Trust and Innovation within the Firm: Evidence from Matched CEO-Firm Data*

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Abstract

This paper shows that CEO's trust enhances innovation within firms, a novel micro-foundation for the well-known trust-growth relationship. I build a new matched CEO-firm-patent dataset covering 5,753 CEOs in 3,598 US public firms and 700,000 patents during 2000-2011. To identify CEO's trust's effect, I exploit variations in (i) generalized trust across CEOs' ethnic origins, inferred from their last names using de-anonymized historical censuses, and (ii) CEOs' bilateral trust towards inventors. Following CEO turnovers, a one standard deviation increase in CEO's generalized trust is associated with 6% more future patents and 4-6% higher average patent quality. Changes in CEO's bilateral trust towards inventors in different countries or from different ethnic origins have comparable effects on inventors' patenting, controlling for CEO and other fixed effects. The effect is driven entirely by higher-quality patents, consistent with a model in which CEO's trust incentivizes researchers to undertake high-risk explorative R&D. Furthermore, across and within firms, CEO's generalized trust is associated with a text-analysis-based measure of firm's trust culture computed from one million online employee reviews.

Keywords: Trust, Innovation, Exploration, CEO, Corporate culture, Cultural transmission.

JEL Classification: O31, O32, Z13, M12, M14.

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Virtually every commercial transaction has within itself an element of trust.

—Arrow (1972)

1 Introduction

Arrow (1974, c.1, p.23) emphasized trust as "an important lubricant of a social system," as it is impossible to fully contract upon all possible states of nature. Such an emphasis on the role of trust across social sciences, economics included,[1] has been accompanied by a wealth of empirical support on the association of trust and macroeconomic development and growth (as surveyed by Algan and Cahuc 2013, 2014). The evidence broadly highlights trust as a deep-root determinant of development and growth through its positive influence on the accumulation and allocation of factors of production (Knack and Keefer 1997; La Porta et al. 1997; Guiso et al. 2004, 2006, 2008a, 2009; Tabellini 2010; Algan and Cahuc 2010, among others).

Above and beyond factors of production, modern macroeconomics has stressed the crucial role of productivity growth by innovation as the sole driver of economic growth in the long run.[2] Thus, to understand the basis of the connection between trust and long-term growth, it is important to investigate whether trust can bolster innovation.[3]

This paper focuses on the role of CEO's trust on the process of research and innovation within the firm, as the firm is arguably the most important innovative actor in the economy, and the CEO wields significant influence on its culture. In my empirical approach, I assemble a large matched CEO-firm dataset covering 5,753 US CEOs in 3,598 US public firms between 2000 and 2011, which are associated with 700,000 patents and over one million inventors. Building on the economics of inherited cultural norms (Bisin and Verdier, 2001; Giuliano, 2007), I measure a CEO's inherited generalized trust as the average trust among US residents of the same ethnic origin. Similarly, I

[1] The economic literature on trust has built on seminal work by sociologists and political scientists on trust and development, including Banfield (1958), Gambetta (1988), Coleman (1990), Putnam et al. (1993), Putnam (2000), Fukuyama (1995), among others.

[2] Following Solow's (1956) insight that accumulation of production factors does not sustain long-term economic growth, the subsequent literature has mostly focused on productivity growth, especially as the result of knowledge accumulation and innovation, from Arrow (1962a) to endogenous growth theory (Romer, 1986, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991).

[3] Relatedly, Nunn (2012) surveys the larger literature on the cultural origins of long-term economic development, including, e.g., religion (Barro and McCleary, 2003, 2018), work ethic (Becker and Woessmann, 2009), and individualism (Gorodnichenko and Roland, 2017). The macro correlation between trust and innovation has been briefly suggested by Hall and Jones (1999) on TFP and Algan and Cahuc (2014) on R&D and patents.

compute a CEO's bilateral trust directed towards researchers in different ethnic groups based on average bilateral trust between the corresponding country pairs (highlighted in Guiso et al., 2009). A CEO's ethnic origin is inferred from his last name using de-anonymized historical US censuses (pioneered by Kerr and Lincoln, 2010).

In the first empirical design, I exploit CEO turnovers to estimate the effect of CEO's trust on future patent count and patent quality. In the second one, I estimate how a CEO's bilateral trust towards different ethnic groups affects patents filed by inventors in different overseas R&D labs within multinational firms, and by inventors of different ethnic origins in the same US firm, in each case controlling for CEO and other stringent fixed effects. I further examine the distributional effect on patent quality to understand how the effect operates via researcher's risk taking. I also provide evidence that CEO's trust transmits to corporate culture, partly via the selection of corporate leaders.

My measure of CEO's inherited trust exploits the role of cultural origin in shaping an individual's cultural traits, as emphasized in the economic literature on transmitted and inherited cultural values, such as the theoretical foundation by Bisin and Verdier (2000, 2001); Tabellini (2008); Guiso et al. (2008a), and the empirical evidence in Giuliano (2007); Fernández and Fogli (2009); Algan and Cahuc (2010); Guiso et al. (2016), among others. First, I construct a probabilistic mapping between CEOs' last names and ethnic origins from four de-anonymized US censuses, which contain the names and ancestry of the US population between 1910 and 1940. Second, I compute an ethnic-specific measure of trust for 36 different ethnic origins most common in the US using responses to the trust question in the US General Social Survey (GSS), considering only respondents in highly prestigious occupations that are comparable to the CEO sample (following Guiso et al., 2006; Algan and Cahuc, 2013, 2014, and the related literature.) Each CEO's inherited trust measure is the weighted average of ethnic-specific trust based on his likely ethnic composition. Although imperfect, this measure captures an important component of CEO's individual trust, and likely produces unbiased estimates of the latter's true effect.

To assess the role of generalized trust, the first empirical strategy uses firm fixed effects to exploit changes in CEOs and subsequent changes in patenting within the same firm over time, controlling for CEO's observable characteristics. The identifying condition is supported by the empirical evidence that both timing of CEO change and the new CEO's trust are not related to the firm's past patenting activities or performance. I find that a one standard deviation increase in CEO's inherited generalized trust, equivalent to the difference between Greek and English averages, is associated with a 6.3% increase in the number of patents filed. For the average firm in my sample, the additional patents are worth close to $7 million annually. This effect is even larger among firms undergoing exogenous CEO transitions due to CEO's retirements or deaths, and robust to controlling for a large set of country of origin characteristics and ethnic of origin socioeconomic conditions and cultural traits.

To separate the role of trust from other CEO's unobservable characteristics such as management style or ability, the second empirical strategy exploits within-CEO variation in CEO's bilateral trust towards different ethnic groups and the corresponding variation in patents by inventors from those different ethnicities, using CEO fixed effects. I calculate bilateral trust measures for directed pairs of CEO's and inventors' countries of origin using Eurobarometer data.[4] Patent inventors' countries of origin are inferred from either their addresses (for inventors in overseas R&D labs of multinational firms) or their last names (for US-based inventors). Within the same firm-year under the same CEO, a one standard deviation increase in CEO's directed bilateral trust towards an inventor country of origin is associated with a 3-5% increase in patents by inventors from the corresponding R&D lab or ethnicity, after controlling for a broad range of time-variant fixed effects at the firm-by-year, CEO, and inventor country levels. These results are robust to adding even more stringent firm-by-inventor country fixed effects, and accounting for possible alternative explanations such as favoritism or better information flows and coordination between CEOs and researchers.

To explain those empirical facts, I propose a mechanism that trust induces innovation by encouraging researchers to take risky explorative paths. It arises from a minimal two-period model of a researcher (agent) and a CEO (principal) who only observes outcomes, but cannot observe or contract on the researcher's type and behaviors (a natural feature of research activities, as emphasized since Arrow, 1962b). In each period, a "good" researcher faces the choice between (i) exploration, a high-risk high-return project that can result in innovation or failure with probability known only to her, and (ii) exploitation, a risk-free low-return common path that surely signals a good type from a bad one.[5] On the other hand, failure means either that the researcher's exploration is unsuccessful, or that she is a "bad" type.[6] Considering those elements, the CEO decides to whether rehire or

[4]These bilateral trust measures have been exploited by Guiso et al. (2009) in the context of international trade, Bloom et al. (2012) in delegation to subsidiaries, Giannetti and Yafeh (2012) in syndicated bank loan interests, Ahern et al. (2015) in mergers and acquisitions, and Bottazzi et al. (2016) in venture capital flows.

[5]March (1991) first emphasized the trade-off between exploration and exploitation in the context of research and innovation. I follow Manso (2011) in modelling research as the choice between exploration and exploitation. Unlike Manso (2011), which studies the implementation of either path, I focus on how the CEO's prior belief of the researcher's type, i.e., trust, affects innovation outcomes.

[6]In this setting, a bad research is understood as someone who lacks ability or willingness to undertake appropriate courses of actions. By normalization, I assume that the bad type always fails.

fire the researcher in period 2 based on her period 1's outcome.

In this setting, the CEO's trust in the researcher is modeled as his prior belief about the researcher's type, reflecting Gambetta's (1988) definition of trust as "the subjective probability with which an agent assesses that another agent or group of agents will perform a particular action." A more trusting CEO is more likely to interpret observed failure as being due to bad luck rather than bad type, therefore more likely to tolerate failure. In anticipation, a good researcher will be more likely to undertake exploration, thereby producing more innovation. The model thus predicts that higher trust induces more innovation through encouraging exploration (versus exploitation). These results resonate with Manso's (2011) and Aghion et al.'s (2013) models of innovation, which also imply that tolerating failure and reducing career risk help induce risky innovation. However, while Manso (2011) suggests that this objective could be achieved with long-term incentives and Aghion et al. (2013) with monitoring, this model instead emphasizes the enabling role of trust.[7] It further highlights the possible suboptimality of excessive trust due to too much retention of bad researchers, which resonates with Butler et al.'s (2016) view on "the right amount of trust", and suggests that trust is a substitute for the CEO's commitment capacity.[8]

To empirically distinguish this mechanism that trusted researchers take more risk from other mechanisms in which trust induces more effort by researchers,[9] I test the model's key empirical implication of stronger variance in innovation quality under more trusting CEOs, using patent quality measures such as future citation count. Consistent with the risk-taking mechanism, trust increases only high-quality patents, but not low-quality ones, thereby increasing average patent quality as measured by citations or average patent value by 4-6%. In addition, I find that trust is most effective in inducing innovation in firms with high researcher quality, and only among those firms does trust have a positive impact on firm's future performance.

I further link CEO's culture to firm's culture, measured from Sull's (2018) text analysis of almost one million employee reviews on Glassdoor.com, one of the largest career intelligence websites

[7]More broadly, this paper relates to the literature on contractual and financial arrangements to incentivize innovation (Ederer and Manso, 2011; Lerner, 2012), which also includes for example Lambert's (1986) consideration of incentivizing an agent's risk taking, and evidence from Azoulay et al. (2011); Ederer and Manso (2013); Lerner and Wulf (2007); González-Uribe and Groen-Xu (2017) on the effects of Manso-type contractual incentives (i.e., tolerance of failure and long-term incentives) on innovation.

[8]That is, when commitment to tolerance of failure is not possible, trust helps implement it. This result formalizes the intuition on the reliance between trust and commitment studied in the literature of sociology of organization, such as Klein Woolthuis et al. (2005).

[9]For example, one such mechanism can be conceived based on the large literature on delegation in organization since Aghion and Tirole (1997), such as Acemoglu et al. (2007) and Bloom et al. (2012). Accordingly, trust is modeled as the preference congruence between the principal and the agent, and more trust leads to more delegation to researchers, inducing them to put in more effort, thereby producing more innovation.

worldwide. The dataset covers many dimensions of employees' sentiments based on O'Reilly et al. (1991, 2014) across 500 large US public firms between 2008 and 2017. In specifications with CEO controls and industry fixed effects, or even firm fixed effects, CEO's inherited trust is associated with stronger corporate trust culture. Further evidence also suggests cultural transmission via the selection of directors, in that under a more trusting CEO, out-going directors are less trusting whereas newly appointed directors and those who remain throughout the CEO's tenure are more trusting. In that regard, this paper also provides new findings supporting the role of corporate culture in determining corporate outcomes,[10] and shows a channel through which corporate culture can be influenced: by an injection of culture from the top, as suggested by Van den Steen (2010).

This paper's results on the effect of CEO's trust on firm's innovation provide a possible micro-foundation for the macro relationship between long-term economic outcomes and trust, as evidenced in Guiso et al. (2006), Tabellini (2010), and Algan and Cahuc (2010), among others. As it shows that trust can spur innovations by solving contractual shortcomings, a high-trust society possesses not only the advantage of higher investment and accumulation of factors of production (or even better allocative efficiency), but also the potential to innovate more and thus grow productivity faster in the long run.[11] This mechanism helps explain the macroeconomic differences not only in development levels but also in growth rates across countries.[12] Separately, this paper extends the empirical literature of more traditional determinants of R&D and patents by highlighting the role of cultural factors, as distinct from government policies such as tax credits and grants (e.g., Howell, 2017; Dechezleprêtre et al., 2018, and Cohen's 2010 survey).

The results on CEO's trust also contribute to a growing body of empirical evidence that corporate executives, especially CEOs, matter for firm decisions and performance (e.g., Bertrand and Schoar, 2003; Bennedsen et al., 2010; Smith et al., 2017, and Bertrand's 2009 survey) and corporate culture (e.g., correlations between survey answers on corporate culture and performance in Guiso et al., 2015 and Graham et al., 2018). This paper highlights a new factor, trust, that fits the description of manager styles as coined by Bertrand and Schoar (2003).[13]

[10] E.g., Guiso et al. (2015), Grennan (2014), Gibbons and Kaplan (2015); Martinez et al. (2015), Graham et al. (2018).

[11] This statement holds in the large class of endogenous growth model à la Aghion and Howitt (1992) in which sustained innovation maintains long-term growth.

[12] From a macro perspective, Doepke and Zilibotti (2014) summarizes theories on the relationship between cultural traits (such as risk attitude, patience, and trust), entrepreneurship, and growth. Reviews by Durlauf et al. (2005) and Caselli (2005) provide evaluations of the crucial roles of productivity growth in explaining cross-country differences in growth and income level, respectively.

[13] Recent studies have started to explore a broad range of CEO characteristics (Malmendier and Tate, 2005, 2009; Kaplan et al., 2012; Kaplan and Sørensen, 2017; Gow et al., 2016) and practices (Bandiera et al., 2015, 2020). In

Beyond the economics literature, the interplay between management and trust and other cultural traits has been examined in sociology of organization and management, e.g., in seminal studies by O'Reilly et al. (1991, 2014), and other work on organization culture such as Schein (1985) or Hofstede et al. (1991). The corporate culture of trust has been notably highlighted as a crucial determinant of innovation (Nooteboom and Stam, 2008), which can be either substitute for or complement to formal control (Knights et al., 2001; Klein Woolthuis et al., 2005). This paper broadens this literature with a large-scale sample of firms, and with inherited trust computed systematically from surveys of opinions. It is also directly related to corporate leaders's expressed views on pro-innovation policies: In a recent *McKinsey & Company*'s qualitative survey among executives of major firms worldwide, most answers stress the key role of trust in boosting corporate innovation (Barsh et al., 2007, 2008).

The rest of the paper is organized as follows. Section 2 provides descriptions of the data. Sections 3 and 4 describe the within-firm and within-CEO empirical strategies and the corresponding empirical results. Section 5 studies the mechanism through risk-taking and exploration both theoretically and empirically. Section 6 provides evidence of the transmission of trust within the firm, and Section 7 concludes.

2 Data and inherited trust measure

2.1 Patents as a measure of innovation

I follow the literature on innovation in using patent and citation counts as measures for innovation.[14] My data come from PATSTAT, the largest available worldwide patent database covering patents from the 1900s up to 2016. It brings together over 80 million patent documents from over 60 patent offices and has complete coverage of patents from all major offices, including the United States Patent and Trademark Office (USPTO) and the European Patent Office (EPO). This makes PATSTAT especially suitable for studies with a cross-country perspective.

The dataset contains all information in the patent document, including application and publication dates, backward and forward citations, technology classification, and patent family. These data allow me to construct more nuanced measures of patent quality besides citation count, such

particular, this literature has linked the corruption culture from a CEO's cultural background to firm's misconducts (DeBacker et al., 2015; Liu, 2016).

[14] Patent is not the perfect measure of innovation (Hall et al., 2014). However, to the extent that the use of patents to protect notable innovations is common within an industry, my focus on patents is unlikely subject to a serious bias if I only consider within-firm or within-industry variations. At worst, it likely underestimates the effect of trust on innovation.

as patent explorativeness, patent disruptiveness, technological scope, etc. (details in appendix A.2). PATSTAT also records the names and addresses of each patent's inventors, which enables me to link patents to inventors' countries of residence or origin and construct patent count at the firm-by-inventor country level (details in subsection 4.1).

To avoid double-counting inventions, I classify patents in the same patent family (i.e., a set of patents protecting the same invention across several jurisdictions) as one single patent, and assign this patent to the year of its earliest application date. As it takes up to 1.5 years for a patent application to be published and on average 5 years for a patent to gain 50% of its lifetime citations (Squicciarini et al., 2013), I focus on patents filed before 2012 for which PATSTAT data is more comprehensive. Finally, I assign patents to firms using the matching implemented by the EPO and the OECD that is available on Bureau van Dijk's ORBIS platform.

2.2 CEO's inherited trust measure

I obtain information on firms' CEOs, senior executives, and board directors of US publicly listed firms from BoardEx. The dataset spans from 2000 to 2016, covers almost all US publicly listed firms in this period, and includes rich information on the executives' background and employment history. Among these variables, the executives' names are essential for the measurement of inherited trust. In addition, I also use information on the timing of their positions, gender, education, and employment history (details in appendix A.3).

Measuring CEO's inherited trust. I measure a CEO's inherited generalized trust based on (i) his ethnic origin(s) as inferred from his last name and (ii) measures of inherited trust among US residents of the same ethnic origin(s). That is,

$$trust_d = \sum_e w_{de} \times ethtrust_e \tag{1}$$

where $ethtrust_e$ is the average trust measure among US descendants of immigrants from country e, and w_{de} is the probability that CEO d is a US descendant of immigrants from that country.

I follow the literature on inherited trust (e.g., Guiso et al., 2006; Algan and Cahuc, 2010) in computing $ethtrust_e$ using individual-level data on trust attitude and ethnic origins from the US General Social Survey (GSS), a representative survey of social attitudes among US residents conducted between 1972 and 2014 with a total of 60,000 respondents. A respondent's trust attitude is measured by the standard generalized trust question *"Generally speaking, would you say that most* *people can be trusted or that you can't be too careful in dealing with people?"*, which has been experimentally validated in trust game settings (Berg et al., 1995) by Fehr et al. (2002), Sapienza et al. (2013), and Falk et al. (2016).[15] His ethnic origin is captured by the question *"From what countries or part of the world did your ancestors come?"*, which covers 36 most common ethnic origins in the US, including all major European countries in addition to Canada, Mexico, China, and India. To better match the CEO sample, I only consider respondents in highly prestigious occupations. The baseline $ethtrust_e$ measure is then the average trust attitude of selected GSS respondents whose self-reported ethnic origin is e (Table A1). In addition, I construct an alternative trust measure that also take into account other demographic characteristics such as gender, education, age, and birth cohort, to best predict trust using LASSO. (See appendix B.1 for further details.)

Next, I construct a probabilistic mapping between a CEO's last name and different ethnic origins (w_{de}'s) using historical de-anonymized US censuses in 1910, 1920, 1930, and 1940 (Kerr and Lincoln, 2010; Liu, 2016). These censuses contain individual-level data on birthplace and ancestry of the whole US population during 1910-1940, merged with individual names obtained from the Minnesota Population Center. Across four censuses there are 80 million individuals with foreign birthplaces or ancestry, sharing among them five million unique last names. I only consider 75,000 last names with at least 100 observations and allow each last name to be mapped to multiple ethnic origins with probabilities proportional to their numbers of observations. Separately, I also compile lists of most common last names in 50 different countries from multiple sources and use these lists to cross-check and supplement the baseline census-based mapping. (See appendix B.2 for further details.)

83% of the CEO sample could be mapped to their ethnic origins based on their last names and they are not statistically different from the remaining 17% across all observable characteristics (Panel A of Table A3). Three most common ethnic origins among CEOs are Irish, German, and English, which together account for about half of the CEO sample (Table A2), very similar to the ethnic origin distribution among GSS respondents in highly prestigious occupations. The average CEO's inherited trust measure is 0.56, which is considerably higher than the average GSS trust measure of 0.38 but comparable to that of 0.51 among those in prestigious occupations.[16] Despite the high total shares of three most common ethnic origins among CEOs, Figure 1 shows that there remains meaningful variation in their inherited generalized trust measure.

[15] As robustness checks, I also compute alternative $ethtrust_e$ measures using other trust questions in the GSS and other surveys (see Panel C of Table A7 for details).

[16] This is consistent with Fehr and List's (2004) experimental findings that CEOs exhibit more trusting behavior,

Figure 1: Distribution of CEO's Inherited Trust Measure

Notes: This figure shows the 1st-99th percentile distribution of CEO's GSS-based inherited generalized trust measure as described in subsection 2.2 for 5,753 CEOs in the baseline sample. The solid vertical line corresponds to the 50th percentile of the distribution. The dashed vertical lines correspond to the 10th and 90th percentiles.

Validity of inherited trust measure. A growing literature highlights the role of cultural origin in shaping individual trust and other cultural traits. Bisin and Verdier (2000, 2001), Tabellini (2008), and Guiso et al. (2016) provide theoretical mechanisms for cultural transmission of preferences and beliefs from parents to children. Empirical evidence on intergenerational cultural transmission includes the strong correlation by ethnicity between trust attitude and other values among descendants of US immigrants, and related traits, behaviors, and outcomes in their home countries (see surveys by Fernández, 2011 and Algan and Cahuc, 2013, 2014), and the strong within-family correlation between parents' and children's trust and risk attitudes in Germany (Dohmen et al., 2012). Following this literature, I verify the existence of trust transmission by comparing the US-population GSS-based $ethtrust_e$ with an equivalent measure for the countries of origin's populations, calculated from the World Value Survey. The correlation between these two trust measures is high, at around 0.6, consistent with the view that descendants of US immigrants inherit a large part of their cultural traits from their ancestries, as shown by Giuliano (2007) and Fernández and Fogli (2009).

Ideally, one would like to observe each CEO's individual trust attitude, yet measuring this latent variable is a formidable challenge. Even if one could administer a trust survey or a trust game among CEOs, the resulting measure would still embody large measurement errors.[17] While

use punishment less often, and consequently reach substantially higher efficiency levels than undergraduate students.

[17] Falk et al. (2016) find that the correlation between trust measures of the same individual elicited from trust games

the inherited trust measure misses (i) the individual-specific component of trust, it smoothes out (ii) those individual-level measurement errors. In appendix B.3, I assess the relative sizes of (i) and (ii) using parameters from the literature. The results suggest that the baseline inherited trust measure is better than an individual-level survey-based trust measure and about 80% as precise as an individual-level game-based measure. Furthermore, using the inherited trust measure does not introduce attenuation bias as in the case of classical measurement errors but likely produces unbiased estimates of the true effect (details in appendix B.4).[18]

Separately, one may worry that the last name-ethnic origin mapping only captures an individual's patrilineage. However, the majority of the CEOs in my sample were born in the 1940s and 1950s, a time during which ethnic segregation and intra-ethnic marriage was ubiquitous in the US (e.g., Eriksson and Ward, 2018). Relatedly, Dohmen et al. (2012) provide evidence of positive assortative mating based on trust and risk attitudes in a representative sample of German population, and Pan et al. (2018) find that uncertainty avoidance measures constructed from CEOs' last names and from their mothers' maiden names are highly correlated. Finally, 98% of my CEO sample are male, hence name changing due to marriage is not a concern.

Measuring CEO's bilateral trust. Similar to his inherited generalized trust measure, CEO d's bilateral trust directed towards individuals from country c is calculated as

$$bitrust_{dc} = \sum_{e} w_{de} \times ethbitrust_{ec} \tag{2}$$

where $ethbitrust_{ec}$ is a measure for how much a person from country of origin e trusts a person from country of origin c. This country-pair-level bilateral trust measure ($ethbitrust_{ec}$) comes from the Eurobarometer surveys' question *"I would like to ask you a question about how much trust you have in people from various countries. For each, please tell me whether you have a lot of trust, some trust, not very much trust, or no trust at all."* The surveys cover respondents from 16 EU countries and ask about their trust attitude towards 28 countries, including some non-EU countries such as Russia, Japan, and China.[19] Existing studies using the same measure have shown that bilateral

conducted one week apart is 0.6, suggesting a considerable amount of measurement errors. Results from other studies on the stability of experimental and survey measures of preferences are consistent with this finding (see survey by Chuang and Schechter, 2015). Of course, if one can administer *many* trust surveys or games on the same individual, one can more precisely average out individual trust. Yet this option is highly infeasible, especially among CEOs.

[18] In essence, using the inherited trust measure is similar to using the cell-average of the right hand side variable as a new regressor, a very helpful procedure when one only observe cell averages (see Angrist and Pischke, 2009, c. 2).

[19] Unlike the GSS, Eurobarometer surveys are conducted in Europe. However, given the evidence of intergenerational transmission of trust attitude, it seems reasonable to use the Eurobarometer-based bilateral trust measure as a proxy for the bilateral trust among US descendants of European immigrants.

trust matters to a wide range of economic activities, from cross-country trade (Guiso et al., 2009) to venture capital investment (Bottazzi et al., 2016) and within-firm internal organization (Bloom et al., 2012). The CEO's bilateral trust measure $bitrust_{dc}$ is available for CEOs whose ethnic origins are among the 16 surveyed countries, which make up 45% of the CEO name-matched sample. (See appendix B.1 and B.2 for further details.)

2.3 Baseline sample

To construct the baseline sample, I combine patent data from PATSTAT and CEO data from BoardEx with US public firms' performance data from Compustat, excluding firms in the financial industry and those whose headquarters are outside of the US. I only consider firms with at least one name-matched CEO (92% of the firm sample) and further restrict the sample to firms and CEOs for which all key variables are non missing. The final baseline sample consists of 3,598 US public firms and 5,753 corresponding CEOs, with 29,384 firm-by-year-by-CEO observations during the period between 2000 and 2011 (Table A3). About 60% of these firms are R&D performing and patenting firms, filing a total of 700,000 patent applications between 2001 and 2012. Over this 12-year period, each firm has on average 1.7 name-matched CEOs and about two thirds of the firms have more than one CEOs. 98% of the CEOs are male, each CEO has an average tenure of 7 years, and very few CEOs have ever been the chief executive of more than one firm in the sample.[20]

3 Within-firm effect of CEO's generalized trust

3.1 Within-firm empirical strategy

To study the relationship between CEO's generalized trust and firm's innovation, I first consider a within-firm specification with firm and year fixed effects:

$$\text{arsinh}(pat_{f,t+1}) = \beta_1 trust_d + \xi \mathbf{X}_{ft} + \zeta \mathbf{Z}_{dt} + \theta_f + \omega_t + \varepsilon_{fdt}. \tag{3}$$

Each observation represents a firm f in a year t with its current CEO d. $pat_{f,t+1}$ is firm f's forward patent application count in year $t+1$. As patent distribution is skewed, I use its inverse hyperbolic sine transformation $\text{arsinh}(pat_{f,t+1})$ as the main outcome variable instead of raw patent count (following Card and DellaVigna, 2017). The main explanatory variable $trust_d$ is CEO d's inherited generalized trust measure, normalized by its standard deviation. The specification includes a full set

[20]It is therefore not possible to estimate CEO fixed effects using Abowd et al.'s (1999) method, as in Bertrand and Schoar's (2003) application on top managers.

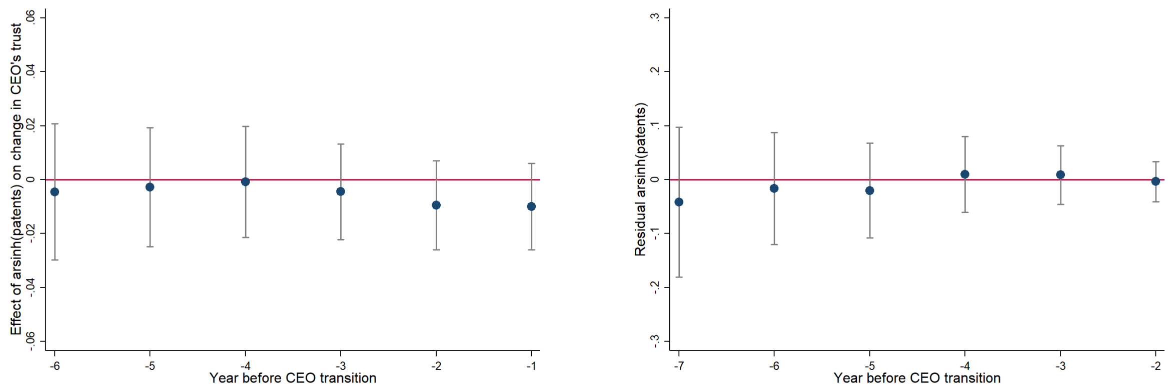
of firm fixed effects θ_f, which controls for all firm-level time-invariant characteristics that correlate with either firms' innovation capability or selection of CEO. In addition, equation (3) also controls for firm's time-variant characteristics $\mathbf{X}_{ft}$ (including firm's age, assets, and sales), CEO's time-variant characteristics $\mathbf{Z}_{dt}$ (including CEO's age, gender, education dummies, and tenure in firm), and a set of year fixed effects ω_t (to account for macro-level cyclicality in innovation). Standard errors are clustered by CEO's main ethnic origin, which is the level of the source of variation in treatment following Abadie et al.'s (2017) advice.[21]

The coefficient of interest β_1 represents the effect of CEO's trust on firm's patents. With the inclusion of firm and year fixed effects, equation (3) identifies β_1 from changes in CEOs and subsequent changes in patenting within the same firm over time, akin to a difference-in-differences specification. The common trend identifying assumption, which requires that trends in potential outcomes be mean-independent of changes in CEO's trust, conditional on covariates, is necessary for the interpretation of β_1 as the causal effect of CEO d's trust on firm f's patents. Under this assumption, β_1 is unlikely the result of reverse causality or confounded by firm f's time-variant unobservable characteristics that affect both the firm's choice of CEO and its innovation outputs (e.g., changes in firm's strategy driven by the board). However, there remains the caveat that firm's patents can be driven by other omitted CEO's attributes that correlate with trust. This concern is addressed in Section 4 by the within-CEO design that allows for CEO fixed effects.

To formally test for common trends, I regress the change in CEO's trust in each CEO transition event on firm's patent application counts in different years before the transition, controlling for firm's and CEO's pre-change characteristics. The resulting coefficients are all small and not statistically different from zero, indicating that there is no association between firm's pre-change patenting and subsequent change in CEO's trust (Figure 2A, details in appendix C.1). Figure A1 further shows that change in CEO's trust does not correlate with firm's other pre-change characteristics, such as R&D expenditure, employment, sales, or total assets. Separately, Figure 2B plots the average patent application count by the number of years before the transition for the full sample of firms (details in appendix C.2). The flat pre-trend in patents indicates that the timing of the CEO transition is not driven by a trend in patenting, suggesting that reverse causation is unlikely a concern in this setting.

[21] All key results in this section are robust to a wide range of alternative specification choices, such as employing alternative patent count transformations, alternative CEO's trust measures, additional controls and fixed effects, alternative standard error clustering schemes, alternative sample restrictions, and alternative estimation models. These robustness checks are reported in Table A7 and discussed in appendix C.5.

Figure 2: Pre-Change Patents and Change in CEO's Trust



A. Common trend B. Pre-trend

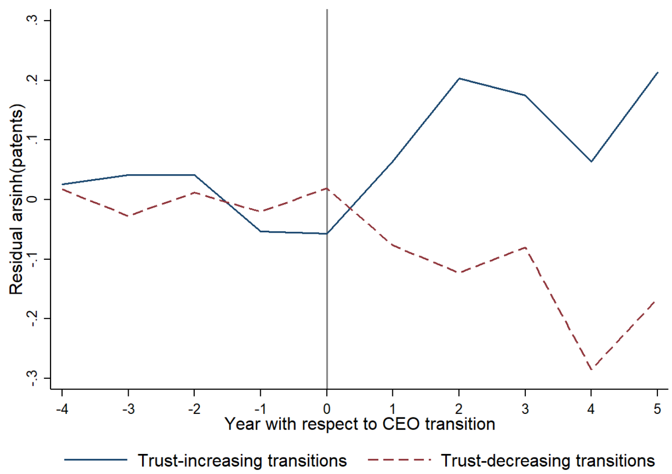
Notes: **Subfigure A** plots the coefficients from regressing the change in CEO's trust in each CEO transition event on firm's patent application counts in different years before the transition, controlling for pre-change firm's and CEO's characteristics (equation A1, details in appendix C.1). **Subfigure B** plots the average patent application count by the number of years before the transition for the full sample of firms, after partialling out the covariates (equation A4, details in appendix C.2). Estimates are shown with their 95% confidence intervals.

3.2 Baseline effect of CEO's trust on firm's patents

Figure 3's event-study graph, which plots firms' patent application count by year with respect to CEO transition year (year 0), visually summarizes the paper's key empirical finding. The solid blue line groups together all CEO transitions in which the new CEOs are *more* trusting than their predecessors and the dotted red line corresponds to those in which the new CEOs are *less* trusting. The two lines closely track each other in the years before CEO transitions but diverge visibly post-CEO change: firms that experience an increase in CEO's trust after the transition also experience increases in patenting in post-transition years and vice versa. Table A5 further shows that while the difference in average pre-transition patents between these trust-increasing and trust-decreasing CEO transitions is small and not statistically different from zero (by matching), the difference in their post-transition patents is large, positive, and statistically significant at 5% level. The rather immediate effect that peaks in years 2 and 3 is consistent with the observation that patent applications are often timed quite closely to R&D (e.g., Hall et al., 1986). I also find that CEO's trust effect is largest in industries with short lag between R&D and patents, such as ICT, and close to zero in industries with long R&D horizon, such as pharmaceuticals (Table A8).

Baseline CEO's trust effect. Table 1 estimates equation (3), which exploits changes in CEOs and subsequent changes in patenting within the same firm over time, using the full baseline sample

Figure 3: Patents by Change in CEO's Trust (Matched Sample)



Notes: This figure plots firms' average residual patent application count, after partialling out (i) firm and CEO controls, and (ii) firm's industry and year fixed effects, by year with respect to CEO transition year (year 0). Among the sample of CEO transitions in which both predecessor's and successor's tenures are at least 5 years, each transition in which the new CEOs are *more* trusting than their predecessors is matched to a transition in which the new CEOs are *less* trusting than their predecessors based on their average pre-transition residual patent counts to address mean reversion. (Figure A2 presents the equivalent event-study graph without this matching procedure.) The solid blue line groups together all trust-increasing CEO transitions and the dotted red line corresponds to their matched trust-decreasing CEO transitions. Each group's annual average residual patent counts are plotted relative to the group's pre-transition mean, which is normalized to 0.

described in subsection 2.3. Column (1) reports a basic specification without any firm or CEO controls, column (2) the baseline specification, and column (3) an augmented specification with industry-by-year fixed effects to account for industry-level patenting cyclicality. The resulting CEO's trust estimates are almost identical across these three columns and imply that one standard deviation increase in CEO's trust is associated with 6.3% increase in firm's patent filing, statistically significant at 1% level.[22] This effect is even larger when patent quality is accounted for, at 10.0% using forward citation count (column 4) or 11.3% using patent value computed from firms' excess stock returns on patent grant dates (column 5, following Kogan et al., 2017). For the average baseline firm, this translates into 1.1 additional patents annually, or $6.8 million in monetary value. This economically substantial impact is driven by both positive and negative changes in CEO's trust (Figure A3), yet not by a corresponding increase in R&D investments (Table A6).

[22]Inherited trust's standard deviation at ethnicity level is 0.11, equal to the difference between Greek and English average inherited trust levels.

Table 1: Baseline Effect of CEO's Trust on Firm's Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**arsinh(Future patent applications)**							
Specification:	No controls	Baseline spec.	Add. ind. trends	Forward cites	Patent value	Retired or died	Country controls	Other traits
CEO's trust	0.059***	0.063***	0.066***	0.100***	0.113***	0.095**	0.045**	0.058**
	(0.018)	(0.019)	(0.019)	(0.031)	(0.041)	(0.045)	(0.020)	(0.025)
Firm & Year FEs	X	X	X	X	X	X	X	X
CEO & Firm controls		X	X	X	X	X	X	X
Industry × Year FEs			X					
Home country controls							X	
Other cultural traits								X
Observations	29,384	29,384	29,384	29,384	20,218	3,756	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,168	372	3,598	3,598

Notes: This table reports the baseline effect of CEO's inherited trust on firm's patents using equation (3). Baseline sample includes all observations of firm f × year t × its current CEO d. The dependent variable is the inverse hyperbolic sine of firm f's patent application count in year $t+1$. The explanatory variable is CEO d's inherited trust measure, standardized by its standard deviation at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Columns (4) and (5)'s dependent variables weight patent applications by their forward citations (column 4) and patent values (i.e., firm f's excess stock return on patent grant date as estimated by (Kogan et al., 2017, column 5). Column (6) focuses on transitions in which the preceding CEOs retire between the age of 63 and 67 or die in or within 1 year of leaving the office. Column (7) additionally controls for CEO's home country's macroeconomic characteristics, including ln(GDP), ln(population), GDP growth rate, high school graduate share, average percentile ranking of World Bank governance indices, ln(US exports + US imports), and ln(total patent applications filed at the country's patent office). Column (8) additionally controls for CEO's other inherited cultural traits, including work ethic, risk preference, time preference (i.e., patience), and CEO's ethnic group's high income share. (See appendix D for further details.) Standard errors are clustered by CEO's main ethnicity. *** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Robustness checks. These results are robust to a wide range of alternative specification choices as reported in Table A7 and discussed in appendix C.5. They include (i) additionally controlling for employment and R&D stocks or flows (Panel A), (ii) estimating a semi-log Poisson count model instead of OLS (Panel A), (iii) clustering standard errors by firm and clustering two-way by CEO's main ethnic origin and firm (Panel B), (iv) using $\ln(1 + pat_{f,t+1})$, winsorized, or raw $pat_{f,t+1}$ as the outcome variable (Panel B), (v) employing CEO's trust measures estimated using LASSO or computed using data from the World Value Survey, the Global Preference Survey, or other trust questions in the GSS (Panel C), (vi) excluding female or interim CEOs (Panel D), (vii) restricting the sample to only patenting firms, patenting periods, or patenting years (Panel D), (viii) considering further-forward patent application counts in year $t+2$ or $t+3$ (Panel E), and (ix) constructing the sample from CEO transition events and including event fixed effects (Panel F). Most notably, Panel C shows that while all alternative trust measures yield positive and statistically significant estimates of the CEO's trust effect, the coefficient is reassuringly larger and more precise when the CEO's trust measure becomes closer to that of the US CEO population. This pattern implies that, if there could be an omitted factor that could explain the relationship between CEO's trust and firm's innovation, then its measurement must also improve as trust is better measured.

Exogenous CEO transitions. To better address reverse causality, column (6) zooms into special cases in which common trends are better warranted: CEO transitions following CEO's retirements or deaths (e.g., Fee et al., 2013; Bennedsen et al., 2010). As the need to replace the existing CEO arises exogenously, the timing of the transition is likely exogenous to firm's other decisions. Even when subsequent CEO appointment is endogenous to firm's underlying characteristics, under the assumption that those characteristics do not change in the event of an exogenous transition, firm fixed effects sufficiently address firm's endogenous new CEO selection. Guided by this intuition, column (6) restricts the sample to transitions in which the preceding CEOs naturally retire around the age of 65 or prematurely die in or soon after leaving the office (details in appendix A.3), which yields a comparable CEO's trust estimate of 9.5% (see Table A9 for additional results). This result indicates that CEO's characteristics matter to firm's innovation, much in line with the literature on CEO's impact on firm's performance (see survey by Bertrand, 2009).

Potential confounding factors. Columns (7) and (8) further show that the CEO's trust estimate is robust to controlling for a host of potential confounding factors related to the CEO's origins. Column (7) includes the set of all macroeconomic variables measuring CEO's home country's level of development and technological capabilities that have been shown to be related to country-level trust measure by Algan and Cahuc's (2013; 2014) surveys, including GDP, population, GDP growth, high school graduate share, governance quality index, trade volume with the US, and patent application volume. Similarly, column (8) controls for a rich set of other inherited cultural traits with economic significance at both macro and microeconomic levels, such as work ethic, risk preference, time preference (i.e., patience), together with CEO's ethnic group's socioeconomic characteristics. In both columns, the magnitude and precision of the CEO's trust estimate is not affected by any of those factors. (For more detailed results and discussion, see Tables A10-A12 and appendix D.2.)

4 Within-CEO effect of CEO's bilateral trust

4.1 Within-CEO empirical strategy

Despite the evidence discussed so far, there remain other CEO personal characteristics that one cannot observe, measure, or directly control for, such as ability, management style, or preference for innovation. Those characteristics can correlate with CEO's trust and at the same time have direct effects on firm's innovation. To address this concern, I exploit within-CEO variation in CEO's bilateral trust towards different groups of inventors and the corresponding variation in patenting among those different inventor groups. Such within-CEO variation allows me to include a full set of CEO fixed effects in the following equation:

$$\text{arsinh}(pat_{fc,t+1}) = \beta_2 bitrust_{dc} + \theta_{ft} + \kappa_c + \omega_d + \varepsilon_{fdct}. \quad (4)$$

Each observation is a combination of firm f by year t by its CEO d by inventor country c. The outcome variable $pat_{fc,t+1}$ is firm f's total patent count by inventors from country c in year $t+1$. The main explanatory variable $bitrust_{dc}$ measures how much CEO d trusts individuals from country c (details in subsection 2.2). Besides the crucial CEO fixed effects (ω_d), equation (4) also controls for inventor country fixed effects (κ_c) that absorb all inventor country's baseline characteristics (e.g., development level, institution quality, technological comparative advantage, inventor pool quality), and for firms' time-variant characteristics with firm-by-year fixed effects (θ_{ft}). Given these stringent sets of fixed effects, any remaining variations would have to be at the firm-inventor country pair or CEO-inventor country pair levels. To control for potential confounding factors by those variations, I additionally include firm-by-inventor country fixed effects or an array of CEO-inventor country pairwise controls in the robustness checks. The coefficient β_2 then captures the effect of CEO's bilateral trust toward individuals in a country on corresponding patent count by inventors from that country. Standard errors are clustered by CEO's main ethnicity-inventor country pair.[23]

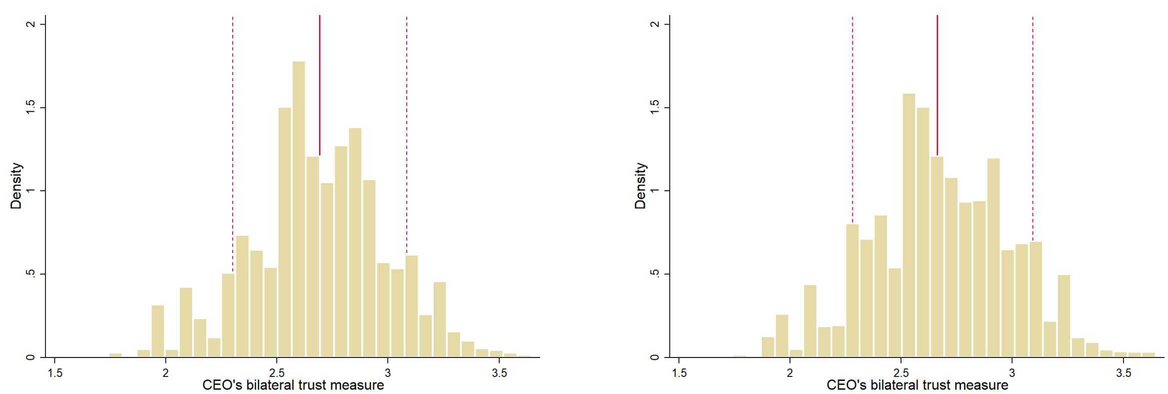
To construct the outcome variable pat_{fct}, I use information on patent inventors' addresses or last names to allocate patents to different inventor countries or origins (e.g., Foley and Kerr, 2013). For non-US-based inventors, I assign the corresponding patents to the countries where the inventors reside, which likely coincide with where firms' R&D labs are located. About 30% of the patents in my sample are by those overseas R&D labs of US-based multinational firms, most of which are in Europe, Japan, and China. For the remaining US-based inventors, I infer their ethnic origins from their last names, then assign the corresponding patents to their inventors' countries of origin

[23] All results are robust to two-way clustering by (i) CEO's main ethnicity-inventor country pair and (ii) firm.

accordingly. The variable pat_{fct} is the sum of all patents filed by firm f in year t that are assigned to country c. (See appendix A.2 for further details.)

The baseline sample used to estimate equation (4) includes all firm f-inventor country c pairs such that firm f has patents by inventors from country c in at least one year during the study period (i.e., $pat_{fct} > 0$ for some $t \in [2000, 2012]$). If a firm-inventor country pair satisfies this condition, then it is included in the baseline sample even in the years when the pair has zero patent to avoid biases arising from selection into patenting over time. β_2 therefore captures both the intensive and the extensive margins of CEO's bilateral trust effect on inventors' patenting. Using non-US addresses to identify inventors' countries of residence results in a sample of 3,481 firm-by-country dyads, covering 730 firms with R&D labs in 27 countries and 960 CEOs. Additionally employing last names to identify US-based inventors' countries of origin gives a larger sample of 8,554 firm-by-country dyads, covering 1,263 firms with inventors from 27 countries and 1,654 CEOs (Table A4). Figure 4 shows substantial variation in the distribution of the CEO's bilateral trust measure in both samples.

Figure 4: Distribution of CEO's Bilateral Trust towards Researchers



A. Non-US-based inventors

B. All inventors

Notes: This figure shows the distribution of CEO's bilateral trust measure as described in subsection 2.2 for CEO-inventor country pairs in the baseline bilateral samples. Subfigure A corresponds to the bilateral trust sample in which an inventor's country is inferred from his patent-listed address for non-US-based inventors. Subfigure B corresponds to the bilateral trust sample in which an inventor's country is additionally inferred from his last name for US-based inventors. The solid vertical line corresponds to the 50^{th} percentile of the distribution. The dashed vertical lines correspond to the 10^{th} and 90^{th} percentiles.

4.2 Effect of CEO's bilateral trust on inventors' patents

Table 2 reports the effect of CEO's bilateral trust towards individuals in a country on corresponding patent application count by inventors from that country, estimated using equation (4). In both panels, columns (1) to (4) employ the bilateral trust sample constructed from only non-US-based inventors and columns (5) to (8) use both non-US- and US-based inventors. The baseline bilateral trust specification (equation 4) is reported in columns (1) and (5) of Panel A. In addition, I fully interact the sets of firm, CEO, and inventor country dummies with year dummies in columns (2) and (6). Columns (3) and (7) further include firm-by-inventor country fixed effects to control for specific characteristics of each R&D lab or inventor group in the firm that are not already captured by firm or inventor country fixed effects.[24] Finally, columns (4) and (8) weight patents by their forward citation counts to account for patent quality.

The CEO's trust coefficients in columns (1) and (4), which estimate the effect of CEO's bilateral trust on patents after controlling for firm's time-variant and CEO's characteristics, implies that one standard deviation increase in CEO's bilateral trust towards a country is associated with 5% (9%) increase in patents (quality-weighted patents) by the R&D lab in that country, both statistically significant at 5% level. This effect is of the same magnitude as the baseline CEO's trust effect of 6% (10%) reported in Table 1 and robust to adding even more stringent fixed effects (columns 2 and 3). Columns (5) to (8) report similar pattern among both non-US-based and US-based inventors, although the effect of CEO's bilateral trust in this sample is expectedly smaller (3% compared to 5%) for two reasons. First, as the differences among US-based inventors from different home countries are less salient, CEOs' bilateral trust towards those inventors are likely less heterogenous. Second, organizationally, CEOs are also less likely to implement differentiating policies towards different groups of US-based inventors than towards R&D labs in different countries.[25] On the other hand, also considering US-based inventors allows us to cover a much larger share of the patent pool, which results in both a larger estimation sample and more precisely-estimated coefficients.

It should also be noted that the within-firm effects of CEO's generalized trust on firm's total patents are also statistically positive among the subsamples of firms included in these bilateral trust samples (Table A14, column 1). This implies that the reported bilateral trust effect reflects

[24] This within-R&D lab/inventor group specification mirrors equation (3)'s within-firm specification. That is, it exploits (i) changes in CEO's bilateral trust towards different R&D labs or inventor groups in the same firm following a change in CEO and (ii) subsequent changes in patenting by the corresponding R&D labs or inventor groups, after controlling for other CEO characteristics with CEO fixed effects. Similar to Figure 2A, Figure A4 shows that pre-change patents at R&D lab or inventor group level do not predict the change in CEO's bilateral trust towards the corresponding R&D lab or inventor group (i.e., the common trend identifying assumption).

[25] The Eurobarometer bilateral trust measure is also likely a better proxy for CEO's bilateral trust towards non-US-based inventors, who are actual residences in the surveyed countries, than that towards US-based ones. Consistent with this view that the bilateral trust effect is expectedly weaker towards US-based inventors, Table A13 shows that estimating equation (4) using an alternative bilateral trust sample constructed from only US-based inventors yields an even smaller CEO's bilateral trust coefficient of 2%, statistically significant at 10% level.

Table 2: CEO's Trust Effect in Bilateral Trust Samples

Panel A. Main results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**arsinh(Future patent applications)**							
Sample:	Non-US-based inventors				All inventors			
CEO's bilateral trust	0.052**	0.051**	0.034*	0.095**	0.026**	0.025**	0.013**	0.051***
	(0.023)	(0.024)	(0.021)	(0.039)	(0.011)	(0.011)	(0.006)	(0.018)
Firm × Year FEs	X	X		X	X	X		X
CEO FEs	X		X	X	X		X	X
Inventor country FEs	X			X	X			X
CEO × Year FEs		X				X		
Inv. country × Year FEs		X				X		
Firm × Inv. country FEs			X				X	
Year FEs			X				X	
Observations	23,284	23,284	23,284	23,284	56,942	56,942	56,942	36,942
Firm × Inv. country's	3,481	3,481	3,481	3,481	8,554	8,554	8,554	8,554
Firms	730	730	730	730	1,263	1,263	1,263	1,263

Panel B. Further controlling for CEO-inventor country pairwise characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**arsinh(Future patent applications)**							
Sample:	Non-US-based inventors				All inventors			
CEO's bilateral trust	0.047*	0.042*	0.052**	0.052**	0.016	0.024*	0.023**	0.027**
	(0.029)	(0.025)	(0.024)	(0.024)	(0.013)	(0.013)	(0.011)	(0.011)
Common language dummy		0.057				0.011		
		(0.047)				(0.025)		
Geographical distance (1000km)			-0.002				-0.011	
			(0.019)				(0.011)	
Genetic distance (z-score)				0.018				-0.019
				(0.084)				(0.053)
Excl. same-country pairs	X				X			
Firm × Year FEs	X	X	X	X	X	X	X	X
CEO FEs	X	X	X	X	X	X	X	X
Inventor country FEs	X	X	X	X	X	X	X	X
Observations	20,878	23,284	23,284	22,881	51,936	56,942	56,942	55,444
Firm × Inv. country's	3,145	3,481	3,481	3,421	7,932	8,554	8,554	8,323
Firms	496	730	730	728	1,020	1,263	1,263	1,263

Notes: **Panel A:** This panel reports the effect of CEO's bilateral trust towards a country on patents by inventors from that country using equation (4). Samples include all observations of firm f × year t × its current CEO d × country c such that firm f has patents by inventors from country c during 2000-2012. An inventor's country is inferred from his patent-listed address for non-US-based inventors in columns (1) to (4), and additionally from his last name for US-based inventors in columns (5) to (8). The dependent variable is firm f's total patent application count by inventors from country c in year $t+1$. The explanatory variable is CEO d's bilateral trust towards individuals from country c, standardized by its standard deviation at country pair level. Standard errors are clustered by CEO's main ethnicity × inventor country.

Panel B: This panel additionally controls for other CEO-inventor country pairwise characteristics besides bilateral trust using equation (4) as described above. Columns (1) and (5) exclude same-country CEO-inventor country pairs. Columns (2) to (6) control for CEO-inventor country pairwise distances, including: (i) whether the countries share a common language (columns 2 and 6), (ii) weighted geographical distance between the countries (columns 3 and 7), and (iii) weighted genetic distance between the countries' populations (Spolaore and Wacziarg, 2016, columns 5 and 8).

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

more than just a reallocation of innovation outputs among different R&D labs or inventor groups within the same firm, but the real positive impact of trust on innovation. Table A14 further shows that CEO's trust works largely through the intensive margin, as its impact comes mostly from existing R&D labs and researchers (columns 5 and 6) instead of new ones that arrive with the CEO (columns 7 and 8).

Other potential explanations. Panel B considers different potential confounding factors at CEO-inventor country pair level. As CEOs may differentially favor inventors in their home countries or from the same ethnic groups, I exclude all CEO-inventor country pairs such that the inventor country is the same as the CEO's main home country (columns 1 and 5), or control for the geographical distance between CEO's and inventor's home countries (columns 2 and 6). Bilateral trust is also correlated with cultural proximity, which could directly impact R&D outputs through improving different aspects of the CEO-researcher working relationship (e.g., screening, communication, coordination). To investigate this, I include CEO's-inventors' home countries pairwise linguistic or genetic distances, proxies for their ease of interaction and cultural proximity, in columns (3), (4), (7), and (8) (see Spolaore and Wacziarg, 2016 for details). The CEO's bilateral trust coefficients remain statistically significant across all of these robustness checks in both bilateral trust samples. More importantly, they are similar to Panel A's estimates in magnitude, suggesting that the reported CEO's bilateral trust effect is unlikely driven solely by favoritism, affinity, or similarity along different dimensions.

Table A15 further compares the effects of trust and trustworthiness. In a horse race, the coefficient on $bitrust_{dc}$, the baseline bilateral trust variable measuring CEO d's bilateral trust towards inventors from country c, is large and statistically significant, while the coefficient on $invbitrust_{cd}$, a new variable $invbitrust_{cd}$ that measures inventors from country c's trust towards CEO's,[26] is practically zero (column 3). Alternatively, column (4) estimates the effect of $bitrust_{dc}$ while controlling more flexibly for $invbitrust_{cd}$ using a full set of $invbitrust_{cd}$ decile dummies, and column (5) does the reverse. The resulting coefficients show that among observations with very similar $invbitrust_{cd}$, $bitrust_{dc}$ is still strongly associated with patent outcome (column 4), yet the reverse does not hold (column 5). The evidence thus suggests that it is the CEO's trust toward the inventors that is the main driver of the CEO's trust effect.

[26] $invbitrust_{cd} = \sum_e w_{de} \times ethbitrust_{ce}$ where $ethbitrust_{ce}$ is the bilateral trust measure for how much a person from country of origin c trusts a person from country of origin e.

5 Evidence of mechanism via greater risk taking

To explain the effect of CEO's trust on firm's innovation, subsection 5.1 sets up a model linking trust to innovation through greater tolerance of failure and risk taking. I do not argue that this is the only explanation of the empirical facts presented so far. However, I will discuss how risk taking could be empirically distinguished from alternative mechanisms in which CEO's trust improves the outcomes of all R&D projects in subsection 5.2 and present empirical evidence in support of the risk taking mechanism in subsections 5.3 and 5.4.

5.1 A model of trust, risk taking, and innovation

Set up. My starting point is a two-period principal agent game with asymmetric information, in which the principal is the CEO and the agent is the researcher.

Researcher. The researcher could be of good (bad) type with probability θ $(1-\theta)$. A bad researcher represents one who lacks ability or willingness to take the appropriate courses of actions. The CEO knows neither the researcher's type nor θ. In each period, a bad researcher always shirks and produces s^L, while a good researcher chooses between exploitation and exploration. Exploitation is a low-cost, safe R&D project that requires no effort cost and produces $s^M > s^L$ with certainty. Exploration is a high-cost, risky R&D project that requires effort cost c and produces $s^H > s^M + c$ (innovation) with probability π and s^L (failure) with probability $1-\pi$. π is independently drawn from the uniform distribution on $[0,1]$ in each period and privately observed by the good researcher before choosing which project to pursue. The CEO observes the researcher's output at the end of each period, but not her action.[27]

In this setting, the crucial trade-off between the *exploitation* of well-known approaches and the *exploration* of new untested approaches that could lead to innovation was first emphasized by March (1991), and has since then been widely studied both theoretically and empirically (see survey by Ederer and Manso, 2011).

CEO. The CEO asks the researcher to carry out R&D at the beginning of period 1 without knowing her type. Simultaneously, he decides on an outcome-contingent contract that maps period 1's potential outcome s^i to (b_1^i, D^i), $i \in \{L, M, H\}$, where b^i is a bonus on top of exogenous fixed wage w for the researcher and $D^i \in \{0,1\}$ denotes whether the CEO would fire $(D^i = 0)$ or rehire $(D^i = 1)$ the researcher after period 1. If the researcher is rehired, the game continues to period

[27] The values of s^L, s^M, s^H, c, and π's uniform distribution are common knowledge. π's uniform distribution can be generalized.

2, in which the CEO specifies contract (b_2^i) and the researcher chooses from the same action set as in period 1. The game ends after period 2's outcome and payment are realized. In the baseline model, the CEO can credibly commit to the contract specified at the beginning of each period.[28]

Trust. Although the CEO does not observe θ, he has his own prior subjective belief that the researcher is good with probability θ^P, which reflects his trust towards the researcher. A more trusting CEO has a higher subjective θ^P than a less trusting one. This concept of trust resonates with Gambetta's (1988) definition of trust as "the subjective probability with which an agent assesses that another agent or group of agents will perform a particular action."[29] This model focuses on studying how this key parameter of CEO's trust affects the players' strategies and the game's outcome.[30]

Payoffs and restrictions. After each period $t \in \{1, 2\}$ with realized outcome $i \in \{L, M, H\}$, the researcher gets $w + b_t^i - c$ (if she chooses exploration) or $w + b_t^i$ (otherwise), and the CEO gets $s^i - b_t^i$.[31] If the researcher is fired at the end of period 1, both players' payoffs in period 2 is zero. The researcher has limited liability with $b_t^i \geqslant 0 \ \forall \ i, t$. That is, the CEO can reward the researcher for good performance but cannot punish her financially for bad outcome. I assume that both players are risk neutral and do not discount future payoff. Introducing risk aversion or time discounting does not affect but strengthen the model's key insights. To satisfy the players' participation constraints, I also restrict the parameters such that the CEO's expected payoff from hiring a good researcher is positive.

It then follows that $D^i = 1$ for $i \in \{H, M\}$, as these outcomes fully reveal that the research is the good type. However, if period 1's outcome is L, the CEO cannot tell if the researcher is bad or if she is good but unlucky. His choice of D^L, i.e., whether to tolerate the researcher's failure, depends on his assessment of which is more likely to be the case, and this assessment depends on his prior subjective belief θ^P.

[28]Alternatively, the contract can be designed as a mapping (specified at the beginning of period 1) between each potential outcome of the game (i, j) to (b^{ij}, D^i) where $i, j \in \{L, M, H\}$ denote the game's outcomes in periods 1 and 2 respectively. This set up is equivalent to the baseline set up under the assumption of credible commitment. In addition, appendix E.3 allows for a menu of contracts, leading to the possibility of a separating equilibrium. In the most general case, all qualitative implications of this section's model remain intact.

[29]Similarly, Guiso et al. (2008b) model trust as a subjective belief about being cheated by the counterpart in a financial transaction.

[30]Here θ^P is assumed to be common knowledge. In fact, it does not matter whether the researcher observes θ^P, as long as the CEO can credibly commit to his rehiring policy $\mathbf{D}$. Appendix E.4 considers the case in which the CEO cannot credibly commit. Furthermore, the researcher's trust is irrelevant in this model, a feature that is corroborated by Table A15's empirical result that, in a horse race, CEO's trust matters while researchers' trust does not.

[31]For notation simplicity, s^L, s^M, and s^H represent R&D project's returns after fixed wage payment, so w does not enter the CEO's payoff.

Researcher's project choice: explore versus exploit. I first separately consider $D^L = 1$ and $D^L = 0$. As a bad researcher always shirks and a good researcher's choice in period 2, if it happens, is the same in both cases, the action to which D^L matters is the good researcher's choice between exploitation and exploration in period 1. Appendix E.1 shows that in both cases, the good researcher follows a cutoff strategy and chooses exploration when period 1's drawn probability of success π_1 is above threshold $\bar{\pi}(D^L)$. Given the researcher's strategy, the CEO indirectly chooses $\bar{\pi}(D^L)$ via setting the bonuses to maximize his expected payoff from hiring a good researcher.

Proposition 1 *For a given set of parameters, $\bar{\pi}^*(1) < \bar{\pi}^*(0)$. That is, tolerance of failure induces more exploration and thereby more innovation.*

The proof is detailed in appendix E.1. The intuition is that a good researcher's period-1 exploration threshold $\bar{\pi}^*(.)$ is increasing in how much the good researcher and the CEO would lose in period-2 payoffs when period-1 exploration fails: these potential foregone payoffs are zero when $D^L = 1$ and positive when $D^L = 0$. When failure is not tolerated and termination implies a large loss in future payoff, a good researcher requires higher probability of success to undertake exploration. Similarly, the CEO also prefers a good researcher to take less exploration risk in period 1 for the same fear of losing his future payoff from a relationship with such good researcher when exploration fails. That is, tolerance of failure enables a good researcher to take risk and explore more often, thereby produces more instances of successful innovation.[32] This result resonates with Manso's (2011) theoretical insights and Azoulay et al.'s (2011) and Tian and Wang's (2014) empirical evidence that the optimal incentive scheme to motivate exploration exhibits tolerance for early failure and reward for long-term success.

CEO's tolerance of failure: rehire versus fire. At the beginning of period 1, the CEO chooses to tolerate failure ($D^L = 1$ instead of $D^L = 0$) if it maximizes his total expected payoff.

Proposition 2 *The CEO chooses $D^L = 1$ iff $\theta^P > \bar{\theta}$. That is, he chooses to tolerate failure when his trust towards the researcher is high enough.*

The proof is detailed in appendix E.2. Intuitively, when observing a bad outcome, a more trusting CEO ascribes more weight to the researcher's being unlucky than her being of the bad

[32]Even when a bad researcher is able to produce s^M with some probability q, and so s^H is the only outcome that fully reveals a researcher's type, I still find that a good researcher chooses more exploitation and less exploration under $D = 0$ unless q is very large. Hence the model's key results are unaffected.

type. As the benefits of incentivizing optimal exploration then outweigh the benefits of screening out bad researchers, he chooses to tolerate failure to avoid mistakenly screening out good researchers in period 2, and to induce more exploration by good researchers in period 1.[33]

It follows directly from Propositions 1 and 2 that:

Corollary 3 *A more trusting CEO induces more exploration, thereby more innovation.*

Appendix E.4 further shows that the results in Propositions 1 and 2 do not depend on the assumption of the CEO's ability to commit to the contract. Indeed, in case of lack of commitment, even when $D^L = 1$ *ex ante*, the good researcher may still take too little risk for fear of getting fired *ex post*, and so an overly trusting CEO may better warranty optimal risk-taking by the researcher (i.e., optimal $\theta^P >$ true θ).

5.2 Differentiating risk taking from other mechanisms

Alternative mechanisms. The above model proposes that a CEO's trust in a researcher's being of the good type improves the latter's incentive to undertake high-risk exploration, resulting in more innovation. Yet there exist alternative mechanisms through which CEO's trust could impact firm's innovation. First, trust could lead to greater delegation by the CEO, which induces more effort from the researcher and thereby improves R&D outcomes (Aghion and Tirole, 1997; Acemoglu et al., 2007; Bloom et al., 2012).[34] More loosely interpreted, trust as preference congruence enhances coordination, leading to better overall outcomes. Second, trust, as catalyst for cooperation (Putnam et al., 1993; Fukuyama, 1995), could also have an essential role in sustaining informal relational contracts (Baker et al., 1999, 2002). That is, when the CEO cannot credibly commit to his policies, the researcher is more likely to cooperate and exert effort if she trusts that the CEO will honor the promised rewards for success. (However, this mechanism is inconsistent with Table A15's result that the trust effect is not driven by researchers' trust towards the CEO.)

More importantly, these alternative mechanisms emphasizes the role of trust in inducing greater effort by the researcher, which improves the expected outcome of all R&D projects, thereby increasing *all* types of innovation. On the other hand, greater risk taking affects the type of R&D projects

[33]Longer horizon, however, may strengthen the CEO's incentive to screen out bad researchers in earlier periods of the game. Yet I find that the key intuitions of the baseline setting go through in a three-period game. A high-trust CEO always rehires the researcher; an average-trust CEO tolerates first but not second time failure; and a low-trust CEO fires the researcher after first time failure in period 1. A good researcher chooses less exploration as termination threat increases, again implying that higher CEO's trust induces more exploration and innovation.

[34]Aghion and Tirole (1997) and Acemoglu et al. (2007) highlight that greater preference congruence between the principal and the agent leads to greater delegation by the principal. Bloom et al. (2012) model trust as preference congruence and find that trust is empirically associated with greater decentralization and better firm's performance.

taken by the researcher, which not necessarily increases the number of low-quality patents. It is thus possible to distinguish between greater risk taking and greater effort by examining the patent quality distribution, as formalized below.

Identifying the mechanisms. First, Table A6 reports that higher CEO's trust is not associated with larger R&D expenditure. This suggests that CEO's trust does not impact the number of independent R&D projects run by the firm (denoted N), but rather the types of projects being chosen as in the risk-taking mechanism, or their realized outcomes as in effort-inducing mechanisms.

Let us consider the R&D project quality distribution $F_T(\cdot)$ indexed by CEO's trust T. A project's quality x is observable only when the project is patented, when $x \geq 0$. Let us also assume that better quality patents are always rarer, i.e., $f_T(x)$ is decreasing on $[0, \infty)$ $\forall$ T, guided by the empirical distribution of patent quality as measured by forward citations (Figure A5).

I parameterize this family of distributions as $F_T(x) = F(\frac{x-\mu(T)}{\sigma(T)})$ where $\mu(T)$ represents project quality mean and $\sigma^2(T)$ project quality variance, both are functions of CEO's trust T. The risk-taking mechanism implies that CEO's trust increases patented innovations through $\sigma(T)$, while under alternative effort-inducing mechanisms it works through improving $\mu(T)$.[35] When patenting is sufficiently difficult, so that the average project is not good enough for patenting, higher T implies higher $N\left[1 - F_T(0)\right] = N\left[1 - F(\frac{-\mu(T)}{\sigma(T)})\right]$, or more patents, under both types of mechanisms, hence it is not possible to distinguish between the two just by examining the effect of CEO's trust on total patent count.

The mechanisms, however, differ in their impacts on the number of patents within a specific low quality range $[c_1, c_2]$, as highlighted in the following proposition under the assumption that $f_T(x)$ is decreasing on $[0, \infty)$ $\forall$ T (details in appendix F.1):

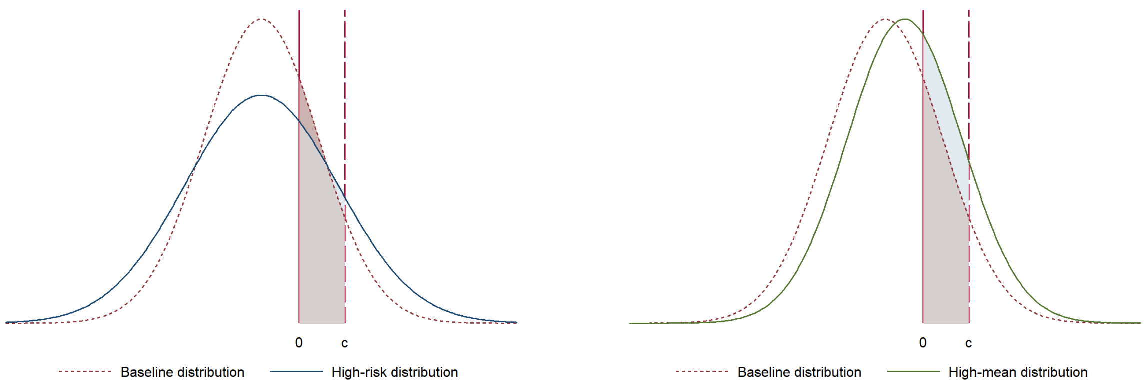
Proposition 4 *Higher $\mu(T)$ increases the number of patents within any quality range $[c_1, c_2] \subset [0, \infty)$. The same is not true for higher $\sigma(T)$.*

That is, any effort-inducing or other mean-shifting mechanism that works through $\mu(T)$ increases not only total patent count but also the number of patents within *any* arbitrary patent quality range, as illustrated by the larger area between $[0, c]$ under the mean-shifted distribution in subfigure 5B. The same prediction does not hold for the risk-taking mechanism that works through $\sigma(T)$ instead. On the contrary, under certain mild conditions, it can be shown that higher $\sigma(T)$

[35]The implicit assumption here is that CEO's trust does not affect the baseline project quality distribution $F(\cdot)$.

decreases the count of patents within the quality range $[c_1, c_2] \subset [0, c]$ for small enough c (details in appendix F.2), as illustrated in subfigure 5A.

Figure 5: Project Quality Distributions under Different Mechanisms



A. Risk-taking mechanism　　　B. Mean-shifting mechanism

Notes: Subfigure A illustrates the spread of project quality distributions under more exploration; subfigure B the rightward shift under greater effort. The dotted red line (both figures) corresponds to the baseline project quality distribution. The solid blue line (top figure) corresponds to the same distribution under high-risk exploration, which is a mean preserving spread of the baseline. The solid green line (bottom figure) corresponds to the same distribution under greater effort, which is rightward shift of the baseline. The solid vertical line at 0 represents the quality threshold above which projects get patented and become observable. The dashed vertical line corresponds to an arbitrary quality threshold c.

These results offer a simple test to identify between the two types of mechanisms by examining the numbers of patents in low quality ranges. Specifically, when one considers patents in brackets of increasing quality, the effects of CEO's trust on the corresponding patent counts increase from negative/zero to positive under the risk-taking mechanism. In contrast, alternative effort-inducing mechanisms predict positive CEO's trust effects on patent counts across different quality brackets.

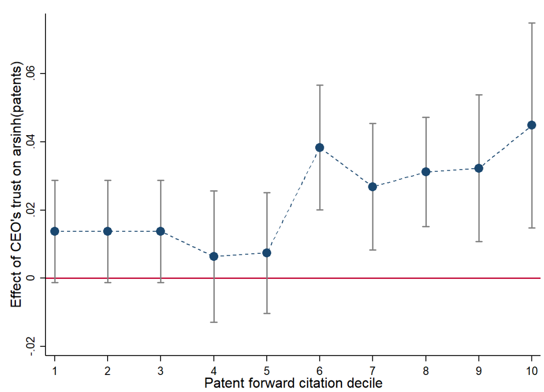
5.3 CEO's trust effect on patent quality distribution

I follow the literature on innovation in measuring patents' quality by their forward citation counts.[36] As forward citations take time to accumulate and vary by technology field, I first compute each patent's citation decile with respect to the universe of patents in its same application technology field-by-year cohort, then sum up the number of patents in each quality decile at the firm-by-year level. The resulting variable pat^q_{ft} counts the number of patents in quality decile q filed by firm f in year t, for $q \in [1, 10]$.

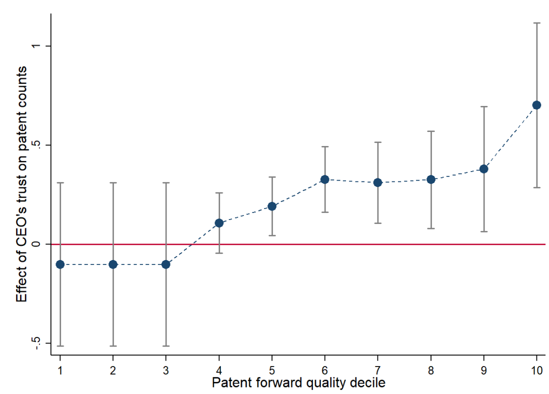
[36] Hall et al. (2005) and Kogan et al. (2017) show that a patent's impact on the firm's market value is highly correlated with its forward citation count. Trajtenberg (1990), Harhoff et al. (1999), and Moser et al. (2015) also find that patent's forward citation count is correlated with patent quality.

Figure 6 plots the CEO's trust effect by patent quality decile, estimated from equation (3) using arsinh(pat^1_{ft}) to arsinh(pat^{10}_{ft}) (subfigure 6A) or winsorized pat^1_{ft} to pat^{10}_{ft} (subfigure 6B) as the outcome variables. The upward-sloping patterns in both subfigures indicate that CEO's trust has larger positive effect on higher-quality patents. In contrast, its effect on patents of below-median quality is not statistically different from zero. Analogous tests at the firm-by-inventor country-by year level using equation (4)'s bilateral trust specification also yield similar results: in both bilateral trust samples, CEO's bilateral trust has the largest effect on patents in the top quality quartile, while its effects on lower-quality-quartile patents are small and statistically insignificant (Table A16).[37] This robust pattern is only consistent with the variance-increasing effect of CEO's trust on the distribution of R&D project quality, and cannot be produced by any mechanism that only shifts the distribution's mean. It thus lends support to risk taking and exploration as the key mechanism at work behind the CEO's trust effect.

Figure 6: CEO's Trust Effect by Patent Quality Decile



A. IHS patent counts



B. Winsorized patent counts

Notes: This figure plots the effects of CEO's trust on firm's patent counts in different quality deciles estimated using equation (3), using as the dependent variable the inverse hyperbolic sine of patent count in subfigure A and winsorized patent count in subfigure B. A patent's quality decile is computed based on its forward citation count with respect to its technology field × year cohort. Estimates are shown with their 95% confidence intervals. Standard errors are clustered by CEO's main ethnicity.

Table A17 provides additional evidence that CEO's trust has larger effect on high-quality patents via estimating this effect on a range of quality-weighted patent counts and average patent quality measures (details in appendix A.2). Most notable is the measure of explorativeness, which considers

[37] As patents are already divided into smaller cells of firm by country by year in this bilateral trust specification, I only further classify them by quality into 4 quartiles instead of 10 deciles. Results from both specifications resonate with Azoulay et al.'s (2011) finding that scientists at Howard Hughes Medical Institute (HHMI) produce high-impact papers at a higher rate than their NIH-funded peers, as HHMI's policies are better at tolerating early failure and rewarding long-term success.

patents with at least 90% of backward citations outside of the firm's existing knowledge stock (e.g., Benner and Tushman, 2002; Brav et al., 2018; Fitzgerald et al., 2019). Columns (1) and (6) of Panel A show that CEO's trust induces disproportionately more explorative patents, leading to improvements in both average citation count per patent (column 7) and average patent value (column 8). These quality increases are consistent with the upward-slopping curves in Figure 6; they are also of sizable magnitude, at 4-6%, statistically significant at 5% level. Panel B reports similar results from the bilateral trust specification, further affirming that CEO's trust increases both the quantity and the quality of innovation, as is expected under more exploration.

5.4 The right amount of trust

Higher trust that leads to more innovation via tolerance of failure, which then induces risk taking and exploration, may not always be optimal. As the model in subsection 5.1 suggests, when tolerance of failure is misplaced, the benefits from encouraging a few good researchers to explore more often could be outweighed by the costs of not screening out many bad ones.[38] This implies that not only would the effect of CEO's trust on firm's innovation decrease with the share of bad researchers in the firm, but CEO's trust could even have negative impacts on firm's performance when it is misplaced.

As data on the complete pool of researchers in each firm are not available, I construct a proxy for past firm-level researcher quality as the residuals from regressing patent count on observable firm and CEO characteristics, controlling for industry and year fixed effects. That is, if there are two firms in the same industry and year with similar observable characteristics, including firm size, R&D scale, and CEO's trust, but different R&D outputs, then this is likely due to the difference in the firms' researcher quality. Using this proxy, Table 3 finds that CEO's trust effects on both patent output (columns 1 and 2) and patent output over R&D expenditure (column 3) significantly increase with the quality of the firm's existing researcher pool, as plotted in Figure A6. Indeed, column (4) reports that CEO's trust has a sizable and statistically significant effect on innovation only among firms whose existing researcher pool quality is in the top two quintiles. Columns (5) to (7) further show that CEO's trust effects on firm's future sales, employment, and total factor productivity also exhibit the same pattern (more details in Table A18). These results thus support the model's implication that trust is most effective at enhancing firm's innovation and performance only when it is well matched to a trustworthy environment. In particular, in a firm with mostly

[38]Analogously, Butler et al.'s (2016) study on the right amount of trust suggests that highly trusting individuals tend to assume too much social risk while individuals with overly pessimistic beliefs can give up profitable opportunities.

low-quality researchers, too much trust by a new CEO can be counterproductive.

Table 3: CEO's Trust Effect by Pre-Transition Researcher Pool Quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Forward:	1 year				2 year		
Dependent variable: Future	**All patents**	**Top qual. patents**	**R&D efficiency**	**All Patents**	**ln(sales)**	**ln(employment)**	**TFP**
CEO's trust	0.066***	0.057***	0.039***		-0.036**	-0.032**	0.006
	(0.018)	(0.015)	(0.013)		(0.017)	(0.013)	(0.013)
Trust × Researcher quality	0.040**	0.039**	0.025**		0.048***	0.034***	0.015
(in pre-transition period)	(0.018)	(0.019)	(0.011)		(0.014)	(0.010)	(0.011)
Trust × Quality quintile 1				0.028			
				(0.042)			
Trust × Quality quintile 2				0.038			
				(0.028)			
Trust × Quality quintile 3				0.065			
				(0.052)			
Trust × Quality quintile 4				0.076**			
				(0.029)			
Trust × Quality quintile 5				0.128***			
				(0.037)			
Firm & Year FEs	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X
Observations	19,506	19,506	19,506	19,506	18,019	17,873	17,238
Events	2,278	2,278	2,278	2,278	2,237	2,224	2,177

Notes: This table explores the heterogeneous effects of CEO's trust on firm's patents by pre-transition researcher pool quality using equation (3) and the sample constructed from CEO transition events (appendix A.5). For each event, I include all firm f × year t × its current CEO d observations that correspond to the predecessor's and successor's terms. The explanatory variable is CEO d's inherited trust measure, standardized by its standard deviation at ethnicity level. Firm-level proxy for researcher pool quality is computed from averaging the residuals from regressing patents on observable firm and CEO characteristics, controlling for 2-digit SIC industry and year fixed effects over the (-1, 0) 2-year pre-transition window. The dependent variables in columns (1) to (4) are the inverse hyperbolic sine of firm f's (i) patent application count (columns 1 and 4), (ii) high-quality (i.e., above median) patent application count (column 2), (iii) and R&D efficiency, calculated as patent application count over lagged R&D expenditure (column 3), in year $t+1$. The dependent variables in columns (5) to (7) are firm f's (i) ln(sales) (column 5), (ii) ln(employment) (column 6), and (iii) TFP computed from value added, employment, and capital following Olley and Pakes (1996) (column 7). Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), arsinh(R&D expenditure), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (4) interacts CEO's trust measure with researcher pool quality quintile dummies (computed based on firm-level proxy for pre-transition researcher pool quality). The remaining columns interact CEO's trust measure with firm-level proxy for pre-transition pool quality. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

5.5 The role of CEO's background and prior exposure

The CEO's knowledge of the R&D process and prior exposure to the firm should influence the effect of trust, understood as a CEO's unconditional prior belief about the quality of the firm's researchers. To investigate this prediction empirically, I estimate how a CEO's education and prior experience affect the CEO's trust effect in Table 4. First, I interact CEO's trust with dummies

Table 4: CEO's Trust Effect and Prior Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**arsinh(Future patent applications)**						
CEO's background:	Education			Experience		First generation	
D variable:	Postgrad. degree	Doctorate degree	Non-MBA P.G. degree	Prior R&D experience	Above 3 yrs in firm	Born/educated abroad	Born abroad
A: Trust × D = 0	0.082***	0.072***	0.092***	0.064***	0.077***	0.059***	0.058***
	(0.019)	(0.016)	(0.023)	(0.017)	0.025)	(0.022)	(0.021)
B: Trust × D = 1	0.052**	0.017	-0.004	0.007	0.054**	0.115*	0.274***
	(0.025)	(0.059)	(0.038)	(0.130)	(0.025)	(0.059)	(0.085)
Difference: B - A	-0.030	-0.056	-0.096*	-0.057	-0.024	0.056	0.216**
	(0.029)	(0.058)	(0.049)	(0.120)	(0.032)	(0.066)	(0.090)
Firm & Year FEs	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598	3,598	3,598

Notes: This table explores the heterogeneous effects of CEO's trust on firm's patents by CEO's background using equation (3). Baseline sample includes all observations of firm f × year t × its current CEO d. The dependent variable is the inverse hyperbolic sine of firm f's patent application count in year $t+1$. The explanatory variable is CEO d's inherited trust measure, standardized by its standard deviation at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies (excluded in columns 1 to 3), tenure in firm (excluded in column 5). Each column interacts CEO's trust measure with a dummy indicating if (i) he has a masters or doctorate degree (column 1), (ii) he has a doctorate degree (column 2), (iii) he has a non-MBA masters or a doctorate degree (column 3), (iv) he has prior R&D experience (column 4), (v) he has been in firm f for more than three years (column 5), (vi) he was born or educated abroad (column 6), or (vii) he was born abroad (column 7). Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

indicating if the CEO has at least a master degree (column 1), a doctorate (column 2), and a postgraduate degree that is not an MBA (column 3). Columns (1) and (2)'s coefficients suggest that CEO's trust effect is halved if the CEO has some postgraduate education and eliminated if the CEO has a doctorate. Most interestingly, the difference is largest in magnitude and statistically significant in column (3), suggesting that it is technical knowledge that reduces the effect of trust. Similarly, columns (4) and (5) report smaller or zero CEO's trust effect among CEOs with prior experience in R&D (column 4) or in the firm (column 5). This pattern is consistent with Figure A7, which shows a slight declining trend in CEO's trust coefficients over the CEO's tenure in the firm. These results imply that trust is a substitute for knowledge of R&D processes and that prior belief becomes less important with exposure and experience.[39]

Finally, the last two columns compare between CEOs who were born and/or education abroad and those likely US-born and/or educated, based on data from Marquis Who's Who and BoardEx

[39]Similarly, in the context of cross-country venture capital, Bottazzi et al. (2016) find that education and work experience reduce the effect of bilateral trust on investment.

(details in appendix A.3). As expected, the CEO's trust coefficients are considerably larger among CEOs who are first-generation immigrants to the US, for whom ethnic-specific inherited trust is likely a more significant component of their individual trust.

6 Transmission of trust within the firm

How does a CEO's trust affect researchers' behaviors if they do not directly interact, especially in a large public firm? It is likely that this phenomenon is enabled both by the CEO's direct influence on firm's policies, which can be observed and even anticipated by researchers, and by the transmission of the CEO's beliefs and preferences through the firm's organizational layers.[40] This subsection reports evidence of this transmission of CEO's trust within the firm.

6.1 Evidence of effect on corporate trust culture

To measure firm's trust attitude, I use Sull's (2018) dataset of employee sentiments that covers over 500 US large public firms. The dataset is constructed from the text analysis of close to one million online employee reviews on Glassdoor.com, one of the largest career intelligence sites worldwide, between 2008 and 2017. It covers a large set of topics related to O'Reilly et al.'s (1991, 2014) 7 dimensions of corporate culture and contains the number of instances each topic appears in a review with positive or negative sentiment. I am most interested in the topic that measures the extent to which employees trust one another, which for ease of exposition I will call *corporate trust culture*. (See appendix A.4 for further details.)

I extend my firm and CEO data to 2016 and match them with review-level sentiment data by firm and year. I then aggregate individual employee's trust sentiment by CEO term and standardize the resulting corporate trust culture measure by its standard deviation. This yields a final sample of 394 observations at firm-by-CEO term level, covering 276 firms, in Table 5. To examine the relationship between CEO's trust and corporate trust culture, I regress this corporate trust culture measure on CEO's inherited trust, controlling for period-average firm's and CEO's characteristics and 3-digit SIC industry fixed effects (columns 2 to 4) or even firm fixed effects (columns 5 to 7). The coefficients report a strong positive association between CEO's trust and corporate trust culture that is not driven by firm's time-invariant characteristics, CEO's approval rate, or CEO's other cultural traits. That is, not only within the same industry but also within the same firm,

[40]Relatedly, González-Uribe and Groen-Xu (2017) also find that longer CEO employment contract is associated with more patenting in a sample of US public firms, which suggests that CEOs can influence innovation activities even in firms where they are hierarchically distant from the inventors.

corporate trust culture is stronger under a more trusting CEO. I further find that this within-firm effect (i) builds up from the very start of the CEO term and peaks after around 4 to 6 years, and (ii) is particularly pronounced among the firm's researchers and managers, suggesting a possible mechanism of transmission of trust via manager selection.

Table 5: CEO's Trust and Corporate Trust Culture

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:				**Corporate trust culture**			
CEO's trust	0.219**	0.208**	0.252***	0.258**	0.387*	0.407*	0.397*
	(0.093)	(0.093)	(0.091)	(0.111)	(0.226)	(0.225)	(0.203)
CEO approval (share)			1.589***	1.525***		1.061	1.024
			(0.534)	(0.540)		(1.058)	(1.057)
High-income share (z-score)				0.119			0.023
				(0.183)			(0.291)
Work ethic (z-score)				-0.033			0.172
				(0.053)			(0.178)
Risk preference (z-score)				-0.139			-0.226
				(0.198)			(0.238)
Patience (z-score)				0.026			0.055
				(0.106)			(0.220)
Industry (SIC3) FEs	X	X	X	X			
Baseline controls		X	X	X	X	X	X
Firm FEs					X	X	X
Observations	394	394	394	394	394	394	394
Firms	276	276	276	276	276	276	276
Industries (SIC3)	89	89	89	89	89	89	89

Notes: This table presents the effect of CEO's trust on measures of corporate culture computed from online employee reviews (Sull, 2018). Sample includes all firm f × CEO d observations over the 2008-2017 period. The dependent variable measures firm f's corporate trust culture (i.e., the extent to which employees trust one another) during CEO d's term. The explanatory variable is CEO d's inherited trust measure, standardized by its standard deviation at ethnicity level. Baseline controls include (i) firm's average age, average age squared, ln(average total assets), ln(average sales), and (ii) CEO's average age, average age squared, gender, education dummies, average tenure in firm (controls are averaged over CEO d's term in firm f). CEO approval rate is computed from online employee reviews. Additional controls for CEO's other cultural traits are as explained in Table A11's notes. Standard errors are clustered by 3-digit SIC industry.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

6.2 Transmission via director selection

Table 6 further suggests that such transmission of trust may be reinforced by the selection of directors. Column (7) shows that the average inherited trust measure among firm's directors improves under a more trusting CEO. This is driven by the facts that both (i) new directors being hired under a more trusting CEO are also more trusting (columns 1 and 4), especially those remaining until the end of the CEO's tenure (columns 2 and 5), and (ii) directors leaving the board under this more trusting CEO are the less trusting ones (columns 3 and 6). These findings resonate with Van den Steen's (2010) theory that screening, self-sorting, and manager-directed learning is the source corporate culture, understood as shared beliefs and values in an organization, and Graham et al.'s (2018) survey-based insight that corporate culture is primarily set by the current CEO. Taken together, Tables 5 and 6 show suggestive evidence that CEO's trust has non-negligible impacts on firm's organization and culture.

Table 6: CEO's Trust and Director Selection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**Individual director's trust**			**Average directors' trust**			
Sample:	New dirs.	Staying dirs.	Leaving dirs.	New dirs.	Staying dirs.	Leaving dirs.	All dirs.
CEO's trust	0.029*	0.037**	-0.047*	0.041**	0.053***	-0.044	0.009**
	0.016)	(0.016)	(0.025)	(0.017)	(0.019)	(0.032)	(0.004)
Observation unit	Director × firm × year × CEO			Firm × year × CEO			
Firm & Year FEs	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X
Observations	17,218	14,428	10,752	10,430	9,293	7,756	29,266
Firms	3,363	3,347	2,862	3,363	3,347	2,862	3,555

Notes: This table reports the association between CEO's trust and directors' trust. Columns (1) to (3): Samples include observations of director r × firm f × year t × its current CEO d over the baseline 2000-2011 period, separately for newly appointed directors (i.e., new directors, column 1), newly appointed directors who stay on the board until the end of the CEO's term (i.e., staying directors, column 2), and directors who leave the board the following year and before the end of the CEO's term (i.e., leaving directors, column 3). The dependent variable is director r's inherited trust measure. Columns (4) to (7): Samples include observations of firm f × year t × its current CEO d. The dependent variable is the average inherited trust measure of all new directors (column 4), all staying directors (column 5), all leaving directors (column 6), and all directors (column 7). Directors who ever serve as the firm's CEO are always excluded. The explanatory variable is CEO d's inherited trust measure. Baseline controls include (i) CEO's age, age squared, gender, education dummies, tenure in firm, and (ii) firm's age, age squared. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

6.3 Qualitative insights on CEO's practice

It is a challenge to understand deeply how CEOs influence innovation processes within the firm via the management of researchers, as it is usually infeasible to obtain large-scale quantitative data on top managers' practices. One relevant attempt is *McKinsey & Company*'s qualitative, open-end survey on leadership that covers 1,458 executives around the world, half of whom are at the senior vice president level or above. The key insights are summarized by Barsh et al. (2007, 2008).[41]

First, the shared insights from many managers echo support for my model's assumptions. The leadership team are often directly involved in personnel decisions regarding innovation, and other big-picture decisions, but do not "have a lot of control over the innovation process," especially in

[41]The survey data are not available to outsiders of *McKinsey & Company*. Another survey on CEO's time use and practices, used by Bandiera et al. (2020), cannot be linked to data on trust.

measuring efforts towards innovation. Similar to my model's setting, while the leadership actively picks and retains innovators, their actions and efforts cannot be observed or monitored. Indeed, regarding personnel decisions, there is a broad range of variation as the model predicts: innovators are only "protected" in about a third to a half of the surveyed firms, and across firms tolerance of failure in innovation varies greatly, with failure in innovation ranging from an opportunity to learn to a significant threat to one's career.

Second, top managers' views on processes that can improve innovation performance also corroborate this paper's insights. The second most agreed-upon answer is about promoting risk taking that encourages innovation. Shortermism and fear of failure are also ranked among the top of inhibitors of innovation. Furthermore, almost all respondents agree that people and corporate culture are the most important determinants of innovation: top managers' top worry is about not having the right talent, and employees are most concerned about firm's culture. In that regard, trust and engagement are seen as the most important for a strong performance in innovation.

To summarize the qualitative insights from the survey, Barsh et al. (2008) recommend fostering an "innovation culture based on trust," in which people trust that it is safe to pursue risky ideas and paths. To put differently, trust is considered an important driver of corporate innovation by corporate leaders.

7 Concluding remarks

Let us recall a well-known tale among generations of employees at IBM, one of the most innovative corporations in the 20$^{\text{th}}$ century that has relied on its culture of tolerance of failure to encourage exploration and innovation. Thomas Watson Sr., IBM's founder, was once discussing a ten million dollar mistake one of his executives had just made. "I guess you want my resignation," said the executive. Watson replied, "You can't be serious. We have just spent ten million dollars educating you."[42] The anecdote highlights this paper's message on the role of such trusting CEOs in inculcating a corporate culture of tolerance of failure, which can lead to more innovation.

More generally, this paper provides a broad range of empirical evidence on the effect of CEO's trust on firm's innovation, measured by patent quantity and quality. I measure a CEO's inherited trust based on his ethnic origins as inferred from his last name. Using within-firm changes in CEOs, I find that one standard deviation increase in CEO's generalized trust is associated with over 6% increase in annual patent counts and 4-6% increase in average patent quality or value. I further use

[42]The anecdote is recounted in Ederer and Manso (2013), based on Bennis and Nanus (1997).

CEO's bilateral trust towards researchers in or from different countries to show that this increase is generated by inventors towards whom the CEO's bilateral trust is stronger, in a specification that controls for firm-by-year, CEO, and inventor country fixed effects. Given the presence of stringent fixed effects and rigorous controls, these findings are unlikely driven by confounding factors such as CEO's country of origin or individual characteristics.

These empirical findings are best understood in a simple principal-agent model of exploration versus exploitation with unobserved researcher's type, in which the CEO's trust encourages a good researcher to undertake high-risk explorative R&D through his tolerance of failure. The model further predicts that (i) CEO trust's effect on innovation is driven by high-quality patents, and (ii) this effect is larger among firms with better researcher quality, both of which are confirmed in the data. I also find that CEO's inherited trust robustly predicts corporate trust culture, even after controlling for firm fixed effects, in a sample of close to 400 major US firms for which measures of corporate culture are constructed from text analysis of online employee reviews.

The paper's results fit in a crucial gap in the recent literature on long-term development and trust, in showing micro-evidence of how trust may affect innovation, the indispensable determinant of productivity growth in the long run. The paper also broadens our understanding of the impact of CEO's traits and styles on firm's decisions, performance, and culture. For corporate policy implications, the paper stresses the important role of trust building from the top down by picking trustful CEOs with the right amount of trust (Butler et al., 2016). Its finding should not be interpreted as suggestions to consider CEOs based on ethnic origins, as within-ethnicity variation in individual trust far outweighs that between ethnicities.

The current set of results still leave out a few important questions to future work. First, it is important to understand in details how tolerance of failure is implemented within a firm's organization. Second, in which contexts is excessive trust conducive to suboptimal innovation and performance? Third, it would be interesting to further examine the trust effect's implications on the sorting of researchers across firms.

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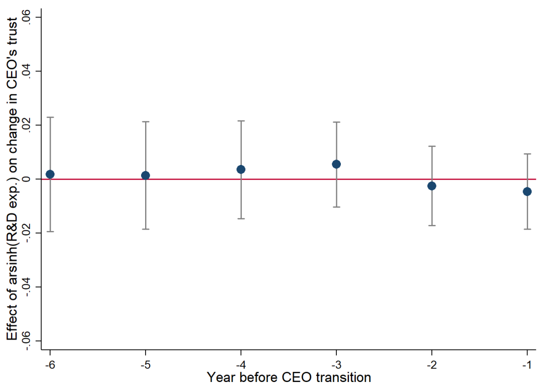
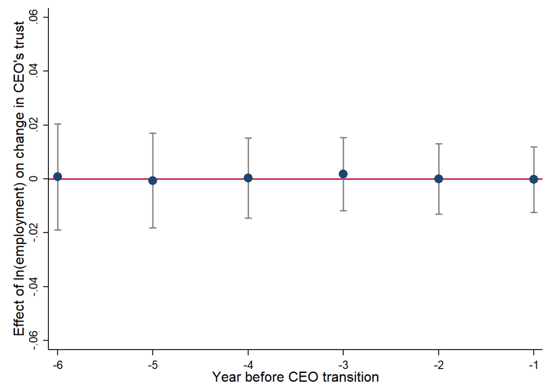
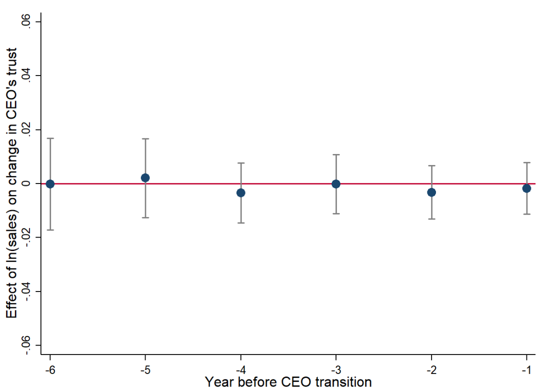
Figure A1: Pre-Change Firm Performance and Change in CEO's Trust



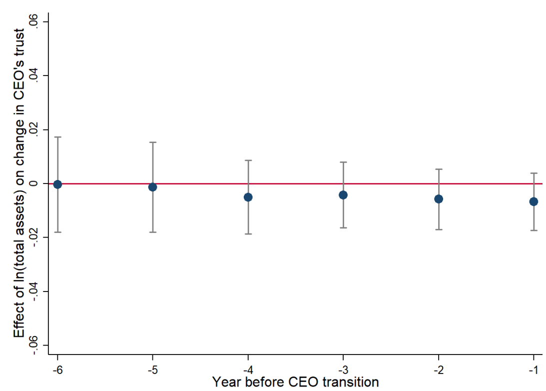
A. Common trend in R&D expenditure



B. Common trend in employment



C. Common trend in sales



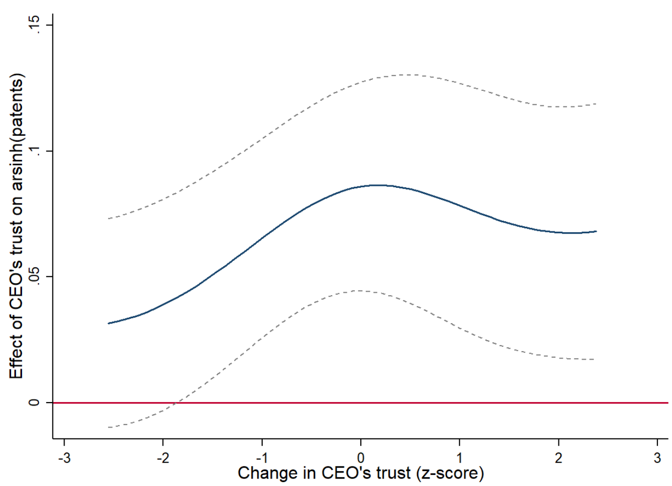
D. Common trend in total assets

Notes: This figure plots the coefficients from regressing the change in CEO's trust in each CEO transition event on firm's characteristics and performance measures in different years before the transition, controlling for pre-change firm's and CEO's characteristics (equation A2, details in appendix C.1). These measures are arsinh(R&D expenditure) in subfigure A, ln(employment) in subfigure B, ln(sales) in subfigure C, and ln(total assets) in subfigure D. Estimates are shown with their 95% confidence intervals.

Figure A2: Patents by Change in CEO's Trust (Non-Matched Sample)

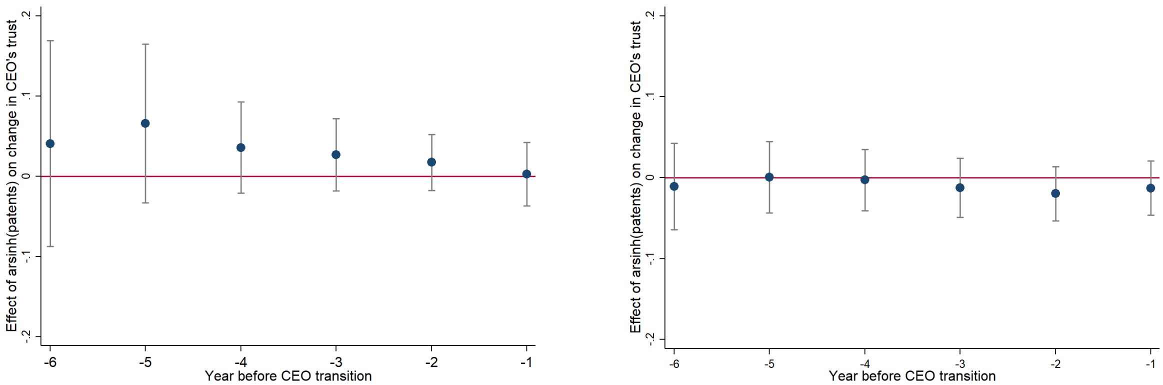
Notes: This figure plots firms' average residual patent application count (after partialling out (i) firm and CEO controls, and (ii) firm's 3-digit SIC industry and year fixed effects) by year with respect to CEO transition year (i.e., year 0). The sample includes CEO transitions in which both predecessor's and successor's tenures are at least 5 years. The solid blue line groups together all CEO transitions in which the new CEOs are *more* trusting than their predecessors (i.e., trust-increasing transitions), and the dotted red line corresponds to those in which the new CEOs are *less* trusting (i.e.,trust-decreasing transitions). Each group's annual average residual patent counts are plotted relative to the group's pre-transition mean, which is normalized to 0.

Figure A3: CEO's Trust Effect by Change in CEO's Trust



Notes: This figure plots semi-parametric estimates of the effect of CEO's trust on firm's patents as a function of the change in CEO's trust after the corresponding transition (i.e., $\Delta trust_E$, the X-axis variable), namely $\frac{\partial \text{arsinh}(pat_{f,t+1})}{\partial trust_d}(\Delta trust_E)$. The point estimate at each value of $\Delta trust_E$ is obtained from the baseline regression in equation (3), weighted by a Gaussian kernel function of $\Delta trust_E$ around that particular value with a bandwidth equal to 20% of the range of $\Delta trust_E$ (details in appendix C.3). Standard errors are clustered by CEO's main ethnicity. The dashed lines indicate the 95% confidence intervals for the CEO's trust coefficients.

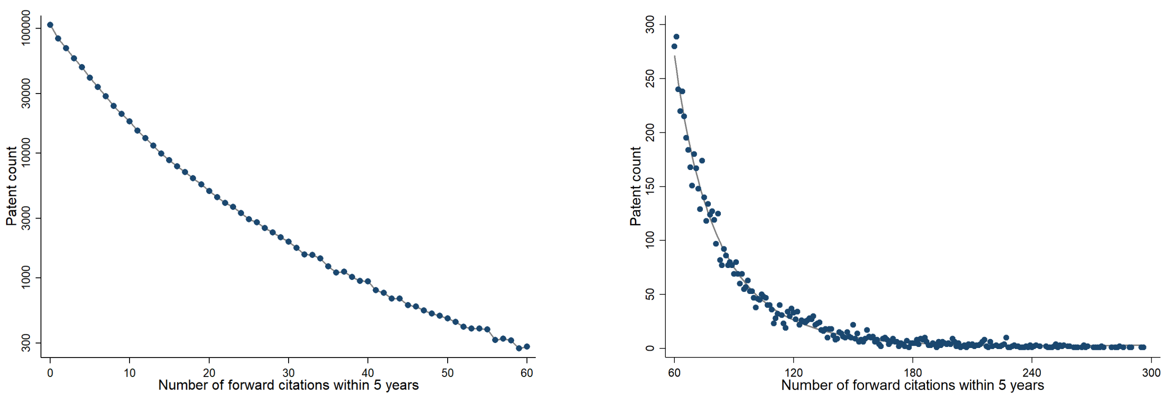
Figure A4: Pre-Change Patents and Change in CEO's Bilateral Trust



A. Non-US-based inventors B. All inventors

Notes: This figure plots the coefficients from regressing the change in CEO's bilateral trust towards inventors in or from a certain country, following a CEO transition, on patent application counts by those inventors in different years before the transition, controlling for pre-change firm's and CEO's characteristics (equation A3, details in appendix C.1). Subfigure A corresponds to the bilateral trust sample in which an inventor's country is inferred from his patent-listed address for non-US-based inventors. Subfigure B corresponds to the bilateral trust sample in which an inventor's country is additionally inferred from his last name for US-based inventors. Estimates are shown with their 95% confidence intervals.

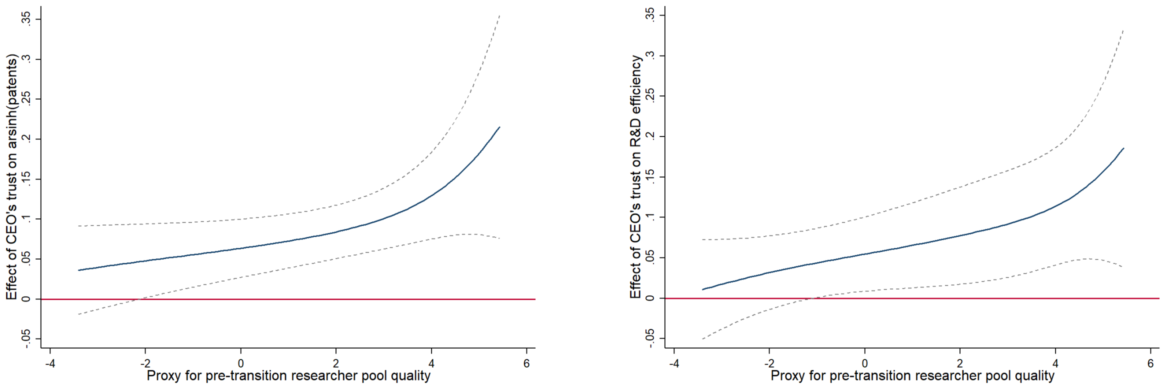
Figure A5: Distribution of Patent's Forward Citation Count



A. 0^{th}-99^{th} percentile B. 99^{th}-99.99^{th} percentile

Notes: This figure plots the number of patents by their 5-year forward citation counts among 679,000 patent families filed during 2000-2012 by firms in the baseline sample. Subfigure A covers 672,000 patents in the 0^{th}-99^{th} percentile of 5-year forward citation count, using log scale for the Y axis. Subfigure B covers 7,000 patents in the 99^{th}-99.99^{th} percentile of 5-year forward citation count.

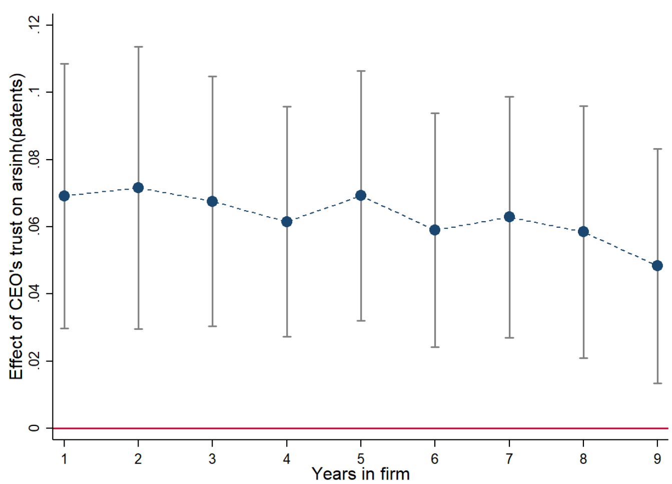
Figure A6: CEO's Trust Effect by Pre-Transition Researcher Pool Quality



A. Effect on patents B. Effect on R&D efficiency

Notes: This figure plots semi-parametric estimates of the effect of CEO's trust on firm's patents as a function of pre-transition researcher pool quality ($prequal_E$, the X-axis variable). Proxy for $prequal_E$ is computed from the residuals from regressing patents on observable firm and CEO characteristics, controlling for 2-digit SIC industry and year fixed effects (subsection 5.4) over the (-1, 0) 2-year pre-transition window. The point estimate at each value of $prequal_E$ is obtained from the baseline regression in equation (3), weighted by a Gaussian kernel function of $prequal_E$ around that particular value with a bandwidth equal to 20% of the range of $prequal_E$ (details in appendix C.3). Standard errors are clustered by CEO's main ethnicity. Subfigure A reports CEO's trust effect on firm's future patents, namely $\frac{\partial \text{arsinh}(pat_{f,t+1})}{\partial trust_d}(prequal_E)$. Subfigure B reports CEO's trust effect on firm's future R&D efficiency, namely $\frac{\partial \text{arsinh}(rdprod_{fd,t+1})}{\partial trust_d}(prequal_E)$, in which $rdprod_{fd,t+1}$ is calculated as patent application count in year $t+1$ over lagged R&D expenditure in year t. The dashed lines indicate the 95% confidence intervals for the CEO's trust coefficients.

Figure A7: CEO's Trust Effect by Tenure in Firm



Notes: This figure plots the effect of CEO's trust on firm's patents by the CEO's tenure in the firm, estimated using equation (A6) (details in appendix C.4). Estimates are shown with their 95% confidence intervals.

Table A1: GSS Inherited Trust Measure by Ethnic Origin

Rank	Ethnic origin	Trust measure	Rank	Ethnic origin	Trust measure
1	Belgium	0.727	19	Japan	0.500
2	Sweden	0.629	20	Romania	0.500
3	Switzerland	0.622	21	India	0.494
4	Norway	0.619	22	Arabic	0.478
5	Denmark	0.603	23	Other Asian	0.478
6	Canada	0.600	24	Italy	0.470
7	England and Wales	0.593	25	China	0.468
8	Hungary	0.587	26	Greece	0.467
9	Lithuania	0.577	27	Austria	0.465
10	Ireland	0.565	28	Spain	0.423
11	Russia and former USSR	0.565	29	Finland	0.419
12	Scotland	0.553	30	Portugal	0.368
13	Germany	0.553	31	Mexico	0.368
14	Netherlands	0.551	32	Philippines	0.356
15	Czechslovakia	0.551	33	West Indies (Hispanic)	0.353
16	Yugoslavia	0.533	34	Africa	0.265
17	France	0.529	35	Other Spanish	0.246
18	Poland	0.523	36	West Indies (non-Hispanic)	0.200

Notes: This table reports inherited trust measure by ethnic origin, $ethtrust_e$, computed as the average trust attitude (0 – low trusting, 1 – high trusting) of GSS respondents whose (i) self-reported ethnic origin is e and (ii) GSS occupation prestige score is at least 50 (subsection 2.2). The standard deviation of this inherited trust measure at ethnicity level is 0.115.

Table A2: GSS Ethnic Origins of CEOs

Baseline sample			Name-matched sample		
Rank	Ethnic origin	Share of CEOs	Rank	Ethnic origin	Share of CEOs
1	Ireland	19.5%	1	Ireland	18.8%
2	Germany	18.7%	2	Germany	18.0%
3	England and Wales	16.6%	3	England and Wales	17.2%
4	Canada	10.0%	4	Canada	10.1%
5	Russia and former USSR	8.1%	5	Russia and former USSR	8.3%
6	Italy	6.7%	6	Italy	6.6%
7	Scotland	3.3%	7	Scotland	3.2%
8	Sweden	2.7%	8	Sweden	2.6%
9	Poland	2.2%	9	Poland	2.2%
10	Austria	1.6%	10	Australia	1.6%
11	Norway	1.6%	11	Norway	1.5%
12	China	1.2%	12	China	1.1%
13	Mexico	0.9%	13	Mexico	0.9%
14	India	0.7%	14	India	0.9%
15	Netherlands	0.7%	15	Netherlands	0.8%
16	Denmark	0.7%	16	Denmark	0.7%
17	Czechslovakia	0.6%	17	Czechslovakia	0.6%
18	Hungary	0.5%	18	Hungary	0.5%
	N = 5,753			N = 7,027	

Notes: This table reports the distribution of CEOs' ethnic origins as inferred from their last names (subsection 2.2) for (i) 5,753 CEOs in the baseline sample, and (ii) 7,027 name-matched CEOs.

Table A3: Baseline Sample's Descriptive Statistics

Panel A. CEO's characteristics

Sample:	**Baseline**		**Name-matched**		**Unmatched**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Inherited generalized trust (baseline)	0.56	(0.04)	0.56	(0.04)	-	-
Inherited generalized trust (LASSO)	0.55	(0.09)	0.55	(0.09)	-	-
Inherited generalized trust (full GSS)	0.45	(0.04)	0.45	(0.04)	-	-
Gender (1 – male, 0 – female)	0.97	(0.18)	0.97	(0.17)	0.98	(0.15)
CEO's age in 2000	48.2	(9.1)	48.6	(9.3)	48.1	(9.12)
Highest degree: Bachelor	0.37	(0.48)	0.36	(0.48)	0.34	(0.47)
Highest degree: Masters	0.43	(0.49)	0.43	(0.49)	0.42	(0.49)
Highest degree: Doctor	0.18	(0.38)	0.18	(0.38)	0.21	(0.41)
Has MBA degree	0.34	(0.48)	0.34	(0.47)	0.35	(0.48)
Has non-MBA postgrad degree	0.28	(0.45)	0.29	(0.45)	0.31	(0.46)
Has prior R&D experience	0.02	(0.14)	0.02	(0.13)	0.02	(0.14)
Age when becoming CEO	50.1	(8.5)	50.3	(8.7)	49.9	(8.9)
Prior tenure in firm (yrs)	6.44	(8.18)	6.59	(8.36)	6.70	(8.57)
Tenure as CEO (yrs)	7.23	(6.14)	7.23	(6.32)	7.22	(6.11)
# CEOs	5,753		7,027		1,466	

Panel B. Firm's characteristics

Sample:	**Baseline**		**Name-matched**		**Unmatched**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Patent applications p.a.	18.0	(149.7)	15.9	(138.8)	5.2	(25.2)
arsinh(patent applications)	1.00	(1.62)	0.93	(1.56)	0.86	(1.36)
Citation-weighted patents p.a.	202.9	(1,953)	176.1	(1,764)	59.7	(230.5)
arsinh(citation-weighted patents)	1.72	(2.56)	1.61	(2.49)	1.55	(2.34)
Firm's age in 2000	11.3	(15.4)	12.1	(15.2)	8.7	(13.7)
# years in sample	7.5	(3.6)	9.5	(3.1)	8.4	(3.8)
# CEOs in sample	1.68	(0.88)	2.13	(1.13)	1.17	(0.41)
# matched CEOs in sample	1.68	(0.88)	1.85	(1.00)	0.00	(0.00)
Is R&D performing firm	0.60	(0.49)	0.59	(0.49)	0.63	(0.48)
Is patenting firm	0.55	(0.50)	0.57	(0.49)	0.55	(0.50)
Total assets p.a. ($mil)	3,472	(14,957)	3,460	(19,541)	1,676	(9,198)
Total sales p.a. ($mil)	2,924	(12,765)	2,824	(13,163)	2,179	(12,373)
Employment p.a. ('000)	10.76	(51.72)	9.94	(46.68)	5.20	(15.10)
R&D stock p.a. ($mil)	297.1	(2,003)	272.5	(1,895)	82.0	(271.4)
R&D expenditure p.a. ($mil)	71.9	(466.4)	66.1	(442.8)	23.7	(90.6)
# Firms	3,598		4,000		345	

Notes: **Panel A** reports the descriptive statistics of CEO's characteristics for (i) 5,753 CEOs in the baseline sample, (ii) 7,027 name-matched CEOs, and (iii) 1,466 unmatched CEOs. **Panel B** reports the descriptive statistics of firm's characteristics for (i) 3,598 firms in the baseline sample (considering only firm × year observations that correspond to name-matched CEOs), (ii) 4,000 firms having at least one name-matched CEOs (considering all firm × year observations in the study period), and (iii) 345 firms having no name-matched CEO. Inherited generalized trust measure ranges from 0 – low trusting to 1 – high trusting. p.a. stands for per annum.

Table A4: Bilateral Trust Samples' Descriptive Statistics

Panel A. CEO's characteristics

Sample:	Non-US-based inventors		All inventors	
# associated inventor countries	4.8	(5.2)	6.8	(6.1)
Bilateral trust (towards inventor country)	2.69	(0.31)	2.67	(0.32)
Inherited generalized trust (baseline)	0.55	(0.04)	0.55	(0.04)
Gender (1 – male, 0 – female)	0.97	(0.16)	0.97	(0.16)
CEO's age in 2000	48.4	(8.8)	48.3	(8.8)
Highest degree: Bachelor	0.35	(0.48)	0.36	(0.48)
Highest degree: Masters	0.45	(0.50)	0.44	(0.50)
Highest degree: Doctor	0.19	(0.39)	0.18	(0.38)
Has MBA degree	0.37	(0.48)	0.37	(0.48)
Has non-MBA postgrad degree	0.29	(0.45)	0.28	(0.45)
Has prior R&D experience	0.03	(0.16)	0.02	(0.15)
# CEOs	960		1,654	

Panel B. Firm's characteristics

Sample:	Non-US-based inventors		All inventors	
# associated inventor countries	4.8	(5.1)	6.8	(6.1)
Patent applications p.c. p.a.	1.5	(10.7)	3.0	(21.3)
arsinh(patent applications)	0.39	(0.85)	0.68	(1.03)
Citation-weighted patents p.c. p.a.	11.9	(69.9)	30.5	(222.5)
arsinh(citation-weighted patents)	0.86	(1.59)	1.59	(1.90)
Firm's age in 2000	14.0	(16.6)	12.6	(15.7)
# years in sample	6.4	(3.7)	6.4	(3.7)
# CEOs in sample	1.4	(0.6)	1.4	(0.6)
Total assets p.a. ($mil)	4,840	(20,729)	3,983	(17,037)
Total sales p.a. ($mil)	3,960	(12,921)	3,294	(11,490)
Employment p.a. ('000)	12.4	(36.8)	10.7	(35.0)
R&D stock p.a. ($mil)	803.3	(3,234)	479.3	(2,491)
R&D expenditure p.a. ($mil)	189.1	(735.4)	113.4	(567.0)
# Firms	730		1,263	

Notes: This table reports the descriptive statistics of CEO's and firms' characteristics for (i) CEOs and firms in the bilateral trust sample based on inventors' patent-listed non-US addresses, and (ii) CEOs and firms in the bilateral trust sample based on inventors' addresses (for non-US based inventors) or last names (for US-based inventors). Bilateral trust measure ranges from 1 – least trusting to 4 – most trusting. Inherited generalized trust measure ranges from 0 – low trusting to 1 – high trusting. p.c. stands for per country; p.a. stands for per annum.

Table A5: Average Patents Before and After CEO Transitions

Variable:	Average residual arsinh(patents)		
Sample:	Before transition	After transition	Difference
Trust-increasing CEO transitions	-0.146	-0.012	0.135*
	(0.056)	(0.052)	(0.076)
Trust-decreasing CEO transitions	-0.088	-0.216	-0.128*
	(0.053)	(0.051)	(0.073)
Difference	-0.058	0.204***	0.262**
	(0.077)	(0.073)	(0.106)

Notes: This table reports the average residual patent application count (after partialling out (i) firm and CEO controls, and (ii) firm's 3-digit SIC industry and year fixed effects) in the 5 years before and after CEO transitions, separately for trust-increasing and trust-decreasing transitions as described in Figure 3's notes. There are 61 trust-increasing CEO transitions, each of which is matched to a trust-decreasing CEO transition based on their average pre-transition residual patent counts (resulting in a total of 44 unique matched trust-decreasing CEO transitions). Pre-transition period covers years -5 to 0; post-transition period covers years 1 to 5.

Table A6: Effect of CEO's Trust on R&D

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	arsinh(R&D expenditure)			arsinh(R&D stock)		
Forward :	0 year	1 year	2 year	0 year	1 year	2 year
CEO's trust	0.028	0.018	0.020	-0.014	0.001	0.018
	(0.032)	(0.027)	(0.029)	(0.019)	(0.018)	(0.019)
Firm & Year FEs	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X
Observations	29,384	28,125	26,710	29,384	28,125	26,710
Firms	3,598	3,558	3,487	3,598	3,558	3,487

Notes: This table reports the baseline effect of CEO's inherited trust on R&D expenditure and stock using equation (3). Baseline sample includes all observations of firm f × year t × its current CEO d. The dependent variable is the inverse hyperbolic sine of firm f's R&D expenditure or stock in year $t + k$ for $k \in [1, 3]$. The explanatory variable is CEO d's inherited trust measure, standardized by its standard deviation at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A7: Robustness Checks for CEO's Trust Effect on Firm's Patents

Panel A. Alternative control variables and Poisson model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**Future patent applications**						
Transformation:	arsinh(.)						win.
Specification:	No controls		Baseline	Additional controls			Poisson
CEO's trust	0.059***	0.063***	0.063***	0.066***	0.063***	0.060***	0.168***
	(0.018)	(0.017)	(0.019)	(0.019)	(0.019)	(0.018)	(0.069)
ln(employment)				0.101***			
				(0.012)			
arsinh(R&D stock)					0.015*		
					(0.008)		
arsinh(R&D exp.)						0.092****	
						(0.011)	
Firm & Year FEs	X	X	X	X	X	X	X
CEO controls		X	X	X	X	X	X
Firm controls			X	X	X	X	X
Observations	29,384	29,384	29,384	28,506	29,384	29,384	17,536
Firms	3,598	3,598	3,598	3,548	3,598	3,598	1,915

Notes: This table reports the robustness checks for the baseline effect of CEO's inherited trust on firm's patents using equation (3). In the baseline specification, (i) the sample includes all observations of firm f × year t × its current CEO d; (ii) the dependent variable is the inverse hyperbolic sine of firm f's patent application count in year $t+1$; (iii) the explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level; (iv) baseline controls include firm's age, age squared, ln(total assets), ln(sales), and CEO's age, age squared, gender, education dummies, tenure in firm; and (v) standard errors are clustered by CEO's main ethnicity. **Panel A:** Column (1) excludes all controls; column (2) excludes firm controls. Column (3) reports the baseline specification. Column (4) additionally controls for ln(employment); column (5) arsinh(R&D stock); column (6) arsinh(R&D expenditure). Column (7) estimates a semi-log Poisson count model with winsorized $pat_{f,t+1}$ as the dependent variable.

Panel B. Alternative clustering schemes, weighting schemes, and patent transformations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**Future patent applications**						
Transformation:	arsinh(.)				ln(1+.)	win.	raw
Specification:	Alternative clusterings		Alternative weights		Alternative transformations		
CEO's trust	0.063***	0.063***	0.069***	0.056***	0.053***	1.462**	4.464***
	(0.022)	(0.022)	(0.020)	(0.019)	(0.015)	(0.584)	(1.293)
Clustering scheme	Firm	Two-way					
Weighting scheme			Eth. HHI	Main eth.			
Firm & Year FEs	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598	3,598	3,598

Panel B: Column (1) clusters standard errors by firm. Column (2) clusters standard errors two-way by CEO's main ethnicity and firm. Column (3) weights each observation by the precision of CEO d's last name-ethnic origin mapping, measured as $\sum_e w_{de}^2$. Column (4) measures CEO d's inherited trust based on his main ethnic origin, i.e., $trust_d = ethtrust_{e_d^*}$ where $e_d^* = \text{argmax}_e(w_{de})$, and weights each observation by the precision of that main ethnic origin $w_{de_d^*}$. Columns (5) to (7) use $ln(1 + pat_{f,t+1})$, winsorized $pat_{f,t+1}$, and raw $pat_{f,t+1}$ as the dependent variable.

Panel C. Alternative trust measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**arsinh(Future patent applications)**						
Trust measure:	Baseline	LASSO	Full GSS	WVS	GPS	Fairness	Helpful
CEO's trust	0.063***	0.067***	0.041**	0.030**	0.037**	0.063***	0.058***
	(0.019)	(0.021)	(0.018)	(0.011)	(0.015)	(0.021)	(0.021)
Firm & Year FEs	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598	3,598	3,598

Panel C: Column (1) reports the baseline specification. Column (2) uses CEO's inherited trust measure constructed from all commonly observable characteristics of CEOs and GSS respondents, including ethnic origin, age, gender, education, and birth cohort, using LASSO; column (3) CEO's ethnic origin and GSS trust question, considering the full sample of respondents; column (4) CEO's ethnic origin and World Value Survey (WVS) trust question, considering only upper middle class respondents; column (5) CEO's ethnic origin and Global Preference Survey (GPS) trust questions, considering only high skill respondents (details in appendix D.1). All trust-question measures are standardized by the standard deviation of GSS-based inherited trust measure at ethnicity level. Columns (6) and (7) employ alternative trust questions in the GSS to construct CEO's inherited trust measure. Column (6) uses the "distrust" question *"Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair?"*. Column (7) uses the question *"Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves?"*.

Panel D. Alternative sample restrictions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**Future patent applications**						
Transformation:	arsinh(.)			arsinh(.)		ln(.)	$\mathbb{1}_{.>0}$
Specification:	Alternative samples			Patenting samples			Ext. margin
CEO's trust	0.063***	0.061***	0.075***	0.086***	0.103***	0.099***	0.009
	(0.019)	(0.020)	(0.020)	(0.025)	(0.025)	(0.026)	(0.006)
Sample excluding	Single-tons	Female CEOs	Interim CEOs				
Sample including				Patent firms	Patent periods	Patent years	
Firm & Year FEs	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X
Observations	29,195	28,523	28,909	19,146	14,881	11,265	29,384
Firms	3,409	3,550	3,558	2,266	2,068	1,982	3,598

Panel D: Column (1) excludes singletons; column (2) female CEOs; column (3) interim CEOs. Column (4) includes only firms f's that patent during 2000-2012; column (5) years t's that are within firm f's first and last patenting years during 2000-2012; column (6) firms f's that patent in year $t+1$ ($pat_{f,t+1} > 0$). Column (7) uses a dummy indicating if firm f patents in year $t+1$ ($\mathbb{1}_{pat_{f,t+1}>0}$) as the dependent variable.

Panel E. Alternative time lags before patent filing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	**arsinh(Future patent applications)**								
Forward:	0-year	1-year	2-year			3-year			
CEO's trust	0.069***	0.087***	0.046*	0.074**	0.086**	0.039*	0.047	0.084***	0.134***
	(0.014)	(0.026)	(0.027)	(0.029)	(0.038)	(0.023)	(0.028)	(0.029)	(0.049)
Sample including	Year T	$T-1$	T	$T-1$	$T-2$	T	$T-1$	$T-2$	$T-3$
Firm & Year FEs	X	X	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X	X	X
Observations	29,384	26,202	29,384	26,202	20,793	29,384	26,202	20,793	16,242
Firms	3,598	3,552	3,598	3,552	3,301	3,598	3,552	3,301	3,013

Panel E: Column (1) uses $arsinh(pat_{f,t})$ as the dependent variable. Column (2) uses $arsinh(pat_{f,t+1})$ as the dependent variable and excludes the last year of CEO d's tenure. Columns (3) to (5) use $arsinh(pat_{f,t+2})$ as the dependent variable. Columns (4) and (5) exclude the last year and the last 2 years of CEO d's tenure. Columns (6) to (9) use $arsinh(pat_{f,t+3})$ as the dependent variable. Columns (7) to (9) exclude the last year, the last 2 years, and the last 3 years of CEO d's tenure. T denotes the last year of CEO d's tenure in firm f.

Panel F. Alternative CEO transition event sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**Future patent applications**						**D(arsinh**
Transformation:	arsinh(.)					$\mathbb{1}_{.>0}$	**(patent))**
CEO's trust	0.070***	0.071***		-0.002	0.111***	0.023**	
	(0.018)	(0.019)		(0.013)	(0.022)	(0.011)	
Trust × Change in trust		0.013					
		(0.012)					
Post-transition			-0.056***				
			(0.018)				
Post-transition × Trust-increasing			0.087***				
			(0.021)				
Preceding CEO's trust							-0.016***
							(0.005)
Dep. var. mean							*0.688*
Event sample				Not patenting pre-trans.	Patenting pre-trans.	Patenting pre-trans.	
Event & Year FEs	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X
Observations	20,389	20,389	19,504	8,788	11,601	11,601	2,444
Events	2,446	2,446	2,343	1,130	1,316	1,316	2,444

Panel F: This panel employs a sample constructed from CEO transition events and event fixed effects (instead of firm fixed effects) (details in appendix A.5). For each event, I include all firm f × year t × its current CEO d observations that correspond to the predecessor's and successor's terms. Column (1) reports the baseline CEO's trust effect using this sample. Column (2) interacts CEO's trust measure with $\Delta trust_E$, the difference between the successor's and predecessor's standardized trust measures. Column (3) presents a difference-in-differences specification in which the post-transition dummy is interacted with a dummy indicating the transition is a trust-increasing event. Columns (4) to (6) employ subsamples of firms having zero patent (column 4) or having patented (columns 5 and 6) in the pre-transition period. Column (6) uses a dummy indicating if firm f patents in year $t+1$ ($\mathbb{1}_{pat_{f,t+1}>0}$) as the dependent variable. Column (7) reports $\hat{\beta}$ from estimating: $\Delta\,\text{arsinh}(pat_E) = \beta trust_E^{pre} + \xi\Delta\mathbf{X}_E + \zeta\Delta\mathbf{Z}_E + \varepsilon_E$, in which (i) each observation E is a CEO transition event, (ii) $\Delta\,\text{arsinh}(pat_E)$, $\Delta\mathbf{X}_E$, and $\Delta\mathbf{Z}_E$ are the differences between post- and pre-transition average patents, firm's, and CEO's characteristics respectively, and (iii) $trust_E^{pre}$ is the trust measure of the preceding CEO.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A8: CEO's Trust Effect across Firm Sizes and Industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**arsinh(Future patent applications)**							
Sample:	Full sample		Patent period		IT/Electronics	Non-IT/Elec.	Pharma/Chemistry	Non-Pharma/Chem.
	By asset	By emp.	By asset	By emp.				
CEO's trust					0.105**	0.047**	0.019	0.062***
					(0.041)	(0.019)	(0.063)	(0.020)
Trust × Size quintile 1	0.020	0.011	0.076***	0.077				
	(0.033)	(0.036)	(0.026)	(0.051)				
Trust × Size quintile 2	0.014	0.049	0.120*	0.161***				
	(0.032)	(0.031)	(0.061)	(0.053)				
Trust × Size quintile 3	0.132***	0.141***	0.154**	0.172***				
	(0.043)	(0.028)	(0.068)	(0.052)				
Trust × Size quintile 4	0.084**	0.045	0.094	0.090				
	(0.039)	(0.035)	(0.057)	(0.055)				
Trust × Size quintile 5	0.077***	0.075**	0.098**	0.028				
	(0.022)	(0.031)	(0.045)	(0.046)				
Firm & Year FEs	X	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X	X
Observations	29,384	28,713	14,881	14,586	6,958	22,426	3,310	26,074
Firms	3,598	3,577	2,068	2,054	884	2,715	438	3,161

Notes: This table explores the heterogeneous effects of CEO's trust on firm's patents by firm size and industry using equation (3). Baseline sample includes all observations of firm f × year t × its current CEO d. The dependent variable is the inverse hyperbolic sine of firm f's patent application count in year $t+1$. The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Columns (1) to (4) interact CEO's trust measure with firm's size quintile dummies, computed with respect to firm's 3-digit SIC industry × year cohort using total assets (columns 1 and 3) or employment (columns 2 and 4) as firm size measure. Columns (1) and (2) use the full baseline sample; columns (3) and (4) use the patent-period subsample (details in Table 1's notes). Columns (5) corresponds to the subsample of firms in ICT and electronic industries (i.e., computer and data processing services (SIC3 code 737), computer and office equipment (SIC3 code 357), electronic and other equipment (SIC2 code 36)) and column (6) the remaining subsample. Column (7) corresponds to the subsample of firms in pharmaceutical and chemical industries (i.e., chemicals and allied products (SIC2 code 28)) and column (8) the remaining subsample. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A9: CEO's Retirement and Death Events

Panel A. Including all years in each event

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent var:	**arsinh(Future patent applications)**						**D(arsinh(pat))**
Sample:	Retired 64-65	Retired 64-66	Retired 63-67	Died transition yr	Died transition yr+1	Retired or died	Retired or died
CEO's trust	0.281***	0.104**	0.083*	0.410	0.400	0.095**	
	(0.095)	(0.042)	(0.047)	(0.308)	(0.279)	(0.045)	
Preceding CEO's trust							-0.024**
							(0.012)
Observations	913	2,285	3,440	253	353	3,756	386
Events	92	230	346	34	46	386	386

Panel B. Excluding transition years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent var:	**arsinh(Future patent applications)**						**D(arsinh(pat))**
Sample:	Retired 64-65	Retired 64-66	Retired 63-67	Died transition yr	Died transition yr+1	Retired or died	Retired or died
CEO's trust	0.328***	0.137**	0.124**	0.736**	0.780***	0.142**	
	(0.103)	(0.060)	(0.056)	(0.363)	(0.300)	(0.054)	
Preceding CEO's trust							-0.029**
							(0.012)
Event & Year FEs	X	X	X	X	X	X	
Baseline controls	X	X	X	X	X	X	
Observations	825	2,073	3,126	217	306	3,400	377
Events	91	228	342	29	40	377	377

Notes: This table reports CEO's trust effect in subsamples of transitions following CEO's retirements or deaths. Columns (1) to (6) estimate equation (3). Each subsample includes all firm f $\times$ year t $\times$ its current CEO d observations that correspond to the predecessor's and successor's terms of the relevant transitions (Panel A) and that are not the transition years (Panel B). Columns (1) to (3)'s subsamples include transitions in which the preceding CEO retired at 65, between 64 and 66, or between 63 or 67 respectively. Columns (4) and (5)'s subsamples include transitions in which the preceding CEO died in or within one year of the transition year. Column (6) combines column (3)'s and column (5)'s subsamples. The dependent variable is the inverse hyperbolic sine of firm f's patent application count in year $t+1$. The explanatory variable is CEO d's inherited trust measure, standardized by its standard deviation at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (7) estimates $\Delta\,\text{arsinh}(pat_E) = \beta trust_E^{pre} + \xi\Delta\mathbf{X}_E + \zeta\Delta\mathbf{Z}_E + \varepsilon_E$, in which (i) each observation E is a CEO transition event included in column (6)'s subsample, and (ii) $trust_E^{pre}$ is the trust measure of the departing CEO. Standard errors are clustered by CEO's main ethnicity in columns (1), (2), (3) and (6). Robust standard errors are reported for columns (4), (5), and (7).
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A10: Controlling for CEO's Home Country's Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**arsinh(Future patent applications)**					
CEO's trust	0.053***	0.061***	0.058***	0.060***	0.067***	0.045**
	(0.017)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)
ln(GDP)	0.003					-0.015
	(0.013)					(0.027)
ln(Population)	-0.013					-0.006
	(0.011)					(0.020)
GDP growth (%)	0.005**					0.004*
	(0.002)					(0.002)
High school grads (share)		-0.001				-0.000
		(0.000)				(0.001)
Governance quality (percentile)			0.022			0.008
			(0.055)			(0.102)
ln(US trade volume)				0.005		0.020*
				(0.008)		(0.010)
ln(Patent applications)					-0.007	-0.003
					(0.005)	(0.012)
Firm & Year FEs	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598	3,598

Notes: This panel controls for CEO's home country' macroeconomic characteristics using equation (3). Baseline sample includes all observations of firm f $\times$ year t $\times$ its current CEO d. The dependent variable is the inverse hyperbolic sine of firm f's patent application count in year $t+1$. The explanatory variable is CEO d's inherited trust measure, standardized by its standard deviation at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. CEO's home country controls include ln(GDP), ln(population), and GDP growth rate (column 1), high school graduate share (column 2), average percentile ranking of World Bank governance indices (column 3), ln(US exports + US imports) (column 4), and ln(total patent applications filed at the country's patent office) (column 5). Column (6) controls for all those variables. Each time-varying home-country variable h_{dt} is calculated as $h_{dt} = \sum_e w_{de} \times h_{et}$ where h_{et} is the value of h in the home country of ethnicity e in year t and w_{de} is the probability that CEO d is of ethnicity e. Further details on variable construction are available in appendix D.1. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A11: Controlling for Other Cultural Traits

Panel A. Main results

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**asinh(Future patent applications)**					
CEO's trust	0.068***	0.059***	0.059***	0.066***	0.058**	0.055**
	(0.018)	(0.019)	(0.019)	(0.024)	(0.025)	(0.025)
High-income share (z-score)	0.043**				0.054**	0.050*
	(0.017)				(0.027)	(0.027)
Work ethic (z-score)		0.012			0.025	0.025
		(0.020)			(0.019)	(0.018)
Risk preference (z-score)			0.010		0.006	0.004
			(0.018)		(0.018)	(0.017)
Patience (z-score)				-0.004	0.003	0.003
				(0.019)	(0.023)	(0.021)
GDP growth (%)						0.004*
						(0.002)
ln(US trade volume)						0.007
						(0.007)
Firm & Year FEs	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598	3,598

Notes: This panel controls for CEO's other inherited cultural traits using equation (3). Baseline sample includes all observations of firm f $\times$ year t $\times$ its current CEO d. The dependent variable is the inverse hyperbolic sine of firm f's patent application count in year $t+1$. The explanatory variable is CEO d's inherited trust measure, standardized by its standard deviation at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (1) controls for the share of respondents earning at least $25,000 annually (i.e., GSS's highest income bracket) in CEO's ethnic groups. Column (2) controls for CEO's inherited work ethic, derived from the GSS question: *"Some people say that people get ahead by their own hard work; others say that lucky breaks or help from other people are more important. Which do you think is most important?"*. Columns (3) and (4) control for CEO's inherited risk preference (column 3) and time preference (i.e., patience, column 4), as measured by the Global Preference Survey (Falk et al., 2018). Column (5) controls for all of those variables. Column (6) further controls for CEO's home country's GDP growth rate and ln(US exports + US imports). Further details on variable construction are available in appendix D.1. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Panel B. Other measures of other cultural traits

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**arsinh(Future patent applications)**					
Other cultural traits:	Socioeconomic characteristics				Confidence	
CEO's trust	0.059***	0.060***	0.063***	0.052**	0.062***	0.082***
	(0.020)	(0.019)	(0.018)	(0.024)	(0.018)	(0.022)
Occupation prestige	0.015					
	(0.015)					
Average schooling years		0.014				
		(0.015)				
College graduates (share)			0.073			
			(0.100)			
Protestants (share)				0.033		
				(0.054)		
Confidence in science					0.018	
					(0.032)	
Confidence in Congress						0.039*
						(0.021)
Confidence in Federal Govt.						-0.036
						(0.035)
Confidence in Supreme Court						0.019
						(0.023)
Firm & Year FEs	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598	3,598

Notes: This panel explores alternative GSS-based measures of CEO's other inherited cultural traits as additional controls in equation (3). Columns (1) to (4) control for (i) average GSS occupational prestige score (column 1), (ii) average years of schooling (column 2), (iii) share of college graduates (column 3), and (iv) share of Protestants (column 4), among respondents in CEO's ethnic groups. Columns (5) and (6) control for CEO's inherited confidence in the scientific community (column 5) and three branches of the government (column 6), derived from the GSS question *"I am going to name some institutions in this country. As far as the people running these institutions are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them?"*. Cultural trait controls in columns (1), (4), (5), and (6) are standardized by their standard deviations at ethnicity level. Further details on variable construction are available in appendix D.1. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A12: Global Preference Survey's Trust and Other Cultural Traits

Panel A. Using GPS-based CEO's inherited trust measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**arsinh(Future patent applications)**						
CEO's trust (GPS)	0.037**	0.046***	0.035**	0.037**	0.044***	0.039**	0.042***
	(0.015)	(0.015)	(0.014)	(0.016)	(0.012)	(0.015)	(0.012)
Risk preference		-0.020					0.008
		(0.019)					(0.025)
Patience			0.012				-0.010
			(0.014)				(0.021)
Positive reciprocity				-0.005			-0.001
				(0.020)			(0.025)
Negative reciprocity					-0.026***		-0.035***
					(0.006)		(0.013)
Altruism						-0.010	0.011
						(0.013)	(0.019)
Firm & Year FEs	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598	3,598	3,598

Panel B. Using baseline GSS-based CEO's inherited trust measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**arsinh(Future patent applications)**						
CEO's trust (GSS)	0.063***	0.059***	0.066***	0.063***	0.057***	0.069***	0.053*
	(0.019)	(0.019)	(0.024)	(0.018)	(0.019)	(0.020)	(0.027)
Risk preference		0.010					0.033
		(0.018)					(0.025)
Patience			-0.004				-0.021
			(0.019)				(0.021)
Positive reciprocity				0.004			-0.010
				(0.014)			(0.025)
Negative reciprocity					-0.006		-0.029**
					(0.007)		(0.013)
Altruism						0.013	0.027
						(0.011)	(0.020)
Firm & Year FEs	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598	3,598	3,598

Notes: This table employs inherited trust measure and other cultural trait measures constructed in the same way as the baseline inherited trust measure but using Falk et al.'s (2018) Global Preference Survey (GPS) instead of the GSS. Baseline sample includes all observations of firm f × year t × its current CEO d. The dependent variable is the inverse hyperbolic sine of firm f's patent application count in year $t+1$. The explanatory variable in **Panel A** is CEO d's GPS-based inherited trust measure, and in **Panel B** his baseline GSS-based inherited trust measure; each standardized by its respective standard deviation at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (1) reports the baseline effect of CEO's GPS-based inherited trust. Column (2) controls for CEO's inherited risk preference; column (2) patience; column (3) positive reciprocity; column (4) negative reciprocity; column (5) altruism. Column (6) controls for all those variables. Further details on variable construction are available in appendix D.1. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A13: CEO's Trust Effect in US-Based Inventor Bilateral Trust Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**arsinh(Future patent applications)**							
Quality weight:	Patent count			Forward cites	Patent count			
CEO's bilateral trust	0.021*	0.021*	0.011*	0.045**	0.006	0.021	0.018*	0.022**
	(0.011)	(0.011)	(0.007)	(0.019)	(0.012)	(0.013)	(0.011)	(0.011)
Common language dummy						0.004		
						(0.024)		
Geographical distance (1000km)							-0.013	
							(0.010)	
Genetic distance (z-score)								-0.045
								(0.050)
Excl. same-country pairs					X			
Firm × Year FEs	X	X		X	X	X	X	X
CEO FEs	X		X	X	X	X	X	X
Inventor country FEs	X			X	X	X	X	X
CEO × Year FEs		X						
Inv. country × Year FEs		X						
Firm × Inv. country's FEs			X					
Year FEs			X					
Observations	49,597	49,597	49,597	49,597	44,943	49,597	49,597	48,240
Firm × Inv. country's	7,329	7,329	7,329	7,329	6,756	7,329	7,329	7,122
Firms	1,163	1,163	1,163	1,163	925	1,163	1,163	1,163

Notes: This table reports the effect of CEO's bilateral trust towards a country on patents by inventors from that country using equation (4). Samples include all observations of firm f × year t × its current CEO d × country c such that firm f has patents by inventors from country c during 2000-2012. An inventor's country is inferred from his last name only for US-based inventors. The explanatory variable is CEO d's bilateral trust towards individuals from country c, standardized by its standard deviation at country pair level. The dependent variable is firm f's total patent application count by inventors from country c in year $t+1$. Column (4)'s dependent variable further weights patent applications by their forward citations. Column (5) excludes same-country CEO-inventor country pairs. Columns (6) to (8) control for CEO-inventor country pairwise distances, including: (i) whether the countries share a common language (column 6), (ii) weighted geographical distance between the countries (column 7), and (iii) weighted genetic distance between the countries' populations (column 8) (Spolaore and Wacziarg, 2016). Standard errors are clustered by CEO's main ethnicity × inventor country.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A14: Margins of CEO's Bilateral Trust Effect

Panel A. Non-US-based inventor bilateral trust sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	**Future patent application**								
Sample:	Generalized trust sample	Bilateral trust sample							
		Full sample		Patenting sample		Intensive margin		Extensive margin	
Transformation:	arsinh(.)	arsinh(.)	$\mathbb{1}_{>0}$	arsinh(.)	ln(.)	arsinh(.)	$\mathbb{1}_{>0}$	arsinh(.)	$\mathbb{1}_{.>0}$
CEO's generalized trust	0.126***								
	(0.027)								
CEO's bilateral trust		0.052**	0.027***	0.082**	0.111*	0.072*	0.027*	0.026*	0.014
		(0.023)	(0.009)	(0.038)	(0.057)	(0.043)	(0.014)	(0.015)	(0.012)
Firm & Year FEs	X								
Firm × Year FEs		X	X	X	X	X	X	X	X
CEO FEs		X	X	X	X	X	X	X	X
Inventor country FEs		X	X	X	X	X	X	X	X
Observations	6,915	23,284	23,284	11,835	7,047	10,552	10,552	12,732	12,732
Firm × Inv. country's		3,481	3,481	2,597	2,338	1,903	1,903	1,861	1,861
Firms	724	730	730	625	582	486	486	592	592

Panel B. All inventor bilateral trust sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	**Future patent application**								
Sample:	Generalized trust sample	Bilateral trust sample							
		Full sample		Patenting sample		Intensive margin		Extensive margin	
Transformation:	arsinh(.)	arsinh(.)	$\mathbb{1}_{>0}$	arsinh(.)	ln(.)	arsinh(.)	$\mathbb{1}_{>0}$	arsinh(.)	$\mathbb{1}_{.>0}$
CEO's generalized trust	0.095***								
	(0.028)								
CEO's bilateral trust		0.026**	0.012**	0.046***	0.064***	0.026*	0.009	0.010	0.007
		(0.011)	(0.005)	(0.017)	(0.019)	(0.015)	(0.006)	(0.014)	(0.009)
Firm & Year FEs	X								
Firm × Year FEs		X	X	X	X	X	X	X	X
CEO FEs		X	X	X	X	X	X	X	X
Inventor country FEs		X	X	X	X	X	X	X	X
Observations	11,931	56,942	56,942	32,834	21,588	33,058	33,058	23,884	23,884
Firm × Inv. country's		8,554	8,554	6,674	6,081	5,718	5,718	3,389	3,389
Firms	1,256	1,263	1,263	1,085	1,081	990	990	990	990

Notes: This table reports CEO's generalized and bilateral trust effects on patents among the samples of firms included in bilateral trust analyses. In **Panel A**, an inventor's country is inferred from his patent-listed address for non-US-based inventors; in **Panel B**, an inventor's country is additionally inferred from his last name for US-based inventors. In each panel, column (1) reports CEO's generalized trust effect on firm's patents among the sample of firms included in the corresponding panel's bilateral trust sample, using equation (3) (i.e., observation unit is firm f × year t × its current CEO d, see Table 1's notes for further details). Columns (2) to (9) report CEO's bilateral trust effect on inventors' patents using equation (4) (i.e., observation unit is firm f × year t × its current CEO d × country c, see Table 2's notes for further details). Columns (2) and (3) employ all observations such that firm f has patents by inventors from country c during 2000-2012. Column (4) considers only observations such that year t is within the first and last years that firm f has patents by inventors from country c during 2000-2012. Column (5) includes only observations such that firm f has patents by inventors from country c in year $t+1$ ($pat_{fc,t+1} > 0$). Columns (6) and (7) employ only observations such that firm f has patents by inventors from country c *before* CEO d assumes position. Columns (8) and (9) employ only observations such that firm f has patents by inventors from country c *after* CEO d assumes position. The dependent variable in columns (3), (7), and (9) is a dummy indicating if firm f has patents by inventors from country c in year $t+1$ ($\mathbb{1}_{pat_{fc,t+1}>0}$). Standard errors are clustered by CEO's main ethnicity in columns (1) and by CEO's main ethnicity × inventor country in columns (2) to (9).

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A15: Directions of CEO-Inventor Bilateral Trust

Panel A. Non-US-based inventor bilateral trust sample

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**arsinh(Future patent applications)**					
Direction of bilateral trust:	CEO to inventors		Inventors to CEO		Both	
Quality weight:	Patent count		Patent count		Patent count	Forward cites
CEO-toward-inventors bilateral trust	0.102***	0.138***			0.100**	0.217***
	(0.025)	(0.052)			(0.044)	(0.076)
Inventors-toward-CEO bilateral trust			0.076**	-0.016	0.003	-0.045
			(0.032)	(0.055)	(0.047)	(0.077)
Firm × Year FEs	X	X	X	X	X	X
CEO FEs	X	X	X	X	X	X
Inventor country FEs	X	X	X	X	X	X
Inventors-to-CEO trust decile FEs		X				
CEO-to-inventors trust decile FEs				X		
Observations	12,863	12,863	12,863	12,863	12,863	12,863
Firm × Inventor country's	2,009	2,009	2,009	2,009	2,009	2,009
Firms	580	580	580	580	580	580

Panel B. All inventor bilateral trust sample

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**arsinh(Future patent applications)**					
Direction of bilateral trust:	CEO to inventors		Inventors to CEO		Both	
Quality weight:	Patent count		Patent count		Patent count	Forward cites
CEO-toward-inventors bilateral trust	0.041**	0.049*			0.030	0.067*
	(0.016)	(0.028)			(0.026)	(0.039)
Inventors-toward-CEO bilateral trust			0.037***	0.029	0.013	0.009
			(0.014)	(0.026)	(0.023)	(0.035)
Firm × Year FEs	X	X	X	X	X	X
CEO FEs	X	X	X	X	X	X
Inventor country FEs	X	X	X	X	X	X
Inventors-to-CEO trust decile FEs		X				
CEO-to-inventors trust decile FEs				X		
Observations	32,648	32,648	32,648	32,648	32,648	32,648
Firm × Inventor country's	5,005	5,005	5,005	5,005	5,005	5,005
Firms	1,072	1,072	1,072	1,072	1,072	1,072

Notes: This table explores the effects of different directions of bilateral trust on patents using equation (4). Samples include all observations of firm f × year t × its current CEO d × country c such that (i) firm f has patents by inventors from country c during 2000-2012, and (ii) both bilateral trust variables are non-missing. An inventor's country is inferred from his patent-listed address for non-US-based inventors in **Panel A**, and additionally from his last name for US-based inventors in **Panel B**. The explanatory variables are (i) CEO d's bilateral trust towards individuals from country c, and (ii) individuals from country c's bilateral trust towards CEO d, both standardized by their same standard deviations at country pair level. The dependent variable is firm f's total patent application count by inventors from country c in year $t+1$. Decile dummies in columns (2) and (4) are computed with respect to the relevant bilateral trust sample. Standard errors are clustered by CEO's main ethnicity × inventor country. *** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A16: Bilateral Trust Effect by Patent Quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**arsinh(Future patents in each quality quartile)**							
Sample:	Non-US-based inventors				All inventors			
Quality quartile:	1st	2nd	3rd	4th	1st	2nd	3rd	4th
CEO's bilateral trust	0.017	0.014	0.017	0.027*	0.004	0.006	0.008	0.024***
	(0.012)	(0.011)	(0.015)	(0.016)	(0.006)	(0.005)	(0.007)	(0.009)
Firm × Year FEs	X	X	X	X	X	X	X	X
CEO FEs	X	X	X	X	X	X	X	X
Inventor country FEs	X	X	X	X	X	X	X	X
Observations	23,284	23,284	23,284	23,284	56,942	56,942	56,942	56,942
Firm × Inv. country's	3,481	3,481	3,481	3,481	8,554	8,554	8,554	8,554
Firms	730	730	730	730	1,263	1,263	1,263	1,263

Notes: This table reports the heterogenous effects of CEO's bilateral trust on patents in different quality quartiles using equation (4). Samples include all observations of firm f × year t × its current CEO d × country c such that firm f has patents by inventors from country c during 2000-2012. An inventor's country is inferred from his patent-listed address for non-US-based inventors in columns (1) to (4), and additionally from his last name for US-based inventors in columns (5) to (8). The explanatory variable is CEO d's bilateral trust towards individuals from country c, standardized by its standard deviation at country pair level. The dependent variable is firm f's total patent application count by inventors from country c in year $t+1$ in each patent quality quartile, with 1 being the bottom quartile and 4 the top. A patent's quality quartile is computed based on its forward citation count with respect to its technology field × year cohort. Standard errors are clustered by CEO's main ethnicity × inventor country.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A17: CEO's Trust Effect on Quality-Weighted Patents

Panel A. Effect of CEO's generalized trust on quality-weighted patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**arsinh(Future quality-weighted patents)**					**Share**	**arsinh**	**arsinh**
Quality measure:	Explorative pat.	Destructive pat.	Backward NPL cites	Tech. scope	Granted USPTO	**(Explor. pat.)**	**(Avg. cites)**	**(Avg. value)**
CEO's trust	0.065***	0.044***	0.103**	0.061**	0.056***	0.011**	0.044**	0.060**
	(0.014)	(0.015)	(0.031)	(0.025)	(0.014)	(0.004)	(0.020)	(0.024)
Firm & Year FEs	X	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,284	29,384	29,384	20,218
Firms	3,598	3,598	3,598	3,598	3,168	3,598	3,598	3,168

Panel B. Effect of CEO's bilateral trust on quality-weighted patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**arsinh(Future quality-weighted patents)**							
Sample:	Non-US-based inventors				All inventors			
Quality measure:	Backward NPL cites	Tech. scope	Granted USPTO	Average cites	Backward NPL cites	Tech. scope	Granted USPTO	Average cites
CEO's bilateral trust	0.053*	0.100***	0.038*	0.063**	0.046***	0.051***	0.023**	0.032***
	(0.032)	(0.034)	(0.020)	(0.025)	(0.016)	(0.016)	(0.010)	(0.011)
Firm × Year FEs	X	X	X	X	X	X	X	X
CEO FEs	X	X	X	X	X	X	X	X
Inventor country FEs	X	X	X	X	X	X	X	X
Observations	23,238	23,238	23,238	23,238	56,942	56,942	56,942	56,942
Firm × Inv. country's	3,481	3,481	3,481	3,481	8,554	8,554	8,554	8,554
Firms	730	730	730	730	1,263	1,263	1,263	1,263

Notes: **Panel A:** This panel reports CEO's generalized trust effect on quality-weighted patents using equation (3). Baseline sample includes all observations of firm f × year t × its current CEO d. The dependent variable is the inverse hyperbolic sine of firm f's patent application count in year $t+1$, weighted by: explorative patents (i.e., patents mostly citing knowledge that is new to the firm, column 1); disruptive patents (i.e., patents that destabilize the status quo, column 2); backward citations to non-patent (i.e., scientific) literature (column 3); patent technological scope (column 4); and granted USPTO patents (column 5) (details in appendix A.2). The dependent variable in column (6) is the share of explorative patents; column (7) the inverse hyperbolic sine of the average forward citations per patent; and column (9) the inverse hyperbolic sine of the average patent value (i.e., firm f's excess stock return on patent grant date as estimated by Kogan et al., 2017); all computed among patents filed by firm f's in year $t+1$ (or set to zero if firm f has no patent application in year $t+1$). The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Standard errors are clustered by CEO's main ethnicity.

Panel B: This panel reports CEO's bilateral trust effect on quality-weighted patents using equation (4). Samples include all observations of firm f × year t × its current CEO d × country c such that firm f has patents by inventors from country c during 2000-2012. An inventor's country is inferred from his patent-listed address for non-US-based inventors in columns (1) to (4), and additionally from his last name for US-based inventors in columns (5) to (8). The explanatory variable is CEO d's bilateral trust towards individuals from country c, standardized by its standard deviation at country pair level. The dependent variable is firm f's total patent application count by inventors from country c in year $t+1$, weighted by: backward citations to non-patent (i.e., scientific) literature (columns 1 and 5); patent technological scope (columns 2 and 6); and granted USPTO patents (columns 3 and 7). The dependent variable in columns (4) and (8) is the inverse hyperbolic sine of the average forward citations per patent among patents filed by inventors from country c (in firm f) in year $t+1$ (or zero if inventors from country c in firm f have no patent application in year $t+1$). Standard errors are clustered by CEO's main ethnicity × inventor country.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A18: Effect of CEO's Trust on Firm Future Performance

Panel A.

Dependent variable: Future	(1) **ln(sales)**	(2) **ln(employment)**	(3) **ln(capital)**	(4) **TFP(KL)**	(5) **TFP(KLM)**	(6) **Tobin's Q**
CEO's trust	-0.036**	-0.032**	-0.022	0.006	0.000	0.148*
	(0.017)	(0.013)	(0.025)	(0.013)	(0.026)	(0.076)
Trust × Researcher quality	0.048***	0.034***	-0.000	0.015	0.031	0.128**
(in pre-transition period)	(0.014)	(0.010)	(0.013)	(0.011)	(0.018)	(0.057)
Firm & Year FEs	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X
Observations	18,019	17,873	16,782	17,238	7,719	17,807
Events	2,237	2,224	2,149	2,177	1,421	1,588

Panel B.

Dependent variable: Future	(1) **ln(sales)**	(2) **ln(employment)**	(3) **ln(capital)**	(4) **TFP(KL)**	(5) **TFP(KLM)**	(6) **Tobin's Q**
Trust × Quality quintile 1	-0.153***	-0.154***	-0.068	0.007	-0.008	-0.078
	(0.040)	(0.035)	(0.047)	(0.036)	(0.041)	(0.071)
Trust × Quality quintile 2	-0.119**	-0.044	-0.063*	-0.046	-0.076	0.007
	(0.046)	(0.030)	(0.036)	(0.030)	(0.052)	(0.094)
Trust × Quality quintile 3	0.039	0.002	0.006	0.035	-0.005	0.055
	(0.058)	(0.043)	(0.049)	(0.060)	(0.106)	(0.157)
Trust × Quality quintile 4	0.058**	0.069**	0.104**	-0.008	-0.026	0.185
	(0.024)	(0.026)	(0.051)	(0.032)	(0.052)	(0.177)
Trust × Quality quintile 5	0.034	-0.000	-0.056	0.051*	0.117***	0.542*
	(0.045)	(0.027)	(0.050)	(0.027)	(0.041)	(0.310)
Firm & Year FEs	X	X	X	X	X	
Baseline controls	X	X	X	X	X	
Observations	18,019	17,873	16,782	17,238	7,719	17,807
Events	2,237	2,224	2,149	2,177	1,421	1,588

Notes: This table explores the heterogeneous effects of CEO's trust on firm's patents by pre-transition researcher pool quality using equation (3) and the sample constructed from CEO transition events (appendix A.5). For each event, I include all firm f × year t × its current CEO d observations that correspond to the predecessor's and successor's terms. The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level. Firm-level proxy for researcher pool quality is computed from averaging the residuals from regressing patents on observable firm and CEO characteristics, controlling for 2-digit SIC industry and year fixed effects over the (-1, 0) 2-year pre-transition window. The dependent variables measure firm f's performance in year $t+2$, including: ln(sales) (column 1); ln(employment) (column 2); ln(capital) (column 3); TFP computed from value added, employment, and capital following Olley and Pakes (1996) (column 4); TFP computed from sales, employment, capital, and material following Olley and Pakes (1996) (column 5); and Tobin's Q (column 6). Baseline controls include (i) firm's age, age squared, arsinh(R&D expenditure), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. **Panel A** interacts CEO's trust measure with firm-level proxy for pre-transition pool quality. **Panel B** interacts CEO's trust measure with researcher pool quality quintile dummies (computed based on firm-level proxy for pre-transition researcher pool quality). Standard errors are clustered by CEO's main ethnicity.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

A Data and sample construction

A.1 Firm sample construction

BoardEx to Computstat. I start with BoardEx dataset which contains detailed data on the background of CEOs and top officers for a large set of firms worldwide and select all firms that are both listed and headquartered in the US.[43] I then match the selected BoardEx firms to Compustat using ticker. To ensure that the matching is correct, I manually check all cases in which (i) the matching is not one to one,[44] or (ii) the company names in BoardEx and Compustat do not match. I then use CIK code to verify that the matching is indeed correct. Matched firms are larger than the remaining Compustat firms, with coverage of 55% in terms of firm counts and 85% in terms of total assets among Compustat firms with non-missing total assets between 2000 and 2011.

BoardEx-Compustat to Orbis. Next, I match BoardEx-Compustat firms to Orbis, a global company database provided by Bureau Van Dijk, to obtain the linkage between firms and patents. This patent-to-firm linkage is based on a matching procedure implemented by the EPO and the OECD and is available as part of Orbis.[45] The matching between BoardEx-Compustat and Orbis firms is done via ISIN/CUSIP. I also manually check all cases in which (i) the matching is not one to one, or (ii) the company names in BoardEx/Compustat and Orbis do not match. In addition, I use Orbis' manual search function to look for BoardEx-Compustat firms that cannot be identified in Orbis using ISIN/CUSIP. This results in a close to full match (above 99%) and allows me identify all patent applications owned by the matched firms. As Orbis also contains information on firm's ownership structure, I additionally identify patent applications by subsidiaries that are above 50% owned by one of these firms.

Sample restriction. Finally, I exclude all firms in finance, insurance, and real estate (2-digit SIC codes between 60 and 67), as these industries make up a considerable share of the firm sample but traditionally do not patent their innovations. This results in a sample of 4,345 firms between 2000 and 2011, which then yields a final baseline sample of 3,598 firms after conditioning on firms having at least one CEO (i) whose ethnic origins could be inferred from her last name, and (ii) whose data on gender, age, and education are non-missing (details in appendix A.3). Baseline sample firms are mechanically larger than the remaining ones (Table A3). However, as all key estimates in this paper are within-firm, firm-level selection does not pose threat to their internal validity.

[43] BoardEx and Compustat data were retrieved through the Wharton Research Data Services in May 2017.

[44] This could happen when a firm undergoes a major merger and acquisition (M&A). BoardEx then considers it to be two different firms, one before and one after the M&A, while Compustat considers it to be the same firm if its ticker does not change. I follow BoardEx's approach to ensure that the within-firm identification strategy is valid.

[45] I accessed Orbis platform through the LSE Library Services and retrieved the linkage between firms and patents from Orbis in July 2017. This matching is done based on the names and addresses of patent applicants on patent records, which are available from PATSTAT. In an UK setting, Dechezleprêtre et al. (2018) find that the matching quality is excellent with about 95% of UK and EPO patents being matched to their owning companies.

A.2 Patent and inventor data

My patent data come from the 2016 Autumn Edition of the World Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO). PATSTAT is the world's largest international patent database with over 80 million patent documents from over 60 patent offices, including all the major ones such as the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO), the Japan Patent Office (JPO), and the Chinese Patent and Trademark Office (SIPO). It is thus much more general and suitable for studies with a cross-country perspective than the usual USPTO dataset. PATSTAT data cover patents from the 1900 up to 2016 and contain comprehensive information on patent application and publication dates, applicants and inventors, patent family, technology classification, and backward and forward citations. Given the lag between patent application and patent publication dates, PATSTAT's coverage of patent applications filed in 2015 and especially 2016 is less complete.

Baseline patent counts. Each patent application to a patent office is uniquely identified in both PATSTAT and Orbis by its unique EPODOC application number. In addition to this identifier, PATSTAT reports a unique patent family indicator (DOCDB) which is the same for all patent applications (in different countries) related to the same invention. For the purpose of measuring innovation (i.e., to avoid double-counting inventions that are protected in several countries), I count all patent applications in the same family, irrespective of where they are filed, as one patent and assign this patent to its earliest application year. I only consider patents applications classified as "patent of invention" in PATSTAT, which are equivalent to USPTO's utility patents. The number of patent families filed by a firm (or a group of inventors in a firm) is my primary measure of innovation.[46] Between 2000 and 2012, 2,230 out of 3,598 baseline firms filed at least one patent, and together owned 1.8 million patent applications in 700,000 patent families over this period. In addition, I also construct alternative measures of innovation counting only patent families filed to or granted by the USPTO, which yields similar results (e.g., Table A17).

Patent quality measures. While not all innovations are patented and patenting norms vary across industries, it is reasonable to assume that within the same industry, the most valuable inventions are patented and therefore counting patents screens out the low-value ones.[47] In addition, I utilize various measures of patent quality to adjust for quality variation among patents and, more importantly, directly study this variation as an outcome of interest.

Forward citations. The most commonly-used patent quality measure is forward citation count (i.e., the number of future citations a given patent receives), which has been shown to be positively

[46] I do not use fractional count to account for multiple applicants as this requires obtaining patent-firm linkage for the universe of firms. However, in practice, only a very small share of patents are filed jointly by at least two firms (Dechezleprêtre et al., 2018).

[47] Note that all specifications in this paper include fixed effects below industry level, thereby sufficiently accounting for across-industry heterogeneity in patenting propensity.

correlated with patent quality (Trajtenberg, 1990; Harhoff et al., 1999; Moser et al., 2015) and also firm's market value (Hall et al., 2005; Kogan et al., 2017). In this paper, I use forward citation count to compute: (i) a patent's quality decile relative to its technology field by application year cohort (e.g., Figure 6 and Table A16),[48] (ii) firm's quality-adjusted patent counts (e.g., Tables 1 and 2), and (iii) firm's average patent quality (e.g., Table A17). As forward citations take time to accumulate, I restrict my sample to patents filed before 2012 to allow for sufficient time window to observe patents' forward citations.

Besides forward citations, in Tables 1 and A17, I also employ a range of complementary measures that capture various aspects of patents' characteristic, quality, and value, as listed below.

- *Patent value.* The value of a patent, computed by Kogan et al. (2017), measures a patent's monetary value to a firm from the firm's excess stock return on the patent's grant date. The data cover USPTO patents granted in 2011 or earlier, and therefore are comprehensive only for patents filed in 2008 or earlier.
- *Explorativeness.* The share of "new citations" (i.e., citations to patents or works that have not been developed or cited by the firm in the past) by a patent measures the extent to which it is built on knowledge that is new to the firm (Benner and Tushman, 2002). A patent is considered explorative if at least 90% of its citations are new, which cutoff corresponds to the 25% percentile in new citation share among the patents in my sample.
- *Disruptiveness.* The CD index, developed by Funk and Owen-Smith (2017), indicates whether a patent consolidates or destabilizes the status quo based on whether future patents that build on the focal patent also rely on the focal patent's predecessors. CD index = 1 (maximally destabilizing) if the set of backward citations by its forward citations does not overlap with its own backward citations and vice versa (CD index = -1, maximally consolidating). A patent is considered disruptive if it has a positive CD index.
- *Non-patent backward citations.* The number of scientific papers a patent cite reflects how close the patent is to scientific knowledge and is an indicator of more complex and fundamental knowledge contained in the patent (Branstetter, 2005; Cassiman et al., 2008).
- *Technological scope.* The scope of a patent, defined as the number of distinct technology classes (at IPC4 level) the patent is allocated to, has been shown to be associated with the patent's technological and economic value (Lerner, 1994).

Inventor data. PATSTAT also contains information on patent inventors' names and addresses as they appear on patent records. Based on data on inventors' countries extracted or inferred from their addresses (as provided by PATSTAT), 1,554 firms and 30% of patents in my sample have at least one non-US-based inventors. The share non-US-based inventors in each of these patents

[48] Schmoch (2008) classifies patents into 35 technology fields of balanced size in 6 technology sectors of based on the International Patent Classification (IPC). This classification has subsequently been used in the innovation literature by Squicciarini et al. (2013) and Dechezleprêtre et al. (2018), among others. The bottom three deciles within most cohorts contain mostly patents with zero forward citations.

ranges from 0.5 to 1, with 1 being the median. That is, 60% of these patents are exclusively by non-US-inventors; furthermore, in almost all cases these inventors are based in the same country, consistent with the interpretation that the patents are by overseas R&D labs of multinational firms. The 10 most common locations of those labs, based on their patent contributions, are (in order) Germany, Great Britain, India, Canada, Japan, China, France, Israel, Switzerland, and Italy.[49] As it is possible for one patent to have inventors based in different countries, although this rarely happens, I use fractional count to calculate the number of patents at firm-by-inventor country level.

Data on patent inventors' names in PATSTAT come in much less standardized format as they are extracted from patent records from many different patent offices worldwide. To correctly separate out an inventor's last name (from first and middle names and even addresses), I supplement an algorithmic procedure with manual data cleaning. This allows me to identify 200,000 unique inventor last names from 1.8 million unique inventor name strings with reasonable confidence. Next, I match these last names to ethnic origins using the census-based mapping detailed in B.2, and further manually clean the remaining unmatched ones (details in appendix A.3). By this process, I am able to identify the inventors' countries of origin for 90% of the patent sample based on either their non-US address or last names. I also use fractional count to calculate the number of patent at firm-by-inventor country level, as one patent could have multiple inventors and one inventor could be probabilistically mapped to multiple countries of origin.

A.3 CEO biographical data

I identify a firm's CEO in BoardEx from his position title, that is, if (i) it includes either one of the following phrases: *"CEO," "Chief Executive,"* or *"Principal Executive,"* and (ii) the phrase is not preceded by terms such as deputy, vice, division, group, regional, emeritus, etc. I verify if each firm has one CEO at a point in time, unless there are co/joint-CEOs, and manually check all exceptions. CEO transitions are inferred from the start and end dates of each CEO position.

CEOs' trust measures are computed from their ethnic origins as inferred from their last names (see subsection 2.2). I first map CEOs' last names to ethnic origins using the census-based last name-ethnic origin mapping detailed in appendix B.2. For the remaining CEOs whose last names do not appear with reasonable frequency in the censuses, I handpick out cases in which the last names distinctively belong to an ethnic group and manually search for the origins of unmatched CEO last names that appear with high frequency. For example, compound last names beginning with "Van" are likely Dutch, "Von" German, or "Les" French. (Further details are available upon request.) This results in a final match rate of 83% at CEO level: 77% from census-based mapping, 4% from manual mapping, and 2% from non-US citizenship. Panel A of A3 shows that there is no significant difference between these name-matched 83% and the remaining non-matched 17% across all observable characteristics.

[49] Relevant Eurobarometer bilateral trust measure (i.e., trust towards R&D labs based on their countries of location) is available for 7 out of these 10 countries, except for India, Canada, and Israel.

Besides using CEOs' names to infer their ethnic origins, I also employ data on their nationality, gender, age, education, and employment history. First, I exclude all CEOs who are explicitly not US citizens. They comprise only 4.8% of the 54% of CEOs for whom BoardEx contains nationality information. A quick check reveals that the other 46% represent cases in which the CEOs are obviously US citizens, so that the firm's website does not state their nationality. They are thus counted as US citizens. Second, I classify all degrees associated with each CEO into four different categories: below bachelor, bachelor, masters, and doctorate, and separately identify if a CEO has an MBA degree. I further supplement this classification with relevant information contained in CEOs' titles, such as "Doctor," "JD," or "MBA." The education variable is equal to the highest degree level a CEO has attained, and CEOs with no education information are dropped. BoardEx also provides data on CEOs' educational institutions, which allow me to identify if they have been educated abroad or in the US. Third, I use information on CEOs' employment history to impute their tenure in the respective firms, and to identify whether they have held an R&D related position prior to becoming the CEO. R&D-related positions are those whose title contains either one of the following words (or their derivations): "research," "innovation," "scientific," or "technology."

Finally, based on CEOs' birthplace data from Marquis Who's Who, I manually identify 68 foreign-born CEOs, which information is used in Table 4. The rest of the CEOs are classified as likely US-born, although in many cases their birthplace information is not available. This type of measurement error can only create a downward bias in the difference between foreign-born and US-born CEOs' trust effects.

Retirements and deaths. Table A9 considers transitions due to CEO's retirements or deaths. I define retirement as cases in which the CEOs (i) leave office at the age of or around 65, and (ii) do not have any executive positions afterward. 65 is the official Social Security retirement age and the commonly-used retirement age in the related literature (e.g, Fee et al., 2013). In the data, I also observe a spike in CEO's leaving executive positions for good around 65. CEO's deaths are identified from CEO's year of death as provided by BoardEx. They could be unexpected or the result of long-term health decline. Given that there are very few CEO's deaths while still in position in my sample (only 34 cases), I do not further narrow them down to only sudden deaths as is the standard in the related literature (Nguyen and Nielsen, 2010; Bennedsen et al., 2010).

A.4 Corporate trust culture measure

My measure of firm's trust culture comes from Sull's (2018) text analysis of almost one million employee reviews on Glassdoor.com, which cover over 500 US large public firms between 2008 and 2017. For a large set of topics related to O'Reilly et al.'s (1991, 2014) 7 dimensions of corporate culture (), the dataset contains the number of instances each topic appears in a review with positive or negative sentiment. Examples of topics include [...]. Among those, I am most interested in the topic that measures the extent to which employees trust one another, or "corporate trust culture," under the integrity dimension. The sentiment count is positive if the topic is mentioned positively and vice versa, and is zero if the topic is not at all mentioned in the review. To avoid overweighing long reviews, I recode positive sentiment counts to 1 and negative sentiment counts to -1.[50]

To obtain reliable measure of corporate trust culture that is not driven by a few idiosyncratic reviews, I aggregate review-level sentiment data by CEO term up to 2016 and only keep the CEO terms for which there are at least 100 meaningful reviews, which is the 25$^{\text{th}}$ percentile in terms of review counts. This yields a final sample of 394 observations at firm-by-CEO term level, covering 279 firms, for Table 5. The resulting corporate trust culture is then standardized by its standard deviation at firm-by-CEO term level. All results in Table 5 are robust to using different review count cutoffs. On the other hand, placebo tests show that CEO's trust is not associated with other aspects of corporate culture besides corporate trust culture.

A.5 Complementary transition event sample

Besides the baseline sample (see subsection 2.3) that is used throughout the paper, I also construct a complementary transition event sample in which each event is a CEO transition at a baseline firm during 2001-2011. For each event, the sample includes all the years that correspond to the tenures of the preceding and succeeding CEOs in that transition. That is, each observation in this sample represents a firm f in year t with its current CEO d that corresponds to a CEO transition event E (i.e., CEO d is either the predecessor or the successor in transition event E).

For example, during 2001-2011, EMS Technologies has had three CEOs: Alfred Hansen (2001-2006), Paul Domorski (2006-2009), and Neil Mackay (2009-2011), which maps to two CEO transition events. For the first event, all years between 2001 and 2009 are included in the transition event sample; for the second one, all years between 2006 and 2011. Thus Paul Domorski's tenure between 2006 and 2009 appears twice in the sample, once as the successor in first event and once as the predecessor in the second event. On the other hand, firms that experienced no CEO transition during 2001-2011 are not included in the transition event sample.

The final transition event sample includes 20,389 observations, covering 2,446 CEO transition events with 3,656 CEOs in 1,769 firms. This sample construction allows for the inclusion of transition event fixed effects, which are more stringent than firm fixed effects (Panel F of Table A7). It also facilitates the investigation of common trend and no pre-trend identifying assumption (Figures 2A and A1) and heterogeneous CEO's trust effects (Figures A3 and A6). Finally, a subsample of exogenous CEO transition events due to CEO's retirements or deaths is used Table A9.

[50] Grennan (2014) uses similar approach of text analyzing online employee reviews to measure corporate culture along the 7 dimensions proposed by O'Reilly et al. (1991, 2014). She finds that changes in corporate governance lead to changes in corporate culture and firm's performance.

B Inherited trust measure

B.1 Ethnic-specific trust measure

Generalized trust. The baseline $ethtrust_e$ measure is computed using individual-level data on trust attitude and ethnic origins from the US GSS. A respondent's trust attitude is measured by the standard generalized trust question *"Generally speaking, would you sat that most people can be trusted or that you can't be too careful in dealing with people?"*. Following the literature, I construct a trust indicator equal to 1 if the answer is "Most people can be trusted," and 0 if the answer is "Can't be too careful" or "Other, depends." This grouping makes a clear separation between high trusting individuals as opposed to moderate or low trusting ones (Algan and Cahuc, 2010). The use of GSS-like trust questions to measure trust has been experimentally validated in trust game settings. Notably, Sapienza et al. (2013) show that GSS-like trust questions capture the belief-based component in a Berg et al. (1995) trust game. They find strong correlations between senders' survey answers and their expectations about the amounts returned for large amounts sent, which is the best measure of the senders' expectations of the receivers' trustworthiness. Relatedly, Fehr et al. (2002) and Falk et al. (2016) find that in similar trust games, senders' survey answers are robust predictors of the amounts sent, which in turn are highly correlated with their expectations about the amounts returned by the receivers.

The respondent's ethnic origin is captured by the question *"From what countries or part of the world did your ancestors come?"*, which covers 36 most common ethnic origins in the US, including all major European countries in addition to Canada, Mexico, China, and India (Table A1). As the GSS covers representative samples of the US population, its respondent pool includes not only first- or second-generation immigrants but also their descendants multiple generations down the line. Despite this, only 2.8% of respondents consider themselves as "American only," while 37% report two or three countries of origin, in which case I select the one to which they feel the closest to. In addition to "American only," I also exclude 4 other ethnic categories: "American Indian" (4.4%), "Other Asian" (0.4%), "Other European" (0.3%), and "Other" (0.9%), which together cover less than 9% of total respondents. Finally, to better match the CEO sample, I only consider respondents whose GSS occupation prestige score is in the top 25% (i.e., 50 or above). This covers most respondents in management occupations. While respondents in these highly prestigious occupations are considerably more trusting than the full GSS population (0.51 vs. 0.38), the ordinary and Spearman rank correlations between $ethtrust_e$ computed from this sample and that computed from all GSS respondents are high, at 0.85 and 0.75 respectively.

As robustness checks, I also compute alternative $ethtrust_e$ measures using other trust questions in the GSS and other surveys. Other trust questions in the GSS are (i) *"Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair?"*, and (ii) *"Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves?"*. Other survey sources include the World Value Survey (WVS) and Falk et al.'s

(2018) Global Preference Survey (GPS). In addition, I use LASSO (Tibshirani, 1996) to construct an augmented trust measure that also takes into account other demographic characteristics such as gender, education, age, birth cohort. The LASSO model fitted using GSS data to predict trust based on all available demographic characteristics and their interactions retains all ethnic origin dummies, consistent with the view that ethnic origin plays a meaningful role in shaping individual trust. I then use the model to predict CEOs' trust. Inherited generalized trust measures computed using these different questions, sources, and methods are all highly correlated with one another.

Bilateral trust. Country-pair-level bilateral trust measure ($ethbitrust_{ec}$) comes from the Eurobarometer surveys' question *"I would like to ask you a question about how much trust you have in people from various countries. For each, please tell me whether you have a lot of trust, some trust, not very much trust, or no trust at all."* Following the literature, I recode the answers to 1 (no trust at all), 2 (not very much trust), 3 (some trust), and 4 (a lot of trust) before averaging them by country pair to derive $ethbitrust_{ec}$.

The surveys cover respondents from 16 EU countries and ask about their trust attitude towards 28 countries, including some non-EU countries. The 16 trust-originating countries are France, Belgium, the Netherlands, Germany, Italy, Luxembourg, Denmark, Ireland, Greece, Spain, Portugal, Norway, Finland, Sweden, Austria, and the United Kingdom (with breakdown for England, Wales, Scotland, and Northern Ireland). The 28 trust-receiving countries are the 16 trust-originating countries plus Bulgaria, Switzerland, Czechoslovakia, Hungary, Poland, Romania, Russia, Turkey, Yugoslavia, China, Japan, and the US. The average bilateral trust among 535 directed country pairs for which data is available is 2.32, with a standard deviation of 0.34 and an interquartile range of 0.41. Bilateral trust is expectedly correlated with generalized trust. Although Eurobarometer surveys are conducted in Europe, given the evidence of intergenerational transmission of trust attitude, it seems reasonable to use the Eurobarometer-based bilateral trust measure as a proxy for the bilateral trust among US descendants of European immigrants.

B.2 Mapping last names to ethnic origins

Sample of foreign-origin individuals. I start with de-anonymized full population samples of four US censuses between 1910 and 1940, which contain information on names and birthplaces of the US population. These restricted-access de-anonymized censuses are provided by the Minnesota Population Center through a formal application process. I keep all observations that meet the following criteria: (i) the individual is either male or never-married female; (ii) his last name is non missing; and (iii) either he himself or at least one of his parents was born outside of the US. This results in a sample of 79 million individuals with foreign (i.e., non-US) birthplace or ancestry across four censuses.

Each individual's origin is defined as: (i) his birthplace if it is outside of the US, (ii) his father's birthplace if his own birthplace is in the US or missing, or (iii) his mother's birthplace if both his own and his father's birthplaces are in the US or missing. I further refine this mapping by (i) dropping foreign-born individuals to both US-born parents, (ii) assigning individuals who were born outside of the US and Europe (e.g., Canada, Australia) to his parents' birthplaces if the parents were born in Europe, and (iii) refining coarse birthplace information (e.g., Central Europe) with additional information on mother tongue. However, these adjustments affect less than 1% of the sample. Among the 79 million foreign-origin individuals in the censuses, 87% are originally from Europe, 7% from Canada, 3% from Central America (mostly Mexico), 2% from Asia, and 1% from other parts of the world.

Last name-GSS ethnic origin mapping. Birthplace data in the censuses are coded mostly at country level, while ethnic-specific trust measure derived from the GSS is available for 36 most common ethnicities in the US (Table A1). To address this, I construct a mapping between these two different classifications as follows.

- First, I map a country of origin in the census to an ethnic origin in the GSS if they represent the same country (e.g., Germany, Sweden, Italy) or region (e.g., England and Wales, Scotland).
- Second, I create new "aggregate" GSS ethnic groups (mostly for different regions within Europe) and map the remaining census countries of origin to their corresponding aggregate ethnic groups if possible. For example, Bulgarian, which is not an ethnicity included in the GSS, is mapped to a new ethnic group labeled as Eastern European, which is the aggregate of GSS ethnic groups Czechoslovakian, Hungarian, Polish, Romanian, and Russian.
- Third, I map the remaining countries in the census to existing coarse ethnic groups in the GSS such as African, Arabic, other Asian, other Spanish, or missing.

While this mapping may seem coarse, the fact that the GSS's ethnic classification is designed to cover the most common ethnicities in the US implies that a large share (at least 80%) of foreign-origin individuals in the censuses could be mapped to a GSS ethnic origin under the first step. On the other hand, the remaining ones still need to be accounted for systematically, as dropping them could introduce unwanted selection into the final last name-ethnic origin mapping. The exact correspondence between the census' country of origin and the GSS's ethnic origin classifications is available upon request.

79 million foreign-born individuals in the censuses share among them five million unique last names, the majority of which appear fewer than 10 times. To improve precision, I first filter out aberrant observations by dropping ethnic origins that occur less than 10% of the times for a given last name. I then consider only 75,000 last names that appear for at least 100 times in the remaining sample, which constitute 66% of this sample. The probabilistic mapping between last names and GSS ethnic origins is constructed from the resulting sample. Specifically, I compute w_{se}, the probability that a person with last name s is of ethnicity e as $w_{se} = \frac{n_{se}}{N_s}$, in which n_{se} is the number of individuals with last name s from ethnic origin e, and N_s is the total number of individuals with last name s in the sample. For example, based on this mapping, the last name

Johnson is 78% Swedish and 22% Norwegian; the last name Smith is 32% English, 26% German, 24% Irish, and 18% Canadian.

This last name-GSS ethnic origin mapping is used to compute $trust_d$, the baseline CEO's inherited generalized trust measure, as well as other GSS-based inherited cultural trait measures (details in appendix D.1). For each CEO d, $w_{de} = w_{se}$ where s is the CEO's last name. His main ethnic origin, used for standard error clustering, is defined as $e_d^* = \text{argmax}_e(w_{de})$. The average $w_{de_d^*}$ among CEOs in the baseline sample is high at 71%, so alternatively measuring CEO d's inherited based only on his main ethnic origin ($trust_d = ethtrust_{e_d^*}$) yields quantitatively similar results.

In additional sensitivity tests, I find that lowering the aforementioned 100 observation and 10% share cutoffs to retain more observations does not significantly improve the match rate of CEO last names but slightly reduces the precision of the key estimates. Separately, dropping Canada as a possible ethnic origin also does not change the paper's key findings.

Most common last name supplements. One concern is that data from historical censuses do not capture more recent waves of migration to the US. However, it has been shown that CEOs in the US are predominantly "WASP" (White Anglo-Saxon Protestant), which groups arrived in the US well before the 1940s. Furthermore, to address the concern, I supplement the census-based mapping with lists of most common last names in 50 different countries collected from online sources such as `forebear.com` or `wikipedia.com`. These lists also provide me a way to cross-check the quality of the census-based mapping. First, I develop a list of all last names that could account for at least 0.01% of immigrants in the US. Each last name's predicted share is computed as the share of the last names in its respective country times the share of immigrants from that country in the US foreign-origin population (based on census data between 1960-2015). I then map countries to GSS ethnic origins and add the last names from the list to the census-based mapping. For last names that are already included in the mapping, I find that the census-based mapping is generally consistent with the information from the list.

Last name-WVS country mapping. I employ similar steps as described above to map last names to WVS countries of origin. For this mapping, constructing the correspondence between birthplace data in the censuses and WVS countries of origin is straightforward, as both classifications are at country level and cover close to complete lists of countries worldwide.

Last name-Eurobarometer country mapping. To compute CEOs' bilateral trust measure, I construct the mapping between last names and countries of origin covered in the Eurobarometer also in similar steps. As the Eurobarometer provides bilateral trust measure for only 16 trust-originating and 28 trust-receiving countries, foreign-origin individuals in the census sample who are not from one of these countries are assigned to the "not-covered" category. Furthermore, I construct two separate mappings. The first one considers the 16 trust-originating countries and is used for mapping CEOs' last names. The second one considers the 28 trust-receiving countries and is used for mapping inventors' last names.

After constructing the first mapping that is used for CEOs, I drop all last names with above 20% probability of being from a "not-covered" country of origin, then drop this "not-covered" category and rescale the remaining w_{se}'s so that $\sum_{e\in\mathbf{E}} w_{se} = 1$ where $\mathbf{E}$ is the set of 16 trust-originating countries. That is, the final mapping contains only last names with at least 80% probability of being from countries for which bilateral trust measure is available. The rescaling is required as the CEO's bilateral trust measure is the weighted average of country pairwise bilateral trust.

B.3 Relative magnitude of trust measurement error

Because of the indirect nature of my measure of inherited trust, it is important to gauge the relative magnitude of measurement error, and its impact on the estimate. In what follows, I propose a method to evaluate the extent of measurement error of inherited trust, using existing results from trust game experiments such as Glaeser et al.'s (2000). Denote a person i's trust as T_i, the major ingredient in my theory. As remarked in the literature, the GSS's trust survey question produces a measurement error ϵ_i, so that we only observe surveyed trust as $TS_i = T_i + \epsilon_i$.The empirical ethnic component of trust, as calculated from trust survey, is $TEth_c = \mathbb{E}(TS_i|c) = \mathbb{E}(T_i|c) + \mathbb{E}(\epsilon_i|c)$. In case of an independent error ϵ_i, $TEth_c = \mathbb{E}(T_i|c)$.

My first question is on the relative magnitude of the discrepancy between $TEth_c$ and T_i, namely $R_{TEth} = \frac{\text{Var}(TEth_i)}{\text{Var}(T_i)}$. As $\frac{\text{Var}(TEth_c)}{\text{Var}(TS_i)} = 0.06$ comes straight from the GSS sample, it remains to find $R_T = \frac{\text{Var}(T_i)}{\text{Var}(TS_i)}$.

Consider the experimental setting in Glaeser et al. (2000) in which subjects play a trust game, and their decisions are then linked to their answers to a GSS trust question. Based on the literature on the stability of trust experiments, I suppose that the trust game decision TG_i (a number between 0 and 15 in that context) contains an idiosyncratic error η_i: $TG_i = \gamma T_i + \eta_i$, with a ratio of signal to total variation $R_{TG} = \frac{\text{Var}(\gamma T_i)}{\text{Var}(TG_i)}$. According Falk et al. (2016), this ratio is around 60%. We learn from Glaeser et al. (2000) that the regression of TG_i on TS_i yields a coefficient of $\hat{b}_G$ with a standard error of $\hat{\sigma}_G$. I will make use of those two numbers and R_{TG} to compute R_T.[51]

Using formulae of regressions with measurement errors, I can write $\hat{b}_G = \gamma \frac{\text{Var}(T_i)}{\text{Var}(TS_i)} = \gamma R_T$. Its

[51] There is a debate following Glaeser et al. (2000) on the validity of different trust measures. In defense of trust surveys, Sapienza et al. (2013) argue that the sender's behavior in the trust game, Glaeser et al.'s (2000) preferred measure of trust, is not necessarily a good measure of trust, because it is confounded by other-regarding preferences. In contrast, WVS/GSS trust questions better capture the belief-based component of the trust game, which corresponds better to the concept of trust as defined in Gambetta (1988) and in my model.

standard error can also be written as:

$$\begin{aligned}\hat{\sigma}_G^2 &= \frac{\text{Var}(TG_i - \hat{b}_G TS_i)}{\text{Var}(TS_i)} = \frac{\text{Var}[(\gamma - \gamma R_T)T_i + \eta_i - \gamma R_T \epsilon_i]}{\text{Var}(TS_i)} \\ &= \gamma^2(1-R_T)^2 R_T + \gamma^2 \frac{1-R_{TG}}{R_{TG}} R_T + \gamma^2 R_T^2(1-R_T) \\ &= \gamma^2 R_T(1-R_T) + \gamma^2 \frac{1-R_{TG}}{R_{TG}} R_T.\end{aligned}$$

Replacing $\gamma = \hat{b}_G/R_T$, we obtain:

$$\hat{\sigma}_G^2 R_T = \hat{b}_G^2 \left(1 - R_T + \frac{1-R_{TG}}{R_{TG}}\right) \Rightarrow R_T = \frac{\hat{b}_G^2}{(\hat{b}_G^2 + \hat{\sigma}_G^2)R_{TG}} = \frac{t^2}{t^2+1}\frac{1}{R_{TG}},$$

with $t = \frac{\hat{b}_G}{\hat{\sigma}_G}$ the t-statistic of the test $b_G = 0$. As there are two potential outcomes from trust games in Glaeser et al. (2000), I compute the average of t over the two potential outcomes from trust games in Glaeser et al. (2000) at around 0.50,[52] mapping into $R_T = 0.33$. I thus deduce $R_{TEth} = 0.18$. That is, the ethnic component of trust measures about 18% of the variation in individual trust. Finally, when I use a LASSO model to predict trust using all observables and their interactions, the ratio of predicted variation $\frac{\text{Var}(TEth_c)}{\text{Var}(TS_i)}$ rises to about 0.11, corresponding to $R_{TEth} = 0.33$.

Discussion. A few remarks can be drawn from those exercises. First, one can argue that $TEth_c$ is a much better measure of trust than a simple survey answer TS_i, as the variance of the survey noise ϵ_i far outweighs the variance of individual components $T_i - TEth_c$ (the ratio of variance is $\frac{0.67}{0.27}$, or about 2.5 times). Therefore, it would not have added value even if we could administer a trust survey among CEOs.[53] Second, even if we could run a trust game among CEOs, the ratio of the variance of the experimental noise η_i to the variance of ν_i is about $\frac{0.33 \times \frac{100\% - 60\%}{60\%}}{0.27} \sim 0.81$. That is, using my inherited trust measure is 81% as precise as using trust game results from CEOs. Third, as shown in appendix B.3, while ethnic specific inherited trust likely represents only 18% of inherent individual trust, the benchmark regression likely produces an unbiased of the true effect (there is no attenuation bias as in the case of classical measurement errors). The main intuition from this exercise is that both methods of elicitation of individual trust, either via surveys or via trust games, produce a considerable amount of measurement error, as has been shown throughout the literature. While my method of averaging trust survey answers by ethnic origin misses the individual-specific component of trust, it also helps in smoothing out those measurement errors. Quantitatively, the latter effect can more than compensate the former.

[52] The outcomes are the amount sent by the first player, and the reservation price that the first player considers equivalent to the value of the game. As discussed in Sapienza et al. (2013), those measures should be considered with caution, as they may also include effects due to social preferences, not just beliefs.

[53] Of course, if we can administer *many* trust surveys on the same individual, we can average out much more precisely individual trust. I consider this possibility highly infeasible though.

B.4 Bias due to trust measurement error

The second question regarding measurement error is how much does the discrepancy between $TEth_c$ and T_i affect the estimate of the effect of trust. Let us assume the true relationship between innovation outcome Y_{ft} of firm f in year t and its current CEO d's individual trust T_{dt} as $Y_{ft} = \beta T_{dt} + \theta_f + u_{fdt}$, with a firm fixed effect θ_f, and an independent error term u_{fdt}. When current CEO's ethnic-specific inherited trust $TEth_{ct}$ is used in place of individual trust T_{dt}, the fixed effect estimator is $\hat{\beta}_{TE} = \frac{\text{Cov}(M.Y_{ft}, M.TEth_{ct})}{\text{Var}(M.TEth_{ct})}$, with the firm-demeaning linear operator $M.X_{ft} = X_{ft} - \mathbb{E}_t(X_{ft}|f)$ for each firm f. Also observe that:

$$\begin{aligned}
\text{Cov}(M.Y_{ft}, M.TEth_{ct}) &= \text{Cov}(\beta M.T_{dt} + M.u_{fdt}, M.TEth_{ct}) \\
&= \beta\text{Cov}(M.\mathbb{E}(T_{dt}|c) + M.(T_{dt} - \mathbb{E}(T_{dt}|c)), M.TEth_{ct}) \\
&= \beta\text{Cov}(M.TEth_{ct} - M.\mathbb{E}(\epsilon_{dt}|c), M.TEth_{ct}).
\end{aligned}$$

In case of independent survey measurement error ϵ_{dt}, so that $\mathbb{E}(\epsilon_{dt}|c) = 0$, the expression above is reduced to $\beta\text{Var}(M.TEth_{ct})$. Therefore, using the ethnic component of trust $TEth_{ct}$ in place of individual trust T_{it} does not create any bias in the firm fixed effect specification. In essence, this exercise is similar to taking a cell-average of the right hand side variable, and then use it as a new regressor, a procedure that is very useful especially when one can only observe cell averages (as in Angrist and Pischke, 2009, c. 2).

If the survey measurement error ϵ_{dt} is not mean-independent of the respondent's country, $\hat{\beta}_{TE}$ with be biased from β by $-\frac{\text{Cov}(M.\mathbb{E}(\epsilon_{dt}|c), M.TEth_{ct})}{\text{Var}(M.TEth_{ct})}$. Based on the empirical results, we can assume that there is little autocorrelation over time between different CEOs at the same firm, in which case we can get rid of the operator M to rewrite the bias as $-\frac{\text{Cov}(\mathbb{E}(\epsilon_{dt}|c), TEth_{ct})}{\text{Var}(M.TEth_{ct})}$.

The bias' sign is that of $-\text{Cov}(\mathbb{E}(\epsilon_{dt}|c), TEth_{ct})$, or the opposite of the covariance across countries between ethnic-based inherited trust, and individual survey measurement errors. It is likely negative if, for example, high-trust countries' respondents tend to push their answers higher than the true level of trust, and low-trust countries' respondents tend to lower theirs. There is a technical reason to expect this pattern: Surveyed trust TS_i is a yes-no answer, which naturally exaggerates the variation in the individual trust component T_i. For example, two individuals' beliefs at 60% and 40% will map into two opposite answers of value 1 and 0, respectively.[54] Consequently, the estimator $\hat{\beta}_{TE}$ likely underestimates the true effect of individual CEO's trust on innovation.

[54] There is, however, another reason to expect the covariance to be negative and the bias positive: if the individual belief ranges mostly on one side of 50%, say, from 50% to 100%, then they all correspond to a survey answer of 1. As a stronger belief entails a smaller error term, the covariance is negative. When both effects are taken into account, based on the empirical distribution of survey answers, I can show that under mild conditions, and in most simple simulations, the positive-covariance effect largely dominates, therefore the bias is very probably negative.

C Other empirical specifications

C.1 Common trend in pre-change patents and other characteristics

Figure 2A. Figure 2A plots $\hat{\gamma}_k$'s for $k \in [-6, -1]$ from the following specification:

$$\Delta trust_{fd} = \sum_{k=-7}^{-1} \gamma_k (\text{arsinh}(pat_{ft}) \times D_{ft}^k) + \beta trust_d + \xi \mathbf{X}_{ft} + \zeta \mathbf{Z}_{dt} + \mu_{sk} + \omega_t + \varepsilon_{fdt}, \tag{A1}$$

using the transition event sample (details in appendix A.5), where

- each observation represents a firm f in year t with its current CEO d (who is the predecessor in the respective CEO transition event),
- $\Delta trust_{fd}$ is the difference between CEO d's and his successor's (in firm f) inherited trust measures ($trust_d$ is CEO d's inherited trust measure),
- pat_{ft} is firm f's patent application count in year t,
- D_{ft}^k is an indicator equal to 1 if year t is $|k|$ years before the corresponding CEO transition in firm f,
- $\mathbf{X}_{ft}$ and $\mathbf{Z}_{dt}$ are baseline controls for firm f's and CEO d's time-variant characteristics,
- μ_{sk} is a full set of firm f's 3-digit SIC industry-by-time until the transition fixed effects,
- ω_t is a full set of year fixed effects, and
- standard errors are clustered by firms.

The coefficients γ_k capture whether among firms in the same 3-digit SIC industry, a firm's pre-change patent counts predict its future change in CEO's trust. The resulting $\hat{\gamma}_k$'s are both small in magnitude and statistically insignificant, implying that it is not the case. To put differently, the estimates indicate that firms experiencing different changes in CEO's trust have similar patenting trends before the changes.

Figure A1. Similarly, Figure A1 plots $\hat{\gamma}_k$'s for $k \in [-6, -1]$ from the following:

$$\Delta trust_{fd} = \sum_{k=-7}^{-1} \gamma_k (perfmeasures_{ft} \times D_{ft}^k) + \beta trust_d + \xi \mathbf{X}_{ft} + \zeta \mathbf{Z}_{dt} + \mu_{sk} + \omega_t + \varepsilon_{fdt}, \tag{A2}$$

where $perfmeasure_{ft}$ is (i) arsinh(R&D expenditure) in subfigure A1A, (ii) ln(employment) in subfigure A1B, (iii) ln(sales) in subfigure A1C, and (iv) ln(total assets) in subfigure A1D. All other variables and features are the same as in equation (A1), except for $\mathbf{X}_{ft}$, which does not include ln(sales) and ln(assets). Standard errors are also clustered by firms. The resulting $\hat{\gamma}_k$'s again indicate that among firms within the same 3-digit SIC industry, change in CEO's trust does not correlate with firm's pre-change characteristics and/or performance.

Figure A4. Figure A4 plots $\hat{\gamma}_k$'s for $k \in [-6, -1]$ from estimating the following equation:

$$\Delta bitrust_{fdc} = \sum_{k=-7}^{-1} \gamma_k (\text{arsinh}(pat_{fct}) \times D_{ft}^k) + \beta bitrust_{dc} + \xi \mathbf{X}_{ft} + \zeta \mathbf{Z}_{dt} + \nu_{fk} + \kappa_c + \omega_t + \varepsilon_{fdct}, \tag{A3}$$

using the bilateral trust samples, where

- each observation is a combination of firm f by year t by its CEO d by inventor country c,
- $\Delta bitrust_{fdc}$ is the difference between CEO d's and his successor's (in firm f) measures of bilateral trust towards individuals from country c ($bitrust_{dc}$ is CEO d's bilateral trust towards individual from country c),
- pat_{fct} is firm f's total patent count by inventors from country c in year t,
- D_{ft}^k is an indicator equal to 1 if year t is $|k|$ years before the corresponding CEO transition in firm f,
- $\mathbf{X}_{ft}$ and $\mathbf{Z}_{dt}$ are baseline controls for firm f's and CEO d's time-variant characteristics,
- ν_{fk} is a full set of firm-by-time until the transition fixed effects,
- κ_c and ω_t are full sets of inventor country and year fixed effects, and
- standard errors are clustered by firm.

The γ_k coefficients capture whether within the same firm, future changes in CEO's bilateral trust towards inventors in or from a certain country, following a CEO transition, can be predicted by the inventors' pre-change patent counts. The resulting $\hat{\gamma}_k$'s are both small in magnitude and statistically insignificant, implying that it is not the case.

C.2 Pre-trend in patents

Figure 2B plots $\hat{\gamma}_k$'s for $k \in [-7, -2]$ relative to $\hat{\gamma}_{-1}$ from estimating the following equation:

$$\text{arsinh}(pat_{ft}) = \sum_{k=-7}^{-1} \gamma_k \times D_{ft}^k + \xi \mathbf{X}_{ft} + \zeta \mathbf{Z}_{dt} + \theta_f + \omega_t + \varepsilon_{fdt}, \tag{A4}$$

using the transition event sample (details in appendix A.5), where

- each observation is firm f in year t with its current CEO d (who is the predecessor in the respective CEO transition event),
- pat_{ft} is firm f's patent application count in year t,
- D_{ft}^k is an indicator equal to 1 if year t is $|k|$ years before the corresponding CEO transition in firm f,
- $\mathbf{X}_{ft}$ and $\mathbf{Z}_{dt}$ are baseline controls for firm f's and CEO d's time-variant characteristics,
- θ_f and ω_t are full sets of firm and year fixed effects, and
- standard errors are clustered by firms.

Each coefficient γ_k captures firms' average patent application count $|k|$ years before the next CEO transition (relative to that in the year before the transition), after partialling out (i) baseline firm and CEO controls and (ii) firm and year fixed effects. The resulting $\hat{\gamma}_k$'s are both small in magnitude and statistically insignificant, implying that the timing of the CEO transition is not driven by a trend in pre-change patenting.

C.3 Semi-parametric estimation of heterogeneous CEO's trust effects

Following Do et al. (2017), I modify equation (3)'s baseline difference-in-differences specification to examine the heterogeneous effects of CEO's trust on firm's patents as a function $\beta(\cdot)$ of a variable of interest x, using the transition event sample (details in appendix A.5):

$$\text{arsinh}(pat_{f,t+1}) = \beta(x)trust_d + \xi(x)\mathbf{X}_{ft} + \zeta(x)\mathbf{Z}_{dt} + \theta_E(x) + \omega_t(x) + \varepsilon_{Edt}. \tag{A5}$$

The function $\beta(\cdot)$ is estimated from semi-parametric local linear regressions based on equation (3) at each value of x (the focal point). In each local regression, observations are weighted by a Gaussian kernel function of x around the focal point, with a bandwidth equal to 20% of the total range of x (the shape of the estimated function $\beta(\cdot)$ remains robust to a broad range of cross-validated bandwidth). In Figure A3, the X-axis variable x is the change in CEO's trust after the corresponding transition $\Delta trust_E$. In Figure A6, it is the pre-transition researcher pool quality $prequal_E$ (see subsection 5.4). Standard errors are clustered by CEO's main ethnicity.

C.4 CEO's trust effect by tenure in firm

Figure A7 plots $\hat{\beta}_k$ from estimating the following equation:

$$\text{arsinh}(pat_{f,t+1}) = \sum_{k=1}^{9} \beta_k(trust_d \times tenure^k_{fdt} \times successor_d) + \xi\mathbf{X}_{ft} + \zeta\mathbf{Z}_{dt} + \theta_E + \omega_t + \varepsilon_{Edt}, \tag{A6}$$

using the transition event sample (details in appendix A.5), where

- each observation represents a firm f in year t with its current CEO d (who is either the predecessor or the successor in CEO transition event E),
- $pat_{f,t+1}$ is firm f's patent count in year $t+1$,
- $trust_d$ is CEO d's inherited trust measure,
- $tenure^k_{fdt}$ is an indicator equal to 1 if by year t CEO d has been in firm f for k years,
- $successor_d$ is an indicator equal to 1 if CEO d is the successor in CEO transition event E,
- $\mathbf{X}_{ft}$ and $\mathbf{Z}_{ft}$ are baseline controls for firm's and CEO's time-variant characteristics,
- θ_E and ω_t are full sets of CEO transition event and year fixed effects, and
- standard errors are clustered by CEO's main ethnicity.

C.5 Robustness checks

This subsection discussed the robustness checks for the within-firm effect of CEO's generalized trust (equation 3) as described in Section 3. These robustness checks are reported in Table A7.

Table A7, Panel A. Control variables and Poisson model

Control variables. The first two columns report two basic specifications without any firm or CEO control (column 1) or including only CEO controls (column 2), given that firm controls are also potential outcomes. Column (3) then presents equation (3)'s baseline specification that includes the full set of controls for firm's age, size, and CEO's age, gender, education, and tenure in addition to firm and year fixed effects. The next three columns further add employment (column 4), R&D stock (column 5), or R&D flow (column 6). The resulting CEO's trust estimates are almost identical across these six columns. Indeed, additionally controlling for R&D does not alter the magnitude of the CEO's trust effect on patents, suggesting that it is not the result of increases in R&D investments. This is consistent with Table A6's results that higher CEO's trust is not significantly associated with higher R&D expenditure or higher R&D stock.

Poisson model. Column (7) estimates a semi-log Poisson count model with winsorized $pat_{f,t+1}$ as the outcome variable, instead of OLS, while still allowing for the same set of controls and fixed effects. The Poisson estimate implies that one standard deviation increase in CEO's trust is associated with 16.8% increase in firm's patent filing, considerably larger than the baseline OLS estimate of 6.3%.

Table A7, Panel B. Clustering and weighting schemes and patent transformations

Clustering schemes. The first two columns show that the baseline CEO's trust effect in column (3) of Panel A is robust to standard error clustering by firm (column 1) or clustering two-way by CEO's main ethnic origin and firm (column 2).

Weighting schemes. As the last name-ethnic origin mapping used to construct the CEO's inherited trust measure is probabilistic, in column (3), I weight each observation by the precision of CEO d's last name-ethnic origin mapping, measured as $\sum_e w_{de}^2$. Alternatively, in column (4), I measure CEO d's inherited trust based on his main ethnic origin, i.e., $trust_d = ethtrust_{e_d^*}$ where $e_d^* = \text{argmax}_e(w_{de})$, and weight each observation by the precision of that main ethnic origin $w_{de_d^*}$. In addition, I also perform Monte Carlo simulations in which each CEO d's ethnic origin is drawn according to w_{de}. These exercises all yield positive and statistically significant CEO's trust estimates with magnitude comparable to the baseline effect.

Patent transformations. Most of this paper applies the inverse hyperbolic sine transformation $\text{arsinh}(x) = \ln(x + \sqrt{1 + x^2})$ to patent counts. This transformation takes value 0 at $x = 0$ and approximates $\ln x + \ln 2 + O(\frac{1}{x \ln x})$ for large x. It has been promoted as a substitute for $\ln(1+x)$ by David Card (e.g., Card and DellaVigna, 2017), because one can still interpret changes in $\text{arsinh}(x)$ as close approximates of percentage changes in x for sufficiently large x thanks to its similarity with $\ln x$, while the function's behavior around $x = 0$ approximates $\ln(1 + x) + O(x^2)$.

Alternatively using the $ln(1 + x)$ transformation yields comparable CEO's trust coefficient (column 5). The effect is also robust to using winsorized (column 6) or raw (column 7) patent counts as the outcome variable. Column (6)'s estimate implies that one standard deviation increase in CEO's trust is associated with 1.5 additional patents annually (compared to $6.3\% \times 18.0 = 1.1$ additional patents annually as implied by the baseline estimate). Column (7)'s estimate is much larger, as it is more likely to be driven by outliers.

Table A7, Panel C. Trust measures

LASSO-based trust measure. Column (1) reports the baseline specification using the baseline GSS-based inherited trust measure. In column (2), I use LASSO to predict individual trust attitude from not only ethnic origin but also all other demographic variables commonly available in both BoardEx and GSS, including age, gender, education, and birth cohort (details in appendix B.1). This augmented measure yields a larger CEO's trust coefficient, but not by much (6.7%)), suggesting that the baseline trust measure already captures most of the meaningful variations in individual trust across observable demographic characteristics.

WVS/GPS-based trust measures. Column (3)'s trust measure is constructed from the trust answers of *all* GSS respondents, column (4)'s the trust answers of upper middle class World Value Survey respondents in each ethnicity's home country, and column (5)'s the trust answers of high skilled Global Preference Survey respondents, also in each ethnicity's home country (details in appendix D.1). As these measures are not as close to the US CEO population as the baseline, they expectedly yield smaller, yet still positive and statistically significant, estimates of the CEO's trust effect (4.1%, 3.0%, and 3.7%). Furthermore, that the magnitude and precision of the CEO's trust coefficient increase with the quality of the CEO's inherited trust measure is reassuring, as it is difficult to specify an omitted variable that is always more precisely measured when trust is better measured.

Alternative trust questions. Columns (6) and (7) employ alternative trust questions in the GSS to construct CEO's inherited trust measure. Column (6) uses the "distrust" question *"Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair?"*. Column (7) uses the question *"Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves?"*. While not as popular as the standard trust question, these formulations have also been used in related literature as alternative ways to elicit respondents' trust attitude. Inherited trust measures computed using these alternative questions are highly correlated with the baseline trust measure, thus yielding CEO's trust coefficients that are almost identical to the baseline.

Table A7, Panel D. Sample restrictions and margins of effect

Additional restrictions. Column (1) excludes singleton observations. Column (2) excludes female CEOs for whom ethnic origin inference from last name could be less accurate due to name changing after marriage. Column (3) excludes interim CEOs who do not stay in the position long enough to wield detectable influence. These restrictions does not affect, if not strengthen, the magnitude of the CEO's trust effect.

Patenting samples. The next three columns focus on the subsample of patenting firms. Column (4) considers firms that patent at least once during the study period. Column (5) further narrows the sample down to the years between each firm's first and last patent applications during the study period. Column (6) includes only the years in which the firm does file a patent. Restricting the sample to only patenting firms, patenting periods, or patenting years results in considerably larger CEO's trust coefficients (8.6%, 10.3%, and 9.9% respectively), suggesting that the intensive margin is the dominant force.

Margins of effect. Conditional on firm's patenting, CEO's trust is positively associated with the number of patents being filed by the firm (9.9% in column 6). On the other hand, column (7) shows that higher CEO's trust does not increase the probability of a firm patenting in a given year (0.9%). Columns (4) and (5) of Panel F similarly show that the CEO's trust effect is present only among firms having patented before the respective CEO transitions. Together, these results imply that the CEO's trust effect works mostly through the intensive margin and not the extensive margin.

Table A7, Panel E. Time lags before patent filing

This panel considers further-forward patent counts as the outcome variable. Column (1) looks at contemporaneous patent count. Column (2) employs one-year forward patent count as in the baseline specification but excludes the very last year of the corresponding CEO's tenure, so that the forward patent count does not fall under another CEO's tenure. Similarly, columns (3) to (5) looks at two-year forward patent count and columns (6) to (9) three-year forward. Columns (4) and (5) exclude the last year and the last two years of the corresponding CEO's tenure, and columns (7), (8), and (9) exclude the last year, the last two years, and the last three years. All resulting CEO's trust coefficients are positive and statistically significant across the columns. They suggest that the CEO's trust effect is rather stable over time, especially when potential contamination from successor CEO's trust effect is accounted for (columns 2, 5, and 9).

Table A7, Panel F. CEO transition event sample

This panel employs a sample constructed from CEO transition events and event fixed effects instead of firm fixed effects (details in appendix A.5). Column (1) reports the baseline CEO's trust effect using this sample (7.0%), which is comparable to the baseline CEO's trust effect (6.3%). In column (2), I interact CEO's trust with the change in CEO's trust due to the transition, defined ad the difference between the successor's and predecessor's standardized trust measures. The interaction term is not statistically different from zero, implying that the baseline effect is driven by both trust-increasing and trust-decreasing CEO transitions, consistent with the pattern shown in Figure A3. Indeed, column (3) directly shows that firm's patent count declines after a trust-decreasing transition (-5.6%) and vice versa.

Columns (4) to (6) employ subsamples of firms having zero patent (column 4) or having patented (columns 5 and 6) in the pre-transition period. Consistent with Panel D's evidence of an intensive margin effect, the results suggest that the CEO's trust effect is present only among firms having patented before the respective CEO transitions (11.1% in column 5 vs. -0.2% in column 4). Among those firms, however, higher CEO's trust does increase the probability that they continue to patent after the transitions by 2.3%, as reported in column (6).

Finally, column (7) estimates how preceding CEO's trust is related to the difference in firm's average patent count under the preceding CEO and that under the succeeding CEO. Firms with more trusting CEOs are more likely to experience trust-decreasing CEO transitions afterward due to mean reversion. Column (7) reports that on average, they also file fewer patents afterward. This is consistent with the baseline positive effect of CEO's trust on firm's patents.

Table A8. Firm sizes and industries

This table reports some additional results on heterogeneous effects by firm size and industry. First, interaction terms between CEO's trust and firm's size quintile dummies (with respect to its 3-digit SIC industry) suggest that the effect is largest among medium-size firms (columns 1 and 2). This possibly reflects the observation that it is more difficult for CEOs to have considerable impact on researchers in very large firms, while R&D and innovation may be less relevant for very small ones, unless they already are patenting firms (columns 3 and 4). Second, CEO's trust effect is significantly larger in ICT and electronic sectors (10.5%, column 5), while it is not statistically different from zero among chemical and pharmaceutical firms (column 7). This is consistent with the argument that CEO's trust effect should be more visible where the lag between R&D and patents is shorter, and also where firms are smaller. (The average firm in ICT is about half the size, as measured by employment, of the average firms in the remaining industries. Yet together they file about over half of all the patents in the sample.) Nonetheless, CEO's trust also has positive and statistically significant effect on innovation in other remaining industries, although of smaller magnitude (4.7%, column 6), suggesting that it is not driven by just ICT and electronic firms but ubiquitous across industries.

D Potential confounding factors

D.1 Constructing other inherited cultural trait variables

Similar to $trust_d$ (details in subsection 2.2 and appendix B), each other inherited cultural trait variable $trait_d$ is computed as

$$trait_d = \sum_e w_{de} \times ethtrait_e,$$

where $ethtrait_e$ is ethnicity e's average cultural trait measure and w_{de} is the probability that CEO d is of ethnicity e as summarized below. Further details on the sources and constructions of all inherited cultural trait and home-country macroeconomic variables used in this paper can be found in the table that follows.

General Social Survey (GSS)-based variables. For those, (i) e runs over the GSS ethnic origins, (ii) $ethtrait_e$ is derived from GSS data, and (iii) w_{de} comes from the aforementioned last name-GSS ethnic origin mapping. To compute $ethtrait_e$, I consider only respondents whose GSS occupation prestige score is in the top 25% (i.e., 50 or above) unless otherwise noted.

World Value Survey (WVS)-based variables. For those, (i) e runs over the WVS countries, (ii) $ethtrait_e$ is derived from WVS data, and (iii) w_{de} comes from the aforementioned last name-WVS country mapping. To compute $ethtrait_e$, I consider only respondents who are classified as upper middle class or above. Alternatively employing *all* WVS respondents yields quantitatively similar results.

Global Preference Survey (GPS)-based variables. For those, (i) e runs over the GSS ethnic origins, (ii) $ethtrait_e$ is derived from GPS data, and (iii) w_{de} comes from the aforementioned last name-GSS ethnic origin mapping. To compute $ethtrait_e$, I consider only respondents whose math skill score is in the top 50% (i.e., 6 or above). Alternatively employing *all* GPS respondents yields quantitatively similar results. Separately, GPS data are collected for 76 countries, which cover most of the 36 GSS ethnic origins. Alternatively using country-level last name-GPS country mapping to construct GPS-based cultural trait measures also yields quantitatively similar results.

Home-country macroeconomic variables. Each time-varying home-country variable h_{dt} is computed as $h_{dt} = \sum_e w_{de} \times h_{et}$ where (i) e runs over the GSS ethnic origins, (ii) h_{et} is the value of h in the home country of ethnicity e in year t, and (iii) w_{de} comes from the aforementioned last name-GSS ethnic origin mapping. Home-country macroeconomic variables are available at country level and cover most of the 36 ethnic origins. Alternatively using country-level last name-country mapping (similar to the last name-WVS country mapping) to construct these variables yields quantitatively similar results.

Sources and Constructions of Cultural Trait and Home-Country Variables

Variable	Appears in	Source	Respondent sample	Lastname mapping
Baseline **General Social Survey** trust	Throughout paper	GSS	GSS respondents in prestigious occupations	Lastname-GSS
Full-sample GSS trust	Table A7, Panel C	GSS	All GSS respondents	Lastname-GSS
Alternative trust: Fair	Table A7, Panel C	GSS	GSS respondents in prestigious occupations	Lastname-GSS
Alternative trust: Helpful	Table A7, Panel C	GSS	GSS respondents in prestigious occupations	Lastname-GSS
Work ethic*	Table A11, Panel A	GSS	GSS respondents in prestigious occupations	Lastname-GSS
High-income share*	Table A11, Panel A	GSS	All GSS respondents	Lastname-GSS
Average occupation prestige	Table A11, Panel B	GSS	All GSS respondents	Lastname-GSS
Average schooling years	Table A11, Panel B	GSS	All GSS respondents	Lastname-GSS
College graduate share	Table A11, Panel B	GSS	All GSS respondents	Lastname-GSS
Protestant share	Table A11, Panel B	GSS	All GSS respondents	Lastname-GSS
Confidence in science	Table A11, Panel B	GSS	GSS respondents in prestigious occupations	Lastname-GSS
Confidence in Congress; Federal Government; Supreme Court	Table A11, Panel B	GSS	GSS respondents in prestigious occupations	Lastname-GSS
World Value Survey trust	Table A7, Panel C	WVS	Upper-middle-class WVS respondents	Lastname-WVS
Global Preference Survey trust	Table A7, Panel C Table A12, Panel A	GPS	High skilled GPS respondents	Lastname-GSS
Risk preference*	Table A11, Panel A Table A12	GPS	High skilled GPS respondents	Lastname-GSS
Patience*	Table A11, Panel A Table A12	GPS	High skilled GPS respondents	Lastname-GSS
Positive reciprocity	Table A12	GPS	High skilled GPS respondents	Lastname-GSS
Negative reciprocity	Table A12	GPS	High skilled GPS respondents	Lastname-GSS
Altruism	Table A12	GPS	High skilled GPS respondents	Lastname-GSS
Home-country GPD (growth); population	Table A10	World Development Indicators		Lastname-GSS
Home-country high-school graduate share	Table A10	Barro and Lee (2010)		Lastname-GSS
Home-country governance quality	Table A10	World Governance Indicators		Lastname-GSS
Home-country US trade volumne	Table A10	US Comtrade		Lastname-GSS
Home-country patent applications	Table A10	PATSTAT		Lastname-GSS

* These variables also appear together in Table 5, columns (4) and (7).

D.2 Controlling for potential confounding factors

Home country's characteristics. Table A10 controls for a range of macroeconomic variables measuring CEO's home country's level of development and technological capabilities using equation (3), given firms' inclination to trade with, have business in, or hire from their CEOs' home countries and the potential spillovers from these linkages. These controls include country-by-year-level GDP, population, and GDP growth (column 1), high school graduate share (column 2), governance quality index (column 3), total trade volume with the US (column 4), and total patent applications (column 5), all of which have been shown to be related to country-level trust measure (see surveys by Algan and Cahuc, 2013, 2014). Among them, only GDP growth and trade volume with the US have statistically significant relationships with firm's patenting (column 6). All results remain quantitatively similar if I control flexibly for a second order polynomials of these variables instead. More importantly, across Table A10, the magnitude and precision of the CEO's trust estimate is not affected by any of those factors.

Other cultural traits. Table A11 examines if the CEO's trust effect is driven by other cultural traits that are correlated with trust instead of trust itself using equation (3). First, a CEO's ethnic group's socioeconomic characteristics could impact his skill accumulation, via investments in human capital or exposure to skills (e.g., Bell et al., 2018). Given the strong correlations among self-perceived class, occupational prestige, earnings, and education, in column (1) of Panel A, I use an ethnicity's high-income share as a summary statistics for its socioeconomic characteristics. Alternatively controlling for ethnicity-level occupation prestige, average years of schooling, or college graduate share also yields similar results (columns 1 to 3 of Panel B).

The related literatures on culture and on CEOs have also pointed to some salient cultural values that have economic significance at both macro and microeconomic levels. Among them, Protestant work ethic, which promotes the intrinsic value of work (Weber, 1905), has been shown to influence individual's choices of incentive contract and total work hours (e.g., Liu, 2013; Spenkuch, 2017). In column (2), I measure work ethic using the GSS question on the relative importance of work versus luck as the means to get ahead. Individuals' answer to the same question is also correlated with their preference for redistribution, as shown by Alesina and Angeletos (2005) and Giuliano and Spilimbergo (2013). Alternatively, column (4) of Panel B directly controls for the share of Protestants in CEO's ethnic groups, which yields comparable CEO's trust estimate.

Column (3) considers risk preference, which affects firm's financing decisions and individual's entrepreneurial activities (e.g., Kihlstrom and Laffont, 1979; Pan et al., 2017), and column (4) considers time preference, which strongly correlates with both national and individual education, income, and saving behaviors (e.g., Falk et al., 2018 find that patience explains 40% of the country-level variation in income and is an even more robust predictor of development compared to trust). Both measures of risk and time preferences come from Falk et al.'s (2018) Global Preference Survey (GPS), an experimentally-validated survey dataset covering 80,000 individuals in 76 countries.

Finally, column (5) pools together all the cultural trait controls and column (6) adds the home country controls that are statistically significant in Table A10. As in Table A10, controlling for a multitude of other cultural traits does not significantly alter the magnitude or precision of the CEO's trust estimate, suggesting that it is unlikely confounded by other factors related to the CEO's ethnic origin. In addition, Panel B of Table A11 shows that controlling for CEO's confidence in the scientific community (column 5) or the government (column 6) as proxies for his confidence in the patent system does not affect the CEO's trust coefficient either, further suggesting that this effect is unlikely driven by differential patenting propensity.

Table A12 presents more tests using GPS' trust and other cultural trait measures besides risk and time preferences, including positive reciprocity, negative reciprocity, and altruism, among which only CEO's negative reciprocity has a statistically significant relationship with firm's innovation. Consistent with previous results, the CEO's trust coefficient remains robust to the inclusion of any or all of these traits.

E A model of trust, risk taking, and innovation

The model set up is laid out in subsection 5.1. To solve the model, I first consider two separate cases in which $D^L = 1$ and $D^L = 0$, then compare the CEO's expected payoffs under these two cases to solve for his optimal choice of D^L.

Note that a good researcher's choice in period 2 (conditional on the game's continuing to period 2) is independent of period 1's outcome and therefore is the same under both cases. Specifically, it can be shown that period 2's subgame has a unique Nash equilibrium in which the CEO chooses $(b_2^H, b_2^M, b_2^L) = (b_2^*, 0, 0)$ and the good researcher chooses to explore when $\pi_2 > c/b_2^*$. Separately, a bad researcher always shirks.

Thus, the only researcher's action that is different under $D^L = 1$ and $D^L = 0$ is the good researcher's choice between exploration and exploitation in period 1 given D^L. To reduce notation burden, I omit the outcome superscript L from D^L and the period subscript 1 from π^1, b_i^1 for the rest of appendix E. In addition, let V_2^P denote the CEO's period-2 expected payoff from hiring a good researcher and V_2^A a good researcher's period-2 expected payoff, both are positive under the players' participation constraints.[55]

E.1 Proof of Proposition 1

Proposition 1 *For a given set of parameters, $\bar{\pi}^*(1) < \bar{\pi}^*(0)$. That is, tolerance of failure induces more exploration and thereby more innovation.*

A good researcher chooses exploration over exploitation when it yields higher expected payoff:

$$\begin{aligned} \pi(w + b^H + V_2^A) + (1-\pi)(w + b^L + DV_2^A) - c \quad &> \quad w + b^M + V_2^A \\ \iff \pi \quad &> \quad \bar{\pi}(D) \overset{def}{\equiv} \frac{c + b^M - b^L + (1-D)V_2^A}{b^H - b^L + (1-D)V_2^A}. \end{aligned} \tag{A7}$$

The above condition implies that in both cases, the good researcher follows a cutoff strategy and chooses exploration when the drawn probability of success π is above threshold $\bar{\pi}(D)$.

Given the good researcher's strategy, the CEO indirectly chooses $\bar{\pi}(D)$ via setting the bonuses to maximize his expected payoff from hiring a good researcher. It is optimal for him to set b^L and b^M to zero and only vary b^H to achieve his desired $\bar{\pi}(D)$ threshold. That is, for a given policy $D \in \{0, 1\}$, the CEO chooses b^H to maximize:

$$\int_0^{\bar{\pi}(D)} \left[s^M + V_2^P\right] d\pi + \int_{\bar{\pi}(D)}^1 \left\{\pi\left[s^H - b^H + V_2^P\right] + (1-\pi)\left[s^L + DV_2^P\right]\right\} d\pi, \tag{A8}$$

where $\bar{\pi}(D) = \frac{c+(1-D)V_2^A}{b^H+(1-D)V_2^A}$. Note that b^H does not affect the CEO's payoff from hiring a bad researcher, which is fixed given D. Therefore, by maximizing his expected payoff from hiring a

[55] V_2^P and V_2^A are functions of s^L, s^M, s^H, c, w.

good researcher, the CEO also maximizes his total expected payoff. To further reduce notation burden, I omit the outcome superscript H from b^H for the rest of appendix E.

Expression (A8)'s first order condition with respect to b is:

$$\begin{aligned}
\frac{\partial\bar{\pi}}{\partial b}\left[s^M + V_2^P\right] - \frac{\partial\bar{\pi}}{\partial b}\bar{\pi}\left[s^H - b + V_2^P\right] - \frac{\partial\bar{\pi}}{\partial b}(1-\bar{\pi})(s^L + DV_2^P) - \int_{\bar{\pi}}^1 \pi d\pi &= 0 \\
\iff \left(-\frac{\partial\bar{\pi}}{\partial b}\right)\left\{\bar{\pi}\left[s^H - b - s^L + (1-D)V_2^P\right] - \left[s^M - s^L + (1-D)V_2^P\right]\right\} - \int_{\bar{\pi}}^1 \pi d\pi &= 0 \quad \text{(A9)}
\end{aligned}$$

where $\left(-\frac{\partial\bar{\pi}}{\partial b}\right) = \frac{c+(1-D)V_2^A}{\left[b+(1-D)V_2^A\right]^2}$ and $\int_{\bar{\pi}}^1 \pi d\pi = \frac{1-\bar{\pi}^2}{2}$.

Notice that (i) $\left(-\frac{\partial\bar{\pi}}{\partial b}\right)$, (ii) $\bar{\pi}$, (iii) $\left[s^H - b - s^L + (1-D)V_2^P\right]$, and (iv) $-\int_{\bar{\pi}}^1 \pi d\pi$ are all decreasing in b. Furthermore, (v) $\bar{\pi}\left[s^H - b - s^L + (1-D)V_2^P\right] - \left[s^M - s^L + (1-D)V_2^P\right]$ is non-negative, as any value of b that makes (v) negative and hence the LHS of equation (A9) negative cannot be the CEO's optimal choice. As a result, the LHS of equation (A9) is also decreasing in b in the relevant range of b. This implies that for a given set of parameters s^L, s^M, s^H, c, D, and corresponding V_2^P, V_2^A, equation (A9) has a unique solution b^* that maximizes the CEO's expected payoff in expression (A8).[56] This innovation bonus b^* then induces the good researcher to explore when π is above threshold $\bar{\pi}^* = \frac{c+(1-D)V_2^A}{b^*+(1-D)V_2^A}$.

Comparative static of $\bar{\pi}^*$ with respect to $(1-D)V_2^P$. As the LHS of equation (A9) is decreasing in b and $(1-D)V_2^P$, its unique solution b^* is also decreasing in $(1-D)V_2^P$. It then follows that $\bar{\pi}^*$ is increasing in $(1-D)V_2^P$, as $\bar{\pi}^*$ is decreasing in b^*.

Comparative static of $\bar{\pi}^*$ with respect to $(1-D)V_2^A$. Let's rewrite b and $\frac{\partial\bar{\pi}}{\partial b}$ in terms of $\bar{\pi}$:

$$\begin{aligned}
b = \frac{c+(1-D)V_2^A}{\bar{\pi}} - (1-D)V_2^A &= \frac{c}{\bar{\pi}} + \left(\frac{1}{\bar{\pi}} - 1\right)(1-D)V_2^A, \\
\frac{\partial\bar{\pi}}{\partial b} = \frac{c+(1-D)V_2^A}{(b+(1-D)V_2^A)^2} &= \frac{\bar{\pi}^2}{c+(1-D)V_2^A}.
\end{aligned}$$

Next, let's also rewrite the first order condition with respect to b (equation A9) in terms of $\bar{\pi}$:

$$\begin{aligned}
\frac{\bar{\pi}^2}{c+(1-D)V_2^A}\left\{\bar{\pi}\left[\Delta_{HL} - \frac{c}{\bar{\pi}} - \left(\frac{1}{\bar{\pi}} - 1\right)(1-D)V_2^A\right] - \Delta_{ML}\right\} - \frac{1-\bar{\pi}^2}{2} &= 0 \\
\iff \bar{\pi}\Delta_{HL} - \Delta_{ML} - \left[\left(\frac{1}{\bar{\pi}^2} - 1\right)\frac{c+(1-D)V_2^A}{2} + c + (1-\bar{\pi})(1-D)V_2^A\right] &= 0, \quad \text{(A10)}
\end{aligned}$$

where $\Delta_{HL} = s^H - s^L + (1-D)V_2^P$ and $\Delta_{ML} = s^M - s^L + (1-D)V_2^P$, both are positive. As the LHS of equation (A10) is increasing in $\bar{\pi}$, it has a unique solution $\bar{\pi}^*$. Furthermore, as the LHS of equation (A10) is decreasing in $(1-D)V_2^A$, this unique solution $\bar{\pi}^*$ is increasing in $(1-D)V_2^A$.

[56] The LHS of equation (A9) is positive at $b = c$ and negative at $b = s^H$, which guarantees that it crosses zero at some value of b between c and s^H.

Comparative static of $\bar{\pi}^*$ with respect to D. As $(1-D)V_2^P$ and $(1-D)V_2^A$ are both decreasing in D, it follows that $\bar{\pi}^*$ is also decreasing in D, as $\bar{\pi}^*$ is increasing in $(1-D)V_2^P$ and $(1-D)V_2^A$. That is, for a given set of parameters s^L, s^M, s^H, c, and corresponding V_2^P, V_2^A, $\bar{\pi}^*(1) < \bar{\pi}^*(0)$.

E.2 Proof of Proposition 2

Proposition 2 *The CEO chooses $D^L = 1$ iff $\theta^P > \bar{\theta}$. That is, he chooses to tolerate failure when his trust towards the researcher is high enough.*

Recall from appendix E.1 that for a given policy D, there exists a unique $b^*(D)$ that maximizes the CEO's total expected payoff conditional on D. Under policy D and $b^*(D)$, the good researcher chooses exploration when π if above threshold $\pi^*(D)$, and the CEO's expected payoff from hiring a good researcher is $V_1^P(D)$.[57] It can be shown that $V_1^P(1) > V_1^P(0) > 0$. Indeed, under $D = 0$, the good researcher is less willing to choose exploration than what is optimal for the CEO. In addition, the CEO also has to provide additional exploration incentive for the good researcher through bonuses, i.e., $b^{H*}(0) > b^{H*}(1)$. As a result, $V_1^P(1) > V_1^P(0)$.

At the beginning of period 1, the CEO chooses $D \in \{0,1\}$ to maximize his total expected payoff unconditional on D. His total expected payoff under $D = 1$ is:

$$\theta^P \left[V_1^P(1) + V_2^P\right] + 2(1-\theta^P)s^L, \tag{A11}$$

and his total expected payoff under $D = 0$ is:

$$\theta^P \left\{V_1^P(0) + \left[1 - \frac{(1-\bar{\pi}^*(0))^2}{2}\right] V_2^P\right\} + (1-\theta^P)s^L. \tag{A12}$$

The CEO chooses $D = 1$ (tolerance of failure) over $D = 0$ iff his payoff under $D = 1$ (expression A11) is greater than that under $D = 0$ (expression A12); that is, iff $\theta^P > \bar{\theta}$, where:

$$\bar{\theta} \overset{def}{\equiv} \frac{-2s^L}{2\left[V_1^P(1) - V_1^P(0)\right] + \left[1 - \bar{\pi}^*(0)\right]^2 V_2^P - 2s^L}. \tag{A13}$$

Furthermore, as $V_1^P(1) > V_1^P(0)$ and $s^L < 0$, $\bar{\theta}$ is always between 0 and 1. This inequality implies that the CEO chooses to tolerate failure when his trust towards the researcher is high enough.

E.3 Allowing for a menu of contracts

Subsection 5.1 considers only pooling equilibria, as the CEO can only offer one single contract to the researcher. Given the presence of both adverse selection and moral hazard, it is not possible for the CEO to achieve first best outcome in this baseline setting. However, one may wonder if the CEO could do better by offering a menu of contracts that induces the researcher to reveal her type through her contract choice. This appendix argues that either (i) it is not possible for the CEO to

[57] Both $\pi^*(D)$ and $V_1^P(D)$ are functions of s^L, s^M, s^H, c, w, and D.

improve his payoff with such separating contracts, compared with that in subsection 5.1's baseline case, or (ii) it may be possible for the CEO to improve his payoff, but introducing separating contracts does not change the baseline case's key result that a more trusting CEO induces more exploration and hence more innovation.

First, it should be noted that the optimal pooling contract described in subsection 5.1 already maximizes the CEO's payoff under the constraint that his decision to tolerate failure D has to be the same for both researcher types. When this pooling decision is $D = 1$, inefficiency arises from the CEO's inability to screen out bad researchers, and when it is $D = 0$, inefficiency comes from suboptimal exploration by good researchers. Thus, for the CEO to do better by offering a menu of contracts, it must be the case that the contract chosen by the good researcher (the high contract) entails that $D = 1$ while the one chosen by the bad researcher (the low contract) entails that $D = 0$. To satisfy her incentive compatibility, the bad researcher's period-1 payoff after period 1's failure under the low contract must be at least her total payoff after failure in both periods under the high contract, which is at least twice the wage, or $2w$.[58] That is, the CEO's payoff from the low contract is at most $s^L - w$, where s^L is the negative payoff from failure (after fixed wage payment for one period w) and w is the additional information rent paid to motivate the bad researcher to choose the low contract.

Let us consider two separate cases: (i) when $s^L > -w$, and (ii) when $s^L \leq -w$. In both cases, the CEO pays a bad research as much as he would pay her under the pooling contract in which $D = 1$ (the long-term pooling contract). However, his payoff from hiring a bad research under separating contracts ($s^L - w$), compared with that under the long-term pooling contract ($2s^L$), differs between the two cases.

Case 1: $s^L > -w$. As $s^L - w < 2s^L$, the CEO cannot be better off by offering separating contracts, compared with the long-term pooling contract: By the low contract he losses more from the bad researcher, while by the high contract he extracts no more from the good researcher. Intuitively, when a failed R&D project still has positive returns *before* wage payment ($s^L + w > 0$),[59] the CEO is strictly better off by rehiring the bad researcher in period 2, considering that he has to pay her w regardless, either as period-1 information rent or as period-2 wage. Furthermore, as the CEO's payoff under the long-term pooling contract is at best his payoff under the optimal pooling contract, it follows that his payoff under the separating contracts is also not better than his optimal pooling equilibrium's payoff. To put differently, it is not possible for the CEO to improve upon his optimal pooling equilibrium's payoff with a menu of contracts that induces a separating equilibrium.

[58] Note that the assumption that the researcher has limited liability enters the argument here, as it implies that the good researcher cannot accept a payoff below w in case of failure in the first period in order to signal her type.

[59] Recall from subsection 5.1 that s^L, s^M, and s^H represent R&D project's returns *after* fixed wage payment.

Case 2: $s^L \leq -w$**.** By a similar argument, when $s^L - w \geq 2s^L$, the CEO can improve upon the long-term pooling contract by offering separating contracts. Intuitively, when failure is detrimental ($s^L + w \leq 0$), the CEO is weakly better off by firing the bad researcher after period 1, even when he already pays her period-2 wage, to avoid additional costs associated with failed R&D.

However, whether the CEO prefers this menu of contracts to the pooling contract in which $D = 0$ (the short-term pooling contract) depends on the CEO's prior belief about the researcher θ^P. That is, the CEO chooses the separating contracts over the short-term pooling contract when:

$$\theta^P \left[V_1^P(1) + V_2^P\right] + (1-\theta^P)(-w) > \theta^P \left\{V_1^P(0) + \left[1 - \frac{(1-\bar{\pi}^*(0))^2}{2}\right] V_2^P\right\} \Longleftrightarrow \theta^P > \bar{\theta}_{sep}. \quad \text{(A14)}$$

Note that inequality (A14) is analogous to (A11) > (A12), with s^L replaced by $-w$. That is, in case of a large cost of failure $|s^L|$, the separating contract helps the CEO limit the damage. Then, similar to proposition 2, inequality (A14) implies that when his trust towards the researcher is high enough, the CEO chooses the separating contract, which tolerates failure by the good researcher and thereby induces more exploration and innovation.

Summary. Results from this appendix and subsection 5.1 indicate that the CEO chooses either the long-term pooling contract or the separating contracts over the short-term pooling contract when:

$$\theta^P \left[V_1^P(1) + V_2^P\right] + (1-\theta^P) \max(s^L, -w) > \theta^P \left\{V_1^P(0) + \left[1 - \frac{(1-\bar{\pi}^*(0))^2}{2}\right] V_2^P\right\} \Longleftrightarrow \theta^P > \bar{\theta}_{com},$$

where

$$\bar{\theta}_{com} \stackrel{def}{\equiv} \frac{-2\max(s^L, -w)}{2\left[V_1^P(1) - V_1^P(0)\right] + \left[1 - \bar{\pi}^*(0)\right]^2 V_2^P - 2\max(s^L, -w)} = \min(\bar{\theta}, \bar{\theta}_{sep}).$$

That is, when θ^P is high enough, the optimal contract(s) chosen by the CEO always entail(s) tolerance of failure towards the good researcher. This induces more exploration by the good researcher and thereby more innovation, compared with that under the short-term pooling contract chosen by the CEO when θ^P is low.

E.4 No credible commitment to tolerance of failure

This appendix considers the case when the CEO cannot credibly commit to being tolerant of failure, the key decision that drives the model's results. In this setting, his decision whether to tolerate period 1's bad outcome is based on his updated belief at the end of period 1, with the aim to maximize his period-2 payoff. As bad outcome happens with probability $1 - \theta^P$ due to a bad researcher and with probability $\theta^P \frac{(1-\bar{\pi})^2}{2}$ due to good researcher's bad luck ($\bar{\pi}$ is the good researcher's exploration threshold), the CEO's updated belief after observing period 1's bad outcome is:

$$\theta^U = \frac{\theta^P(1-\bar{\pi})^2}{2(1-\theta^P)+\theta^P(1-\bar{\pi})^2}. \tag{A15}$$

He then chooses to rehire the researcher if his period-2 expected payoff is larger than his outside option of zero. That is, when:

$$\frac{\theta^P(1-\bar{\pi})^2}{2(1-\theta^P)+\theta^P(1-\bar{\pi})^2}V_2^P + \frac{2(1-\theta^P)}{2(1-\theta^P)+\theta^P(1-\bar{\pi})^2}s^L > 0$$
$$\iff \theta^P > \bar{\theta}_{post}(\bar{\pi}) \stackrel{def}{\equiv} \frac{-2s^L}{(1-\bar{\pi})^2V_2^P - 2s^L}. \tag{A16}$$

In an equilibrium in which the CEO chooses to tolerate failure (i.e., $D=1$), the good researcher's exploration threshold in period 1 is $\bar{\pi} = \bar{\pi}^*(1)$. This is then an equilibrium only when $\theta^P > \bar{\theta}_{post}(\bar{\pi}^*(1))$. Vice versa, in an equilibrium in which the CEO chooses not to tolerate failure (i.e., $D=0$), the good researcher's exploration threshold is $\bar{\pi} = \bar{\pi}^*(0)$. This is then an equilibrium only when $\theta^P \le \bar{\theta}_{post}(\bar{\pi}^*(1))$. In addition, as $\bar{\pi}^*(1) < \bar{\pi}^*(0)$ (Proposition 1) and $s^L < 0$, it follows that $\bar{\theta}_{post}(\bar{\pi}^*(1)) < \bar{\theta}_{post}(\bar{\pi}^*(0))$. The game's equilibrium can be summarized up as follows.

Proposition 5 *When the CEO cannot credibly commit to being tolerant of failure, the game's equilibrium depends on his prior belief θ^P.*
(i) If $\theta^P > \bar{\theta}_{post}(\bar{\pi}^*(0))$, the CEO credibly chooses to tolerate failure (i.e., $D=1$) and the good researcher chooses exploration in period 1 when $\pi_1 > \bar{\pi}^*(1)$.
(ii) If $\theta^P \le \bar{\theta}_{post}(\bar{\pi}^*(1))$, the CEO chooses not to tolerate failure (i.e., $D=0$) and the good researcher chooses exploration in period 1 when $\pi_1 > \bar{\pi}^*(0)$.
(iii) If $\bar{\theta}_{post}(\bar{\pi}^*(1)) < \theta^P \le \bar{\theta}_{post}(\bar{\pi}^*(0))$, there are two equilibria: one in which the CEO tolerates failure (i.e., $D=1$) as in (i), and one in which he does not (i.e., $D=0$) as in (ii).

Comparison with the baseline model. Recall from appendix E.2 that in the baseline model when the CEO can credibly commit to tolerance of failure, he chooses so (i.e., $D=1$) when his prior belief θ^P is above threshold $\bar{\theta}$ (equation A13):

$$\theta^P > \bar{\theta} \stackrel{def}{\equiv} \frac{-2s^L}{2\left[V_1^P(1) - V_1^P(0)\right] + \left[1-\bar{\pi}^*(0)\right]^2 V_2^P - 2s^L}.$$

As $V_1^P(1) > V_1^P(0)$ and $s^L < 0$, it follows that $\bar{\theta} < \bar{\theta}_{post}(\bar{\pi}^*(0))$ (see equation A16). The intuition is that the CEO's *ex ante* cutoff $\bar{\theta}$ takes into consideration $V_1^P(1) - V_1^P(0)$, the gain from optimal exploration in period 1 under $D=1$, and therefore $\bar{\theta}$ is lower than his *ex post* cutoff $\bar{\theta}_{post}(\bar{\pi}^*(0))$, which does not internalize this gain.

As a result, for $\theta^P \in (\bar{\theta}, \bar{\theta}_{post}(\bar{\pi}^*(0)))$, without the capacity to commit, there always exists an equilibrium in which the CEO does not tolerate period 1's bad outcome (i.e., $D=0$), even though it is *ex ante* optimal for him to do so (i.e., $D = 1$) (Proposition 5).[60] Furthermore, if it is also the case that $\bar{\theta} < \bar{\theta}_{post}(\bar{\pi}^*(1))$,[61] then for $\theta^P \in (\bar{\theta}, \bar{\theta}_{post}(\bar{\pi}^*(1)))$, this non-tolerant equilibrium is the unique equilibrium, and the CEO cannot at all implement the *ex ante* desirable policy of tolerance of failure. These problems are alleviated only if the CEO can credibly commit to his *ex ante* decision, as in the baseline model, or if he is high trusting with $\theta^P > \bar{\theta}_{post}$. This result implies that trust acts as a substitute for commitment.

E.5 The right amount of trust

While more trust induces more innovation, what is a CEO's "right amount of trust" that optimizes his payoff?[62] When the CEO can credibly commit to his policy of tolerance of failure D^L, an objective CEO (one who holds the correct belief of the probability of the good type $\theta^P = \theta$) always chooses the optimal policy. However, a CEO with too high or too low trust may not, if his level of trust θ^P is on the wrong side of $\bar{\theta}$, compared with θ. For instance, when the researcher pool is too bad to tolerate failure ($\theta < \bar{\theta}$), but the CEO is over-trusting ($\theta^P > \bar{\theta}$), his tolerance of failure leads to costly excessive innovation. In contrast, when the researcher pool is good ($\theta > \bar{\theta}$) but the CEO is under-trusting ($\theta^P < \bar{\theta}$), his intolerance of failure leads to inefficiently low level of innovation.[63]

Without the ability to commit to his policy, the objective CEO's policy needs not be optimal. Indeed, an uncommitted CEO would decide on D^L at the end of period 1 solely based on his period-2 payoff, without internalizing the gain from optimal exploration in period 1 under tolerance of failure. As a result, tolerance of failure is a unique equilibrium only when $\theta^P > \bar{\theta}_{post}$, with the new $\bar{\theta}_{post} > \bar{\theta}$ (details in appendix E.4). When the true θ falls between $\bar{\theta}$ and $\bar{\theta}_{post}$, it is *ex ante* optimal but *ex post* inefficient to tolerate period 1's failure. An objective CEO therefore cannot implement the *ex ante* optimal policy due to his inability to credibly commit to it, while an over-trusting CEO (one with $\theta^P > \bar{\theta}_{post}$) can. In other words, trust acts as a substitute for commitment and enables the over-trusting CEO to outperform the objective one in this setting.

[60] In this case, there is another equilibrium in which he does tolerate period 1's failure.

[61] The relationship between $\bar{\theta}$ and $\bar{\theta}_{post}(\bar{\pi}^*(1))$ is ambiguous and depends on the parameter set.

[62] Butler et al.'s (2016) study on the right amount of trust suggests that highly trusting individuals tend to assume too much social risk while individuals with overly pessimistic beliefs can give up profitable opportunities.

[63] Consistent with this insight, subsection 5.4 shows that CEO's trust effects on both innovation and firm's performance are larger among firms with likely better researcher quality.

F Framework for differentiating different mechanisms

F.1 Proof of Proposition 4

As the count of patents within quality range $[c_1, c_2]$ is $N\left[F(\frac{c_2-\mu(T)}{\sigma(T)}) - F(\frac{c_1-\mu(T)}{\sigma(T)})\right] \overset{def}{\equiv} Y(\mu(T), \sigma(T))$, the effects of changes in μ and σ on patent count within quality range $[c_1, c_2]$ are:

$$\frac{\partial Y}{\partial \mu} = N\left[f\left(\frac{c_2-\mu}{\sigma}\right)\left(\frac{-1}{\sigma}\right) - f\left(\frac{c_1-\mu}{\sigma}\right)\left(\frac{-1}{\sigma}\right)\right], \tag{A17}$$

$$\frac{\partial Y}{\partial \sigma} = N\left[f\left(\frac{c_2-\mu}{\sigma}\right)\left(-\frac{c_2-\mu}{\sigma^2}\right) - f\left(\frac{c_1-\mu}{\sigma}\right)\left(-\frac{c_1-\mu}{\sigma^2}\right)\right]. \tag{A18}$$

Recall the assumptions from subsection 5.2 that better quality patents are always rarer (i.e., $f'(x)$ is decreasing on $[0, \infty)$ $\forall$ T). This assumption implies that $f\left(\frac{c_2-\mu}{\sigma}\right) < f\left(\frac{c_1-\mu}{\sigma}\right)$ as $c_1 < c_2$. As a result, $\frac{\partial Y}{\partial \mu}$ in expression A17 is positive, indicating that higher $\mu(T)$ increases the number of patents within any quality range $[c_1, c_2] \subset [0, \infty)$. On the other hand, expression A18 does not have an unambiguous sign: while $f\left(\frac{c-\mu}{\sigma}\right)$ is decreasing in c over the $[c_1, c_2]$ interval, $c - \mu$ is always increasing in c.

F.2 Patent quality under mean-preserving spread

Proposition 4 suggests that it is possible to identify the mechanism at work (i.e., through $\mu(T)$ or $\sigma(T)$) under conditions that warranty $\frac{\partial Y}{\partial \sigma} < 0$, namely, for ranges of c where $f\left(\frac{c-b}{\sigma}\right)\left(\frac{c-\mu}{\sigma^2}\right)$ is increasing in c. This condition is quite easy to satisfy for small c, at least among distributions in the exponential family, such that when c is small, $f\left(\frac{c-\mu}{\sigma}\right)$ decreases less fast than $c - \mu$ increases. The following proposition illustrates a special case:

Proposition 6 *Let's consider the family of normal distribution* $\frac{x-\mu(T)}{\sigma(T)} \sim \mathcal{N}(0, 1)$ *and assume that* $\mu'(T) = 0$ *(i.e., no mean-shifting mechanism at work). Higher* $\sigma(T)$ *decreases the count of patents of quality within any range* $[c_1, c_2] \subset [0, \mu + \sigma(T)]$.

The proposition's statement is equivalent to $\frac{\partial Y}{\partial \sigma}$ in expression A18 being negative, itself equivalent to $f\left(\frac{c-\mu}{\sigma}\right)\left(\frac{c-\mu}{\sigma^2}\right)$ being increasing in c over the $[c_1, c_2]$ interval. This happens when its derivative with respect to c: $\frac{1}{\sigma^2}\left[\frac{1}{\sigma}f'\left(\frac{c-\mu}{\sigma}\right)(c-\mu) + f\left(\frac{c-\mu}{\sigma}\right)\right]$, is nonnegative. When f is a standard normal distribution density, it is equivalent to $-\frac{1}{\sigma^2}(c-\mu)^2 + 1 \geq 0 \Leftrightarrow |c - \mu| \leq \sigma$, satisfied over $c \in [0, \mu + \sigma(T)]$.