Trust, Innovate, Grow

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Abstract

We investigate the impact of social trust on technological innovation and economic growth. Using a large international sample of 10,205 industry-year observations constructed using both publicly traded and privately held firms across 43 countries over the 1990-2008 period, our analysis shows that social trust has a positive effect on innovation activities in a country. We further find support for three economic mechanisms, namely, the collaboration channel, the tolerance channel, and the funding channel. Finally, we show that trust promotes economic growth and productivity gains, mainly in industries with more innovation potential.

Keywords: Culture, Social trust, Innovation, Economic growth, Productivity gain
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1. Introduction

Globally economic activities are regulated by two types of constraints: legal institutions and social norms. As an explicit constraint examined by an extensive literature, a country's legal system, when effective, can protect corporate stakeholders, promote financial market development, and spur economic growth (La porta et al., 1998; La Porta, Lopez-de-Silanes, and Shleifer, 2006, 2008; Brown, Martinsson, and Petersen, 2013). However, the enforcement of legal rules can be difficult and costly in many countries. In contrast, the detection of social norm violations is easy and the punishment by the community and society at large is swift (Guiso, Sapienza, and Zingales, 2008, 2010, 2015). This suggests that social norms can play an important role in regulating the behavior of parties involved in economic transactions. Firms, as key entities of value creation in an economy, operate in contracting environments shaped jointly by legal institutions as well as social norms. Yet we know little about on how social norms affect specific corporate policies and outcomes, especially those with long-term economic implications. In this paper we aim to advance our understanding of this issue by focusing on a key dimension of social norms, i.e., interpersonal trust, and an important value driver and growth engine for firms, technological innovations. Specifically, we investigate the relation between trust and corporate innovation and how such a relation translates into economic growth and productivity improvements.

Trust is defined as the subjective belief that an individual assigns to the event that a potential counterparty takes an action that is at least not harmful to that individual (Gambetta (1988)). As with other aspects of culture, trust is deeply rooted in individuals' ethnic, religious, familial, and social backgrounds and is a relatively persistent behavioral trait (Putnam, 1993; Fukuyama, 1995; Guiso, Sapienza, and Zingales, 2006, 2010). It has also been shown that trust acts as a substitute for formal institutions at the country level (Guiso, Sapienza, and Zingales, 2004; Carlin, Dorobantu, and Viswanathan, 2009; and Aghion et al. (2010)). From economists' perspective, a central question is whether social trust matters for an economy's long-term growth, and if so, how. According to Kogan et al. (2014) and Chang et al. (2014), innovation is a key contributor of economic growth in the 20th and 21st centuries. Therefore, it is of critical importance to understand the link between trust and innovation. We propose two competing hypotheses as to how trust affects innovation activities in an economy based on existing theories, empirical findings, and prevailing views.

In our first hypothesis, we postulate that a higher level of trust in a society may enhance innovation. We believe that there are at least three plausible reasons underlying this hypothesis. First, innovation is a costly and risky process that often requires the efforts of more than a single individual or firm. Therefore, the success of innovation hinges critically on the effectiveness of collaboration within a firm or across firms (sometimes in the form of strategic alliances and joint ventures). A higher level of social trust within a firm or across firms can encourage inventors to share ideas and knowledge with each other, because they worry less about the possibility that their intellectual inputs are expropriated by their peers. The free exchange of intellectual assets increases the likelihood and efficiency of collaboration and results in more innovation. We call this view *the collaboration channel*.

Second, the theoretical model of Manso (2011) and the experimental study of Ederer and Manso (2013) show that optimal incentive contracts that motivate innovation should exhibit substantial tolerance for early failure and reward long-term success. A high level of trust on the part of investors can provide managers with some insurance against early failure, because investors in high-trust environments are less likely to attribute bad outcomes to managerial opportunism and penalize managers for them. Consistent with this argument, Hilary and Huang (2015) show that firms located in U.S. counties where trust is more prevalent utilize lower-power compensation schemes and are less likely to fire their CEOs. Therefore, a greater tolerance for short-term failure by more trusting investors encourages managers to take more risk and target a firm's long-term growth, which can potentially boost the innovation output. We term this view *the tolerance channel*.

Third, innovative firms typically have an expanded set of investment opportunities. As a result, they are likely to exhaust internal capital and rely heavily on external equity finance (Brown, Fazzari, and Petersen, 2009; Brown, Martinsson, and Petersen, 2012). When the financial market cannot observe the full spectrum of managerial actions, managers steer their investment choices toward the safer and shorter-term ones to mitigate information asymmetry and funding difficulties. Trust reduces investors' concern about managerial moral hazard and increases the likelihood of firms to obtain funding (Bottazzi, Da Rin and Hellmann, 2011; Duarte, Siegel, and Young, 2012). Therefore, trust can promote corporate innovation through lowering firms' financial constraints and allowing firms to pursue riskier and longer-term investments. We call this view *the funding channel*.

On the other hand, there are also considerations suggesting that a higher level of trust in a society may impede corporate innovation. A key ingredient for innovation is a healthy dose of skepticism among collaborating parties over the process of decision making. Peer challenging and monitoring can lead to refined ideas, improved processes and elevated efforts, thereby increasing the odds of successful and impactful innovations. However, when collaborating parties are too trusting of each other, they could develop affinity and reduce peer skepticism. Under weak skepticism, participants in the process of innovation devote insufficient efforts to monitoring and challenging each other, and innovation activities may fail to deliver a desired outcome. A related but separate channel through which trust may reduce the efficacy of the innovative process is that when investors are too trusting of firms and too willing to provide capital, managers may feel unnecessary to expend sufficient energy and time on developing an impactful research and development (R&D) agenda, and as a result, marginal proposals and ideas may get funded.

We test the two competing hypotheses using a large international sample of 10,205 industry-year observations constructed using both publicly traded and privately held firms across 43 countries over the 1990-2008 period. Following the previous literature (La Porta et al., 1997; Guiso, Sapienza, and Zingales, 2008a, b; Ahern, Daminelli, and Fracassi, 2015; Pevzner, Xie, and Xin, 2015), we define social trust as the average response in each country and year to the following question in the World Values Surveys (WVS): "*Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people*?" To measure the innovation output, we collect global patent information from the Orbis patent database.[1] This dataset allows us to observe both the number of patents a country generates and the number of citations they receive post-registration. Accordingly, we are able to explore the effect of social trust on both the quantity and the quality of innovation output.

Our baseline results show that the level of trust in a country is positively related to its innovation output. This relationship is both economically and statistically significant. For example, a one standard deviation increase in a country's social trust is associated with increases

[1] Compared to the National Bureau of Economic Research (NBER) Patent and Citation database that is compiled based on the United States Patent and Trademark Office (USPTO), the Orbis database has a much broader coverage. In addition to the patents filed in the U.S. administrated by the USPTO, the Orbis database covers patents filed in 93 non-U.S. patent offices (including national patent offices and regional and international organizations, such as the European Patent Office (EPO) and the African Intellectual Property Organization). Therefore, we are able to directly measure a country's innovation level using the Orbis database, instead of inferring it indirectly through the NBER database.

in the number of patents and the number of citations by 59% and 55%, respectively. This is consistent with the second hypothesis that a higher level of trust in a society *enhances* innovation. Our findings continue to hold in an extensive set of robustness checks using alternative model specifications and innovation measures, as well as additional tests to address the endogeneity issue.

We further provide supporting evidence of three underlying economic channels through which social trust promotes innovation, namely, *the collaboration channel*, *the tolerance channel*, and *the funding channel*. First, we find that the effect of trust on innovation is more pronounced in countries with weaker contract enforceability or poorer intellectual property protection. This evidence suggests that social trust, as an effective informal contract mechanism, enhances innovators' collaboration and thus spurs innovation. Second, social trust plays a more important role in spurring innovation in countries with weaker employee protection or lower bankruptcy efficiency. This finding supports the notion that social trust as a tolerance mechanism promotes firms' innovation by alleviating innovators' concern about the adverse consequences of innovation failure. Third, following Rajan and Zingales (1998) and Brown, Martinsson, and Petersen (2013), we use a country's financial disclosure, and auditing and accounting standards as proxies for financial market development. We find that the effect of social trust on innovation is stronger for countries with lower financial disclosure score or weaker auditing and accounting standards.

Finally, we examine two important questions: first, does social trust affect a country's economic growth; second, if so, does trust affect growth through the innovation channel? Given that an economy grows due to either improvement in productivity or capital accumulation, we calculate both industry value added growth as total growth and the growth of industry total factor productivity (TFP) for each country and industry. We first show that social trust has a positive effect on industry value added growth and industry TFP growth. More importantly, social trust promotes industry value added growth and industry TFP growth mainly through enhancing the innovation output in innovative industries.

Our study lies at the intersection of two major strands of literature, one on culture in general and trust in particular and the other on innovation and growth. Our study is the first to investigate the effect of trust on corporate innovative investment in a multi-country setting. While previous research on international innovation has identified a number of country-level variables that explain differences in innovation outputs and efficiency across countries, we provide the first evidence on whether a country's informal institutions, in particular social trust, affect the innovation process. To the extent that innovation activities contribute to economic growth, we contribute to the trust literature by providing evidence on an important channel through which trust promotes value creation in a country.

The rest of the paper is organized as follows. Section 2 describes sample construction and reports summary statistics. Section 3 presents our main empirical findings and a variety robustness checks. Section 4 explores plausible underlying economic channels through which social trust affects innovation. Section 5 discusses the relation between trust, innovation, and economic growth. Section 6 concludes.

2. Data, variables, and sample

2.1. Data and sample

We construct our innovation output variables based on Bureau van Dijk's Orbis patent database, which records global patents filed to 94 regional, national, and international patent offices. The source of the database is the Worldwide Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO). The Orbis patent database links 36 million ultimately granted patents to both public and private firms in the Orbis database from 1850 to 2012.

The Orbis patent database has a much wider coverage than the National Bureau of Economic Research (NBER) Patent and Citation database since the NBER database only records patent filings to the U.S. Patent and Trademark Office (USPTO). Previous international studies on innovation, e.g., Acharya and Subramanian (2009), Hsu, Tian, and Xu (2014), and Acharya, Baghai, and Subramanian (2014), mainly rely on the NBER database to construct innovation output measures. However, as acknowledged in these studies, doing so may lead to a sampling bias since many countries, especially emerging economies, do not file patent applications to the USPTO and this proportion varies across countries over time (Chang, McLean, Zhang, and Zhang, 2015). The Orbis database overcomes this bias since it covers patents filed by firms to both domestic and overseas patent offices.

We collect data on social trust from the World Values Surveys (WVS), which are available since 1987. We extract industry level data at the two-digit International Standard Industrial Classification (ISIC) from the United Nations Industrial Development Organization Industrial Statistics (UNIDO) database and country level data from the World Development Indicator (WDI) database compiled by the World Bank.

Our initial sample covers industries in countries that are jointly covered by the Orbis, the WVS, the UNIDO, and the WDI databases. We match patent data with industry level data using the crosswalk from the International Patent Classification (IPC) to the ISIC provided by Lybbert and Zolas (2014).[2] We further filter the sample according to the following criteria. First, due to

[2] We are grateful to Travis J. Lybbert and Nikolas J. Zolas for sharing their data on the "Algorithmic Links with Probabilities (ALP) Industry Level-to-Patent/Technology Level Crosswalk". Specifically, the ALP concordance is

the limited coverage of the UNIDO database, our sample only includes manufacturing industries with two-digit ISIC codes from 15-37.[3] Second, we exclude countries that have no patent at all during the entire sample period following previous studies, e.g., Hirshleifer, Low, and Teoh (2012). Third, we remove the U.S. from our sample but use it to control for industry level patenting activities or innovation opportunities over time following previous studies, e.g., Acharya and Subramanian (2009), Hsu, Tian, and Xu (2014), and Moshirian et al. (2015). Our final sample consists of 23 industries in 43 countries from 1990-2008.[4] Due to missing values for some control variables, our main sample is an unbalanced panel with 10,205 industry-country-year observations.

2.2. Measuring innovation output

Following previous studies (e.g., Aghion, Van Reenen, and Zingales, 2013; Seru, 2014), we measure innovation output by employing two proxies. The first proxy is the number of successful patent applications by firms in each ISIC industry for each country in each year (*Pat*).[5] Although innovation output is not directly observable, patents offer a good indicator of the level of innovation output since patenting is one of the most important means for firms to protect their intellectual property. However, a firm may protect its invention in multiple jurisdictions by applying for patent protection to patent office in different countries, which is

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constructed using probability weighting, meaning that the weights provided for each industry level-patent level matching is between 0 and 1. All weights by industry or technology class should also sum up to one. See Lybbert and Zolas (2014) for a detailed description.

[3] Manufacturing industries are the most innovative industries according to the 2008 Business R&D and Innovation Survey by the National Science Foundation (available at http://www.nsf.gov/statistics/infbrief/nsf11300). Furthermore, patenting innovation is important to manufacturing industries since these industries heavily rely on patents as a means of appropriating new technologies (Cohen, 1995).

[4] We choose 1990 as the sample starting year because social trust data have a more comprehensive coverage since 1990, and choose 2008 as the end year because the UNIDO data are incomplete after 2008. As a robustness check, we include data prior to 1990 and find the results are not affected. In addition, there is, on average, a two to three year lag between the patent application date and the patent grant date according to Hall, Jaffe, and Trajtenberg (2001). However, since our sample period ends in 2008, the impact of this concern on our study is negligible.

[5] We use the patent application date rather than the grant date in the analysis because applicate date is closer to the actual time of inventions compared with the grant date according to Hall, Jaffe, and Trajtenberg (2001).

recorded by the Orbis patent database. To solve this issue, we count one patent per innovation. For example, if a Chinese firm patents an innovation in China, the U.S., and Japan then we would count this as one Chinese patent. Besides, a patent application on the same invention can be filed to different patent offices on different dates. To determine the actual year of innovations for these cases, we choose the earliest application date for an innovation.

However, patent counts only reflect the quantity rather than the quality of a firm's inventions. As more significant patents are expected to be cited more frequently by other patents, forward citations of patents reflect the quality of a firm's innovation and better capture the technological or economic significance of the firm' inventions (Hall, Jaffe, Trajtenberg, 2005). Consequently, we use the number of citations made to firms' patents in each ISIC industry for each country in each year as the second proxy for innovation output. Since patents in certain technology class and year tend to receive more citations (Hall, Jaffe, Trajtenberg, 2005), we adjust raw citations using the time-technology class fixed effects recommended by prior literature, e.g., Atanassov (2013), Hirshleifer, Low, and Teoh (2012), and Chang, Fu, Low, and Zhang (2015). Specifically, the citation counts adjusted for time-technology class fixed effects are defined as raw citation counts scaled by the average citations in the same year and in the same technology class (*Tcite*).

Despite the wide acceptance and usage of the above measures in previous literature (e.g., Acharya and Subramanian, 2009; Hsu, Tian, and Xu, 2014; Moshirian et al., 2015) to capture the technological advances and the output of innovation, these measures are subject to certain limitations. For example, not all innovations meet the patenting criteria and firms may keep their technology secret for strategic purposes.

2.3. Measuring social trust

Following previous literature, e.g., La Porta et al. (1997), Guiso, Sapienza, and Zingales (2008a,b), and Pevzner, Xie, and Xin (2015), we define social trust as the average response to the question "*Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people*?" in each country year (*Trust*). In particular, we code the response to this question as one if a survey participant reports that most people can be trusted and zero otherwise, and then calculate the mean of the response in each country year as our measure of social trust.

2.4. Control variables

We control for several industry and country characteristics that may potentially be correlated with social trust and innovation. The first variable we consider is a country's macroeconomic conditions since social trust is positively associated with economic development (La Porta et al., 1997; Knack and Keefer, 1997). In addition, wealthier countries may innovate more (Acharya and Subramanian, 2009; Acharya, Baghai, and Subramanian, 2013). We hence use the logarithm of GDP per capita in real terms at constant national prices in 2005 U.S. dollars (*Ln*(*GDP*)) as a proxy for a country's macroeconomic conditions.

Second, free trade may encourage firms to patent their innovations and to protect domestic sales and to secure foreign sales (Acharya and Subramanian, 2009; Hsu, Tian, and Xu, 2014; Chang, McLean, Zhang, and Zhang, 2015). Moreover, Guiso, Sapienza, and Zingales (2009) show that a higher level of social trust, as an important dimension rooted in culture, promotes international trade. We thus include the logarithm of import plus export over GDP (*Trade*) to capture the trade openness of a country.

Third, we control for a country's financial development. Hsu, Tian, and Xu (2014) document financial development as an important determinant of a country's patenting activities.

Guiso, Sapienza, and Zingales (2004, 2008b) find that social trust promotes financial development. We hence include in the regressions the financial development in a country, which is defined as the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP (*FinDev*).

Fourth, to account for the size and the heterogeneous development of different industries in a country, we add as an additional control the logarithm of value added in a two-digit ISIC industry in a country in each year (*Ln*(*VA*)), where industry value added is computed in real terms at constant national prices in 2005 U.S. dollars.

Finally, as pointed out by Hall, Jaffe, and Trajtenberg (2001), patenting propensity in different industries varies over time.[6] We thus control for the time trend of industry-level patenting activities. Specifically, we follow Acharya and Subramanian (2009) and Moshirian et al. (2015) and include the median number of patents applied by U.S. firms for each ISIC industry in each year as a proxy for the industry level patenting intensity (*Intensity*). We choose the U.S. as the benchmark to adjust for the time trend because the U.S. has the most comprehensive patent data across different technology class over time, the most developed financial market to fund the technological growth opportunities, and the most favorable research environment over the world.

2.5. Variables for analyses of economic growth

In the analyses on the effect of social trust on economic growth, the dependent variables that we use are annual growth of industry value added and annual growth of industry total factor productivity (TFP). Meanwhile, we control for initial conditions of factor inputs, such as industry value added (*VA*), industry capital stock (*K*), and total number of employees in each industry

[6] See Hall, Jaffe, and Trajtenberg (2001) and Cohen, Nelson, and Walsh (2000) for a detailed discussion on this pattern.

(*Emp*), in the regressions following previous literature, e.g., Fogel, Morck, and Yeung (2008) and Chang, McLean, Zhang, and Zhang (2015).[7]

According to the standard Cobb-Douglas production function, annual growth of industry value added is defined as the annual change of the logarithm of industry value added ($\Delta Ln(VA)$), while annual growth of industry TFP is defined as the annual change of the logarithm of industry TFP ($\Delta Ln(TFP)$). Since industry TFP data are not immediately available in the UNIDO database, we need to construct $\Delta Ln(TFP)$ using the production function in Eq. (1) (country, industry and time subscripts are omitted for concision):

$$Ln(VA) = Ln(TFP) + \alpha Ln(K) + (1-\alpha)\, Ln(Emp) \quad (1),$$

where α and 1- α are capital and labor shares in the output. Assuming standard values of 0.3 and 0.7 for capital share (α) and labor shares (1-α) in the production function (Caselli, 2005), we compute annual industry TFP growth according to Eq. (2) below:

$$\Delta Ln(TFP) = \Delta Ln(VA) - 0.3\, \Delta Ln(K) - 0.7\, \Delta Ln(Emp) \quad (2)$$

However, data on *K* in Eq. (1) and (2) are not immediately available from the UNIDO database either, though data on VA and *Emp* can be directly obtained. We thus follow Caselli (2005) and construct series of capital stocks for each industry in each country using the perpetual inventory method by assuming that the economy under consideration is in its steady state. Specifically, according to Harberger (1978), the initial capital stock K_0 is defined in Eq. (3) as follows:

$$K_0 = \frac{I_0}{g+\delta} \quad (3),$$

where I_0 represents gross fixed capital formation for a given industry for the first year when the data are available, g corresponds to the average annual growth rate of industry value added in

[7] Variables in dollar values are computed in real terms at constant national prices in 2005 U.S. dollars.

that industry for the period 1963-2008,[8] and δ constitutes the depreciation rate of physical capital that is set to 6%. After determining the initial capital stock K_0, we then compute capital stocks for the subsequent years according to Eq. (4) below:

$$K_t = (1 - \delta) \times K_{t-1} + I_{t-1} \tag{4}$$

Using the above approach, we are able to compute industry value added growth, industry TFP growth as well as initial conditions of factor inputs, i.e., the logarithm of industry value added ($Ln(VA)$), the logarithm of industry capital stock ($Ln(K)$), and the logarithm of industry labor force ($Ln(Emp)$).

2.6. Sample distribution

Panel A of Table 1 reports the distribution of the aggregate patent and citation counts and the average social trust score by country. Column (1) shows the number of observations for each country. Columns (2) and (3) report the aggregate innovation measures. Specifically, in column (2), Japan has 232,096 patents, the largest number among all countries, followed by Korea, Germany, and China, while Indonesia has only 5 patents, which is the lowest among all sample countries, followed by Jordan, Morocco, and Philippines. However, column (3) indicates that the citations of patents by Japanese and German firms are much larger than those by Korean and Chinese firms, which suggest a noticeably larger impact of innovations by Japanese and German firms. The observation that patents in developed countries are more technologically significant than those in emerging economies highlights the importance of using patent citations as a measure of innovation output.

[8] 1963 is the first year when data on industry value added are available in the UNIDO database. Calculating the average growth from the first year is recommended by previous literature, e.g., Nehru and Dhareshwar (19993) and Caselli (2005).

Social trust also displays large cross-country variations as shown in column (4). In particular, Sweden and Norway have the highest scores of 0.656 and 0.653 followed by China and Finland, while Brazil and Philippines have the lowest scores of 0.048 and 0.071 followed by Malaysia and Turkey.

[Insert Table 1 about here]

Panel B of Table 1 presents the sample distribution of average values of industry innovation output, industry value added (in millions of U.S. dollars), and industry innovation intensity across 23 industries. Columns (2) and (3) indicate that patents and patent citations vary significantly across different industries. Specifically, industries of machinery and equipment (ISIC 29), office, accounting, and computing machinery (ISIC 30), and chemicals and chemical products (ISIC 24) have the highest number of patent and citation counts, which produce an average of 199.41, 187.17, and 178.36 patents and 418.49, 437.31, and 426.67 patent citations, respectively. On the contrary, recycling (ISIC 37), leather (ISIC 19), and tobacco (ISIC 16) industries have the lowest number of 0.64, 4.98, and 6.66 patents and 0.79, 7.72, and 9.54 citations, respectively.

Moreover, as observed in column (4), industries that contribute the highest value added are food and beverage industry (ISIC 15) and chemical industry (ISIC 24) with an average value of $75.2 billion and $73.9 billion, respectively, while industries that contribute the lowest value added are recycling industry (ISIC 37) and leather industry (ISIC 19) with an average value of $0.3 billion and $1.2 billion, respectively, in the sample countries. Finally, column (5) shows that innovation intensity defined using the U.S. data follows a generally similar pattern as the average number of patents and patent citations in our sample countries.

2.7. Summary statistics

We report the summary statistics of the variables in Panel A of Table 2. We report the statistics of innovation output measures in Panel A.1. The means of *Pat* and *Tcite* are 86.96 and 177.92, respectively. The standard deviations of these two variables are quite large, which are 226.88 and 578.64, respectively. Given that innovation measures are highly skewed, we use the logarithm of one plus each innovation output proxy, i.e., *Ln*(1+*Pat*) and *Ln*(1+*Tcite*), in the regression analyses. The statistics of explanatory variables are reported in Panel A.2. For country level variables, the mean of *Trust* is 0.31, and the means of *Ln*(*GDP*), *Trade* and *FinDev* are 2.53, -0.82, and 1.47, respectively. With respect to industry level variables, we find that the means of *Ln*(*VA*) and *Intensity* are 7.27 and 0.1, respectively. In Panel A.3, we report variables used in the analyses of economic growth with a sample of 6,864 country-industry-year observations. For output growth measures, the means of annual growth of industry value added (*ΔLn*(*VA*)) and annual growth of industry TFP (*ΔLn*(*TFP*)) are -1.5% and -2%, respectively.[9] For initial conditions of factor inputs, the means of *Ln*(*VA*), *Ln*(*K*) and *Ln*(*Emp*) are 7.41, 9.84, and 10.6, respectively.

[Insert Table 2 about here]

In Panel B of Table 2, we show the Pearson correlation matrix of the main variables in Panels A.1 and A.2. The correlation between *Ln*(1+*Pat*) and *Ln*(1+*Tcite*) is fairly high around 0.9. More importantly, the correlation between two measures of innovation output, i.e., *Ln*(1+*Pat*) and *Ln*(1+*Tcite*), and trust are 0.45 and 0.43, respectively, which are significant at the 1% level. Consistent with previous literature, we find that social trust has a positive and significant correlation with *Ln*(*GDP*), *Trade*, *FinDev*, and *Ln*(*VA*) at the 1% level. We turn to multivariate tests in the next section.

[9] Similar to previous studies, e.g., Arizala, Cavallo, and Galindo (2009) and Samaniego and Sun (2015), we also find some unreasonably large values for *ΔLn*(*VA*) and *ΔLn*(*TFP*) in our sample, which might be due to the data error in the UNIDO database.

3. Empirical findings

3.1. Baseline results

We empirically examine the effect of social trust on innovation outcomes by estimating the baseline regression model in Eq. (5) below.

$$Innovation_{i,j,t} = \alpha + \beta Trust_{j,t-1} + \gamma' X_{i,j,t-1} + Industry_i + Year_{t-1} + \varepsilon_{i,j,t-1} \quad (5),$$

where *Innovation* represents the two innovation output measures, i.e., *Ln*(1+*Pat*) and *Ln*(1+*Tcite*), in industry *i*, country *j* and year *t*. Our main explanatory variable is *Trust* in country *j* measured in year *t*-1. *X* represents control variables in industry *i*, country *j*, and year *t*-1 described in Section 2.4. To account for time-invariant industry characteristics and business cycles, we also include in the regressions industry and year fixed effects.[10] Our key interest is in β, which captures the effect of social trust on innovation. The standard errors of the estimated coefficients allow for clustering of observations by country.

[Insert Table 3 about here]

The baseline results are reported in Table 3. In columns (1) and (2), we report results of regressions with year fixed effects only. In columns (3) and (4), we report results of regressions with industry and year fixed effects. Empirical findings in Table 3 indicate that social trust has a positive and significant effect on industry level innovation output measured by both the number of patents and the number of citations of patents with *t*-statistics from 2.2 to 3.9. The positive effect of social trust on corporate innovation is not only statistically significant but also

[10] Social trust in a country evolves slowly and thus the trust measure is persistent although there are some slightly small time-series variations. As a robustness check, we further include country fixed effects in the regressions and find similar results. To be parsimonious, we report the results of regressions with additional controls and country fixed effects in Section 3.2.1.

economically significant. Specifically, increasing social trust by one standard deviation (0.151) increases *Pat* and *Tcite* by 59% and 55% from their means, respectively.[11]

The signs on coefficients of control variables are generally consistent with previous literature. For example, we find that *Ln*(*GDP*) has a positive effect on innovation in most regressions. We also find that *Trade* has a positive impact on innovation, which implies that a country has more needs to protect its inventions when it trades products more often with the rest of the world. In addition, *FinDev* has a positive and significant effect on innovation in regressions with both industry and year fixed effects, which supports the positive role of financial market in promoting innovation. We also find that *Ln*(*VA*) is positively associated with innovation at the 1% level for all regressions, confirming that larger industries are more likely to have more patents. Finally, *Intensity* is positively related to innovation output despite not significant in all regressions, implying that industrial patenting propensity follows the time trend to some extent.

Collectively, the empirical evidence of the baseline regressions presented in Table 3 is consistent with our conjecture that social trust encourages industry innovation output in a country.

3.2. Tests on endogeneity

Although the baseline results in Section 3.1 suggest a strong positive impact of social trust on innovation output, the results could be subject to endogeneity biases. For instance, some potential omitted variables could be correlated with both social trust and innovation, thus leading to a spurious relation. The other possible endogeneity issue is reverse causality, i.e., technology

[11] Because $d[Ln(1+y)]/dx = 1/(1+y)\times dy/dx$, $dy = d[Ln(1+y)]/dx\times(1+y)\ dx$. For example, when quantifying the effect of the change in *Trust* (dx) on the change in *Pat* (dy), we increase *Trust* by one standard deviation (0.151), so dx = 0.151. The change in *Pat* (dy) from its mean value (86.956) is then equal to 3.873×(1+86.956)×0.151 = 51.439, which amounts to 59% of the mean value of *Pat*.

development affects trust among individuals in a society, although the likelihood is extremely low since social trust, as a dimension of national culture formed innately, evolves slowly. To address these endogeneity concerns, we adopt two approaches. First, we try to include all possible omitted variables in the regressions. While we still include all control variables in Eq. (5) in the new tests, the coefficients of these variables are omitted for brevity. Second, we use an instrumental variable approach to mitigate any remaining endogeneity concern.

3.2.1. Controlling for potential omitted variables

To mitigate the concern on omitted variables, we first include additional country level controls. Then we further add Hofstede's cultural dimensions. Finally, we replace Hofstede's cultural dimensions with the cultural dimensions in the WVS and include country fixed effects in the regressions.

The first variable we consider is political risk. On one hand, Svendsen, Svendsen, and Graeff (2012) argue that political instability hampers the emergence and maintenance of social trust. On the other hand, Hoti and McAleer (2006) and Masino (2015) show that high political risk in a country discourages innovators' risk taking and thus adversely affects their incentive to innovate. As a result, political risk seems to be related to both social trust and innovation. We include as an additional control the political risk index (*PoliticalRisk*) compiled by the International Country Risk Guide (ICRG) to further capture a country's political risk. A higher political risk index indicates lower political risk.[12]

Human capital is another variable that could be related to both social trust and innovation. Papagapitos and Riley (2009) find that social trust contributes to higher levels of educational

[12] Specifically, the political risk index in the ICRG consists of 12 components that measure the government stability, socioeconomic conditions, investment profile, internal conflict, external conflict, corruption, military in politics, religious tensions, law and order, ethnic tensions, democratic accountability, and bureaucracy quality, respectively. The index is computed as the sum of the score of each component, which varies from 0 to 100.

attainment across countries by securing a fair return on people's investment in human capital. In the meanwhile, Benhabib and Spiegel (2005) provide evidence that human capital plays a positive role as an engine for innovation by providing essential intellectual support. Thus it is possible that the positive impact of social trust on innovation is driven by the higher education attainment in a country. We then include in the regressions the logarithm of human capital index (*HCI*) recorded in the Penn World Table (PWT) version 8.0 to, which captures the average education level in a country.

Religious beliefs negatively affect social trust since religious believers may "consider others as wicked or at least ignorant of and less prone to adhere to important moral insights" and "develop a stronger sense of group boundaries" (Berggren and Bjørnskov, 2011).[13] In addition, Benabou, Ticchi, and Vindigni (2015) reveal a robust negative association between religiosity and innovation output across countries although their religiosity measure does not include Muslim and oriental religions such as Buddhism and Hinduism. Since religiosity affects both social trust and innovation in a country, we include variables that represent a country's dominant religion in the regressions. Specifically, we construct five binary variables to denote the dominant religion such as Catholic, Protestant, Orthodox, Muslim, or Buddhism in each country as in Djankov, McLiesh, and Shleifer (2007) and include them in the regressions together with the political risk index and the human capital index. The results are reported in columns (1) and (2) in Panel A of Table 4.[14] We find that the results remain unchanged after we include these additional controls.

[13] The study of Wang and Gordon (2011) shows that eastern religions have a positive impact on trust, while western religions such as Catholic and Orthodox have a negative impact. Protestant has no significant impact.

[14] In an untabulated test, we further control for a country's investor protection, enforcement of insider trading laws, legal origin, red tape, foreign direct investment as well as government expenditures and find our results are not affected.

Next, social trust only captures one dimension of the national culture, which might be correlated other cultural dimensions. Furthermore, among these dimensions, uncertainty avoidance, power distance, and individualism are documented to be negatively associated with firms' risk-taking incentive, and thus discourage firms to innovate (Li et al., 2013; Chen et al., 2015).[15] Accordingly, we include in the regressions these three cultural dimensions by Hofstede. The results are reported in columns (3) and (4) of Panel A of Table 4, showing that the major findings do not change qualitatively after the inclusion of these additional cultural dimensions.

[Insert Table 4 about here]

Finally, we consider two alternative cultural dimensions in the WVS, i.e., individualism and hierarchy.[16] Different from Hofstede's culture indices, the cultural dimensions in the WVS have time-series variations and hence are more updated. We replace the three culture dimensions in columns (3) and (4), i.e., uncertainty avoidance, power distance, and individualism, with these two new proxies together with country fixed effects that account for the time-invariant country characteristics, and re-estimate the regressions.[17] The results in columns (5) and (6) indicate that social trust still has a positive and significant impact on patents and citations at the 5% level, suggesting that the effect of social trust on innovation is less likely to be driven by a country's political stability, education level, national culture as well as other time-invariant country characteristics.

[15] Hofstede's cultural indices include 6 dimensions, i.e., power distance, individualism, uncertainty avoidance, masculinity, long-term orientation, and indulgence.

[16] Specifically, individualism is between 0 and 1, with 0 representing completely agreeing with the statement of "Incomes should be made more equal" and 1 representing completely agreeing with the statement of "We need larger income differences as incentives for individual effort". Hierarchy is between 0 and 1, with 0 representing that the survey participant agrees with the statement of "One should follow one's superior's instructions only when one is convinced that they are right" and 1 representing that the survey participant agrees with the statement of "One should follow instructions even when one does not fully agree with them".

[17] Since religiosity indicators and Hofstede's culture dimensions are time invariant, we do not include country fixed effects in the regressions in columns (1) to (4).

3.2.2. Instrumental variable approach

To further address the endogeneity concern such as the omitted variable bias and to establish the forward causality from social trust to innovation, we employ an instrumental variable approach in a two-stage least squared (2SLS) framework.

The instrumental variable we choose is the intentional homicide per thousand population (*Homicide*) from the United Nations Surveys of Crime Trends and Operations of Criminal Justice System Series provided by the University of Michigan,[18] where intentional homicide is defined as unlawful death purposefully inflicted on a person by another person.[19] According to Hilary and Huang (2015), crimes such as intentional homicide can adversely affect the trust among people in the society. However, intentional homicide rate is unlikely to affect individuals' incentive to innovate except through changing their perception on trust. Hence this instrument seems to satisfy both the relevance and exclusion criteria.

We report the results of the 2SLS regressions in Panel B of Table 4. In the first stage regression in column (1), we observe that *Homicide* has a negative and significant impact on the trust in a country with a *t*-statistic of -3.6. The other variable that is marginally significantly associated with social trust is *FinDev*. More importantly, the instrumental variable that we use also passes the weak instrument test with a *p*-value of less than 0.01. In the second stage regressions, we replace the actual value of social trust with the predicted value from the first stage regression and conduct regressions with the same set of control variables in the baseline

[18] The data can be retrieved from http://www.icpsr.umich.edu/icpsrweb/NACJD/studies/26462.

[19] In an unreported test, we use ethnic homogeneity as an alternative instrumental variable since Dinesen and Sønderskov (2015) show that ethnic diversity reduces social trust. However, we do not expect that ethnic homogeneity positively affects innovation through the channel other than affecting social trust. We find that in the first stage, ethnic homogeneity has a positive and significant effect on trust. In the second stage, social trust has a positive and significant effect on innovation outcomes. However, since the number of missing variables for this instrument leads to a reduction of sample size by 50%, we do not report the results.

regression in Eq. (5). The results in columns (2) and (3) indicate that the instrumented *Trust* has a positive and significant effect on *Ln*(1+*Pat*) and *Ln*(1+*Tcite*) at the 1% level.

Although endogeneity issue is a concern that we can never completely rule out, the totality of the empirical evidence in Table 4 points to a causal relation between social trust and an enhancement of innovation.

3.3. Robustness tests

To verify the validity of our results, we conduct a battery of robustness tests in this section by employing various alternative variables and model specifications. For brevity, the results of these robustness checks are reported in Tables A1 to A8 in the Internet Appendix.

First, we investigate the nonlinear effect of social trust on innovation.[20] In doing so, we include in Eq. (5) the squared term of *Trust* ($Trust^2$) together with *Trust* and re-estimate the regression model. The results indicate that innovation output improves as social trust increases but does decline after social trust reaches the value of 0.5 (approximately at the 90th percentile of the sample), suggesting that the nonlinear relation between social trust and innovation has no material impact on our major findings.

Second, to further account for the effect of industry size, we replace *Ln*(1+*Pat*) and *Ln*(1+*Tcite*) with the logarithm of one plus per capita patent counts (*Ln*(1+*PatE*)) and the logarithm of one plus per capita citation counts (*Ln*(1+*TciteE*)) in the regressions, where *PatE* and *TciteE* are defined as *Pat* and *Tcite* scaled by the total number of employees in each two-digit ISIC industry, respectively. We find that the results are not affected by using per capita innovation output as dependent variables.

[20] Bidault and Castello (2010) argue that a certain level of tension is beneficial for creativity as it encourages critical thinking. As a result, too much trust may impede innovation.

Third, we employ as dependent variables two alternative measures of innovation output, i.e., the logarithm of one plus the number of innovative firms (*Ln*(1+*Nfirm*)) and the logarithm of one plus patent family size (*Ln*(1+*PatFam*)), where an innovative firm is defined as a firm with non-zero patent and patent family size is defined as the number of filings of a particular patent application around the world, respectively. We find that the results are robust to these two alternative measures of innovation output.

Fourth, to capture the impact of time-invariant industry characteristics in each particular country, we include country-industry fixed effects in the regressions. We find that the coefficient estimates of *Trust* are positive and significant at the 1% level in all regressions, suggesting that time-invariant country-industry characteristics are less likely to explain our results.

Fifth, we include industry-year fixed effects in the regressions to account for the effect of time-varying industry-specific characteristics, such as worldwide industrial development, industry mergers waves, etc. We find that the results still hold after the inclusion of industry-year fixed effects.

Sixth, to further mitigate the concern on the presence of residual correlation in both country and year dimensions, we employ a two-way clustering by clustering standard errors at both country and year following the suggestion of Petersen (2009). We find that our baseline results are robust to the two-way clustering.

Seventh, to capture the long-term nature of innovation process (Manso, 2011), we measure trust in year *t*-5 (*Trust_lag5*) instead of year *t*-1 in Eq. (5). We find that the results are robust to this model specification that takes into account the delayed effect of innovation output to social trust.

Last, following Hsu, Tian, and Xu (2014), we conduct an analysis at the technology-class level. Specifically, we aggregate all variables at the two-digit IPC class and re-estimate Eq. (5) with technology-class fixed effects instead of industry fixed effects.[21] We find that the baseline results do not change qualitatively.

In sum, the results of above tests show that our major findings are not affected by different alternative variable definitions and model specifications, and thus indicate that our findings that social trust promotes innovation are robust.

4. Economic mechanisms

The baseline regression results show that social trust enhances corporate innovation at the industry level in a country. In this section, we further identify the specific channels through which social trust has such a positive impact by exploring the cross-sectional difference in results.

4.1. The collaboration channel

Innovation requires teamwork (Dougherty, 1992; Van de Ven, 1986). Therefore, the success of innovation hinges critically on the effectiveness of collaboration within a firm or across firms. Strong legal institutions on contracting, such as strong contract enforceability and intellectual property protection, encourage collaboration among innovators by allowing them to capture the rents from those highly risky innovative projects (Seitz and Watzinger, 2013; Lerner, 2009) and thus promote innovation output. However, writing and enforcing contracts on to-be-developed innovative products are particularly challenging and expensive. Meanwhile, a strong legal protection on innovators' intellectual inputs from the expropriation by their peers can be remarkably costly as it requires robust monitoring.

[21] The technology class level analysis is at the two-digit IPC code but our results are robust if we use the three-digit IPC code. In an untabulated test, we also aggregate industry level data to the country level and conduct an analysis at the country level and find similar results.

On the contrary, trust as an inexpensive informal contracting mechanism encourages the free exchange of intellectual assets and increases the likelihood and efficiency of collaboration (Durante, 2010), which are essential for innovation success. Therefore, trust can serve as a substitute for strong legal institutions on contracting (Al-Najjar and Casadesus-Masanell, 2001; Chami and Fullenkamp, 2002). We thus expect that the effect of social trust on innovation is stronger in countries with weaker legal institutions on contracting, where the costs of collaboration are higher.

To examine our conjecture, we employ two proxies for legal institutions, i.e., the contract enforceability index constructed by Djankov et al. (2003) and the intellectual property protection index created by Park (2008).[22] We first partition the sample according to the sample median of these two variables and then examine the effect of social trust on innovation in countries with high and low contract enforceability index and high and low intellectual property protection index, respectively.[23] The results are presented in Panels A and B of Table 5.

[Insert Table 5 about here]

We find that the positive effect of social trust on innovation is more pronounced in countries with weaker contract enforceability or poorer intellectual property protection. Specifically, the coefficient estimates of *Trust* are positive and significant for the subsample of countries with low contract enforceability index or low intellectual property protection index but insignificant for the subsample of countries with high contract enforceability index or high intellectual property protection index. These results suggest that social trust, as an effective

[22] The contract enforceability index, which has a scale from 0 (the lowest enforceability) to 10 (the highest enforceability), measures the relative degree to which contractual agreements are honored and complications presented by language and mentality differences. The intellectual property protection index is based on five unweighted scores that cover (i) inventions that are patentable; (ii) membership in international treaties; (iii) duration of protection; (iv) enforcement mechanisms; and (v) restrictions. For more information on the indices see Djankov et al. (2003) and Park (2008), respectively.

[23] Since our partitioning variables in this section are country-level variables, we partition the sample by country rather than by country-industry, which leads to unbalanced numbers of observations for the two subsamples.

informal contracting mechanism, enhances innovators' collaboration and thus promotes innovation. We also compare the coefficients on *Trust* between subsamples with strong and weak contract enforceability and those with strong and weak intellectual property protection by conducting the *F*-tests. We find that the coefficients between the two groups are significantly different with *p*-values of less than 0.05 except for the test on the subsamples with *Ln*(1+*Tcite*) as the dependent variable and the intellectual property protection index as the partitioning variable, which has a *p*-value of 0.11.

4.2. The tolerance channel

Innovation involves a high probability of failure due to its dependence on various unpredictable conditions (Holmstrom, 1989). Given that the agent is risk averse, the optimal incentive scheme that nurtures innovation should exhibit substantial tolerance for early failure and reward for long-term success (Manso, 2011). Strong legal protections on innovators, such as employee protection and efficient corporate bankruptcy, alleviate their concerns on the adverse impact of innovation failure and hence encourage their risk-taking incentive and innovation success (Acharya, Baghai, and Subramanian, 2014; Acharya and Subramanian, 2009). However, legal protections on innovators and the associated enforcement can impose additional costs on the society, e.g., increased labor expenses and welfare expenditures, additional coordination efforts and restructuring costs in the bankruptcy etc.

Different from these expensive legal protections, social trust allows innovators to take actions without fear of the adverse consequences of innovation failure, forming an effective low-cost insurance scheme to the innovators and thus enhancing their risk-taking incentive in the innovation process. Hence we expect that the positive impact of social trust on innovation is stronger for countries with poorer employment protection and lower bankruptcy efficiency, where the costs of innovation failure are higher.

To test this conjecture, we empirically examine how our results vary depending on a country's employee protection and bankruptcy efficiency by partitioning the sample into countries with strong and weak employee protection and those with high and low bankruptcy efficiency according to the sample median of employee protection index in Botero et al. (2004) and bankruptcy efficiency measure in Djankov et al. (2008), respectively.[24] We then re-estimate the regressions for subsamples of countries with strong and weak employee protection and those with high and low bankruptcy efficiency separately. The results are reported in Panels A and B of Table 6.

[Insert Table 6 about here]

We find that social trust promotes innovation output only in the subsample of countries with weak employee protection or low bankruptcy efficiency, where the coefficient estimates of *Trust* are positive and significant at the 1% level. The coefficient estimates of *Trust* in the subsample of countries with strong employee protection or high bankruptcy efficiency, however, are insignificant. These findings support the notion that social trust as a tolerance mechanism promotes firms' innovation by alleviating innovators' concern on adverse consequences of innovation failure. Comparing the coefficients on *Trust* between subsamples with strong and weak employee protection and those with high and low bankruptcy efficiency in the *F*-tests, we find that the coefficients between the two groups are significantly different with *p*-values of 0.00-0.07.

[24] The employee protection index is computed as a sum of the employment laws index, collective relations laws index, and social security laws index. A higher employee protection index indicates better employee protection. Bankruptcy efficiency is defined as the present value of the terminal value of the firm after bankruptcy costs, which takes into account whether a firm continues as a going concern, bankruptcy costs, the time to resolve insolvency and the lending rate. A higher value of bankruptcy efficiency measure indicates higher bankruptcy efficiency.

4.3. The funding channel

Innovative projects need external funding (Brown, Fazzari, and Petersen, 2009; Brown, Martinsson, and Petersen, 2012, 2013). However, in an environment of high information opaqueness, the cost of capital can be unreasonably high especially for innovative firms, which may hinder these firms' incentive to innovate. A high level and effectiveness of financial disclosure and stringent auditing and accounting standards help improve the information transparency (Rajan and Zingales, 1998), which effectively lower the cost of capital and thus promote innovation. Notwithstanding, the implementation of these rules and regulations can be fairly costly as it may incur both monitoring costs for regulators and compliance costs for firms.

Trust, on the other hand, may serve as an inexpensive way of reducing the information asymmetry between investors and firms. For example, Pevzner, Xie, and Xin (2014) provide evidence that in high trust countries, markets are more reactive to information. Garrett, Hoitash, and Prawitt (2014) find that trust encourages information production and information sharing, and thus improves financial reporting quality. The study of Jha and Chen (2015) shows that audit fees are significantly higher for firms headquartered in low trust county in the U.S. As a result, we expect to find a more evident effect of social trust on innovation in countries with less financial disclosure and less stringent auditing and accounting standards, where the information environment is more opaque.

To examine this conjecture, we partition the sample according to the sample median of a country's financial disclosure score and the strength of auditing and accounting standards, respectively,[25] and re-estimate the regression model in Eq. (5) separately for the subsamples of

[25] Financial disclosure score is obtained from the *Global Competitiveness Report* 1999, which measures the level and effectiveness of financial disclosure in different countries. This score has been used in many existing studies such as Gelos and Wei (2002) and Jin and Myers (2006). Strength of auditing and accounting standards is from the

countries with high and low financial disclosure score and those with strong and weak auditing and accounting standards. We report the results in Panels A and B of Table 7.

[Insert Table 7 about here]

These results indicate that the effect of social trust on innovation is stronger for subsamples of countries with lower financial disclosure score or weaker auditing and accounting standards as the coefficient estimates of *Trust* are all positive and significant at the 1% level. The coefficient estimates of *Trust* for subsamples of countries with higher financial disclosure score and stronger auditing and accounting standards are insignificant. These findings are consistent with our hypothesis that social trust promotes innovation through improving firms' information transparency. Furthermore, we find that the coefficients on *Trust* between subsamples of countries with high and low financial disclosure score and those with strong and weak auditing and accounting standards are all statistically different at the 5% level.

5. Trust, innovation, and economic growth

5.1. Effect of trust on innovation output depending on industry innovativeness

In Section 4, we document that social trust promotes industry innovation output through facilitating the collaboration among innovators, providing insurance to innovators against the adverse impact of innovation failure, and improving innovative firms' information transparency. However, all the three mechanisms are more relevant for more innovation-intensive industries. In this section, we examine the inter-industry difference in innovation output across countries with different levels of social trust.

Similar to Acharya and Subramanian (2009), we partition the sample according to the sample median of industry innovation intensity (*Intensity*) defined as the median number of

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Global Competitiveness Report 2003-2004 as it is the first time that *Global Competitiveness Report* compiles this measure.

patents held by a U.S. firm in a two-digit ISIC industry in each year.[26] Then we estimate the regressions for subsamples of innovative vs. non-innovative industries separately. We present the results in Table 8.

[Insert Table 8 about here]

We find that social trust has a positive and significant effect on innovation output in both innovative and non-innovative industries: coefficient estimates of *Trust* are significant at the 1% level for both subsamples of innovative and non-innovative industries. However, we observe that the magnitude of coefficient estimates of *Trust* is higher for more innovative industries. We further compare the difference in the magnitude by conducting *F*-tests and find a significant difference at the 1% level. These findings suggest that social trust has a larger positive impact on innovation output in more innovative industries, which are consistent with our hypothesis that trust promotes innovation through enhancing innovators' collaboration, encouraging innovators' risk-taking incentive, and improving innovative firms' information environment.

5.2. Effect of trust on economic growth depending on industry innovativeness

Although our findings indicate that social trust plays a positive role in encouraging innovation output in a country, there is still an unanswered but important question: Does social trust affect a country's economic growth through innovation? In this section, we investigate this question by empirically examining the effect of social trust on industry value added growth and how the effect differs between innovative and non-innovative industries. Specifically, we first

[26] To examine the inter-industry difference in innovation output, Acharya and Subramanian (2009) include in the regressions the interaction term of the main explanatory variable and *Intensity*. Doing so forces the coefficient estimates on other control variables to be the same, which might be quite different between innovative vs. non-innovative industries. Our tests, however, allow different coefficient estimates on explanatory variables between innovative and non-innovative industries. As a robustness check, we also use the interaction term of *Trust* and *Intensity* and find similar results.

examine the effect of social trust on economic growth by estimating the regression model in Eq. (6):

$$\Delta Ln(VA)_{i,j,[t-1,t]} = \alpha + \beta Trust_{j,t-1} + \gamma' Z_{i,j,t-1} + Industry_i + Year_{t-1} + \varepsilon_{i,j,t-1} \quad (6),$$

where $\Delta Ln(VA)$ represents the growth of industry value added from year *t*-1 to year *t* in industry *i* and country *j*. The main explanatory variable is still *Trust* in country *j* and year *t*-1. Z represents control variables in industry i, country j and year t-1 described in Sections 2.4 and initial conditions of factor inputs in industry i, country j and year t-1 described in Section 2.5. The results are presented in column (1) of Table 9. Consistent with previous literature (e.g., La Porta et al., 1997; Knack and Keefer, 1997; Zak and Knack, 2001), we find that social trust does have a positive effect on industry value added growth and this effect is statistically significant at the 5% level.

[Insert Table 9 about here]

Next we examine innovation as a channel through which social trust promotes economic growth. If innovation is indeed a channel, we expect that the positive effect of social trust on industry value added growth is more pronounced for innovative industries than for non-innovative industries. In doing so, we split the sample into high and low innovation intensity groups according to the sample median *Intensity*, and estimate regressions separately for the two groups. The results are presented in columns (2) and (3) of Table 9. We find that the positive effect is mainly driven by innovative industries: the coefficient estimate of *Trust* is only significant for high innovation intensity industries but insignificant for low innovation intensity industries. Moreover, the magnitude of the coefficient estimate of *Trust* for innovative industries is significantly larger than that for non-innovative industries with a *p*-value of 0.07. These results suggest that social trust has a positive effect on economic growth through enhancing innovation output in more innovative industries.

5.3. Effect of trust on productivity depending on industry innovativeness

Literature documents that innovation promotes a country's economic growth mainly through enhancing the country's productivity growth (Solow, 1957; Romer, 1986). In this section, we directly tackle this issue by examining the effect of social trust on industry TFP growth and inter-industry difference in productivity growth across countries with different levels of social trust. Similar to the prediction on the effect of trust on industry value added growth, we expect to find a positive effect of social trust on industry productivity growth and a stronger effect in more innovative industries. To examine the conjecture, we first estimate the regression model in Eq. (7) below:

$$\Delta Ln(TFP)_{i,j,[t-1,t]} = \alpha + \beta Trust_{j,t-1} + \gamma' Z_{i,j,t-1} + Industry_i + Year_{t-1} + \varepsilon_{i,j,t-1} \quad (7),$$

where $\Delta Ln(TFP)$ represents the growth of industry TFP from year t-1 to t in industry i and country j. Other variables are the same as in Section 5.2. We then partition the sample into high and low innovation intensity groups according to the sample median *Intensity*, and estimate regressions separately for the two groups. The results are presented in Table 10.

[Insert Table 10 about here]

In column (1), we find that the coefficient estimate of *Trust* is positive and significant at the 10% level, suggesting that social trust does improve industry TFP growth. More importantly, the results in columns (2) and (3) indicate that social trust promotes productivity growth mainly through enhancing innovation output in innovative industries as the coefficient estimate on *Trust* is highly significant for high innovation intensity industries but insignificant for low innovation intensity industries. Comparing the difference in magnitude of the coefficients on *Trust*, we find a greater effect of social trust in high innovation intensity industries than that in low innovation intensity industries and the difference is significant at the 1% level. These results suggest that social trust has a positive effect on productivity growth through fostering firms' innovation especially in innovative industries.

Taken together, the empirical evidence in Sections 5.2 and 5.3 complements the findings in previous studies, e.g., La Porta et al. (1997), Knack and Keefer (1997) and Zak and Knack (2001), by identifying innovation as a source for the positive relation between social trust and economic growth. Furthermore, such a positive effect is likely to be permanent as a result of an improvement in productivity growth.

6. Conclusion

We investigate two competing views on the relation between trust and innovation using a large sample of observations drawn from 43 countries around the world. Our analyses indicate that social trust has a positive effect on the innovation activities in a country. This is consistent with the conjecture that trust promotes the sharing of ideas and exchange of information and encourages risk taking, thereby enhancing the efficiency and output of the innovative process. Also consistent with this hypothesis, the effect of trust on innovation also exhibits variations across a number of country and industry characteristics. In particular, the role of trust in the innovative process is more important in countries with poor legal enforcement, property protection, employment protection, and financial market development, and in industries with higher innovation intensity. Finally, we show that innovation created in a high-trust environment contributes more to economic growth through enhancing productivity growth, further attesting the beneficial role of trust in the innovation process.

References

Acharya, V.V., Baghai, R., Subramanian, K., 2013. Labor laws and innovation. Journal of Law and Economics 68, 2059 – 2116.

Acharya, V.V., Baghai, R., Subramanian, K., 2014. Wrongful discharge laws and innovation. Review of Financial Studies 27, 301 – 346.

Acharya, V.V., Subramanian, K., 2009. Bankruptcy codes and innovation. Review of Financial Studies 22, 4949 – 4988.

Aghion, P., Van Reenen, J., Zingales, L., 2013. Innovation and institutional ownership. American Economic Review 103, 277-304.

Al-Najjar, N.I., Casadesus-Masanell, R., 2001. Trust and discretion in agency contracts. Harvard Business School Strategy Unit Working Paper.

Arizala, R., Cavallo, E., Galindo, A., 2009. Financial development and TFP growth: Cross-country and industry-level evidence. Inter-American Development Bank Working Paper.

Atanassov, J., 2013. Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting. Journal of Finance 68, 1097 – 1131.

Bénabou, R., Ticchi, D., Vindigni, A., 2015. Religion and innovation. NBER Working Paper.

Benhabib, J., Spiegel, M.M., 2005. Chapter 13 Human capital and technology diffusion. Handbook of Economic Growth 1, 935 – 966.

Berggren, N., Bjørnskov, C., 2011. Is the importance of religion in daily life related to social trust? Cross-country and cross-state comparisons. Journal of Economic Behavior & Organization 80, 459 – 480.

Bidault, F., Castello, A., 2010. Why too much trust is death to innovation? MITSloan Management Review 51, 33-38.

Botero, J.C., Djankov, S., La Porta, R., Lopez-de-Silanes, F., Shleifer, A., 2004. The regulation of labor. Quarterly Journal of Economics 119, 1339-1382.

Brown, J., Fazzari, S. M., Petersen, B.C., 2009. Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. Journal of Finance 64, 151-185.

Brown, J.R., Martinsson, G., Petersen, B.C., 2012. Do financing constraints matter for R&D? European Economic Review 56, 1512-1529.

Brown, J.R., Martinsson, G., Petersen, B.C., 2013. Law, stock markets, and innovation. Journal of Finance 68, 1517-1549.

Caselli, F., 2005. Accounting for cross-country income differences in Phillipe Aghion and Steven N. Durlauf (eds.) Handbook of Economic Growth 1A, 679-741.

Chami, R., Fullenkamp, C., 2002. Trust and efficiency. Journal of Banking & Finance 26, 1785 – 1809.

Chang, X., Fu., K, Low, A., Zhang, W., 2015. Non-executive employee stock options and corporate innovation. Journal of Financial Economics 115, 168-188.

Chang, X., Mclean, R.D., Zhang, B., Zhang, W., 2015. Innovation and productivity growth: Evidence from global patents, Working Paper.

Chen, Y., Podolski, E.J., Veeraraghavan, M., 2015. National culture and corporate innovation. Working Paper.

Cohen, W. M., 1995. Empirical studies of innovative activity. Handbook of the Economics of Innovation and Technical Changes. Basil Blackwell, Oxford.

Cohen, W.M., Nelson, R.R., Walsh, J.P., 2000. Protecting their intellectual assets: appropriability conditions and why U.S. manufacturing firms patent (or not). NBER Working Paper.
Dinesen, P.T., Sønderskov, K.M., 2015. Ethnic diversity and social trust: Evidence from the micro-context. American Sociological Review 80, 550 – 573.
Djankov, S., La Porta, R., Lopez-de-Silanes, F., Shleifer, A., 2003. Courts. Quarterly Journal of Economics 118, 453-517.
Djankov, S., McLiesh, C., Shleifer, A., 2007. Private credit in 129 countries. Journal of Financial Economics 84, 299 – 329.
Djankov, S., Hart, O., McLiesh, C., Shleifer, A., 2008. Debt enforcement around the world. Journal of Political Economy 116, 1105-1149.
Dougherty, D., 1992. Interpretive barriers to successful product innovation in large firms. Organization Science 3, 179-202.
Duarte, J., Siegel, S., Young, L., 2012. Trust and credit: The role of appearance in peer-to-peer lending. Review of Financial Studies 25, 2455 – 2484.
Durante, R., 2010. Risk, cooperation and the economic origins of social trust: An empirical investigation. Working Paper.
Fogel, K., Morck, R., Yeung, B., 2008. Big business stability and economic growth: Is what's good for GM good for America? Journal of Financial Economics 89, 83-108.
Garrett, J., Hoitash, R., Prawitt, D., 2014. Trust and financial reporting quality. Journal of Accounting Research 52, 1087-1125.
Gelos, R.G., Wei, S.-J., 2002. Transparency and international investor behavior. NBER Working Paper.
Guiso, L., Sapienza, P., Zingales, L., 2004. The role of social capital in financial development. American Economic Review 2004, 526.
Guiso, L., Sapienza, P., Zingales, L., 2008a. Social capital as good culture. Journal of the European Economic Association 6, 295-320.
Guiso, L., Sapienza, P., Zingales, L., 2008b. Trusting the stock market. Journal of Finance 63, 2557 – 2600.
Guiso, L., Sapienza, P., Zingales, L., 2009. Cultural biases in economic exchange. Quarterly Journal of Economics 124, 1095 – 1131.
Hall, B.H., Jaffe, A.B., Trajtenberg, M., 2001. The NBER patent citations data file: Lessons, insights and methodological tools. NBER Working Paper.
Hall, B.H., Jaffe, A.B., Trajtenberg, M., 2005. Market value and patent citations. Rand Journal of Economics 36, 16 – 38.
Harberger, A.C., 1978. Perspectives on capital and technology in less developed countries. In: M. J. Artis and A. R. Nobay (Eds.): Contemporary Economic Analysis, London, 42–72.
Hilary, G., Huang, S., 2015. Trust and contracting. INSEAD Working Paper.
Hirshleifer, D., Low, A., Teoh, S.H., 2012. Are overconfident CEOs better innovators? Journal of Finance 67, 1457 – 1498.
Holmstrom, B., 1989. Agency costs and innovation, Journal of Economic Behavior and Organization 12, 305-327.
Hoti, S., McAleer, M., 2006. How does country risk affect innovation? An application to foreign patents registered in the USA. Journal of Economic Surveys 20, 691 – 714.
Hsu, P.-H., Tian, X., Xu, Y., 2014. Financial development and innovation: Cross-country evidence. Journal of Financial Economics 112, 116 – 135.

Jha, A., Chen, Y., 2015. Audit fees and social capital. The Accounting Review 90, 611-639.
Jin, L., Myers, S.C., 2006. R^2 around the world: New theory and new tests. Journal of Financial Economics 79, 257-292.
Knack, S., Keefer, P., 1997. Does social capital have an economic pay-off? A cross-country investigation. Quarterly Journal of Economics 112, 1251 - 1288.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R.W., 1997. Trust in large organizations. American Economic Review 87, 333 – 338.
Lerner, J., 2009. The empirical impact of intellectual property rights on innovation: Puzzles and clues. American Economic Review 99, 343 – 348.
Li, K., Griffin, D.W., Yue, H., Zhao, L., 2013. How does culture influence corporate risk-taking? Journal of Corporate Finance 23, 1-22.
Lybbert, T.J., Zolas, N.J., 2014. Getting patents and economic data to speak to each other: An 'Algorithmic Links with Probabilities' approach for joint analyses of patenting and economic activity. Research Policy 43, 530-542.
Manso, G., 2011. Motivating innovation. Journal of Finance 66, 1823-60.
Masino, S., 2015. Macroeconomic volatility, institutional instability and the incentive to innovate. Review of Development Economics 19, 116-131.
Moshirian, F., Tian, X., Zhang, B., Zhang, W., 2015. Financial liberalization and innovation. Working Paper.
Nehru, V., Dhareshwar, A., 1993. A new database on physical capital stock: Sources, methodology and results. Revista de Analisis Economico 8, 37-59.
Papagapitos, A., Riley, R., 2009. Social trust and human capital formation. Economic Letters 102, 158 – 160.
Park, W., 2008, International patent protection, 1960-2005. Research Policy 37, 761-766.
Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies 22, 435 – 480.
Pevzner, M., Xie, F., Xin, X., 2015. When firms talk, do investors listen? The role of trust in stock market reactions to corporate earnings announcements. Journal of Financial Economics 117, 190 – 223.
Rajan, R.G., Zingales, L., 1998. Financial dependence and growth. American Economic Review 88, 559-586.
Romer, P. M., 1986. Increasing returns and long-run growth. Journal of Political Economy 94, 1002-1037.
Samaniego, R.M., Sun, J.Y., 2015. Productivity growth and structural transformation. Review of Economic Dynamics, forthcoming.
Seitz, M., Watzinger, M., 2013. Contract enforcement and R&D investment. Working Paper.
Seru, A., 2014. Firm boundaries matter: Evidence from conglomerates and R&D activity. Journal of Financial Economics 111, 381-405.
Solow, R., 1956. A Contribution to the theory of economic growth, Quarterly Journal of Economics 70, 65-94.
Svendsen, G.L.H., Svendsen, G.T., Graeff, P., 2012. Explaining the emergence of social trust: Denmark and Germany. Historical Social Research 37, 252 – 267.
Van de Ven, A.H., 1986. Central problems in the management of innovation, Management Science 32, 590-607.
Wang, L., Gordon, P., 2011. Trust and institutions: A multilevel analysis. Journal of Socio-Economics 40, 583 – 593.

Zak, P.J., Knack, S., 2002. Trust and growth. Economic Journal 111, 295 – 321.

Table 1: Sample distribution

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. In Panel A, *#Pat* is the total number of patents in a particular country over the sample period. *#Tcite* is the total number of patent citations adjusted for time-technology class fixed effects in a particular country over the sample period. *Trust* is the country average and is defined using the WVS.

Panel A: Sample distribution by country

Country	(1)	(2)	(3)	(4)
	N	*#Pat*	*#Tcite*	*Trust*
Argentina	256	75	114	0.183
Australia	332	10,863	28,590	0.439
Brazil	336	444	920	0.048
Bulgaria	235	188	52	0.267
Canada	172	23,916	129,428	0.389
Chile	268	104	164	0.205
China	349	121,780	55,955	0.547
Colombia	222	24	71	0.124
Czech Republic	282	5,077	1,739	0.288
Estonia	162	79	59	0.215
Finland	417	21,620	43,763	0.534
France	43	15,450	6,212	0.187
Germany	229	132,115	348,250	0.335
Hong Kong	30	617	1,718	0.411
Hungary	392	1,253	555	0.269
India	374	3,567	8,651	0.357
Indonesia	156	5	56	0.478
Israel	133	4,413	25,143	0.235
Italy	66	2,383	3,309	0.292
Japan	410	232,096	715,657	0.417
Jordan	140	7	0	0.287
Korea	425	157,061	222,314	0.308
Latvia	253	120	24	0.247
Lithuania	184	29	5	0.219
Malaysia	46	82	45	0.088
Mexico	398	486	2,211	0.260
Morocco	157	13	0	0.200
Netherlands	40	7,499	13,309	0.445
New Zealand	110	714	1,590	0.503
Norway	232	3,023	4,015	0.653
Philippines	184	14	80	0.071
Poland	397	7,120	526	0.244
Romania	222	722	140	0.193
Russia	262	5,351	4,758	0.256
Saudi Arabia	47	117	552	0.530
Singapore	128	3,270	12,515	0.147
Slovenia	285	894	336	0.164
South Africa	279	2,033	3,331	0.176
Spain	399	25,201	5,945	0.306
Sweden	263	23,708	43,013	0.656
Switzerland	268	49,420	95,954	0.405
Turkey	394	4,280	672	0.113
United Kingdom	228	20,149	33,920	0.299
Total	10,205	887,383	1,815,662	0.302

Table 1: Sample distribution (cont'd)

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. In Panel B, all values are industry average at the two-digit ISIC. *#Pat* is the total number of patents in a two-digit ISIC industry for each country in each year. *#Tcite* is the total number of patent citations adjusted for time-technology class fixed effects in a two-digit ISIC industry for each country in each year. *VA* is value-added (in $millions) in a two-digit ISIC industry for each country in each year. *Intensity* is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars.

Panel B: Sample average by industry

ISIC	ISIC description	(1)	(2)	(3)	(4)	(5)
		N	*#Pat*	*#Tcite*	*VA*	*Intensity*
15	Food and beverages	494	76.445	184.746	75,208	0.103
16	Tobacco products	337	6.657	9.541	20,160	0.094
17	Textiles	485	138.987	265.577	48,516	0.118
18	Wearing apparel, fur	459	133.578	246.279	42,874	0.184
19	Leather, leather products and footwear	396	4.975	7.723	1,227	0.036
20	Wood products (excluding furniture)	492	20.798	30.171	8,695	0.037
21	Paper and paper products	483	33.213	57.740	27,236	0.074
22	Printing and publishing	476	98.640	174.163	21,529	0.099
23	Coke, refined petroleum products, nuclear fuel	397	31.486	69.391	27,817	0.069
24	Chemicals and chemical products	474	178.364	426.670	73,888	0.122
25	Rubber and plastics products	489	32.911	71.098	35,602	0.066
26	Non-metallic mineral products	489	67.242	117.533	43,878	0.037
27	Basic metals	479	85.081	156.224	62,818	0.048
28	Fabricated metal products	480	145.798	310.279	11,903	0.071
29	Machinery and equipment, not else classified	480	199.413	418.486	61,198	0.159
30	Office, accounting and computing machinery	354	187.165	437.310	1,948	0.208
31	Electrical machinery and apparatus	476	57.346	92.373	54,824	0.060
32	Radio, television and communication equipment	375	135.215	288.302	8,915	0.107
33	Medical, precision and optical instruments	469	159.433	360.183	22,416	0.193
34	Motor vehicles, trailers, semi-trailers	476	90.416	174.161	63,114	0.212
35	Other transport equipment	393	31.475	53.276	3,227	0.115
36	Furniture; manufacturing, not else classified	476	34.384	50.635	4,391	0.055
37	Recycling	276	0.639	0.786	308	0.031

Table 2: Summary statistics

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Pat* and *Tcite* are the total number of patents and the total number of patent citations adjusted for time and technology class fixed effects in a two-digit ISIC industry for each country in each year. *Trust* is defined using the WVS. *Ln*(*GDP*) is the log of GDP per capita (in $thousands). *Trade* is the log of a country's imports plus exports as a fraction of GDP. *FinDev* is the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP. *Intensity* is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. *VA*, *K*, and *Emp are* value-added (in $millions), capital stock (in $millions), and total number of employees in a two-digit ISIC industry for each country in each year. *ΔLn*(*VA*) and *ΔLn*(*TFP*) are value added growth and TFP growth. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. Figures in bold in Panel B are statistically significant at the 1% level.

Panel A: Descriptive statistics

Variables	Mean	SD	Min	Q1	Median	Q3	Max
Panel A.1: Measures of innovation output (N = 10,205)							
Pat	86.956	226.879	0.000	0.250	4.162	38.655	1,071.686
Ln(1+*Pat*)	2.195	2.098	0.000	0.223	1.641	3.680	6.978
Tcite	177.919	578.637	0.000	0.000	1.857	39.945	3,606.328
Ln(1+*Tcite*)	2.073	2.398	0.000	0.000	1.050	3.712	8.191
Panel A.2: Explanatory variables (N = 10,205)							
Trust	0.305	0.151	0.028	0.195	0.290	0.400	0.680
Ln(*GDP*)	2.534	0.833	0.289	2.022	2.515	3.271	3.889
Trade	-0.819	0.736	-2.890	-1.290	-0.786	-0.212	1.137
FinDev	1.468	1.047	0.195	0.700	1.103	1.966	5.065
Ln(*VA*)	7.266	2.152	-0.027	5.926	7.376	8.671	16.795
Intensity	0.100	0.057	0.023	0.058	0.092	0.123	0.275
Panel A.3: Measures of economic growth (N = 6,864)							
ΔLn(*VA*)	-0.015	0.282	-1.250	-0.120	0.014	0.128	0.853
ΔLn(*TFP*)	-0.020	0.304	-1.281	-0.128	0.013	0.132	0.871
Ln(*VA*)	7.414	2.197	-0.027	6.089	7.518	8.865	16.795
Ln(*K*)	9.836	3.707	0.035	7.684	9.288	11.100	19.689
Ln(*Emp*)	10.598	1.791	3.738	9.393	10.721	11.847	14.220

Panel B: Correlation matrix

	Ln(1+*Pat*)	*Ln*(1+*Tcite*)	*Trust*	*Ln*(*GDP*)	*Trade*	*FinDev*	*Ln*(*VA*)
Ln(1+*Tcite*)	**0.895**						
Trust	**0.448**	**0.428**					
Ln(*GDP*)	**0.474**	**0.522**	**0.314**				
Trade	**0.157**	**0.206**	**0.135**	**0.661**			
FinDev	**0.491**	**0.586**	**0.263**	**0.443**	**0.313**		
Ln(*VA*)	**0.535**	**0.486**	**0.114**	**0.118**	**-0.335**	**0.241**	
Intensity	**0.193**	**0.166**	-0.004	0.001	-0.001	0.000	0.008

Table 3: Effect of social trust on innovation

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Ln*(1+*Pat*) is the log of one plus total number of patents in a two-digit ISIC industry for each country in each year. *Ln*(1+*Tcite*) is the log of one plus total number of patent citations adjusted for time and technology class fixed effects in a two-digit ISIC industry for each country in each year. *Trust* is defined using the WVS. *Ln*(*GDP*) is the log of GDP per capita. *Trade* is the log of a country's imports plus exports as a fraction of GDP. *FinDev* is the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP. *Ln*(*VA*) is the log of value-added in a two-digit ISIC industry for each country in each year. *Intensity* is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)	(3)	(4)
	Ln(1+*Pat*)	*Ln*(1+*Tcite*)	*Ln*(1+*Pat*)	*Ln*(1+*Tcite*)
Trust	**4.041****	**2.856*****	**3.873*****	**3.613*****
	(2.2)	**(2.8)**	**(3.1)**	**(3.9)**
Ln(*GDP*)	0.490	1.663*	0.433	0.672***
	(0.5)	(1.9)	(1.5)	(3.2)
Trade	0.725	0.743***	0.270	0.103
	(1.5)	(2.7)	(0.9)	(0.3)
FinDev	0.126	0.078	0.398***	0.745***
	(1.2)	(0.7)	(2.9)	(4.5)
Ln(*VA*)	0.292***	0.308***	0.478***	0.428***
	(5.7)	(6.3)	(4.1)	(3.6)
Intensity	7.112***	6.972***	1.094	1.709
	(9.6)	(7.6)	(0.8)	(1.1)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Observations	10,205	10,205	10,205	10,205
R-squared	0.80	0.80	0.65	0.67

Table 4: Tests on endogeneity

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. In Panel A, *PoliticalRisk* is the political risk rating compiled by the *International Country Risk Guide* (ICRG). *HCI* is the log of human capital index from Penn World Table (PWT) 8.0. *Catholic*, *Protestant*, *Orthodox*, *Muslim*, and *Buddhism* are binary variables that take the value of one if a country's primary religious belief is one of these six religions, and zero otherwise. In columns (3) and (4), *UncertAvoid*, *PowerDist*, and *Individualism* are Hofstede culture dimensions. In columns (5) and (6), *Individualism* and *Hierarchy* are culture dimensions in WVS. Control variables are the same as those in Table 3. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Controlling for potential omitted variables

Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(1+*Pat*)	*Ln*(1+*Tcite*)	*Ln*(1+*Pat*)	*Ln*(1+*Tcite*)	*Ln*(1+*Pat*)	*Ln*(1+*Tcite*)
Trust	**2.949*****	**2.773*****	**3.574*****	**2.742*****	**3.194****	**2.134****
	(3.2)	**(2.8)**	**(3.9)**	**(2.9)**	**(2.7)**	**(2.4)**
PoliticalRisk	1.501	-0.677	1.225	-0.581	-0.946	-1.905**
	(1.2)	(-0.4)	(1.0)	(-0.5)	(-1.2)	(-2.0)
HCI	0.940	-0.364	0.023	-0.734	4.540***	4.233**
	(0.8)	(-0.3)	(0.0)	(-0.7)	(3.6)	(2.5)
Catholic	-1.111***	-0.927*	-1.356***	-0.834		
	(-3.0)	(-1.8)	(-3.5)	(-1.7)		
Protestant	-1.135***	-0.429	-1.084**	-0.649		
	(-2.8)	(-0.7)	(-2.5)	(-1.2)		
Orthodox	-0.744**	-0.579	-1.020*	-0.028		
	(-2.4)	(-1.1)	(-1.9)	(-0.0)		
Muslim	-1.349***	-1.496***	-1.764***	-1.436***		
	(-3.1)	(-2.9)	(-3.9)	(-2.8)		
Buddhism	0.223	1.160	0.097	1.462**		
	(0.4)	(1.7)	(0.1)	(2.2)		
UncertAvoid_H			0.005	0.001		
			(0.5)	(0.2)		
PowerDist_H			0.017*	0.002		
			(1.9)	(0.1)		
Individualism_H			0.000	-0.022**		
			(0.0)	(-2.2)		
Individualism_W					-2.222**	-1.020*
					(-2.5)	(-2.0)
Hierarchy_W					-1.533**	-0.473
					(-2.4)	(-0.6)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	No	No	No	No	Yes	Yes
Observations	9,895	9,895	9,895	9,895	8,882	8,882
R-squared	0.73	0.74	0.74	0.74	0.87	0.85

Table 4: Tests on endogeneity (cont'd)

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. In Panel B, *Homicide* is the intentional homicide counts per thousand population for each country in each year. Control variables are the same as those in Table 3. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Instrumental variable approach

Dependent variables	(1)	(2)	(3)
	1st Stage	2nd Stage	
	Trust	*Ln*(1+*Pat*)	*Ln*(1+*Tcite*)
Homicide	**-0.039*****		
	(-3.6)		
$\widehat{Trust}$		**7.348*****	**5.143*****
		(4.7)	**(2.9)**
Ln(*GDP*)	0.058	0.073	0.437
	(1.3)	(0.3)	(1.6)
Trade	-0.041	0.386	0.182
	(-1.1)	(1.4)	(0.6)
FinDev	0.026*	0.247*	0.650***
	(2.0)	(1.9)	(4.4)
Ln(*VA*)	-0.000	0.583***	0.525***
	(-0.0)	(6.0)	(4.4)
Intensity	0.025	0.998	1.854
	(0.5)	(0.9)	(1.4)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Joint test of excluded instruments	$F(1,42) = 13.08$ Prob > $F = 0.00$	N/A	N/A
Observations	9,363	9,363	9,363
R-squared	0.31	0.64	0.68

Table 5: Effect of social trust on innovation depending on costs of coordination

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Contract enforceability index* is from Djankov et al. (2003). Contract enforceability index is defined as high (low) if it is above (below) the sample median. *Intellectual property protection index* is from Park (2008). Intellectual property protection index is defined as high (low) if it is above (below) the sample median. Control variables are the same as those in Table 3. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)	(3)	(4)
	Ln(1+*Pat*)		*Ln*(1+*Tcite*)	
Panel A: Partitioning the sample according to contract enforceability index				
	High	Low	High	Low
Trust	**1.168**	**7.714*****	**1.357**	**6.003*****
	(1.1)	**(4.5)**	**(0.7)**	**(3.9)**
Ln(*GDP*)	0.528	0.876*	0.933**	0.925*
	(1.4)	(2.1)	(2.5)	(2.1)
Trade	0.536	0.247	0.684	0.111
	(1.3)	(0.4)	(1.3)	(0.2)
FinDev	0.273	0.643	0.627*	0.971*
	(1.7)	(1.0)	(1.9)	(1.9)
Ln(*VA*)	0.765***	0.338**	0.755***	0.284**
	(5.6)	(2.6)	(3.3)	(2.4)
Intensity	4.090***	-0.263	4.497**	0.381
	(3.1)	(-0.1)	(2.9)	(0.2)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Test of equal coefficients	***p*-value = 0.00**		***p*-value = 0.04**	
Observations	3,573	4,028	3,573	4,028
R-squared	0.77	0.58	0.68	0.53
Panel B: Partitioning the sample according to intellectual property protection index				
	High	Low	High	Low
Trust	**0.915**	**5.739****	**1.346**	**4.001*****
	(0.8)	**(2.9)**	**(0.9)**	**(4.2)**
Ln(*GDP*)	0.906**	0.519	1.243***	0.457*
	(2.6)	(1.4)	(3.1)	(1.9)
Trade	0.439	-0.415	0.565	-0.621**
	(1.2)	(-1.2)	(1.3)	(-2.6)
FinDev	0.329**	0.262	0.755***	0.526**
	(2.4)	(0.9)	(4.2)	(2.6)
Ln(*VA*)	0.694***	0.305**	0.671***	0.208***
	(5.8)	(2.6)	(3.4)	(2.9)
Intensity	3.087***	1.957	4.309***	2.503*
	(2.9)	(1.4)	(3.7)	(2.0)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Test of equal coefficients	***p*-value = 0.03**		***p*-value = 0.11**	
Observations	4,691	4,389	4,691	4,389
R-squared	0.78	0.52	0.74	0.52

Table 6: Effect of social trust on innovation depending on costs of failure

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Labor protection* is the sum of employment laws index, collective relations laws index, and social security laws index from Botero et al. (2004). Labor protection is defined as strong (weak) if it is above (below) the sample median. *Bankruptcy efficiency* is from Djankov et al. (2008). Bankruptcy efficiency is defined as low (high) if it is below (above) the sample median. Control variables are the same as those in Table 3. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)	(3)	(4)
	Ln(1+*Pat*)		*Ln*(1+*Tcite*)	
Panel A: Partitioning the sample according to labor protection				
	Strong	Weak	Strong	Weak
Trust	**0.318**	**5.675*****	**1.713**	**4.700*****
	(0.4)	**(3.7)**	**(1.3)**	**(5.0)**
Ln(*GDP*)	0.628	0.456	0.117	0.920***
	(1.0)	(1.3)	(0.2)	(3.9)
Trade	0.621	-0.008	1.103	-0.459
	(1.1)	(-0.0)	(1.5)	(-1.3)
FinDev	0.536**	0.438**	0.738***	0.805***
	(2.5)	(2.4)	(3.5)	(4.2)
Ln(*VA*)	0.550***	0.400***	0.599***	0.280***
	(3.6)	(2.9)	(3.3)	(2.9)
Intensity	1.548	1.491	2.470	1.685
	(1.2)	(0.9)	(1.4)	(1.0)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Test of equal coefficients	***p*-value = 0.00**		***p*-value = 0.06**	
Observations	5,226	4,508	5,226	4,508
R-squared	0.71	0.70	0.67	0.73
Panel B: Partitioning according to bankruptcy efficiency				
	High	Low	High	Low
Trust	**0.794**	**6.270*****	**0.512**	**3.944*****
	(0.7)	**(3.1)**	**(0.3)**	**(3.6)**
Ln(*GDP*)	0.468	0.691*	0.851	0.602**
	(0.8)	(1.9)	(1.3)	(2.5)
Trade	0.582	-0.195	0.628	-0.306
	(1.6)	(-0.7)	(1.6)	(-1.6)
FinDev	0.378*	0.357**	0.632**	0.523***
	(2.0)	(2.3)	(2.2)	(4.7)
Ln(*VA*)	0.672***	0.324***	0.669***	0.239***
	(4.8)	(3.4)	(4.1)	(3.5)
Intensity	1.597	1.554	1.980	2.233
	(0.9)	(1.7)	(1.0)	(1.7)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Test of equal coefficients	***p*-value = 0.01**		***p*-value = 0.07**	
Observations	5,179	4,652	5,179	4,652
R-squared	0.72	0.56	0.70	0.52

Table 7: Effect of social trust on innovation depending on financial market development

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Financial disclosure* is from the *Global Competitiveness Report* 1999-2000. Financial disclosure in a country is defined as transparent (opaque) if it is above (below) the sample median. *Strength of auditing and accounting standards* is from the *Global Competitiveness Report* 2003-2004. Auditing and accounting standards are defined as strong (weak) if it is above (below) the sample median. Control variables are the same as those in Table 3. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)	(3)	(4)
	Ln(1+*Pat*)		*Ln*(1+*Tcite*)	
Panel A: Partitioning the sample according to financial disclosure				
	Transparent	Opaque	Transparent	Opaque
Trust	**1.202**	**7.784*****	**1.213**	**5.712*****
	(1.0)	**(4.8)**	**(0.8)**	**(3.8)**
Ln(*GDP*)	1.074***	1.086**	1.157***	1.034*
	(3.1)	(2.2)	(2.9)	(2.0)
Trade	0.542	-0.091	0.659	-0.364
	(1.3)	(-0.2)	(1.4)	(-0.8)
FinDev	0.547***	0.312	0.698***	0.698**
	(3.5)	(0.8)	(3.7)	(2.2)
Ln(*VA*)	0.660***	0.369***	0.689***	0.331***
	(4.7)	(3.0)	(3.8)	(2.9)
Intensity	4.460**	-0.978	5.786***	-0.209
	(2.8)	(-0.4)	(3.0)	(-0.1)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Test of equal coefficients	***p*-value = 0.00**		***p*-value = 0.03**	
Observations	4,349	4,546	4,349	4,546
R-squared	0.79	0.60	0.73	0.50
Panel B: Partitioning the sample according to strength of auditing and accounting standards				
	Strong	Weak	Strong	Weak
Trust	**0.947**	**7.137*****	**0.948**	**5.396*****
	(0.9)	**(4.5)**	**(0.7)**	**(4.3)**
Ln(*GDP*)	0.767**	0.875***	1.017**	1.014***
	(2.3)	(3.2)	(2.3)	(3.9)
Trade	0.619	0.037	0.849*	-0.308
	(1.7)	(0.1)	(1.7)	(-0.7)
FinDev	0.216	0.416**	0.422*	0.957***
	(1.4)	(2.2)	(1.9)	(4.7)
Ln(*VA*)	0.693***	0.350***	0.657***	0.284**
	(5.6)	(3.3)	(3.3)	(2.5)
Intensity	1.207	0.078	1.760	0.301
	(0.7)	(0.0)	(0.9)	(0.2)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Test of equal coefficients	***p*-value = 0.00**		***p*-value = 0.02**	
Observations	3,845	6,313	3,845	6,313
R-squared	0.75	0.68	0.67	0.70

Table 8: Effect of social trust on innovation in innovative vs. non-innovative industries

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. An industry is defined as non-innovative (innovative) if innovation intensity in the industry is below (above) the sample median, where innovation intensity is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Control variables are the same as those in Table 3. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)	(3)	(4)
	Ln(1+*Pat*)		*Ln*(1+*Tcite*)	
	Non-innovative	Innovative	Non-innovative	Innovative
Trust	**3.303*****	**4.450*****	**2.816*****	**4.422*****
	(2.8)	**(3.4)**	**(3.3)**	**(4.4)**
Ln(*GDP*)	0.278	0.599**	0.535**	0.831***
	(0.9)	(2.0)	(2.6)	(3.6)
Trade	0.314	0.210	0.119	0.052
	(1.0)	(0.7)	(0.3)	(0.1)
FinDev	0.349**	0.446***	0.683***	0.808***
	(2.6)	(3.1)	(4.0)	(5.0)
Ln(*VA*)	0.469***	0.485***	0.384***	0.462***
	(3.7)	(4.3)	(3.0)	(4.1)
Intensity	0.806	0.932	6.770**	1.149
	(0.4)	(0.9)	(2.3)	(0.9)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Test of equal coefficients	***p*-value = 0.00**		***p*-value = 0.00**	
Observations	5,093	5,097	5,093	5,097
R-squared	0.62	0.68	0.62	0.70

Table 9: Effect of trust on economic growth depending on industry innovativeness

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *VA*, *K*, and *Emp are* value-added (in $millions), capital stock (in $millions), and total number of employees in a two-digit ISIC industry for each country in each year. *ΔLn*(*VA*) is annual growth of value added. An industry is defined as non-innovative (innovative) if innovation intensity in the industry is below (above) the sample median, where innovation intensity is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Other variables are defined in the legend of Table 3. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)	(3)
	ΔLn(*VA*) Full sample	*ΔLn*(*VA*) Non-innovative	*ΔLn*(*VA*) Innovative
Trust	**0.094****	**0.060**	**0.127*****
	(2.7)	**(1.4)**	**(3.3)**
Ln(*VA*)	-0.085***	-0.091***	-0.081***
	(-5.7)	(-6.8)	(-4.9)
Ln(*K*)	-0.003	-0.003	-0.003
	(-0.7)	(-0.7)	(-0.7)
Ln(*Emp*)	0.087***	0.090***	0.085***
	(6.5)	(7.8)	(5.5)
Ln(*GDP*)	0.041**	0.052***	0.032*
	(2.5)	(3.4)	(1.7)
Trade	0.003	-0.006	0.011
	(0.2)	(-0.4)	(0.6)
FinDev	0.014	0.014	0.013
	(1.5)	(1.7)	(1.3)
Intensity	0.955***	1.133*	1.088***
	(3.3)	(1.8)	(3.6)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Test of equal coefficients	NA	*p*-value = 0.07	
Observations	6,864	3,427	3,417
R-squared	0.26	0.30	0.23

Table 10: Effect of trust on productivity growth depending on industry innovativeness

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *VA*, *K*, and *Emp are* value-added (in $millions), capital stock (in $millions), and total number of employees in a two-digit ISIC industry for each country in each year. *ΔLn*(*TFP*) is annual growth of TFP. An industry is defined as non-innovative (innovative) if innovation intensity in the industry is below (above) the sample median, where innovation intensity is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Other variables are defined in the legend of Table 3. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)	(3)
	ΔLn(*TFP*) Full sample	*ΔLn*(*TFP*) Non-innovative	*ΔLn*(*TFP*) Innovative
Trust	**0.070***	**0.024**	**0.114*****
	(1.7)	**(0.5)**	**(2.9)**
Ln(*VA*)	-0.089***	-0.089***	-0.089***
	(-6.5)	(-6.7)	(-6.1)
Ln(*K*)	-0.001	-0.002	-0.001
	(-0.3)	(-0.4)	(-0.2)
Ln(*Emp*)	0.099***	0.102***	0.097***
	(8.3)	(8.7)	(7.5)
Ln(*GDP*)	0.064***	0.065***	0.063***
	(3.7)	(3.9)	(3.4)
Trade	0.001	0.002	0.000
	(0.0)	(0.1)	(0.0)
FinDev	0.008	0.007	0.008
	(1.0)	(0.8)	(1.0)
Intensity	0.737**	0.181	0.868***
	(2.6)	(0.3)	(3.0)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Test of equal coefficients	NA	*p*-value = 0.00	
Observations	6,864	3,427	3,417
R-squared	0.21	0.23	0.19

Internet Appendix for
"Trust, Innovate, Grow"

This Internet Appendix provides supplemental analyses and robustness tests to the main results presented in "Trust, Innovate, Grow". The tables are organized as follows:

In this section, we run several tests to check the robustness of baseline results. First, we investigate the nonlinear effect of social trust on innovation. Bidault and Castello (2010) argue that a certain level of tension is beneficial for creativity as it encourages critical thinking. As a result, too much trust may impede innovation. To examine this premise, we include in Eq. (1) the squared term of *Trust* ($Trust^2$) together with *Trust* and re-estimate the regression model. We present the regression results in Table A1. We find that *Trust* and $Trust^2$ are positively and negatively associated with innovation output, respectively, which are significant at the 5% level. These results indicate that innovation output improves as social trust increases but declines after social trust reaches the value of 0.5, which is approximately at the 90th percentile of the sample. Although our findings provide some limited supportive evidence to Bidault and Castello's (2010) claim, these findings also suggest the impact of the nonlinear relation between social trust and innovation is not material in our setting.

Second, to further account for the effect of industry size, we replace *Ln*(1+*Pat*) and *Ln*(1+*Tcite*) with the logarithm of one plus per capita patent counts (*Ln*(1+*PatE*)) and the logarithm of one plus per capita citation counts (*Ln*(1+*TciteE*)) in the regressions, where *PatE* and *TciteE* are defined as *Pat* and *Tcite* scaled by the total number of employees in each two-digit ISIC industry, respectively. We present the regression results in Table A2. We find that the results are not affected by using per capita innovation output as the dependent variables, which suggest that the size effect is less likely to be the driving force of our results.

Third, following previous literature (e.g., Acharya and Subramanian, 2009; Ernst, Richter, and Riedel, 2013) we employ as dependent variables two alternative measures of innovation output, i.e., the logarithm of one plus the number of innovative firms (*Ln*(1+*Nfirm*)) and the logarithm of one plus patent family size (*Ln*(1+*PatFam*)), where an innovative firm is defined as a firm with non-zero patents and patent family size is defined as the number of filings of a particular patent application around the world, respectively. We present the regression results in Table A3. We find that the results are robust to these two alternative measures of innovation output.

Fourth, to capture the impact of time-invariant industry characteristics in each particular country, we include country-industry fixed effects in the regressions. We present the regression results in Table A4. We find that the coefficient estimates of *Trust* are positive and significant at the 1% level in all regressions, suggesting that time-invariant country-industry characteristics are less likely to be able to explain our results.

Fifth, we include industry-year fixed effects in the regressions to account for the effect of time-varying industry-specific characteristics, such as worldwide industrial development, industry mergers waves, etc. As an industry-year variable, *Intensity* is subsumed by industry-year fixed effects, and thus is removed from the regressions. We report the results in Table A5. We find that the results still hold after the inclusion of industry-year fixed effects.

Sixth, to further mitigate the concern on the presence of residual correlation in both country and year dimensions, we employ a two-way clustering by clustering standard errors at both country and year following the suggestion of Petersen (2009). We present the regression results in Table A6 and find that our baseline results are robust to the two-way clustering as the coefficient estimates of *Trust* are all positive and significant at the 1% level.

Seventh, to capture the long-term nature of innovation process (Manso, 2011), we measure trust in year *t*-5 (*Trust_lag5*) instead of year *t*-1 in Eq. (1). We then re-estimate the regressions and present the results in Table A7. We find that the results are robust to this model specification that takes into account the delayed effect of innovation output to social trust. The coefficient estimates of *Trust_lag5* are all positive and significant at the 1% level, suggesting that the effect of trust is long lasting.

Last, following Hsu, Tian, and Xu (2014), we conduct an analysis at the technology-class level. Specifically, we aggregate all variables at the two-digit International Patent Classification (IPC) class and re-estimate Eq. (1) with technology-class fixed effects instead of industry fixed effects. We present the regression results in Table A8. We find that the baseline results do not change qualitatively as the coefficient estimates of *Trust* are positive and significant at the 1% level in all the regressions.

References

Acharya, V. V., Subramanian, K., 2009. Bankruptcy codes and innovation. Review of Financial Studies 22, 4949-4988.

Bidault, F., Castello, A., 2010. Why too much trust is death to innovation? MITSloan Management Review 51, 33-38.

Ernst, C., Richter, K., Riedel, N., 2014. Corporate taxation and the quality of research and development. International Tax and Public Finance 21, 694-719.

Hsu, P.-H., Tian, X., Xu, Y., 2014. Financial development and innovation: Cross-country evidence. Journal of Financial Economics 112, 116-135.

Manso, G., 2011. Motivating innovation. Journal of Finance 66, 1823-60.

Petersen, M. A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies 22, 435-80.

Table A1: Nonlinear effect of trust on innovation

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Ln*(1+*Pat*) is the log of one plus total number of patents in a two-digit ISIC industry for each country in each year. *Ln*(1+*Tcite*) is the log of one plus total number of patent citations adjusted for time and technology class fixed effects in a two-digit ISIC industry for each country in each year. *Trust* is defined using the WVS. *Ln*(*GDP*) is the log of GDP per capita. *Trade* is the log of a country's imports plus exports as a fraction of GDP. *FinDev* is the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP. *Ln*(*VA*) is the log of value-added in a two-digit ISIC industry for each country in each year. *Intensity* is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)
	Ln(1+*Pat*)	*Ln*(1+*Tcite*)
Trust	12.730***	12.243***
	(4.9)	(3.7)
$Trust^2$	-12.636***	-12.311**
	(-3.5)	(-2.6)
Ln(*GDP*)	0.371	0.611***
	(1.2)	(2.8)
Trade	0.319	0.151
	(1.1)	(0.5)
FinDev	0.351***	0.698***
	(2.9)	(4.7)
Ln(*VA*)	0.505***	0.455***
	(4.8)	(4.3)
Intensity	1.084	1.699
	(0.8)	(1.2)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Observations	10,205	10,205
R-squared	0.68	0.69

Table A2: Using per capita innovation output as dependent variables

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Ln*(1+*PatE*) is the log of one plus total number of patents in a two-digit ISIC industry over total number of employees in the industry for each country in each year. *Ln*(1+*TciteE*) is the log of one plus total number of patent citations adjusted for time and technology class fixed effects in a two-digit ISIC industry over total number of employees in the industry for each country in each year. *Trust* is defined using the WVS. *Ln*(*GDP*) is the log of GDP per capita. *Trade* is the log of a country's imports plus exports as a fraction of GDP. *FinDev* is the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP. *Ln*(*VA*) is the log of value-added in a two-digit ISIC industry for each country in each year. *Intensity* is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)
	Ln(1+*PatE*)	*Ln*(1+*TciteE*)
Trust	0.899***	1.085***
	(5.1)	(3.4)
Ln(*GDP*)	0.233***	0.363***
	(4.1)	(3.7)
Trade	0.102	0.040
	(1.0)	(0.3)
FinDev	0.116***	0.251***
	(2.8)	(3.9)
Ln(*VA*)	0.028	0.029
	(1.0)	(0.8)
Intensity	0.688	2.038*
	(0.9)	(1.9)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Observations	9,589	9,589
R-squared	0.52	0.49

Table A3: Using alternative measures of innovation output

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Ln*(1+*Nfirm*) and *Ln*(1+*PatFam*) are the log of one plus the number of innovative firms and the log of one plus the patent family size in a two-digit ISIC industry for each country in each year. *Trust* is defined using the WVS. *Ln*(*GDP*) is the log of GDP per capita. *Trade* is the log of a country's imports plus exports as a fraction of GDP. *FinDev* is the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP. *Ln*(*VA*) is the log of value-added in a two-digit ISIC industry for each country in each year. *Intensity* is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)
	Ln(1+*NFirm*)	*Ln*(1+*PatFam*)
Trust	4.099***	4.062***
	(2.8)	(3.5)
Ln(*GDP*)	0.711*	0.412
	(2.0)	(1.5)
Trade	0.215	0.411
	(0.7)	(1.4)
FinDev	0.268**	0.379***
	(2.2)	(2.8)
Ln(*VA*)	0.517***	0.539***
	(4.3)	(4.7)
Intensity	0.129	0.708
	(0.2)	(0.5)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Observations	10,205	10,205
R-squared	0.68	0.68

Table A4: Controlling for country-industry fixed effects

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Ln*(1+*Pat*) is the log of one plus total number of patents in a two-digit ISIC industry for each country in each year. *Ln*(1+*Tcite*) is the log of one plus total number of patent citations adjusted for time and technology class fixed effects in a two-digit ISIC industry for each country in each year. *Trust* is defined using the WVS. *Ln*(*GDP*) is the log of GDP per capita. *Trade* is the log of a country's imports plus exports as a fraction of GDP. *FinDev* is the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP. *Ln*(*VA*) is the log of value-added in a two-digit ISIC industry for each country in each year. *Intensity* is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)
	Ln(1+*Pat*)	*Ln*(1+*Tcite*)
Trust	3.270***	2.194***
	(3.0)	(2.7)
Ln(*GDP*)	1.304	2.262**
	(1.2)	(2.4)
Trade	0.403	0.470**
	(1.2)	(2.0)
FinDev	0.243**	0.181
	(2.4)	(1.6)
Ln(*VA*)	-0.086	0.018
	(-1.1)	(0.7)
Intensity	0.592	1.313
	(0.9)	(1.6)
Year fixed effects	Yes	Yes
Country-industry fixed effects	Yes	Yes
Observations	10,205	10,205
R-squared	0.95	0.93

Table A5: Controlling for industry-year fixed effects

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Ln*(1+*Pat*) is the log of one plus total number of patents in a two-digit ISIC industry for each country in each year. *Ln*(1+*Tcite*) is the log of one plus total number of patent citations adjusted for time and technology class fixed effects in a two-digit ISIC industry for each country in each year. *Trust* is defined using the WVS. *Ln*(*GDP*) is the log of GDP per capita. *Trade* is the log of a country's imports plus exports as a fraction of GDP. *FinDev* is the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP. *Ln*(*VA*) is the log of value-added in a two-digit ISIC industry for each country in each year. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)
	Ln(1+*Pat*)	*Ln*(1+*Tcite*)
Trust	3.869***	3.609***
	(3.1)	(3.8)
Ln(*GDP*)	0.431	0.671***
	(1.5)	(3.1)
Trade	0.272	0.104
	(0.9)	(0.3)
FinDev	0.398***	0.746***
	(2.8)	(4.4)
Ln(*VA*)	0.482***	0.431***
	(4.0)	(3.5)
Industry-year fixed effects	Yes	Yes
Observations	10,205	10,205
R-squared	0.66	0.67

Table A6: Two-way clustering by country and year

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Ln*(1+*Pat*) is the log of one plus total number of patents in a two-digit ISIC industry for each country in each year. *Ln*(1+*Tcite*) is the log of one plus total number of patent citations adjusted for time and technology class fixed effects in a two-digit ISIC industry for each country in each year. *Trust* is defined using the WVS. *Ln*(*GDP*) is the log of GDP per capita. *Trade* is the log of a country's imports plus exports as a fraction of GDP. *FinDev* is the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP. *Ln*(*VA*) is the log of value-added in a two-digit ISIC industry for each country in each year. *Intensity* is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country and year. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)
	Ln(1+*Pat*)	*Ln*(1+*Tcite*)
Trust	3.873***	3.613***
	(3.1)	(4.0)
Ln(*GDP*)	0.433	0.672***
	(1.5)	(3.3)
Trade	0.270	0.103
	(0.9)	(0.3)
FinDev	0.398***	0.745***
	(2.9)	(4.3)
Ln(*VA*)	0.478***	0.428***
	(4.1)	(3.6)
Intensity	1.094	1.709
	(0.9)	(1.4)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Observations	10,205	10,205
R-squared	0.65	0.67

Table A7: Lagging trust for five years

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Ln*(1+*Pat*) is the log of one plus total number of patents in a two-digit ISIC industry for each country in each year. *Ln*(1+*Tcite*) is the log of one plus total number of patent citations adjusted for time and technology class fixed effects in a two-digit ISIC industry for each country in each year. *Trust_lag5* is defined using the WVS and lagged for five years. *Ln*(*GDP*) is the log of GDP per capita. *Trade* is the log of a country's imports plus exports as a fraction of GDP. *FinDev* is the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP. *Ln*(*VA*) is the log of value-added in a two-digit ISIC industry for each country in each year. *Intensity* is the median number of patents held by a U.S. firm in a two-digit ISIC industry in each year. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)
	Ln(1+*Pat*)	*Ln*(1+*Tcite*)
Trust_lag5	3.996***	3.787***
	(3.5)	(4.0)
Ln(*GDP*)	0.243	0.539**
	(0.8)	(2.3)
Trade	0.489	0.213
	(1.5)	(0.6)
FinDev	0.362**	0.673***
	(2.7)	(4.2)
Ln(*VA*)	0.607***	0.564***
	(5.2)	(4.4)
Intensity	0.571	0.648
	(0.4)	(0.4)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Observations	7,667	7,667
R-squared	0.69	0.69

Table A8: Technology-class level analysis

The sample consists of countries with granted patents jointly covered by the UNIDO Industrial Statistical database, the BVD Orbis database, and the WVS between 1990 and 2008. We only count each innovation once, i.e., an innovation patented in different countries is counted as one patent. *Ln*(1+*Pat*) is the log of one plus total number of patents in a two-digit IPC technology class for each country in each year. *Ln*(1+*Tcite*) is the log of one plus total number of patent citations adjusted for time and technology class fixed effects in a two-digit IPC technology class for each country in each year. *Trust* is defined using the WVS. *Ln*(*GDP*) is the log of GDP per capita. *Trade* is the log of a country's imports plus exports as a fraction of GDP. *FinDev* is the ratio of stock market capitalization plus domestic credit provided by the banking sector over GDP. *Ln*(*VA*) is the log of value-added in a two-digit IPC technology class for each country in each year. *Intensity* is the median number of patents held by a U.S. firm in a two-digit IPC technology class in each year. Variables in dollars are computed in real terms at constant national prices in 2005 US dollars. The *t*-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedastic consistent errors, which are clustered by country. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables	(1)	(2)
	Ln(1+*Pat*)	*Ln*(1+*Tcite*)
Trust	3.534***	3.114***
	(2.9)	(3.9)
Ln(*GDP*)	0.382	0.464*
	(1.2)	(1.9)
Trade	0.228	0.110
	(0.7)	(0.2)
FinDev	0.004***	0.007***
	(2.8)	(4.0)
Ln(*VA*)	0.579***	0.490**
	(3.7)	(2.7)
Intensity	0.381	0.275
	(1.4)	(0.9)
Year fixed effects	Yes	Yes
Tech class fixed effects	Yes	Yes
Observations	7,930	7,930
R-squared	0.68	0.65