cultural theoretical frameworks predict relationships between societal culture and innovative capability.

Many previous studies of effects of culture on aspects of innovative activity have focused on developed or OECD countries (Dwyer et al., 2005; Kaasa & Vadi, 2010; Kostis et al., 2018; Lee et al., 2013; Van Everdingen & Waarts, 2003). We extend this literature by using data from countries across the world to derive generalizable insights. Similarly, whereas other studies have used measures of

innovation such as labour productivity growth (Kostis et al., 2018), technology adoption (Lee et al., 2013), innovation diffusion rates (Dwyer et al., 2005), corporate adoption of ICT infrastructure (Png et al., 2001), European patent applications (Kaasa & Vadi, 2010), or adoption of business software (Van Everdingen & Waarts, 2003), we use country-level measures of innovative capability. In doing so, we link cultural theory to innovation research on innovative capability.

Second, in testing whether tight cultural norms and values matter for innovative capability we contribute to debates about how technology itself progresses. These debates concern the extent to which the trajectory of innovation, or technical progress, either progresses ‘rationally’ or in a utility-maximizing way that is ‘optimal’, or whether it progresses independently of utility-maximizing logics or can even lock into sub-optimal outcomes. Trajectories of technological change do not necessarily follow the most effective or productive paths and can sometimes progress in sub-optimal ways (Arthur, 2013). For example, QWERTY remains the global keyboard standard because of certain path dependencies arising at the time of its development (Kay, 2013), locking users into a sub-optimal innovation outcome. History demonstrates how societal values have often led to stigmatization of commerce, industry, and other economic activity (Baumol, 1996). Similarly, cultural values of a society can shape a country’s social infrastructure- its governmental policies and institutions (Jones & Vollrath, 2013). Market economies may not necessarily have an inherent bias toward innovation but rather profit (Hobsbawm, 1969; Jones & Vollrath, 2013) and state support may be needed to increase societally beneficial innovation (Mazzucato, 2011). Countries differ however in their preferences, or ‘tastes’ (Becker, 1998; Stigler & Becker, 1977) for political and fiscal priorities, including extent of public support for basic research or for the legal protection of intellectual property (Furman, Porter, & Stern, 2002). These preferences derive from a country’s cultural values and may affect a country’s innovative capability.

Similarly, Kuhn (1962) suggests that values of groups of researchers can influence progression of science itself- that it does not necessarily always progress in a purely rational or evidence-based way. We therefore seek to provide some evidence of the extent to which country culture, which is not explicitly rational nor utility-maximizing in its origins or effects, can influence a country's national innovative capability.

Third, we also seek to contribute to recent debates about the influence of country-level culture and the potential contributions of culture to important societal outcomes (Brouwers, 2017; Chaudhary, 2018), and the need for empirical evidence of specifically how knowledge of culture can contribute to other fields, including innovation studies, that are also concerned with important societal outcomes. As discussed, social infrastructure is influenced by cultural values and can influence a country's innovativeness (Jones & Vollrath, 2013), yet many studies in the field of innovation do not include cultural theory or variables in theoretical or empirical models. It is therefore also unclear to what extent exclusion of cultural variables or theory in studies on innovation has introduced bias from omitted variables or omitted theoretical insights.

Having introduced the paper and certain of its intended contributions, it proceeds as follows. First, theory and literature are reviewed. Methods applied in the study are then outlined. Results are reported and discussed. Conclusions are presented, and limitations and recommendations for further research are considered.

Theory and Literature

A large and growing body of research has sought to understand the development of innovation systems (Castellacci & Natera, 2013; Cooke, 2002; Delvenne & Thoreau, 2012; Filippetti & Guy, 2020; Furman & Hayes, 2004; Furman et al., 2002; Kim, Bae, & Byun, 2020). In that systemic properties of national innovation systems (Freeman, 1997; Lundvall et al., 2002; Nelson, 1993) are complex, and a

heterogeneous system cannot itself be ‘tested’ empirically, following Castellacci & Natera (2013) R&D, technological output and scientific output are considered here as three core components of a country’s innovative capability. We conceptualise these as components of a country’s innovation climate¹, rather than its innovation system, so as to differentiate our empirical approach from the tradition of non-empirical national innovation systems research. Our approach extends the same logic used to justify the empirical culture research tradition (Denison, 1996).

Although theoretical perspectives relating innovative capability to innovative capability extend from the classical to the heterodox, they provide complementary insights into complex phenomena. According to Schumpeterian perspectives, innovation is characterized by creative destruction, or constant disruption (Schumpeter, 1939). The evolutionary perspective builds on Schumpeter’s ideas to suggest technology advances largely through an evolutionary process susceptible to multiple influences (Dosi & Nelson, 2010). This has important implications for the role of culture in shaping innovative behaviours. Theorizing in the field of innovation is particularly concerned about states of Schumpeterian disequilibrium (Hall & Rosenberg, 2010), and the inherently disruptive nature of innovation, which makes it difficult to study using comparative statics. Assumptions of rational utility maximization may not only fail to explain aggregated psychological forces associated with cross-cultural values but are also not well suited to modelling states of constant disequilibrium that characterize many forms of technological and scientific progress.

Mainstream innovation literature also contributes insights into the workings of innovative capability. The residual effectiveness with which human labour and physical capital are combined has been termed technical progress (Solow, 1956), or total factor productivity. As discussed, according to

¹ The use of this term helps to differentiate the empirical innovative capability literature from that of national innovation systems which is primarily qualitative.

endogenous growth theory, growth (and therefore human development) is primarily caused by innovation- sharing and spreading ideas, or ‘knowledge recipes’ of how to more productivity combine resources (Romer, 1994).

According to this perspective, the dramatic rise of human living standards over time has been caused by improvements in the combinations (or re-combinations) of resources. A country’s innovativeness is therefore key to its development (Fagerberg, Srholec, & Verspagen, 2010), and its capacity for knowledge creation, absorption, and acquisition can contribute to its national competitive advantage (Ge & Liu, 2022). Hence, knowledge of forces that act on its innovative capability is of particular importance. Country cultural values also tend to correlate strongly with organizational cultural values (House et al., 2004), and organizations can tailor management to match country-level culture within which they are embedded (Javidan & Dastmalchian, 2009).

A country’s innovativeness is also affected by a wide range of economic, political, social, cultural, scientific, and technological influences (Arocena & Sutz, 2000). The causal origin of many of these influences may lie in a country’s unique set of cultural values. Differences in policy regimes and political preferences (Becker, 1998; Furman et al., 2002; Stigler & Becker, 1977) are reflected in cross-country variance that can usefully be exploited to test effects of culture on a country’s innovative capabilities. CTL theory predicts tighter societal cultural norms and values advantage countries in managing disasters (Gelfand, 2020; Gelfand et al., 2011).

Whereas Gelfand et al. (2011) and Uz (2015) cultural norms theoretically pertain to tightness, each GLOBE cultural dimension is theoretically concerned with specific mechanisms through which it can affect real world phenomena. Certain GLOBE dimensions are tight because of the actions of their causal mechanisms, and following other work (Griffith et al., 2000) we term these ‘Type II’ values. Although Griffith et al. (2000) did not focus on cultural tightness/looseness per se, based on

correlation results reported in Table 2, we use a ‘working’ categorization to allocate some of the GLOBE dimensions to our Type II tightness values category (whereas Griffith et al. apply their categorizations to countries). Griffith et al. (2000) found levels of standardization of processes and adoption of technological innovations (Lee et al., 2013) to be lower in Type II countries high in uncertainty avoidance and power distance, and low in individualism (that are more collective). We also categorize future orientation as a Type II, or tight value here for testing.

GLOBE studies define uncertainty avoidance as the extent to which “a culture’s people (should) seek orderliness, consistency, and structure” (Javidan, Stahl, Brodbeck, & Wilderom, 2005, p. 62), and power distance as the extent “to which a culture’s people are (should be) separated by power, authority, and prestige” (Javidan et al., 2005, p. 62). GLOBE studies split Hofstede’s collectivism construct, defining in-group collectivism as the extent “to which a culture’s people (should) take pride in and (should) feel loyalty toward their families, organizations, and employers”, and institutional collectivism as the extent “to which individuals are (should be) encouraged by institutions to be integrated into broader entities with harmony and cooperation as paramount principles at the expense of autonomy and individual freedom” (Javidan et al., 2005, p. 62). They rename Hofstede’s long term orientation construct ‘future orientation,’ the extent to which “a culture’s people are (should be) willing to defer immediate gratification for future benefits” (Javidan et al., 2005, p. 62).

Suggesting that Hofstede confounds assertiveness with gender in his masculinity construct, the GLOBE studies split masculinity into gender egalitarianism- the degree which “a culture’s people (should) support gender equality”, and assertiveness- the degree “to which a culture’s people are (should be) assertive, confrontational, and aggressive” (Javidan et al., 2005, p. 62). They also develop new orientations, such as humane orientation, the degree to which “a culture’s people are (should be) fair, altruistic, generous, caring, and kind toward others” as well as performance orientation, the extent

to which “a culture’s people (should) encourage and reward people for performance” (Javidan et al., 2005, p. 62). Masculinity and the additional GLOBE dimensions associated with it fall outside of the scope of hypothesis testing, as our focus is delimited to effects of CTL on innovative capability.

Certain studies offer insights into mechanisms that relate culture and innovative capability. Bass (1969) extends Rogers’s (1962) work on diffusion of innovations, finding adoption of new ideas and innovations may be higher in Type I (loose) cultures but that based on behaviours of others (collective adoption) may be higher in Type II (tight) cultures. Other findings support this differentiation in that whereas innovation-type ICT adoption tends to predominate in countries with Type I cultures, imitation-type is associated with Type II (tighter) cultures (Lee et al., 2013). Standardization of processes across business contexts may be affected by differences between Type I and II cultures (Griffith et al., 2000), and some cultural values can increase resistance to innovations that threaten to leave some in a society worse off (Rothwell & Wissema, 1986).

Hofstede’s uncertainty avoidance index (but not power distance) has been found to decrease corporate adoption of information technology infrastructure (Png et al., 2001). Masculinity and power distance have been found to be positively associated, and individualism and long-term orientation to be negatively associated, with cross-country diffusion of product innovations (Dwyer et al., 2005). Lower power distance, uncertainty avoidance, family-related collectivism, and masculinity have been found to be associated with higher patenting intensity in the European context (Kaasa & Vadi, 2010). Individualism has been found to positively affect early adoption, long-term orientation to positively affect both early and late adoption, and uncertainty avoidance, masculinity, and power distance values to negatively affect both early and late adoption rates of Enterprise Resource Planning software (Van Everdingen & Waarts, 2003).

Kostis, Kafka and Petrakis (2018) find certain civic culture values such as trust, control, work ethic and honesty values to contribute positively to innovation and obedience to contribute negatively. Innovation and imitation effects of mobile phone adoption patterns have been found to differ according to cultural differences between the United States and South Korea (Lee et al., 2013). Uzuegbunam and Geringer (2021) find cultural looseness to be significantly and positively related to disruptive innovation in adoption of agricultural biotechnology. Certain culture dimensions may act specifically on scientific activity. For example, institutional collectivism, in-group collectivism, uncertainty avoidance, and future orientation have been found to correlate negatively and assertiveness positively with success in basic science (House et al., 2004).

Based on the discussions above, and given that our three indicators of innovative capability- R&D expenditure, technological output, and scientific output are expected to be characterized by inventive activity, the following hypotheses are derived:

Hypothesis 1. *Tight cultural norms are significantly and negatively associated with innovative capability.*

Hypothesis 2: *Type 2 cultural values are significantly and negatively associated with innovative capability.*

Whereas testing tightness relates to a single mechanism, testing Type II cultures provides information on specific mechanisms through which tightness may act on innovative capability. Although studies seem to suggest that tight norms and Type II cultures reduce inventiveness through many channels, cultural tightness may also confer an advantage in implementation-type innovation activities. Recent evidence suggests countries with tighter values have better responses to the COVID-19 pandemic (Cao et al., 2020; Gelfand, 2020). Culture can affect innovation ambidexterity (Lin & McDonough, 2011)- the need to balance exploration and exploitation of knowledge (Andriopoulos & Lewis, 2009; Tushman & O'Reilly, 1996). As such, it is unclear from literature what the overall effects are of

tightness on innovative capability. It is also unclear how these effects differ in countries at different levels of development in innovative capability.

As discussed, Solow's (1956) model of growth suggests developing countries will catch up with developed countries if capital has higher returns in developing countries. Similarly, Romer (1990) suggests knowledge recipes are key to growth and development, but as discussed previously societal culture values can affect resistance to new ideas as well as the creation and dissemination of knowledge (Rothwell & Wissema, 1986). Similarly, social infrastructure (Jones & Vollrath, 2013) can shape policy regimes regarding intellectual property rights, property rights in general, and the forces that generate absorptive capability. According to Romer's (1990) model, unlike Solow's (1956), divergence may be just as likely to occur. All else being equal, countries in which twin problem-solving effects of cultural values and innovative capability align will be expected to develop faster and mitigate threats more effectively than those in which cultural values constrain innovative capability. Countries might be expected to converge (diverge) to the extent that their cultural values support (constrain) their creation or imitation of knowledge recipes. If so, then relationships between cultural values and innovative capability might be expected to be positive and stronger in countries with higher innovative capability. If innovative capability is sensitive to cultural values, then this sensitivity might therefore be expected to differ across countries with different levels of development of innovative capability. The following hypotheses are therefore derived.

Hypothesis 3: *Tight cultures are significantly and more negatively associated with innovative capability in countries with lower levels of innovative capability.*

Hypothesis 4: *Type II cultures are significantly and more negatively associated with innovative capability in countries with lower levels of innovative capability.*

Having derived hypotheses for testing, the methodology applied to test them is now discussed.

Method

Participants

GLOBE data was collected from approximately 17 000 respondents in 951 organisations from 62 countries, across all major regions of the world (see House et al. (2004) for further information about data collection). Our analysis of the world sample includes 46 countries for which data is available for all our tested variables over at least one time period in tests with R&D expenditure as dependent variable, 45 countries with patent production (technological output) as dependent variable, and 46 countries with scientific articles (scientific output) as dependent variable. A list of these countries is provided in the Appendix.

Measures

We use data from Gelfand et al. (2011), Uz (2015), and the GLOBE studies (House et al., 2004). Gelfand et al.s' (2011) data on perceptions of cultural tightness covers 6823 respondents across 22 countries. Using 6-item Likert scales, Gelfand et al.s' scale captures tolerance of deviance and strength of social norms- "the degree to which social norms are pervasive, clearly-defined and reliably imposed within nations" (Gelfand et al., 2011, p. 1102). Their scale adapts measures of situational appropriateness and behavioral constraint (Price & Bouffard, 1974). Detailed information on scale construction and assessments of validity can be found in Gelfand et al. (2011).

We supplement Gelfand et al.'s (2011) perceptions-based measures of cultural tightness with those of Uz (2015), derived from standard deviations. Uz's (2015) index is derived from 101 172 survey responses with final data covering 68 countries. In using this scale, we average scores of West and East Germany to obtain single-country data to merge with data on covariates. Uz's index measures homogeneity in behaviours, norms, and values, and is derived from the 2000 wave of the European

Values Study Group and World Values Survey (EWVS, 2006). Uz derives general (g-factor) and specific (s-factor) domain measures of statistical dispersion of CTL together with a combination measure, which we use here. Higher scores on the Gelfand et al. index indicate tightness, but they indicate looseness on the Uz index.

GLOBE cultural values were developed using a multistage process, including qualitative evaluations using item review, Q-sorting, and back translation, in addition to quantitative evaluations using multilevel confirmatory factor analysis, correlation analysis, and other scale evaluation techniques (Hanges & Dickson, 2004). The questionnaire items take the form of 7-point Likert-type items.²

As discussed, use of R&D expenditure, domestic patents, and scientific and technical journal articles as indicators of innovative capability follows Castellacci and Natera (2013).

In different regressions, Gelfand et al., Uz, and GLOBE (2020) data is merged with longitudinal data on dependent variables and covariates. We include a range of covariates in that they are expected to correlate with differences in cross-country culture. Gross domestic product (GDP) per capita, adjusted for purchasing power parity, captures differences between countries in levels of development, and ability to fund innovative capabilities. It is obtained from the Penn World Tables (Feenstra, Inklaar, & Timmer, 2015). Investment, or gross domestic capital formation's share of GDP, is a measure of the capital intensity of a country, obtained from the United Nations National Accounts Main Aggregates Database (NAMAD) (UN, 2020). From the same source are the share of foreign direct investment (FDI) in GDP and trade variables, the latter the sum of imports and exports divided by GDP. Foreign direct investment (FDI) and trade can facilitate flows of knowledge across countries, thereby enabling innovation. To control for cross-country differences in absorptive capacity, a

² For more detailed information on reliability and validity see Hanges and Dickson (2004)

country's secondary education enrollment ratio as well as its educational spending as a proportion of its GDP are included, both from the World Bank's Development Indicators (WB, 2020). Unemployment as a proportion of total population, also from the World Bank, is included to control for differences between countries in utilization of labour. By including these covariates, we hope to reduce omitted variable bias and improve the chances of obtaining unbiased regression estimates of coefficients of cultural orientations in testing.

Analysis

Whereas others (Aktas, Gelfand, & Hanges, 2015) use GLOBE data to test relationships at different levels of units of analysis, and use multilevel modelling, we do not cross levels in the same way. We delimit our analysis to the country level, which is appropriate in that our innovative capability indicators are sensitive to national policy that reflects unique political priorities shaping fiscal and other resource decisions that differ across countries. Thus, we exploit variance associated with political country borders to test exogenous effects of culture on innovative capability. The analysis applies the following sequential process.

First, univariate analysis is performed, and Table 1 presents descriptive statistics. An innovation index is derived from the three innovation measures to obtain a single measure of their shared variance, using principal components analysis. This index comprises the first factor of unrotated principal component loadings (innovative input=0.661; technological output= 0.470; scientific output=0.585). Plots of the Gelfand et al. and Uz data against this index, shown in Figure 1, provide an overview of descriptive relationships between tightness and innovative capability.

Second, bivariate analysis is undertaken to obtain correlations between all cultural and innovation items for the world sample, as reported in Table 2. Many cross-cultural psychology studies are overrepresented by respondents from Western, educated, industrialized, rich and democratic

(WEIRD) cultures (Nielsen, Haun, Kärtner, & Legare, 2017). Bias can occur if such results are generalised to the global human population, and we therefore also report results for the world sample split into Western and non-Western countries in Table 3. We classify Western countries on a geographic basis, broadly including countries in Western Europe and North America as well as Australia and New Zealand. These countries are listed in Table A of the Appendix. Table 3 reports additional results of tests of significant differences between correlations of the two groups of countries, based on Caci's (2000) method. In regression testing we include covariates to partial out differences between countries, but we report these correlations for comparative reasons in that many previous studies on culture and aspects of innovativeness have used correlational designs (see House et al., 2004).

Third, regression analysis is undertaken to test our hypotheses. Ordinary least squares (OLS) is used to derive a simple associative typology of contributions of cultural orientations to R&D for the world sample. OLS is appropriate for this task, in that estimations of coefficients are expected to be efficient, and also consistent in that endogeneity is theoretically unlikely. The cultural values measures, sampled prior to 2004, are theoretically unlikely to suffer from endogeneity, simultaneity, and reverse causality as determinants of innovative activity. The same tests are performed using negative binomial regression with patents and scientific articles as dependent variables, because they take the form of count data, with Poisson distributions (Hausman, Hall, & Griliches, 1984). Overdispersion is however present, and we therefore use negative binomial instead of Poisson regressions.

These regressions derive coefficients based on averaged values across the pooled data and results are therefore representative of an 'average' country, with coefficients averaged across time. To take advantage of the panel structure of the data, year dummies are included to control for idiosyncratic yearly shocks. These results are reported in Table 4 without year dummies shown.

As discussed, we also test hypotheses that test whether systematic differences exist in the way culture

affects innovation at different levels of development. Quantile regression is therefore used to test R&D and a count data quantile regression technique (Machado & Silva, 2005) is used in regressions with patents and scientific articles as dependent variables. These tests are performed for countries at the 10%, 30%, 50%, 70%, and 90% quantile levels of each dependent variable, and are reported in Table 5. For regression testing, the following six specifications are derived:

$$rnd_{it} = \beta_0 + \beta_1 Tightness + \beta_{10} Z_{it} + \varepsilon_{it} \quad (1)$$

$$patents_{it} = \beta_0 + \beta_1 Tightness + \beta_{10} Z_{it} + \varepsilon_{it} \quad (2)$$

$$articles_{it} = \beta_0 + \beta_1 Tightness + \beta_{10} Z_{it} + \varepsilon_{it} \quad (3)$$

$$rnd_{it} = \beta_0 + \beta_1 UA_i + \beta_2 FO_i + \beta_3 IC_i + \beta_4 IGC_i + \beta_5 PD_i + \beta_6 PO_i + \beta_7 HO_i + \beta_8 GE_i + \beta_9 AS_i + \beta_{10} Z_{it} + \varepsilon_{it} \quad (4)$$

$$patents_{it} = \beta_0 + \beta_1 UA_i + \beta_2 FO_i + \beta_3 IC_i + \beta_4 IGC_i + \beta_5 PD_i + \beta_6 PO_i + \beta_7 HO_i + \beta_8 GE_i + \beta_9 AS_i + \beta_{10} Z_{it} + \varepsilon_{it} \quad (5)$$

$$articles_{it} = \beta_0 + \beta_1 UA_i + \beta_2 FO_i + \beta_3 IC_i + \beta_4 IGC_i + \beta_5 PD_i + \beta_6 PO_i + \beta_7 HO_i + \beta_8 GE_i + \beta_9 AS_i + \beta_{10} Z_{it} + \varepsilon_{it} \quad (6)$$

where β_0 is the constant, and ε_{it} is a residual error component for country i at time t . Eqs (1) and (4) are tested for the period 1996-2016, eqs (2) and (5) for 1991-2016, and eqs (3) and (6) across the years 2003-2016, periods for which data are available for each dependent variable. Tightness is tested using both Gelfand et al. and Uz measures of CTL, so eqs (1-3) are tested separately for each measure. Other independent variables of interest are uncertainty avoidance (UA), future orientation (FO), institutional collectivism (IC), in-group collectivism (IGC), power distance (PD), performance orientation (PO), humane orientation (HO), gender egalitarianism (GE), and assertiveness (AS). Z is a vector of covariate factors, which together with the dependent variables is defined as follows:

Dependent variables

<i>rnd</i>	=	Innovative input: R&D expenditure (% of GDP)
<i>patents</i>	=	Technological output: domestic patent applications
<i>articles</i>	=	Scientific output: scientific journal article publications

Covariate variables

<i>gdppc</i>	=	Natural log of GDP per capita (at US\$ 2011 purchasing power parity prices)
<i>inv</i>	=	Investment as fixed domestic capital formation as a share of GDP (%)
<i>fdi</i>	=	Net inflows of foreign direct investment as a share of GDP (%)
<i>trade</i>	=	Trade as exports plus imports as a share of GDP (%)
<i>sed</i>	=	Secondary education enrollment ratio (%)
<i>edspend</i>	=	Spending on education per GDP (%)
<i>unemp</i>	=	Unemployment as a portion of the population (%)

As discussed, regressions are performed at the country level, with the country as the unit of analysis. Standard errors are clustered at county level to adjust for shared variance between countries and to mitigate heteroskedasticity.

Univariate results and bivariate plots suggest outliers or influential points may be present in the data, such as the Czech Republic, South Korea, and Japan, which could skew regression results. Regression and negative binomial tests were performed to evaluate different approaches to mitigate the problem of outliers, either by winsorising the data, or removing outliers using Hadi's (1994) technique. Based on comparisons, winsorizing was chosen, in that it avoids removal of data and preserves sample size. Data were winsorized to modify 10% of observations in each tail of the distribution. Outliers were not modified for quantile and count data quantile regression tests, which are relatively robust to

outliers, even if they are less efficient, requiring a larger sample size to attain the same power and precision of OLS results. Associations within the 10% level are taken to be significant and are discussed.

Model specification tests were performed. Plots of observed versus predicted variables were found to approximate a 45-degree relationship for each of the specifications, suggesting that models adequately predict tested relationships. Breusch-Pagan/Cook-Weisberg tests suggest heteroscedasticity is present for all models, and robust standard errors are used in all regressions.

According to variance inflation factor (VIF) tests for benchmark OLS models, VIF values for all tested specifications were within the threshold limit of 10. Excessive multicollinearity can depress standard errors and render certain coefficients significant when their true values are not, but these tests suggest that multicollinearity is unlikely to threaten interpretation of the results. Checks of histogram and kernel density plots of the residuals were taken to suggest adequate normality in the distributions of the residuals. Given that our interest is delimited to relationships between cultural and innovation measures, covariate effects are not considered in the discussions that follow.

[PLEASE INSERT FIGURE 1 HERE]

[PLEASE INSERT TABLES 1, 2, 3, 4, AND 5 ABOUT HERE]

Results and discussion

Plots in Figure 1 and zero order correlations reported in Tables 2 and 3 provide comparisons with previous work based on correlation estimates (see Gelfand et al., 2011; House et al., 2004). We also note some differences in the strengths of zero order correlations that differ between Western and non-Western subsamples, shown in Table 4. As discussed, our regression tests control for

developmental and other differences between countries, but these plots and graphs allow comparisons with previous work that has used correlational designs.

Societal tightness norms and innovative capability

According to OLS and negative binomial tests reported in Table 4, tightness is negatively related to R&D in tests of both Gelfand et al. and Uz indices but not significantly associated with technological or scientific output. Hypothesis 1, *that tight cultural norms are significantly and negatively associated with innovative capability* is not supported.

Tight cultures can be characterised by control over individual freedom and behaviour conflicting with that of the group (Triandis, 1989). Tight cultures can be less tolerant of deviant behaviour, (Gelfand et al., 2020) and tend to prioritize rules over freedom, with higher levels of monitoring of individual behaviour (Gelfand et al., 2011). In suppressing individualistic innovative behaviour that deviates from collective norms tightness might reduce R&D through this channel. Social and institutional resistance to innovation is associated with conservatism (Rothwell & Wisserma, 1986) and a country's preferences regarding intellectual property and its 'tastes' for policies more generally (Stigler & Becker, 1977) may be affected by a country's norms of tightness.

These results suggest tight norms reduce R&D activity, even if tightness might confer an advantage in imitation-type (Lee et al., 2013) or exploitative/implementation-type innovative activities. R&D activity might not be as ambidextrous as that of technological or scientific output, in that potential negative effects of tightness dominate positive effects in these tests. Further research should explore implications of these results for literature on innovation ambidexterity (Andriopoulos & Lewis, 2009; Lin & McDonough, 2011; Tushman & O'Reilly, 1996), regarding differences between R&D and both technological and scientific activities. Such research should explore these effects at different levels.

If culture emerges as a societal-level problem solving mechanism (Hofstede, 1980) and if a country's innovative capability also acts as a problem solving mechanism (Castellacci & Natera, 2013), these two mechanisms may misalign in how they affect a country's R&D activities. Instead of working hand in hand as informal and formal problem-solving mechanisms, R&D-driven problem solving may be reduced in countries with tight cultural norms. Although tighter societies may have been more successful in COVID-19 response (Cao et al., 2020), this may possibly have occurred due to conformity or compliance with norms associated with tightness, which might depress R&D activity. Results here support the notion that R&D activity as an aspect of technological change may be difficult to model solely using principles of utility maximization that fail to consider cultural norms (see Arthur, 2013).

Although measures of tightness norms make it possible to test overarching predictions of CTL theory, further tests using GLOBE values allow us to investigate more explicit theoretical predictions pertaining to specific mechanisms through which specific Type II values affect innovative capability.

Type II values and innovative capability

As with tightness norms, all Type II cultural values are negatively associated with R&D. Much R&D is government-funded and although typically less productive than private R&D it targets positive externalities (Hall, Mairesse, & Mohnen, 2010). If tight cultures depress R&D expenditure, this might come at a cost to positive societal externalities.

These results seem to align with other studies that have found cultural values to be negatively associated with technological adoption (Uzuegbunam & Geringer, 2021), process standardization (Griffith et al., 2000), technological adoption (Lee et al., 2013; Png et al., 2001), and rates of innovation diffusion (Dwyer et al., 2005), as well as social and institutional resistance to innovation itself (Rothwell & Wissema, 1986). Many effects tested in this prior work may be captured in our R&D measure. The

workings of a national innovation system might be affected by constraints to its R&D component in countries with tight cultures.

Given that all tight norms and values tested here accord in negative associations with R&D, comparative insights cannot be derived. Tests of technological and scientific output however allow us to identify different theoretical mechanisms or channels through which values seem to affect technological or scientific activity.

Uncertainty avoidance is negatively associated with R&D but is not associated with technological or scientific output. Formalisation and rules-based approaches characterising uncertainty avoidance (House et al., 2004) that may constrain R&D activities might not necessarily be detrimental to technological or scientific activity.

Whereas power distance is negatively associated with R&D, it is positively associated with patents, and is not associated with scientific output. Negative associations of power distance in previous studies with the Global Innovation Index (Rinne, Steel, & Fairweather, 2012) and a composite innovation index (Kedia, Keller, & Jullan, 1992) might reflect use of measures of innovation that overlap with R&D activity. In that it is positively related to patents, power distance may enable technological production through “incentives to aspire to gain power positions through hard work and capability development” (Carl, Gupta, & Javidan, 2004, p. 541). Technological output, measured as patent production, captures dissemination of technical information (WIPO, 2021). Technical, legal, and commercial information made available in patents therefore contributes to adaption and improvement of technology. Patenting activity is also heterogeneous, differing systematically across firms and industries (Nagaoka, Motohashi, & Goto, 2010).

Future orientation is negatively associated with R&D but positively associated with both technological and scientific output. Subordination of individual goals to those of the group regarding planning and

time horizons (House et al., 2004) and suppression of spontaneous activity in favour of planning and delayed gratification that characterises future orientation (Javidan et al., 2005) may constrain R&D but may enable technological and scientific output through this channel. This might be the only channel tested here that positively affects scientific activity. Apart from future orientation no other tight value relates positively to scientific activity. Type II values may have an advantage in imitation-type innovative activities (Lee et al., 2013) associated with exploitation of knowledge rather than exploration. Patents and scientific articles differ from R&D in that they are citation-based and may incorporate less spontaneous and inventive activity in proportion to planned and imitative-type activity.

Of Type II values, only future orientation is positively associated with both technological and scientific output, and only in-group collectivism is consistent in its negative effects across all three types of innovative capability. Suppression and monitoring of individual behaviour that differs from group norms (House et al., 2004) might be a universal channel through which tight values constrain innovative capability.

Social and institutional resistance to innovation can be caused by conservatism (Rothwell & Wisserma, 1986), and in-group collectivism might also capture some degree of resistance to innovative behaviour through this channel. Some have suggested science itself also progresses through changes in values and belief systems, or paradigms, of scientists (see Kuhn, 1962), and not always through generation of novel facts (Lakatos, 1978).

Institutional collectivism, which relates to prioritisation of institutional or organisational over individual interests (House et al., 2004), seems to constrain R&D and technological output but not scientific output. Organisational contexts in which most scientific output is generated may be relatively robust to effects of institutional collectivism on scientific productivity.

Overall, whereas the GLOBE studies find uncertainty avoidance, future orientation, and both collectivism orientations to correlate negatively with country measures of success in basic science (House et al., 2004), only future orientation and in-group collectivism are significant in our regression tests of scientific output.

A key finding here is a ‘watershed’ in signs and significance (sensitivity) of results, between R&D which is negatively and universally related to all tight norms and values, and the other two innovative capability indicators for which results are mixed.

Of the innovation capability indicators, why is R&D uniquely sensitive to cultural tightness? R&D investments typically improve products or services, or processes. R&D investments include expenditures across four main sectors, namely business, government, higher education, and private non-profit, including basic, applied, and experimental types of research (WB, 2020). As discussed, most technological and scientific outputs may incrementally build on citations of previous work, and this might differentiate R&D from technological and scientific research. Further research using case study or other qualitative methodologies should explore additional theoretical mechanisms that differentiate R&D from technological and scientific research.

Whereas Type II values might pose a cost to societally beneficial externalities arising from R&D activities, they might contribute to knowledge and information dissemination through some of their effects on technological output and scientific output. On balance, these results do not support Hypothesis 2, that *Type II cultures are significantly and negatively associated with innovative capability*. Over and above Type II values, tests of the remaining values reveal few coherent patterns, supporting theoretical predictions of CTL theory that tightness may account for most of the variance in tested relationships here.

Effects of tightness norms at different levels of innovative capability

Technology gap literature suggests developmental differences may exist between countries with different levels of technological advancement. We therefore test whether results that generalise across the world sample- of a notional ‘average’ country (reported in Table 4 pertaining to tests of Hypotheses 1 and 2) differ for countries at different quantile levels of innovative capability. Table 5 reports results of quantile and count data quantile regressions. To save space and allow comparisons, three separate panes within the table report testing of the Gelfand et al. (Pane A), Uz (Pane B), and GLOBE values (Pane C) dimensions are reported together in different panes in Table 5. Although covariates are tested in these regressions, they are not included in the tables reported in each pane.

Overall, tests using the Gelfand et al. and Uz tightness measures fail to support Hypothesis 3, that *tight cultures constrain innovative capability more strongly in countries with lower levels of innovative capability*. Tests using the Gelfand and Uz indicators suggest that tight norms constrain R&D activity across almost all quantile levels. Tests of Gelfand et al.’s measure suggests tightness enables technological output at lower quantiles but constrains it at higher quantiles. These results are opposite to those hypothesized. The same tests with the Uz indicator however suggest that tightness constrains technological output at all quantile levels except the lowest.

When scientific output is tested, the Gelfand et al. indicator also conflicts with that of Uz, and results are inconsistent. Some heterogeneity may be present in that specific mechanisms associated with countervailing effects of values at different quantile levels of a country’s development of innovative capability. Tests of specific Type II values are expected to provide insights into this heterogeneity.

Effects of Type II values at different levels of innovative capability

All tested Type II values seem to be relatively consistent in effects on innovative capability across quantile levels, with few exceptions. All Type II values (except for power distance which is not associated with R&D across most quantile levels) seem to constrain R&D and increase technological

and scientific output, except for the collectivism indicators. In-group collectivism is negatively associated with all three innovative capability indicators across almost all quantile levels, as is institutional collectivism with R&D and scientific output. In terms of exceptions, uncertainty avoidance seems to enable technological output at the two highest quantile levels and is not significant otherwise. Non-significance of some tests at the lowest quantile may be due to other characteristics of countries with very low technological output. Overall, these results fail to support Hypothesis 4, *that Type II cultures are significantly and more negatively associated with innovative capability in countries with lower levels of innovative capability*. A country's stage of development in its innovative capability does not seem to confound direct effects of tightness norms and values on innovative capability. These results have implications for debates on contributions of technological gaps regarding development.

Overall, these results present some evidence that cultural forces can exert an influence on extrinsic, or 'economic' outcomes such as a country's innovative capability, which cannot fully be explained by logical principles of economic utility maximisation. These findings support suggestions in the literature that innovation cannot be assumed to proceed optimally (Arthur, 2013; Kay, 2013), but may be subject to other non-rational forces such as cultural values. Empirical innovation analysis might do well to incorporate cross-cultural insights in future work.

Conclusion

Consequences of threats such as the Covid pandemic, geopolitical conflict, climate change, global supply chain shocks and costly supply chain reconfigurations may need to be mitigated by a country's problem-solving innovative capability. Knowing how its innovative capability is affected by its unique configuration of cultural norms and values is key to improving its innovative capability, and its ability to mitigate consequences of threats and disasters.

The objective of this work was therefore to test cultural theory predicting that a country's unique configuration of cultural tightness norms or values can influence outputs of components of its innovative capability. Findings extend empirical work on innovative capability, such as that of Castellacci and Natera (2013) which demonstrates how R&D, technological outputs, and scientific outputs coevolve, to provide some evidence of how tight cultural norms and values may stimulate or constrain the same innovative capabilities.

Findings support some theoretical arguments in the literature, that innovation is difficult to fully model using approaches based on comparative statistics that assume economic utility maximization (see Hall & Rosenberg, 2010). According to Schumpeter (1939), innovation is characterized by a process of creative destruction, whereby it arises from a continual state of dis-equilibrium. If a country's unique configuration of cultural values influences its innovation system, then it would be difficult to fully model these relationships using Walrasian or equilibrium approaches.

Certain overall conclusions derive from these findings. Of the innovation capability components R&D activity seems to be universally sensitive to tightness norms and values. Tight societies might lose out on positive externalities from public components of R&D investment. Whereas technological and scientific outputs build incrementally on previous work and citations, R&D activity may be a broader measure of less incremental innovative activity that is more vulnerable to tight norms and values. Of all indicators, in-group collectivism seems to universally constrain all components of innovative capability.

Whereas tests of tight norms provide helpful insights into relationships with innovative capability, tests of cultural values provide knowledge of specific theoretical mechanisms through which tightness affects innovative activity. Mechanisms associated with future orientation and power distance seem to

work in the same direction to constrain R&D activity but to enable technological output, whereas only future orientation enables both technological and scientific output.

Findings highlight heterogeneity and countervailing theoretical mechanisms associated with different values underlying a country's norms of tightness. Some universality is present in effects of tightness on innovative capability in that they do not seem to differ substantially in countries at different levels of development of innovative capability.

Overall, findings have relevance for those seeking to improve innovativeness at the national level, as well as in business organizations, in that a country's values typically correlate strongly with those of organizations within it (House et al., 2004). Failing to take into careful consideration causal effects of a country's culture on its innovative capability may be costly in light of a host of potentially existential threats to itself and its firms at this time.

Limitations and avenues for further research

Considering methodological challenges shared with other studies that test effects of culture on country-level outcomes, work here uses methods that are widespread in their use (Cao, Li, & Liu, 2020; Gelfand et al., 2021) and are therefore uncontroversial. Limitations of the methodological aspects of the work here are therefore germane to the stream of research that it contributes to.

We link innovation capability and culture literatures. Many empirical studies on technological innovation fail to explicitly incorporate cultural variables as covariates. This may introduce omitted variable bias. To mitigate this bias, econometric studies of technological innovation often use fixed effects to remove time invariant idiosyncratic or unique country-specific cultural variance that might confound an analysis. In so doing, cultural influences on a country's innovation capability seem to

have largely remained excluded from explicit investigation. The extent of these influences, and their potential consequences for innovative capability, have seemingly been unknown.

We are unable to use fixed effects because our independent variables of interest are cultural and are largely time invariant. Fixed effects isolate within-country variance and exclude between-country variance. Research on Hofstede's dimensions suggests that although culture changes slowly over time, relative cultural differences between countries tend to persist (Beugelsdijk et al., 2013; Beugelsdijk & Welzel, 2018). Our approach is therefore appropriate because culture is expected to change slowly over time, and we are primarily interested in cross-country or between-country variance.

In that we do not use fixed effects, our specification and the variables that comprise it are derived from theory that is concerned with cross-country cultural differences. By explicitly including cultural variables as our variables of interest we mitigate omitted variable bias in estimations of innovative capability. If one were to exclude a variable representing culture from a regression-type specification, and if this excluded variable were to correlate with an appropriately included independent variable, then estimated parameters in the incomplete model would be biased and inconsistent (Gujarati & Porter, 2009). Endogeneity would then be present, with incorrectly estimated error variance. Interpretations of significance would give rise to misleading conclusions. Biased and inconsistent estimates would fail to approach their true values as the sample size increases asymptotically.

What then if our specification errs on the side of including one or more non-relevant variables? Including irrelevant variables does not affect bias and consistency- estimated parameters are unbiased and consistent, the error variance is correctly estimated, and hypothesis-testing procedures remain valid, but there is a loss in efficiency- estimated betas will have larger variance and will be less precise in their estimation (Gujarati & Porter, 2009, p. 473). According to Gujarati and Porter (2009, p. 473), the "point is clear: Once a model is formulated on the basis of the relevant theory, one is ill-advised

to drop a variable from such a model.” A less precise estimate would have a larger standard error which is the denominator in the ratio of the estimated coefficient to its standard error. This would produce a smaller t-statistic, with a reduced level of significance. In light of this possibility, OLS is an appropriate technique to maximise efficiency. Its use mitigates potential efficiency losses arising from inclusion of covariates that are not statistically significant but remain in the model for theoretical reasons.

Because cultural norms and values change slowly over time, as predictors their measures exhibit certain characteristics of causal estimators. Their estimated parameters should remain consistent in that they are robust to simultaneity and reverse-causality bias. Our estimations are therefore likely to mitigate endogeneity not only because of reduced omitted variable bias, but also for theoretical reasons in that theory has long ascribed a causal role to culture and its consequences (Hofstede, 1980).

As discussed, in that cultural change occurs very slowly within a country, our estimations exploit between-country variance. This is appropriate for a study of this nature but does not allow us to take advantage of the structure of lags to identify within-country effects. Although this precludes the use of generalised method of moments or other sophisticated techniques to address endogeneity, we suggest that their use is unnecessary because the causal nature of culture is uniquely suited to use of OLS and the techniques we apply here. As discussed, our approach mitigates endogeneity and threats to the consistency of our estimates, and the unique nature of cross-country cultural differences is well suited to the between-country variance captured in our estimations.

Our use of three different sources of appropriate data to represent cultural influences provides robustness checks in analysis and results support convergent and discriminant validity (Campbell & Fiske, 1959). Overall, we suggest that the research design applied here is perhaps the only appropriate approach available to test the relationships under study. In replicating this work, other studies might

use richer data as it becomes available. Case study and causal qualitative studies should extend this research to identify more fine-grained theoretical mechanisms and their boundary conditions that underlie relationships between culture and innovative capability.

As discussed, work here shares limitations with other similar studies. The innovation measures tested here are extensively used in literature, but nevertheless suffer from certain well-known limitations. R&D expenditure, as a percent of GDP, is a broad measure that includes expenditures across different sectors and types of research activity (WB, 2020). Further research should develop more specific measures of innovative capability as richer data becomes more available over time.

In terms of technological output, many patents are developed from previous inventions, many are not generated from R&D, many inventions are never patented, and many patents end up not being used; patenting activity is also heterogeneous, differing systematically across firms and industries (Nagaoka et al., 2010). Scientific output as measured here also captures quantity and not quality, and the nature of research itself differs substantially across fields, making cross-field comparisons difficult.

Innovative capability and culture are expected to exhibit heterogeneity within countries. Country cultures reflect shared history as well as cumulative effects of country-level policy and regulatory frameworks, but substantial sub-cultural and regional heterogeneity may nevertheless be present. Culture is also closely associated with geographic location, which differentiates patterns of innovation modes (Doloreux & Shearmur, 2022). Although specifically testing intra-country and firm- or organisational-level effects was beyond the scope of this study, further research should extend the work here to do so.

Further research should build on findings here to investigate cultural influences on innovative capability at the firm level in light of rapid technological advances that can radically enhance firm-level innovation capability. These advances include those in artificial intelligence (AI) (Dicuonzo, Donofrio,

Fusco, & Shini, 2022), additive manufacturing (Chaudhuri, Naseraldin, & Narayanamurthy, 2022), quantum computing (Gupta, Modgil, Bhatt, Chiappetta Jabbour, & Kamble, 2022), open innovation (Madanaguli et al., 2022), Internet of Things and big data (Sestino et al., 2020), blockchain (Spanò et al., 2021) and digital transformation (Gong & Ribiere, 2021; Raimo et al., 2022), to name a few.

Better understandings of how to further mitigate limitations of this and similar studies may spur improvements in theory development and practice concerned with culture and problem-solving innovative capability. This knowledge may be particularly valuable in a global context facing many challenges, some of which may become existential.

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FIGURES

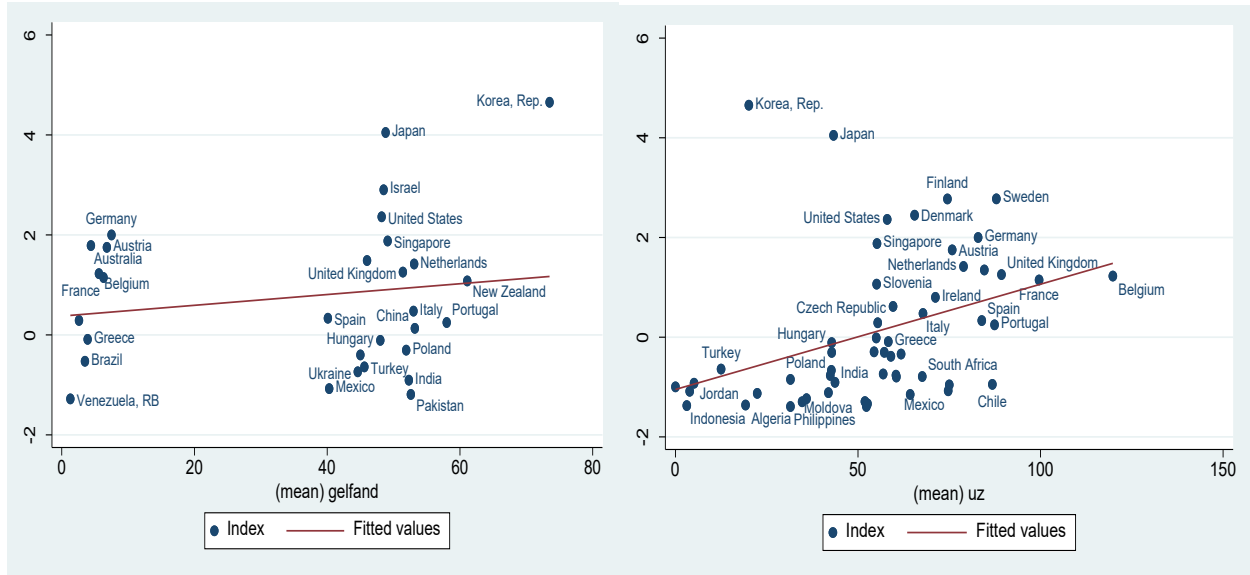


Figure 1

Plots of the averaged values of the innovation index with the Gelfand et al. (2011) index (left) and the Uz (2015) index (right)

TABLES

Table 1

Descriptive statistics

Variable	Abbreviation	Mean	Std. Dev.	Min	Max
Research and development	rnd	0.941	0.943	0.005	4.576
patents	patents	10682.170	58560.160	1.000	1245709.000
Scientific articles	articles	11816.160	43157.700	0	440229.700
Gelfand et al (2011) index	tight	37.56	21.7	1.3	73.5
Uz (2015) index	loose	52.57	26.258	0	119.8
Uncertainty avoidance	UA	4.667	0.588	3.158	5.610
Future orientation	FO	5.480	0.491	2.952	6.203
Power distance	PD	2.752	0.385	2.041	4.355
Institutional Collectivism	IC	4.745	0.505	3.826	5.654
In-group Collectivism	IGC	5.666	0.386	4.063	6.519
Humane Orientation	HO	5.392	0.342	3.394	6.087
Performance Orientation	PO	5.893	0.514	2.348	6.577
Gender egalitarianism	GE	4.484	0.482	3.182	5.172
Assertiveness	AS	3.845	0.662	2.660	5.564
Gross domestic product per capita	gdppc	8.531	1.171	4.877	12.442
Investment	invest	0.216	0.098	0.008	0.989
Foreign direct investment	fdi	2.875	5.643	-37.155	103.337
Trade openness	trade	32.777	27.928	0.128	237.964
Secondary education	sed	63.883	34.673	1.012	163.935
Educational spending	edspend	14.500	4.903	0.000	47.279
Unemployment	unemp	8.522	6.323	0.122	44.157

Note. Data excludes countries with less than a million people.
Std. Dev. Standard Deviation. Min. Minimum. Max. Maximum.
Abbreviations are used in other tables and figures.

Table 2*Correlations between culture and innovation items*

	(1)													
	rnd	patents	articles	tight	loose	UA	FO	PD	IC	IGC	HO	PO	GE	AS
rnd	1													
patents	0.326***	1												
articles	0.400***	0.766***	1											
tight	0.005	0.154***	0.157**	1										
loose	0.348***	-0.041	0.166***	-0.476***	1									
UA	-0.613***	-0.022	-0.132***	-0.105***	-0.641***	1								
FO	-0.397***	-0.119***	-0.196***	0.146***	-0.454***	0.634***	1							
PD	-0.0636	0.097***	0.055	0.389***	-0.273***	0.042*	-0.325***	1						
IC	-0.551***	-0.231***	-0.218***	-0.536***	-0.154**	0.456**	0.502***	-0.367***	1					
IGC	-0.278***	-0.172***	-0.178***	0.028	0.006	0.331**	0.618***	-0.359***	0.370***	1				
HO	0.240***	0.029	0.081*	-0.275***	0.060**	0.030	0.324***	-0.572***	0.0456**	0.169***	1			
PO	-0.175***	-0.137***	-0.051	-0.294***	0.040	0.294***	0.687***	-0.538***	0.453***	0.684***	0.513***	1		
GE	0.222***	-0.096***	0.071	-0.326***	0.716***	-0.483***	-0.168***	-0.502***	0.036*	0.215***	0.240***	0.252***	1	
AS	0.0613	0.359***	0.289**	0.434***	-0.205***	0.155***	0.016	0.303***	-0.216**	-	-0.115***	-0.055***	-0.294***	1
										0.067***				

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3*Correlations and differences between correlations of cultural and innovation items for Western versus non-Western countries***Panel A:** *Tests of differences between Western and non-Western Countries Correlations: z val*

		patents	articles	tight	loose	UA	FO	PD	IC	IGC	HO	PO	GE	AS
Western	rnd	-3.201**	-2.766**	-9.495***	4.855***	5.535***	4.78***	0.931	1.315	-1.192	6.144***	-1.596	-1.551	-4.917***
vs non-Western	patents		11.341***	-1.312	-4.032***	1.657^	6.268***	1.426	0.95	6.691***	1.027	7.394***	5.57***	2.025*
	articles			-1.191	-2.49*	0.017	5.735***	1.141	-0.118	5.754***	1.273	4.318***	4.618***	2.114*

Panel B: *Western countries correlations*

(1)

	rnd	patents	articles	tight	loose	UA	FO	PD	IC	IGC	HO	PO	GE	AS
rnd	1													
patents	0.262***	1												
articles	0.201***	0.973***	1											
tight	-0.407***	0.0975*	0.133	1										
loose	0.232***	-0.221***	-0.209**	-0.350***	1									
UA	-0.693***	-0.0211	0.0131	-0.0908*	-0.305***	1								
FO	-0.544***	0.110**	0.150*	0.468***	-0.0593	0.529***	1							
PD	-0.122*	0.153***	0.155*	0.257***	-0.311***	0.0467	-0.0653*	1						
IC	-0.598***	-0.218***	-0.201**	-0.262***	0.131***	0.523***	0.491***	-0.514***	1					
IGC	-0.238***	0.0994*	0.100	0.483***	-0.000356	0.450***	0.455***	0.462***	-0.122***	1				
HO	0.490***	0.0792*	0.124	-0.451***	0.365***	-0.141***	-0.156***	-0.614***	0.0210	-0.317***	1			
PO	-0.168**	0.206***	0.190**	0.272***	-0.226***	0.304***	0.489***	-0.0551	0.129***	0.365***	0.0872**	1		
GE	-0.0437	0.155***	0.192**	0.122***	0.0972**	-0.172**	-0.149***	-0.184***	0.110***	0.0255	0.119***	-0.0540	1	
AS	-0.0861	0.438***	0.518***	0.482***	-0.150***	0.304***	0.391***	0.259***	-0.241***	0.610***	0.111***	0.365***	0.0480	1

Panel C: *Non Western Countries Spearman Rank Correlations*

(1)

	rnd	patents	articles	tight	loose	UA	FO	PD	IC	IGC	HO	PO	GE	AS
rnd	1													
patents	0.418***	1												
articles	0.397***	0.880***	1											
tight	0.329***	0.176***	0.246***	1										
loose	-0.0708	-0.0214	-0.0135	-0.451***	1									
UA	-0.436***	-0.105***	0.0118	-0.344***	-0.429***	1								
FO	-0.269***	-0.206***	-0.292***	-0.211***	-0.322***	0.536***	1							
PD	0.0579	0.0819**	0.0661	0.494***	-0.00358	-0.203***	-0.543***	1						
IC	-0.535***	-0.263***	-0.193***	-0.762***	-0.287***	0.425***	0.475***	-0.382***	1					
IGC	-0.315***	-0.236***	-0.338***	-0.275***	0.00193	0.310***	0.669***	-0.596***	0.478***	1				
HO	0.106*	0.0271	0.0245	-0.0835*	-0.179***	0.283***	0.557***	-0.547***	0.083***	0.309***	1			
PO	-0.274***	-0.166***	-0.146***	-0.634***	-0.0537	0.479***	0.819***	-0.610***	0.527***	0.747***	0.579***	1		
GE	0.0646	-0.126***	-0.168***	-0.581***	0.647***	-0.261***	0.075***	-0.539***	0.133***	0.373***	0.217***	0.299***	1	
AS	0.252***	0.352***	0.386***	0.426***	0.0799*	-0.140***	-0.207***	0.255***	-0.297***	-0.226***	-0.112***	-0.086***	-0.203***	1

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4*OLS and Negative Binomial Results: Effects of cultural values and norms on innovative capability*

VARIABLES	(1) rnd	(2) patents	(3) articles	(4) rnd	(5) patents	(6) articles	(7) rnd	(8) patents	(9) articles
UA	-0.358*** (0.091)	0.734 (0.564)	0.293 (0.573)						
FO	-0.611*** (0.080)	1.444** (0.651)	1.943*** (0.697)						
PD	-0.945*** (0.163)	2.405*** (0.866)	1.317 (1.143)						
IC	-0.871*** (0.086)	-0.889** (0.360)	-0.602 (0.459)						
IGC	-0.172* (0.089)	-2.664*** (0.671)	-2.395*** (0.563)						
HO	1.244*** (0.148)	3.182*** (0.904)	1.326 (0.929)						
PO	-0.110 (0.118)	-1.319** (0.572)	-0.927 (0.674)						
GE	0.044 (0.081)	0.833* (0.460)	1.135** (0.450)						
AS	0.195*** (0.062)	0.504* (0.305)	0.518 (0.373)						
tight				-0.009*** (0.002)	-0.007 (0.013)	-0.000 (0.010)			
loose							0.010*** (0.002)	0.015 (0.015)	0.015 (0.010)
lngdppc2	0.446*** (0.073)	1.140*** (0.370)	1.592*** (0.451)	0.543*** (0.070)	0.525 (0.331)	0.616* (0.317)	0.513*** (0.053)	0.793** (0.362)	1.162*** (0.323)
gfcfshare	-1.324* (0.709)	-3.422 (2.475)	2.502 (3.855)	-1.154 (0.864)	-2.139 (5.938)	3.214 (4.712)	-0.702 (0.552)	-1.693 (3.465)	2.595 (3.281)
fdi	-0.010*** (0.002)	0.014 (0.009)	0.006 (0.009)	-0.004 (0.003)	-0.002 (0.013)	0.009 (0.009)	-0.016*** (0.003)	-0.015 (0.012)	0.012* (0.007)
tradeopen	-0.004*** (0.001)	-0.044*** (0.004)	-0.032*** (0.006)	-0.003** (0.001)	-0.018*** (0.006)	-0.027*** (0.007)	0.003** (0.001)	-0.036*** (0.009)	-0.036*** (0.005)
sed	-0.002 (0.002)	-0.003 (0.012)	-0.016 (0.015)	0.003 (0.002)	-0.021 (0.013)	-0.003 (0.011)	0.011*** (0.003)	-0.009 (0.012)	-0.017 (0.010)
edspend	0.034*** (0.006)	-0.019 (0.044)	-0.066 (0.040)	-0.025** (0.012)	-0.159** (0.079)	-0.094* (0.050)	-0.002 (0.008)	-0.066 (0.058)	-0.113*** (0.039)
unemp	-0.022*** (0.007)	-0.044 (0.032)	0.008 (0.046)	-0.020** (0.010)	-0.047 (0.036)	-0.026 (0.034)	-0.026*** (0.004)	-0.050 (0.031)	-0.013 (0.022)
Constant	2.532** (1.212)	-14.355 (9.525)	-11.196 (8.962)	-3.218*** (0.748)	8.269* (4.733)	5.586 (4.059)	-5.173*** (0.546)	2.029 (3.396)	0.920 (2.781)
Observations	543	656	459	366	441	276	619	744	522
R-squared	0.748			0.357			0.551		

Note. Coefficients are reported
Robust standard errors are in parentheses
p<0.01*** p<0.01, ** p<0.05, * p<0.1

Table 5

Quantile regression and count data quantile regression results: Effects of cultural norms and values on innovative capability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES	q10	q30	q50	q70	q90	0.10 patents	0.30 patents	0.50 patents	0.70 patents	0.90 patents	0.10 articles	0.30 articles	0.50 articles	0.70 articles	0.90 articles
Panel A															
tight	-	-	-	-	-0.011	0.017***	0.006***	0.001	-	-	0.009***	-	-	-	0.003***
	0.010***	0.013***	0.014***	0.015***	(0.011)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-	-	-	0.325	-2.523	-	-	8.744***	8.592***	15.295**	5.757***	8.760***	5.619***	5.982***	1.792***
	4.340***	3.363***	2.593***	(0.927)	(3.872)	4.370***	1.154***	(0.605)	(0.057)	(0.273)	(0.024)	(0.005)	(0.004)	(0.433)	(0.003)
Observations	366	366	366	366	366	441	441	441	441	441	276	276	276	276	276
Panel B															
loose	0.003*	0.004***	0.011***	0.013***	0.015***	-0.005*	0.005***	0.006***	0.020***	0.006***	0.023***	-0.000	-0.000**	-	0.005***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	0.001***	(0.000)
Constant	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1.490***
	2.958***	3.400***	4.131***	4.894***	6.151***	16.920**	8.267***	4.235***	1.172***	0.573***	9.952***	7.288***	8.957***	3.516***	
	(0.684)	(0.370)	(0.527)	(0.591)	(1.200)	(0.890)	(1.532)	(0.257)	(0.100)	(0.041)	(0.558)	(0.451)	(0.111)	(0.024)	(0.088)
Observations	619	619	619	619	619	744	744	744	744	744	522	522	522	522	522
Panel C															
UA	-	-	-	-	0.190	-0.593	-0.095	0.014	0.204**	0.488***	-0.378*	0.937***	0.631***	0.719***	0.312***
	0.520***	0.515***	0.367***	0.376***	(0.197)	(0.810)	(0.069)	(0.066)	(0.102)	(0.014)	(0.222)	(0.208)	(0.015)	(0.010)	(0.001)
FO	-0.160	-	-	-	-0.252	2.760	1.986***	1.770***	2.096***	2.360***	1.475***	2.993***	2.184***	1.772***	2.047***
	(0.137)	(0.125)	(0.135)	(0.160)	(0.349)	(4.641)	(0.183)	(0.225)	(0.085)	(0.005)	(0.133)	(0.466)	(0.040)	(0.040)	(0.003)
PD	-0.311	-0.406*	-0.004	0.016	0.115	2.070	3.265***	3.208***	2.936***	1.789***	-	0.505**	1.019***	1.437***	-
	(0.349)	(0.242)	(0.242)	(0.188)	(0.260)	(2.843)	(0.652)	(0.560)	(0.156)	(0.005)	1.706***	(0.182)	(0.240)	(0.011)	0.350***
IC	-0.322**	-	-0.343*	-	-	-0.822	-0.254	-0.383	-0.567	-	-	-0.996**	-	-	-

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES	q10	q30	q50	q70	q90	0.10 patents	0.30 patents	0.50 patents	0.70 patents	0.90 patents	0.10 articles	0.30 articles	0.50 articles	0.70 articles	0.90 articles
		0.284***		0.699***	1.584***					1.582***	0.809***		0.355***	0.454***	1.196***
IGC	(0.150)	(0.102)	(0.195)	(0.157)	(0.250)	(1.276)	(0.200)	(0.265)	(0.427)	(0.002)	(0.123)	(0.433)	(0.025)	(0.054)	(0.002)
	-	-0.311*	-0.439**	-0.221	0.282	-2.716	-	-	-	-	-	-	-	-	-
	0.532***						2.320***	1.886***	2.075***	3.145***	0.837***	2.816***	1.714***	1.746***	2.594***
HO	(0.196)	(0.179)	(0.210)	(0.172)	(0.278)	(3.587)	(0.192)	(0.109)	(0.323)	(0.003)	(0.199)	(0.224)	(0.013)	(0.032)	(0.007)
	0.544*	0.670***	0.664***	1.172***	1.674***	1.237	2.991***	3.099***	3.084***	2.366***	-0.619*	0.589	1.448***	1.821***	0.669***
PO	(0.291)	(0.212)	(0.247)	(0.226)	(0.471)	(2.235)	(0.423)	(0.206)	(0.569)	(0.015)	(0.346)	(0.605)	(0.021)	(0.053)	(0.002)
	-0.022	0.059	0.498***	0.090	-0.654	-0.124	-0.491**	-	-	-	-	-	-	-	-
								0.628***	0.947***	0.445***	1.515***	1.618***	1.616***	1.159***	0.586***
GE	(0.133)	(0.126)	(0.173)	(0.247)	(0.504)	(1.739)	(0.200)	(0.134)	(0.230)	(0.007)	(0.366)	(0.028)	(0.028)	(0.012)	(0.005)
	0.201	-0.315*	-0.353**	-0.079	0.729**	0.415	0.629**	0.527**	0.479	0.210***	2.002***	1.413**	0.946***	0.800***	0.408***
AS	(0.228)	(0.189)	(0.162)	(0.103)	(0.320)	(2.067)	(0.255)	(0.231)	(0.642)	(0.014)	(0.111)	(0.586)	(0.029)	(0.015)	(0.003)
	0.212***	0.134*	-0.064	-0.024	0.051	0.469	0.729***	0.382*	0.252***	0.549***	0.902***	-0.188	0.084***	0.277***	0.955***
Constant	(0.076)	(0.074)	(0.064)	(0.080)	(0.111)	(1.965)	(0.167)	(0.224)	(0.055)	(0.005)	(0.104)	(0.222)	(0.015)	(0.018)	(0.002)
	2.158	2.517	1.977	1.152	-5.725	-18.743	-	-	-	-	-	-	-	-	1.680***
							31.572**	27.677**	21.805**	8.232***	9.128***	19.914**	19.492**	20.028**	
							*	*	*			*	*	*	
Observations	(2.252)	(2.030)	(1.819)	(1.462)	(3.832)	(30.208)	(5.321)	(5.236)	(3.728)	(0.252)	(2.044)	(5.369)	(0.060)	(0.698)	(0.053)
	543	543	543	543	543	656	656	656	656	656	459	459	459	459	459

Note. Coefficients are reported
Standard errors in parentheses
Covariates are tested but not reported
*** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A

Countries included in regressions using each dependent variable and as Western or non-Western in correlation tests

Country	rnd	patents	articles	Western	Non-Western
Albania	x	x	x		x
Argentina	x	x	x		x
Australia	x	x	x	x	
Austria	x	x	x	x	
Bolivia	x	x	x		x
Brazil	x	x	x		x
China	x	x			x
Colombia	x	x	x		x
Costa Rica	x	x	x		x
Czech Republic	x	x	x		x
Denmark	x	x	x	x	
Ecuador	x	x	x		x
Egypt, Arab Rep.	x	x	x		x
El Salvador	x	x	x		x
Finland	x	x	x	x	
France	x	x	x	x	
Georgia	x	x	x		x
Greece	x	x	x	x	
Guatemala	x	x	x		x
Hong Kong SAR, China	x	x			x
Hungary	x	x	x		x
India	x	x	x		x
Indonesia	x	x	x		x
Iran, Islamic Rep.	x	x	x		x
Ireland	x	x	x	x	
Israel	x	x	x		x
Italy	x	x	x	x	
Kazakhstan	x	x	x		x
Kuwait	x		x		x
Malaysia	x	x	x		x
Mexico	x	x	x		x
Morocco	x	x	x		x
Netherlands	x	x	x	x	
New Zealand	x	x	x	x	
Philippines	x	x	x		x
Poland	x	x	x	x	

Portugal	x	x	x	x	
Qatar			x		x
Russian Federation	x	x	x		x
Slovenia	x	x	x		x
Spain	x	x	x	x	
Sweden	x	x	x	x	
Switzerland	x	x	x	x	
Thailand	x	x	x		x
Turkey	x	x	x		x
United Kingdom	x	x	x	x	
United States	x	x	x	x	
Zimbabwe			x		x