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

Kieu-Trang Nguyen†

December 27, 2018

Click here for most recent version

Abstract

This paper provides evidence on the effect of trust on innovation within firms. I build a new matched CEO-firm-patent dataset covering 5,753 CEOs in 3,598 large US public firms and 700,000 patents during 2000-2011. To identify the effect of CEO's trust, I exploit variation in generalized trust across the countries of CEOs' ancestry, inferred from their last names using de-anonymized historical censuses, as well as variation in CEOs' bilateral trust towards inventors. First, one standard deviation increase in CEO's generalized trust following a CEO turnover is associated with over 6% increase in firm's future patents. Second, changes in CEO's bilateral trust towards inventors in different countries (i.e., different R&D labs within multinational firms) or from different ethnic origins in the same firm have comparable effects on inventors' patenting, controlling for CEO and other stringent fixed effects. Trust-induced improvements in innovation are driven entirely by higher-quality patents, consistent with a model in which CEO's trust incentivizes researchers to undertake high-risk explorative R&D. Finally, I show that across and within firms, CEO's generalized trust is strongly correlated with a broader corporate culture of trust, as measured from the text analysis of one million online employee reviews. The evidence provides a micro-foundation for the well-known macro relationship between trust and growth.

Keywords: Trust, Innovation, CEO, Leadership, Corporate culture.

*I am indebted to Oriana Bandiera, Catherine Thomas, John Van Reenen, and Robert Gibbons for their advice and guidance. I am also grateful to Philippe Aghion, Ricardo Alonso, Pierre Azoulay, Clare Balboni, Andres Barrios F., Kamran Bilir, Jordi Blanes i Vidal, Robin Burgess, Filipe Campante, Francesco Caselli, Quoc-Anh Do, Thomas Drechsel, Andreas Ek, Benjamin Enke, Daniel Ferreira, Raymond Fisman, Maitreesh Ghatak, Juanita González-Uribe, Jesus Gorrin, Moqi Groen-Xu, Daniel Gross, Chao He, Emeric Henry, Dana Kassem, Sevim Kosem, Danielle Li, Rocco Macchiavello, Steve Pischke, Yona Rubinstein, Raffaella Sadun, Scott Stern, Donald Sull, John Sutton, Claudia Steinwender, Eric Van den Steen, Anh N. Tran, Luigi Zingales, and seminar participants at the LSE and MIT, for their helpful suggestions. I am particularly thankful to Donald Sull for having generously shared his data. All remaining errors are my own.

†London School of Economics and Political Science. Department of Economics, 42 Houghton Street, London WC2A 2AE, United Kingdom. Email: k.nguyen@lse.ac.uk.

"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.[1] This insight is especially relevant in the context of research and innovation, in which the inherent uncertainty of research makes contracts necessarily incomplete (Arrow, 1962). It is thus essential to understand the relationship between trust and innovation, in order to better understand how to incentivize innovation, an important driver of growth.

This paper studies the role of trust on innovation within the firm. I develop a theoretical framework in which the CEO's trust in good researchers encourages their risk-taking, thereby increasing innovation.[2] To test this effect, I assemble a large matched CEO-firm dataset covering 5,753 US CEOs in 3,598 US public firms between 2000 and 2011, associated with 700,000 patents and inventors. I infer a CEO's ethnic origins from her last names using de-anonymized historical US censuses, then measure CEO's inherited generalized trust as ethnic-averaged trust in US samples. Similarly, I compute CEO's bilateral trust towards researchers in different ethnic groups within the same firm based on average bilateral trust between countries (highlighted in Guiso et al., 2009). First, I exploit CEO turnovers to estimate the effect of CEO's trust on patent counts and future citations. Second, 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 firm by year, CEO, and inventor country fixed effects. I further examine trust's effect on the distribution of patent quality to differentiate risk-taking from possible alternative mechanisms.

I model the process of research based on Arrow's (1962) insight that research is inherently uncertain, and by nature difficult to observe and contract on researchers' behaviors. In a simple two-period principal-agent model between a CEO and a researcher, the researcher's type and actions

[1] Arrow's general view on trust has received ample macroeconomic empirical support on the association of trust and development and growth, as surveyed by Algan and Cahuc (2013, 2014). Knack and Keefer (1997), La Porta et al. (1997), Guiso et al. (2004, 2006, 2008a, 2009), Tabellini (2010), and Algan and Cahuc (2010), among others, provide evidence that trust is a deep-root determinant of development and growth, through its channels of influence on the accumulation and allocation of factors of production (such as investments, loans, allocation of capital). This economic literature 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), and others.

[2] While in principle all relations involving researchers inside the firm may matter to its innovative activities, it has been suggested that, in practice, the chief executive may wield significant influence on the firm's culture (e.g., Guiso et al., 2015; DeBacker et al., 2015; Liu, 2016, among others), therefore their trust is of first order importance in studying the firm's trust towards researchers.

are private information, and only outcomes are observable. 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 him, and (ii) exploitation, a risk-free low-return common path that surely signals a good type from a bad one.[3] On the other hand, failure means either that the researcher's exploration is unsuccessful, or that he is a bad type.[4] Considering those elements, the CEO, who inherits a pool of existing researchers in period 1, decides to whether rehire or fire the researcher in period 2 based on his period 1's outcome.

In this setting, the CEO's trust in the researcher is modeled as her prior belief about his type.[5] 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 (2011) and Aghion et al. (2013), whose models 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, my model instead emphasizes the enabling role of trust.[6] It also highlights the possible suboptimality of excessive trust due to too much retention of bad researchers,[7] as well as the role of trust as substitute for the CEO's commitment capacity.[8]

I turn to matched CEO-firm and patent data in the US to study the empirical relationship between CEO's trust and innovation. Innovation outputs, measured by patent counts,[9] are extracted from PATSTAT, a dataset covering close to the universe of patents ever filed from 1900 up to 2016 with 70 million patent documents from over 60 major patent offices all over the world, including

[3] 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), who studies the implementation of either path, I focus on how the CEO's prior belief on the researcher's type, i.e., trust, affects innovation outcomes.

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

[5] My choice to model trust as a belief reflects 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." Similar approach has been used in Guiso et al. (2008b) and Bloom et al. (2012), among others.

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

[7] This result complements Butler et al. (2016) finding on the "right amount of trust," which suggests that highly trusting individuals tend to assume too much social risk while individuals with overly pessimistic beliefs can give up profitable opportunities.

[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] The measure of innovative outputs by patents, correcting for quality or not, is not perfect (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.

the US Patent and Trademark Office (USPTO) and its counterparts in Europe (EPO) and Japan (JPO).[10] In addition to patent counts, I also refine data on patent citations, technological class, family, and inventors' names and addresses to further investigate the mechanism at work.

Detailed data on the background of CEOs and top officers of US public firms are provided by BoardEx. My focus on CEOs is motivated by a growing body of empirical evidence that individual CEOs matter for firm decisions and performance (e.g., Bertrand and Schoar, 2003; Bennedsen et al., 2010; Smith et al., 2017, and the Bertrand, 2009 survey). It proposes a new factor, i.e., trust, that fits the description of manager styles as coined by Bertrand and Schoar (2003) and that contributes to the strand of literature studying how differences in CEO traits relate to differences in firm performance.[11]

Building on the literature on transmitted and inherited cultural values that highlights the role of cultural origin in shaping an individual's cultural traits,[12] I measure a CEO's trust based on her ethnic origins as inferred from her last name and measures of inherited trust among descendants of US immigrants. First, I construct a probabilistic mapping between CEO's last names and ethnic origins from four de-anonymized US censuses.[13] 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).[14] I only select survey answers from GSS respondents in highly prestigious occupations that are similar to the CEO sample. Each CEO's inherited trust measure is the weighted average of ethnic-specific trust based on her likely ethnic composition.

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 observable characteristics such as age, education, and tenure in the firm. 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. I find that one standard deviation in CEO's inherited generalized trust, equivalent to the shift from Greek to English, is associated with over 6% increase in the number of patents filed annually. This result is robust to a large set of controls for country of origin characteristics and ethnic of origin socioeconomic

[10] The PATSTAT dataset is thus much more general and suitable for studies with a cross-country perspective than the usual USPTO dataset. PATSTAT data have since recently been used in research on innovation, such as Dechezleprêtre et al. (2018).

[11] 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, 2017). In particular, this literature has also considered certain aspects of CEO cultural background such as corruption culture and firms' misconducts (DeBacker et al., 2015; Liu, 2016).

[12] E.g., theoretical foundation by Bisin and Verdier (2000), Bisin and Verdier (2001), Tabellini (2008), Guiso et al. (2016); empirical evidence by Giuliano (2007), Fernández and Fogli (2009), Algan and Cahuc (2010), among others.

[13] The four US censuses from 1910 to 1940 contain 80 million individuals with foreign birth places or ancestry, sharing among them five million unique last names, out of which 75,000 last names appear for at least 100 times each. 83% of CEO last names are among those 75,000 sufficiently common last names. The inference of ethnic origin from last names was pioneered by Kerr and Lincoln (2010).

[14] This approach follows Guiso et al. (2006), Algan and Cahuc (2010), and the related literature. I also perform a robustness check with data from the World Value Survey (WVS). Those two surveys cover most of recent cross-country research on the economics of trust since Knack and Keefer (1997) and La Porta et al. (1997).

conditions and cultural traits, suggesting that it is not driven by other ethnic-related characteristics.

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 patents by inventors from those different ethnicities, which allows for a full set of stringent, including CEO, fixed effects. Bilateral trust measures are calculated between CEO's inferred ethnic origin and countries of inventors using Eurobarometer data.[15] Patent inventors' countries of origin are obtained from either their addresses (for inventors in overseas R&D labs of multinational firms) or their last names (for US-based inventors). Under the same CEO, one standard deviation increase in bilateral trust towards an inventor country of origin is associated with 3-5% more patents by inventors from the corresponding R&D lab or corresponding ethnicity, controlling for a broad range of time-variant fixed effects at the firm by year, CEO, and inventor country levels. These results remain stable even in the presence of firm by inventor country fixed effects (i.e., using variation in changes in bilateral trust following CEO changes), and after accounting for possible alternative explanations such as favoritism or better information flows between CEOs and researchers.

To distinguish the proposed mechanism that trust induces innovation via encouraging risk-taking and exploration from other mechanisms in which trust induces more effort by researchers,[16] I develop a formal framework to identify the mechanisms via their different implications on trust's effect on the distribution of patent quality. Using future citation counts and other patent quality measures, I show that, 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 per patent by 4%. In addition, I find that trust is most effective in inducing innovation in firms with likely high researcher quality.

These results on the effect of CEO's trust on firm innovation provide a possible micro-foundation for the macro relationship between long-term economic outcomes and trust, as previously evidenced in Guiso et al. (2006), Tabellini (2010), and Algan and Cahuc (2010), among others.[17] 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 invent more and thus grow productivity faster

[15]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.

[16]For example, there is a large literature on delegation in organization since Aghion and Tirole (1997), such as Acemoglu et al. (2007) and Bloom et al. (2012). In the context of innovation, trust, understood as the preference congruence between the principal and the agent, would lead to more delegation to researchers, which then induce them to put in more effort, thereby producing more innovation.

[17]The larger literature on the cultural origins of long-term economic development has discussed the role of religion (Barro and McCleary, 2003, 2018), work ethic (Becker and Woessmann, 2009), individualism (Gorodnichenko and Roland, 2017), and others as surveyed by Nunn (2012). 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.

in the long run.[18] This mechanism thus helps explain the macroeconomic differences not only in development levels but also in growth rates across countries.[19] Separately, this paper extends the empirical literature of more traditional determinants of R&D and patents, such as tax credit and grant (e.g., Howell, 2017; Dechezleprêtre et al., 2018), as surveyed by Cohen (2010).

I further link CEO's culture to firm's culture, measured from text analysis of almost one million employee reviews on Glassdoor.com, one of the largest career intelligence websites worldwide (from Sull, 2018). 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 (similar to Grennan, 2014). In different specifications with CEO controls, industry fixed effects, and even firm fixed effects (i.e., using variation in changes in CEO's trust following CEO changes), CEO's inherited trust is associated with stronger corporate trust culture. In that regard, this paper also provides new findings supporting the role of corporate culture in determining corporate outcomes.[20] Furthermore, it 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).

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 classic studies by O'Reilly et al. (1991, 2014), and other work on organization culture such as Schein (1985) or Hofstede et al. (1991).[21] My results broaden this literature with a large-scale sample of firms, and with inherited trust computed systematically from surveys of opinions.

The rest of the paper is organized as follows. Section 2 discusses the model of trust and innovation. Section 3 provides descriptions of the data. Sections 4 and 5 describe the within-firm and within-CEO empirical strategies and the corresponding empirical results. Section 6 studies the mechanism through risk-taking and exploration. Section 7 provides further discussions and interpretations, and section 8 concludes.

2 Theoretical framework

This section models how CEO's trust could affect researchers' choices and consequently innovation outcomes. As "trust is an important lubricant of a social system" (Arrow, 1974), it is likely to also impact innovation through other different mechanisms. Therefore, it should be noted that my

[18]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.

[19]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.

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

[21]Notably, the management literature has considered the culture of trust in firms as crucial to innovation (Nooteboom and Stam, 2008), and can be substitute for or complement to formal control (Knights and Willmott, 2001; Klein Woolthuis et al., 2005).

choice to focus on the CEO's trust (instead of the researcher's trust) and this particular model is guided by the empirical evidence presented in the latter part of the paper.

2.1 A model of trust 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 good type with probability θ or bad type with probability $1-\theta$. In this setting, a bad researcher is understood as someone who lacks ability or willingness to take the appropriate courses of actions. The CEO, who is not an expert in science, 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 with certainty. Exploration is a high-cost, risky R&D project that requires effort cost c and produces s^H (innovation) with probability π and s^L (failure) with probability $1-\pi$.[22] π is independently drawn from the unit uniform distribution in each period and privately observed by the good researcher before choosing which project to pursue. The CEO does not know what project is chosen and only observes the outcome produced by the researcher at the end of each period.[23]

CEO. The CEO asks the researcher to carry out R&D at the beginning of period 1 without knowing his type. Simultaneously, she 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 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 2, in which the CEO specifies contract (b_2^i) and the researcher chooses from the same action set as described. The game ends after period 2's outcome and payment are realized. In the baseline model, I assume that the CEO can credibly commit to the contracts specified at the beginning of each period.[24]

Trust. Although the CEO does not observe θ, she has her own prior subjective belief that the researcher is good with probability θ^P, which reflects her trust level towards the agent. A more trusting CEO would have a higher subjective θ^P than a less trusting one.[25] This model focuses on studying how this key parameter of CEO's trust affects her and the researcher's strategies in the

[22]The trade-off between the exploitation of well-known approaches and the exploration of new untested approaches was first emphasized by March (1991) and has since then been widely studied both theoretically and empirically (see survey by Ederer and Manso, 2011).

[23]The values of s^L, s^M, s^H, c and π's uniform distribution are common knowledge and satisfy $s^H - c > s^M > 0 > s^L$. The key results of the model remain under more general assumptions about the distribution of π.

[24]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 credit commitment. I consider relaxing this assumption in subsection 2.2.

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

game and its outcome.[26]

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 he chooses exploration) or $w + b_t^i$ (otherwise) and the CEO gets $s^i - b_t^i$.[27] If the researcher is fired at the end of period 1, both players' payoffs in period 2 is zero.[28] The researcher has limited liability and $b_t^i \geqslant 0 \ \forall \ i, t$. That is, the CEO can reward the researcher for good performance but cannot financially punish him for bad outcome. I also restrict the parameters to satisfy the players' participation constraint, which implies 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 he is good but unlucky. Her choice of whether to tolerate period 1's failure D^L depends on her assessment of which is more likely to be the case, and this assessment depends on her prior subjective belief θ^P.

Solution outline. 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 her optimal choice of D^L. Note that a good researcher's choice in period 2 (conditional on its happening) is independent of period 1's outcome and therefore is the same under both cases. Thus, let V_2^P denote the CEO's period-2 expected payoff from hiring a good researcher and let V_2^A denote a good researcher's period-2 expected payoff, both are positive under the participation constraints discussed earlier.[29]

Researcher's project choice: explore versus exploit. As a bad researcher always shirks, the meaningful action to analyze is a 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 this subsection.

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

$$\pi(w + b^H + V_2^A) + (1-\pi)(w + b^L + DV_2^A) - c > w + b^M + V_2^A \iff \pi > \bar{\pi}(D).^{30} \qquad (1)$$

The above condition implies that in both cases ($D = 1$ and $D = 0$), the researcher follows a cutoff strategy and chooses exploration when the realized probability of success π is above threshold $\bar{\pi}(D)$.

[26] As the CEO's prior belief, or trust, affects R&D outcomes via influencing the researcher's choice, the latter's perception of the former's belief is as important as the belief itself. This is especially true in real life settings where CEOs' influence on firm's policies takes time to materialize and credible commitment to such policies is unlikely. In these settings, the researcher's perception of the CEO's beliefs and preferences is likely based on the collective reputation of the group to which the CEO belongs in addition to the CEO's own reputation based on her past actions.

[27] w is a fixed wage that is set exogenously. 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. I assume that both players are risk neutral and do not discount future payoff. Introducing risk aversion or time discounting does not affect the model's key insights.

[28] The implicit assumption is that the CEO and the researcher cannot immediately find new matches in period 2.

[29] 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 $\pi_2 > c/b_2^*$. V_2^P and V_2^A are functions of s^L, s^M, s^H, c, w.

[30] $\bar{\pi}(D) \overset{def}{\equiv} \frac{c + b^M - b^L + (1-D)V_2^A}{b^H - b^L + (1-D)V_2^A}$.

Given the good researcher's strategy, the CEO indirectly chooses $\bar{\pi}(D)$ via setting the bonuses to maximize her expected payoff from hiring a good researcher. It is optimal for her to set b^L and b^M to zero and only vary b^H to achieve her desired $\bar{\pi}(D)$ threshold.[31] For each value of D, the CEO's maximization problem then has a unique solution $b^*(D)$ that induces the good researcher to explore when π is above threshold $\bar{\pi}^*(D) = \frac{c+(1-D)V_2^A}{b^*(D)+(1-D)V_2^A}$. This leads us to the following proposition:

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

The proof is detailed in appendix A.1. The intuition is that period 1's exploration threshold $\bar{\pi}^*(.)$ is increasing in $(1-D)V_2^A$ and $(1-D)V_2^P$, which represent a good researcher's and the CEO's foregone period-2 payoffs after a bad outcome in period 1.[32] 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 her future payoff from a relationship with such good researcher when exploration fails. Put differently, tolerance of failure enables a good researcher to take more risk and explore more, which then produces more instances of successful innovation.[33] This result resonates with Manso's (2011) insights that the optimal incentive scheme to motivate exploration exhibits tolerance for early failure and reward for long-term success.[34]

CEO's tolerance of failure: rehire versus fire. Let $V_1^P(D)$ denotes the CEO's period-1 expected payoff from hiring a good researcher under policy $D \in \{0,1\}$. It can be shown that $V_1^P(1) > V_1^P(0) > 0$.[35] The CEO chooses to tolerate failure (i.e., $D^L = 1$) if it maximizes her total expected payoff:

$$\theta^P \left[V_1^P(1) + V_2^P\right] + (1-\theta^P)s^L > \theta^P \left\{V_1^P(0) + \left[1 - \frac{(1-\bar{\pi}^*(0))^2}{2}\right] V_2^P\right\} \iff \theta^P > \bar{\theta}.^{36} \qquad (2)$$

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

[31] That is, she chooses b^H to maximize: $\int_0^{\bar{\pi}(D)} \left[s^M + V_2^P\right] d\pi + \int_{\bar{\pi}(D)}^1 \left\{\pi\left[s^H - b^H + V_2^P\right] + (1-\pi)\left[s^L + DV_2^P\right]\right\} d\pi$, where $\bar{\pi}(D) = \frac{c+(1-D)V_2^A}{b^H+(1-D)V_2^A}$ is also a function of b^H.

[32] When $D = 1$ (tolerance of failure), these losses are zero. When $D = 0$, these losses depend on V_2^A and V_2^P.

[33] $\bar{\pi}^*(1) < \bar{\pi}^*(0) \implies \int_{\bar{\pi}^*(1)}^1 \pi d\pi > \int_{\bar{\pi}^*(0)}^1 \pi d\pi$. Furthermore, $\bar{\pi}^*(1)$ represents the optimal level of exploration for the CEO in a single-period game.

[34] Azoulay et al. (2011) and Tian and Wang (2014) among others provide empirical evidence that tolerance of failure induces more innovation in different settings.

[35] Under $D^L = 0$, 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, $V_1^P(1) > V_1^P(0)$. Note that $V_1^P(D)$ is function of s^L, s^M, s^H, c, w, and D.

[36] $\bar{\theta} \overset{def}{\equiv} \frac{-2s^L}{2\left[V_1^P(1)-V_1^P(0)\right]+[1-\bar{\pi}^*(0)]^2 V_2^P - 2s^L}$. As $V_1^P(1) > V_1^P(0)$ and $s^L < 0$, the cutoff $\bar{\theta}$ is always between 0 and 1.

This is a direct result from inequality 2. Intuitively, when observing a bad outcome, a more trusting CEO ascribes more weight to the researcher's being unlucky than him being of the bad type. As the benefits of incentivizing optimal exploration then outweighs the benefits of screening out bad researchers, she chooses to tolerate failure to avoid mistakenly screening out good researchers in period 2 and also to induce more exploration in period 1.

Combining Propositions 1 and 2 yields the prediction that a more trusting CEO induces more innovation, which is the focus of this paper's empirical investigation.

2.2 Model extensions

First, I relax the assumption that the CEO can credibly commit to being tolerant of failure. Appendix A.2 shows that in this setting tolerance of failure is a unique equilibrium only when $\theta^P > \bar{\theta}_{post} > \bar{\theta}$ where $\bar{\theta}_{post}$ is an unique cutoff based on the game's parameters.[37] Furthermore, for $\theta^P \in (\bar{\theta}, \bar{\theta}_{post})$ there always exists an equilibrium in which the CEO does not tolerate period 1's bad outcome, even though it is *ex ante* optimal for her to do so. This equilibrium is even the unique one in some cases. Such problem can be avoided if the CEO can *ex ante* credibly commit to the being tolerant of failure as in the baseline model, or if she is high trusting with $\theta^P > \bar{\theta}_{post}$. In other words, trust acts as a substitute for commitment.

Next, I allow a bad researcher to also be able to produce exploitation outcome with some luck (i.e., with probability q). In this setting, as only innovation outcome (i.e., successful exploration) fully reveals a researcher's type, would a good researcher explores *more* under a less trusting CEO in order to separate himself from the bad ones, even when it is risky to do so? I find that this is not the case unless q is large, for exploitation still provides signaling value for a good researcher when a bad researcher is not too likely to produce the same outcome by luck. Therefore, a less trusting CEO induces more exploitation and less exploration and vice versa, as in the baseline model.[38]

Third, I extend the model to three periods to study if a longer horizon strengthens the CEO's incentive to screen out bad researchers in earlier periods and induces her to adopt a different strategy. The key intuitions of the two-period game go through in this three-period game. A high-trust CEO always rehires the researcher after a bad outcome; an average-trust CEO tolerates first time failure but not the second time; and a low-trust CEO fires the researcher after first time failure in period 1. A good researcher chooses to explore at the optimal level under a high-trust CEO but undertakes less exploration when the termination threat worsens the downside of failure. As in the baseline model, higher trust maps into higher tolerance of failure and induces more exploration and innovation.[39] The results from this three-period game suggest that the findings extend to in longer-horizon settings.

[37] In this setting, the CEO's decision whether to tolerate failure is based on her updated belief at the end of period 1 with the aim to maximize her period-2 payoff. As a result, she does not internalize the gain from optimal exploration in period 1 under tolerance of failure and therefore is less likely to tolerate period 1's bad outcome (i.e., $\bar{\theta}_{post} > \bar{\theta}$).

[38] The proof for this is available upon request.

[39] The proof for this is available upon request.

Finally, how does a CEO with subjective prior θ^P compare to one knowing the true quality of the researcher pool θ? The model implies higher trust *always* induces more innovation, but also more failure. As a result, when the researcher pool is generally bad but the CEO is too trusting, tolerance of failure leads to costly excessive innovation. On the other hand, when the researcher pool is generally good but the CEO is too distrusting, intolerance of failure leads to inefficiently low level of innovation. Furthermore, when the CEO cannot credibly commit to her policies, a more trusting CEO still can outperform an objective one, as then trust helps substitute for commitment. Subsection 6.3 provides evidence consistent with these implications that CEO's trust effects on both innovation and firm's performance are larger among firms with likely better researcher quality.

3 Data and measurement

3.1 Patents as a measure of innovation

I follow the innovation literature in using patent and citation counts as measures for innovation (e.g., Trajtenberg, 1990; Bloom and Van Reenen, 2002; Hall et al., 2005).[40] My patent data come from PATSTAT, the largest available international patent database which covers close to the population of all worldwide patents since the 1900s up to 2016. It brings together nearly 70 million patent documents from over 60 patent offices, including the United States Patent and Trademark office (USPTO) and all other major offices such as the European Patent Office (EPO) and the Japan Patent Office (JPO). I assign patents to firms using the matching procedure implemented by the OECD and made available via Bureau van Dijk's ORBIS platform.[41]

The dataset contains comprehensive information from the patent record, including application and publication dates, backward and forward citations, technology classification, and patent family. These data allow me to construct various measures of patent quality besides forward citation counts, such as backward citations to scientific literature, patent scope, generality index, originality index, etc. (details in appendix B.2). In addition, PATSTAT also provides information on the inventors of each patent, including their names and addresses, as are available on the patent record. This further enables me to link patents to their inventors' countries of residence (based on their addresses) or countries of origin (based on their last names) to construct patent counts at the firm by inventor country level (details in subsection 5.1).

I consider only patents that are classified as "patent of invention" in PATSTAT (equivalent to USPTO's utility patents). 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

[40] As previously mentioned, the measure of innovative outputs by patents, correcting for quality or not, is not perfect (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.

[41] ORBIS also provides information on firm's ownership structure, which allows one to identify and include patents filed by a firm's subsidiaries.

single patent, and assign the patent to the year of its earliest application date. Finally, PATSTAT's patent data are more comprehensive for the years before 2012, 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). As a result, I focus only on patents filed before 2012.

3.2 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, employment history, and compensation. Among these variables, the executives' names are essential for the measurement of inherited trust, as explained below. In addition, I also use information on the timing of their positions, gender, education, employment history, and compensation (details in appendix B.3).

Measuring CEO's inherited trust. I measure a CEO's inherited generalized trust based on her ethnic origins inferred from her last name and measures of inherited trust among descendants of US immigrants. That is,

$$trust_d = \sum_e w_{de} \times ethtrust_e \tag{3}$$

where $ethtrust_e$ is the average trust measure among all descendants of US immigrants from country e and w_{de} is the probability that CEO d is a descendant of US immigrants from that country.[42]

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, covering 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?"*.[43] 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 almost all European countries in addition to Canada, Mexico, China, and India.[44] The baseline $ethtrust_e$ measure is then the average trust attitude of GSS respondents whose self-reported ethnic origin is e (see Table A1). I only consider respondents in highly prestigious occupations (by GSS' classification), in order

[42] I exclude CEOs who are 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.

[43] Following the literature, I construct a trust indicator equal to 1 if the answer to 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).

[44] 37% of respondents report two or three countries of origin, in which case I select the one to which they feel the closest to. I also exclude 5 ethnic categories: "American Indian," "American only," "Other European," "Other Asian," and "Other," which together comprise only 9% of total respondents.

to better match the CEO sample.[45] In addition, I also construct an alternative trust measure that takes into account demographic characteristics such as gender, education, age, and birth cohort.

Next, I construct a probabilistic mapping between a CEO's last name and different ethnic origins (i.e., $\mathbf{W}_d$) using historical de-anonymized US censuses from 1910 to 1940 (e.g., Kerr and Lincoln, 2010; Liu, 2016).[46] These data contain individual-level data on birthplace and ancestry of the whole US population during 1910-1940, merged with information on 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 occurrences and allow each of them to be mapped to multiple ethnic origins with probabilities equal to their shares of occurrences. Separately, I also compile lists of most common last names in 50 different countries from various sources and use these lists to cross-check and supplement the baseline census-based mapping (details in appendix B.4).[47]

83% of the CEO sample are mapped to their ethnic origins based on their last names. Panel A of Table A3 shows that, there ar no significant differences between these name-matched 83% and the remaining non-matched 17% across all observable characteristics. Three most common ethnic origins among CEOs are Irish, German, and English, which together account for about half of the CEO sample (see Table A2). The average CEO's inherited trust measure is 0.56, considerably higher than the average GSS trust measure of 0.38 but comparable to the average trust measure of 0.51 among respondents in highly prestigious occupations. 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.

Validity of inherited trust measure. There is a growing literature in economics that highlights the role of cultural origin in shaping individual trust and other cultural traits. Studies by 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. Empirically, a large body of evidence shows that trust attitude and other values among descendants of US immigrants are strongly correlated with related traits, behaviors, and outcomes of those in their home countries, consistent with intergenerational cultural transmission among US immigrants.[48] Following this

[45]Specifically, I only consider respondents whose GSS occupation prestige score is in the top 25% (i.e., 50 or above), which cover most respondents in management occupations. The correlation (Spearman correlation) between $ethtrust_e$ computed from this sample and that computed from all GSS respondents is 0.85 (0.75).

[46]The US Census Bureau is allowed to release de-anonymized individual census records after 72 years.

[47]One concern is this last name-based mapping only captures an individual's patrilineage. However, given the documented high level of ethnic segregation in the US during the 1940s (Eriksson and Ward, 2018) and high intra-ethnic marriage rates during this period, this is unlikely to be a first order concern. (Note that the majority of the CEOs in my sample were born in the 1940s or 1950s.) Separately, Pan et al. (2018) employ similar approach to identify CEOs' ethnic origins and find that the uncertainty avoidance indices constructed from CEOs' last names and from their mothers' maiden names are highly correlated, which further supports the mentioned observations. Finally, as 98% of my CEO sample are male, name changing due to marriage is not a concern.

[48]See, for example, surveys by Algan and Cahuc (2013, 2014) and Fernández (2011).

literature, I verify the existence of trust transmission by comparing the measure of inherited trust among US immigrants, calculated from the GSS, with an alternative measure based on average trust attitude among the populations of the countries of origin, available from the World Value Survey (WVS). The correlation between the GSS- and WVS-based trust measures is above 0.5 at country level, consistent with the view that immigrants in the US inherit a large part of their cultural traits from their countries of origin, such as shown in Giuliano (2007).[49]

Ideally, one would like to observe each CEO's individual trust attitude, yet this latent variable is incredibly challenging to measure. Even if one could administer a trust survey or a trust game among CEOs, the resulting measure would still be affected by measurement error.[50] The inherited trust measure misses (i) the individual-specific component of trust but also helps smooth out (ii) these measurement errors. In appendix C.1, I develop a framework to assess the relative sizes of (i) and (ii) using parameters from the literature (e.g., Glaeser et al., 2000). 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.[51] 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 C.2).[52]

Finally, as remarked in subsection 2.1, a CEO's trust attitude likely affects her firm's R&D outcome via its influence on firm's policies and consequently researchers' choices. In real life settings, CEOs' influence on firm's policies takes time to materialize and credible commitment to such policies is unlikely. As a result, researchers' perception of their CEO's trust are as important to their choices as the CEO's actual trust attitude. In large firms, this perception are most likely based on the collective reputation of the group to which the CEO belongs (e.g., Tirole, 1996; Macchiavello, 2010; Xu, 2015), most notably her ethnic group as it is a salient feature of her identity. The inherited trust measure precisely captures the CEO's ethnic group's collective reputation of trust attitude and therefore is the key explanatory variable on its own under this interpretation of the mechanism.

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

$$bitrust_{dc} = \sum_{e} w_e \times ethbitrust_{ec} \tag{4}$$

[49]That the correlation is not perfect possibly reflects the fact that immigrants to the US (i) have been non-randomly selected from the original population, and (ii) have somewhat assimilated to the host culture.

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

[51]Of course, if one can administer *many* trust surveys or games on the same individual, one can average out much more precisely individual trust. However, this possibility is highly infeasible.

[52]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).

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-level bilateral trust measure ($ethbitrust_{ec}$) comes from the Eurobarometer, a series of surveys conducted for the European Commission in which individuals in each country are asked the following 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."*,[53] The relevant Eurobarometer surveys cover respondents from 16 EU countries and ask about their trust attitude towards 28 countries, including a number of non-EU countries such as Russia, Japan, and China.[54] Existing studies using the same measure have shown that bilateral 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) to 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 comprise 45% of the CEO name-matched sample (details in appendix B.4).

3.3 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 sector and those whose headquarters are outside of the US. For practical purpose, I only consider firms with at least one name-matched CEO[55] and further restrict the sample to firms and CEOs for which all key variables are non missing. This results in a final baseline sample of 3,598 US public firms and corresponding 5,753 name-matched CEOs, with 29,384 firm by year by CEO observations during the period between 2000 and 2011 (see Table A3). About 60% of these firms are R&D performing firms and patenting firms, sharing among them 700,000 patent applications between 2001 and 2012. Separately, about two thirds of the firms have more than one CEOs during this 12-year period, with an average of 1.7 name-matched CEOs each firm. 98% of the CEOs are male, each CEO has an average tenure of 7 years, and very few CEOs are the chief executive of more than one Compustat firm.

[53] 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 $ethbitrust_{ec}$.

[54] Unlike the GSS, Eurobarometer surveys are conducted among residences of European countries. However, given the discussed 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 descendants of US immigrants.

[55] These firms comprise 92% of the firm sample and are mechanically larger than the remaining 8%. However, as my key estimates are within-firm estimates, any firm-level selection only poses threat to the results' external validity. This is unlikely to be a first order concern given that selected firms cover a large share of the firm sample.

4 Within-firm effect of CEO's generalized trust

4.1 Within-firm empirical strategy

I first consider a difference-in-differences specification with firm fixed effects:

$$\text{asinh}(pat_{fd,t+1}) = \beta_1 trust_{fdt} + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \theta_f + \omega_t + \varepsilon_{fdt}. \quad (5)$$

Each observation represents a firm f in a year t with its current CEO d. $pat_{fd,t+1}$ is firm f's forward patent application counts in year $t+1$.[56] As patent distribution is skewed, I use the inverse hyperbolic sine transformation $\text{asinh}(pat_{fd,t+1})$ as the main outcome variable instead of raw patent counts (following Card and DellaVigna, 2017).[57, 58] The main explanatory variable $trust_{fdt}$ is the time-invariant measure of CEO d's inherited trust attitude, which also corresponds to researchers' perception of CEO d's trust attitude (details in subsection 3.2). To facilitate interpretation, $trust_{fdt}$ is standardized by its standard deviation at ethnic level.[59] The specification includes a full set of firm fixed effects θ_f, which helps control for all firm-level time-invariant characteristics that are correlated with either firms' innovation capability or selection of CEO. In addition, equation 5 also includes controls for firm's time-variant characteristics $\mathbf{X}_{ft}$ (i.e., firm's age, log(assets), log(sale)), CEO's time-variant characteristics $\mathbf{Z}_{dt}$ (i.e., CEO's age, gender, education dummies, tenure in firm), and a set of year fixed effects ω_t that accounts for macro-level cyclicality in innovation. Standard errors are clustered by CEO's main ethnic origin in case there are idiosyncratic factors that are specific to an ethnicity.[60] Alternative specifications that (i) further include controls for employment and R&D stocks or flows, (ii) employ additional industry-by-year fixed effects, or (iii) apply two-way clustering by CEO's main ethnic origin and firm all yield quantitatively similar results.

The coefficient of interest β_1 estimates the effect of CEO's trust on firm's patents. With the inclusion of firm and year fixed effects, equation 5 identifies β_1 from changes in CEOs and subsequent changes in patenting within the same firm over time. The difference-in-differences identifying assumption requires that the trend in potential outcomes be mean-independent from changes in CEO's trust, conditional on covariates. Under this identifying assumption of common trends, β_1 can be interpreted as the causal effect of CEO d on firm f's patents.[61] That is, the effect captured by β_1 is unlikely to be the result of reverse causality or confounded by firm f's time-variant unobservable

[56] Results are robust to using further-forward patent application counts in year $t+2$ or $t+3$.

[57] The inverse hyperbolic sine transformation $\text{asinh}(x) = \ln(x + \sqrt{1+x^2})$ 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 $\ln(x+1)$ by David Card, because one can still interpret changes in $\text{asinh}(x)$ 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 $\ln(1+x) + O(x^2)$.

[58] Results are robust to (i) using $\log(1+pat_{f,t+1})$, winsorized, or raw $pat_{f,t+1}$ as the outcome variable, (ii) estimating a semi-log Poisson count model with $pat_{f,t+1}$ as the outcome variable, instead of OLS.

[59] Inherited trust's standard deviation at ethnic level is 0.11. This equals the difference between Greek and English inherited trust levels.

[60] CEO d's main ethnic origin is $e^*_d = \text{argmax}_e(w_{de})$. Average weight of the main ethnic origin (i.e., average w_{de^*}) among CEOs is 71%.

[61] In a more general setting with $\text{asinh}(pat) = f(trust, \mathbf{X}, \mathbf{Z}, \eta)$, β_1 estimates an average causal effect $\mathbb{E}[\frac{\partial f(trust, \mathbf{X}, \mathbf{Z}, \eta)}{\partial trust}]$.

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).

To formally test for common trend, 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 pre-change firm's and CEO's 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 2).[62] In addition, Figure 3 plots the average patent application counts by the number of years before the transition for the full sample of firms.[63] The flat pre-trend in patents suggests that the timing of the CEO transition is not driven by a trend in patenting, which implies that reverse causation is unlikely to be a concern in this setting.

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

Figure 4 presents the paper's key empirical finding visually with an event-study plot of firms' patent application counts by year with respect to CEO transition year (i.e., year 0). 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).[64] The two lines exhibit similar pre-trends in the years before CEO transitions, but diverge visibly post-CEO change.[65] Firms that experience an increase in CEO's trust after the transition also experience increases in patenting in post-transition years (i.e., the upward-sloping solid line) and vice versa (i.e., the downward-sloping dotted line). In addition, Table A5 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. Figure 4 suggests that CEO's trust does have a considerable effect on firm's innovation.

Table 1 then estimates equation 5, which exploits changes in CEOs and subsequent changes in

[62] Figure 2 plots the coefficients $\hat{\gamma}_k$ for $k \in [-6,-1]$ from estimating: $\Delta trust_{fdt} = \sum_{k=-7}^{-1} \gamma_k(\text{asinh}(pat_{fdt}) \times event_{t-k}) + \beta trust_{fdt} + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \omega_t + \varepsilon_{fdt}$, in which (i) $\Delta trust_{fdt}$ is the difference between CEO d's and her successor's trust measures, (ii) $event_{t-k}$ is an indicator equal to 1 if the transition happens in year $t-k$, and (iii) $\mathbf{X}_{ft}$ additionally includes a full set of firm's 3-digit industry dummies.

[63] Figure 3 plots the coefficients $\hat{\gamma}_k$ for $k \in [-7,-2]$ relative to $\hat{\gamma}_{-1}$ from estimating: $\text{asinh}(pat_{fdt}) = \sum_{k=-7}^{-1} \gamma_k event_{t-k} + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \theta_f + \omega_t + \varepsilon_{fdt}$, in which $event_{t-k}$ is an indicator equal to 1 if the next CEO transition happens in year $t-k$.

[64] To plot Figure 4, I first (i) partial out the covariates by regressing patent application counts on firm's and CEO's controls with firm's industry and year fixed effects, then (ii) average the residuals by year separately for each group of CEO transitions, and finally (iii) normalize these annual averages to their respective group's pre-transition mean. I restrict the sample to CEO transitions in which both predecessor's and successor's tenures are at least 5 years, so that the plotted patent trends are not driven by changes in firm composition. Furthermore, to address possible mean reversion, each trust-increasing transition is matched to a trust-decreasing transition based on their average pre-transition residual patent counts.

[65] Similar event-study plot using all CEO transitions that meet the CEO tenure restriction (Figure A1) also exhibits the same pattern. This provides further evidence in support of the common trend identification assumption discussed in subsection 4.1, as the patent pre-trends in this figure are not guaranteed to coincide by construction.

patenting within the same firm over time, using the full baseline sample described in subsection 3.3. Given evidence of common trend (see subsection 4.1), the coefficient on CEO's trust captures its effect on firm's forward patent count. I first report two basic specifications without any firm or CEO controls (column 1) or without firm controls that could also be outcomes of CEO's trust, such as assets and sale (column 2). Column 3 then presents the 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. Finally, column 4 further adds industry-by-year fixed effects to account for industry-level patenting cyclicality. The resulting CEO's trust estimates are almost identical across these four 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.[66] This equals 1.1 additional patents annually for the average baseline sample firm with value equal to \$3 million in additional R&D,[67] suggesting that CEO's trust also has a substantial impact from an economic perspective.

Figure A2 plots the CEO's trust estimates as a function of the change in CEO's trust (i.e., difference between trust measures of new and old CEOs) and shows that the effect is driven by both positive and negative changes in CEO's trust, similar to the pattern shown in event study Figure 4.[68] Additionally, Table A6 describes and reports results from further robustness checks, some of which are also mentioned in subsection 4.1.

Columns 5 to 7 turn to alternative measures of trust. Column 5 further refines the trust measure with a machine-learning procedure using all variables commonly available in both BoardEx and GSS besides ethnic origin, including age, gender, education, and birth cohort, which demographic characteristics have been shown to predict individual trust attitude.[69] This measure yields a slightly larger CEO's trust coefficient, suggesting that the baseline trust measure captures most of the meaningful variations in individual trust across observable demographic characteristics. Column 6's trust measure uses the trust answers of all GSS respondents, not just those in highly prestigious occupations, and column 7's uses the World Value Survey's (WVS) trust answers collected from each ethnicity's home country, instead of the GSS's. As the baseline trust measure is closer to the US CEO population, one would expect smaller effect using the full-GSS-based measure, and even smaller effect using the WVS-based measure, as shown in columns 6 and 7.[70]

Table A7 focuses on a special subsample of CEO transitions for which the common trend

[66] The inclusion of controls does not affect the magnitude of CEO's trust estimates but helps improve their precision.

[67] Dechezleprêtre et al. (2018) estimate that a patent costs on average 1.8 million in 2007 British pounds.

[68] The graph represents the effect of trust on patent counts as a function of change in CEO's trust, namely $\frac{\partial \text{asinh}(pat_{fd,t+1})}{\partial trust_{fdt}}(\Delta trust_E)$. Each point estimate is obtained from the benchmark regression, weighted by a kernel function around that value of $\Delta trust_E$ (see Do et al., 2017's appendix for details of this method).

[69] I first fit a LASSO model (Tibshirani, 1996) to predict trust attitude from these demographic characteristics and their interactions with ethnic origin, using individual-level data from the GSS. I then use the LASSO-selected model to predict CEOs' trust attitude. It is worth noting that all ethnic origin dummies are retained in the selected model.

[70] The fact 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.

condition is better warranted: transitions following CEO 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 subsequent transition is likely exogenous to firm's other decisions. Even though the replacement CEO choice is endogenous, under the assumption that firm's underlying characteristics do not change in the event of an exogenous transition, firm fixed effects sufficiently control for firm's new CEO selection. I focus on CEO natural retirements around the age of 65 in columns 1 to 3.[71] Column 6 further includes CEO deaths within one year of leaving the office; however, there are only very few such events in my data. The CEO's trust estimates are large, positive, and statistically significant across these subsamples.[72] Although these results should be taken with caution (they are estimated from small subsamples of special events), overall, they suggest that CEO's trust does have impact on firm's innovation. This resonates with findings from existing literature that CEOs matter to firm performance (see survey by Bertrand, 2009).

However, as the same literature has shown that various CEO's and firm's decisions are influenced by CEO's other characteristics, one would be concerned that some may correlate with CEO's trust and directly affect innovation at the same time. I take two approaches to address this concern: first, I control for potential confounding factors related to CEO's origins, and second, I exploit within-CEO variation to control for all CEO observable and unobservable characteristics with CEO fixed effects in the next section (subsection 5). Even though the latter provides better identification of the effect of CEO's trust, the former sheds some light on other factors by CEO's origins that may also have an effect on firm's innovation.

Given firms' inclination to trade with, have business in, or hire from their CEOs' home countries and the possible spillovers from these linkages, Panel A of Table 2 controls for a range of macroeconomic variables that measure the CEO's home countries' level of development and technological capabilities. These controls include country-by-year-level (i) GDP, population and GDP growth (column 1), (ii) high school graduation rate (column 2), (iii) governance quality index, (iv) total trade volume with the US (column 4), and (v) 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).[73] Among these factors, only GDP growth and trade volume with the US seem to have a relationship with firm's patenting (column 6). More importantly, the magnitude and statistical significance of the CEO's trust effect is not affected by the inclusion of these controls across the columns of Panel A.

In Panel B, I turn to examine if the observed effect is driven by other cultural traits instead of trust attitude. First, a CEO's ethnic groups' socioeconomic characteristics could impact her skill accumulation, both directly via investments in human capital and indirectly via exposure

[71] 65 is the official Social Security retirement age and the traditional retirement age used 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.

[72] The estimates' magnitude suggests that CEO's trust is more important to innovation in times of high uncertainty.

[73] For each home-country variable h, the control variable h_{fdt} is calculated as $h_{fdt} = \sum_e w_{de} \times h_{et}$ where h_{et} is the value of h in the home country e in year t and w_{de} is as described in subsection 3.2.

(e.g., Bell et al., 2018). As there are strong correlations among self-perceived class, occupational prestige, earnings, and education, I use an ethnicity's share of college graduates as a summary statistics for its socioeconomic characteristics in column 1.[74] The related literatures on culture and on CEOs have also pointed to some salient cultural values that have economic significance at both macro and individual levels. These include: (i) Protestant work ethic, which has been discussed since Weber (1905) and shown to influence individual's choices of incentive contract and total work hours (e.g., Liu, 2013; Spenkuch, 2017), and (ii) risk preference, which affects national saving behaviors at the macro level and firm's financing decisions at the micro level (e.g., Pan et al., 2017). In column 2, I measure the Protestant work ethic, which promotes the intrinsic value of work, using answers to the GSS question on the relative importance of work versus luck as the means to get ahead.[75] In column 3, risk preference is inferred from the shares of GSS respondents having stock market or mutual fund investments.[76] Finally, column 4 pools together all the cultural trait controls and column 5 adds the home country controls that are statistically significant in Panel A.[77] The inclusions of these variables does not affect the magnitude and statistical significance of the coefficient on CEO's trust very much, implying that this effect is unlikely to be confounded by other factors related to the CEO's ethnic origins.

5 Within-CEO effect of CEO's bilateral trust

5.1 Within-CEO empirical strategy

Despite the evidence discussed so far, there remain many other CEO personal characteristics that one cannot observe, measure, or directly control for, such as ability, management style, or preference for innovation. These characteristics can have direct effects on firm's innovation and be correlated with her trust attitude at the same time. As a result, equation 5's β_1 captures not only the effect of CEO's trust but also the effects of those other characteristics. To address this concern, I exploit within-CEO variation in bilateral trust towards different groups of inventors and 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:

$$\text{asinh}(pat_{fdc,t+1}) = \beta_2 bitrust_{fdct} + \theta_{ft} + \kappa_c + \omega_d + \varepsilon_{fdct}. \tag{6}$$

[74] These variables are derived from corresponding GSS questions similarly to the trust measure (see subsection 3.2).

[75] The question reads *"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?"*. Relatedly, individuals' answer to the same question has been shown to be correlated with their preference for redistribution (Alesina and Angeletos, 2005; Giuliano and Spilimbergo, 2013).

[76] Campbell (2006) shows that risk averse individuals are less likely to participate in the stock market.

[77] Appendix A8 explores alternative measures for socioeconomic status, work ethic, and risk preference derived from the GSS. Appendix A9 presents additional tests using trust and other cultural trait measures derived from the Global Preference Survey (Falk et al., 2018), including risk and time preferences, positive and negative reciprocity, and altruism. All results are quantitatively similar to what are reported in Table 2.

Each observation is a combination of firm f by year t by its CEO d by country c. The outcome variable $pat_{fdc,t+1}$ is firm f's total patent counts by inventors from country c in year $t+1$ (details below). The main explanatory variable $bitrust_{fdct}$ measures how much CEO d trusts individuals from country c, which aligns with researchers from country c's perception of CEO d's trust attitude towards them (details in subsection 3.2). Besides the crucial CEO fixed effects (ω_d), equation 6 also controls for inventor country's baseline characteristics (e.g., development level, institution quality, technological comparative advantage, inventor pool quality) with inventor country fixed effects (κ_c), 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 counts by inventors from that country. Standard errors are clustered by CEO's main ethnicity-inventor country pair.[78]

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 (similar to Foley and Kerr, 2013, details in appendix B.2). In the address-based approach, a patent is assigned to the country where its inventors reside, which is also likely to be where the invention is created.[79] About 30% of my patent sample are by non-US R&D labs of US-based multinational firms, most of these labs are in Europe, Japan, and China. For the remaining US-based patents, I infer their inventors' ethnic origins from the inventors' last names (see subsection 3.2), then assign the corresponding patents to their inventors' countries of origin accordingly (I refer to this as the last name-based approach).[80] The variable pat_{fct} is the sum of all patents filed by firm f in year t that are allocated to country c.

The sample used to estimate equation 6 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.[81] If a firm-inventor country pair satisfies this condition, then it is included in the sample even in the years when the pair has zero patent to avoid biases arising from selection into patenting over time.[82] Therefore, β_2 captures both the intensive and the extensive margins of CEO's bilateral trust effect on inventors' patenting.[83] Using the address-based approach to identify inventors' countries results

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

[79] Compared to patent office's location, inventors' location is a better proxy for where the invention is created, as an invention can be filed for protection in many different jurisdictions. In the few cases in which a patent has multiple inventors living in different countries, I allocate a proportional fraction of the patent to each of those countries.

[80] Similar to CEOs, over 80% of all inventors are mapped to their ethnic origins based on their last names.

[81] That is, $pat_{fct} > 0$ for some $t \in [2000, 2012]$. In addition, the corresponding CEO d's ethnic origins and country c are among the countries surveyed and/or covered by the Eurobarometer, so that $bitrust_{dc}$ is non-missing.

[82] Alternatively, one could estimate equation 6 using the full sample of all firm-inventor country pairs. However, the inclusion of never-patenting firm-inventor country pairs adds considerable computational burden while offering no additional meaningful within-firm or within-CEO variation in patenting.

[83] I discuss approaches to separate these two effect margins in subsection 5.2.

in a sample of 3,481 firm by country dyads, covering 730 firms with R&D labs in 27 countries (outside of the US) and 960 CEOs. Additionally employing the last name-based approach gives a larger sample of 8,554 firm by country dyads, covering 1,263 firms with inventors from 27 countries and 1,654 CEOs (see Table A4). Figure 5 shows the distribution of the CEO's bilateral trust measure in these subsamples.

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

Table 3 reports the effect of CEO's bilateral trust towards individuals in a country on corresponding patent counts by inventors from that country, estimated using equation 6. Columns 1 to 3 consider the bilateral trust sample constructed from only non-US-based inventors and columns 4 to 6 use both non-US- and US-based inventors.[84] The baseline bilateral-trust specification (equation 6) is reported in columns 1 and 4. In addition, I fully interact the sets of firm, CEO, and inventor country dummies with year dummies in columns 2 and 5. Columns 3 and 6 further include firm-by-inventor country fixed effects to control for specific characteristics of each R&D lab or group within in the firm that are not already captured by firm or inventor country fixed effects.[85, 86] The CEO's trust coefficient in column 1, which estimates 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% increase in patents by the R&D lab in that country (statistically significant at 5% level). This effect is similar in magnitude to the baseline CEO's trust effect of 6% reported in Table 1, and is robust to adding even more stringent fixed effects in columns 2 and 3.

Columns 4 to 6 exhibit similar pattern across the different specifications. One would expect that the effect of CEO's bilateral trust is smaller in this subsample (3% compared to 5% in the other subsample) for a couple of reasons. First, as the differences among US-based inventors from different home countries are less salient, CEOs' bilateral trust towards these inventors and these inventors' perception of the CEOs' trust towards them are less heterogenous. Second, from an organizational perspective, CEOs would be more likely to implement differentiating policies towards R&D labs in different countries than towards different groups of US-based. On the other hand, the combined subsample covers a much larger share of the patent pool, which result in a larger estimation sample

[84]Columns 1 and 2 of Table A11 show that the within-in firm effects of CEO's generalized trust on firm's patents are also positive and statistically significant among firms in these subsamples.

[85]However, it is difficult to specify what the potential confounding factors at firm-inventor country level are. An example is that firm f has a large group of inventors in or from country c for firm-country specific reasons that are not already explained by firm-level and country-level characteristics, and firm f is inclined to select CEOs with high bilateral trust towards country c for the same reasons.

[86]This specification mirrors equation 5's within-firm specification, but is at the within-R&D lab/group level instead. That is, it exploits the change in patenting by the same R&D lab or group following a change in CEO, relative to that of other R&D labs or groups in the same firm under the same CEO. Figure A3 reports evidence of the common trend identification condition by showing that pre-change patents at R&D lab or group level do not predict the change in CEO's bilateral trust towards the corresponding R&D lab or group.

and more precisely-estimated coefficients.[87] Together, results from both subsamples are complement and they both imply that CEO's trust positively impacts firm's innovation.

Furthermore, to understand whether this impact comes from existing inventors in the firm (i.e., the intensive margin), or from new R&D labs or groups that arrive with the CEO (i.e., the extensive margin), I focus on smaller subsamples of firm f-inventor country c pairs such that firm f has patents by inventors from country c before the corresponding CEO assumes position (Table A11, columns 5 and 6). Even though the CEO's trust coefficients are less precisely estimated in these subsamples, they are of similar magnitude to the combined bilateral trust effects. This implies that CEO's trust does work through the intensive margin by improving the innovation outputs of existing researchers, as suggested by the model in Section 2.

Table 4 controls for potential confounding factors at CEO-inventor country pair level. An immediate concern is that CEOs may differentially favor inventors in their home countries or from the same ethnic groups (e.g., Do et al., 2017). To address this, 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), and control for the geographical distance between CEO's and inventor's home countries to account for potential "favoritism spillovers" (columns 2 and 6). Next, bilateral trust is correlated with cultural proximity, which could have a direct impact on R&D outputs thanks to better information flows between CEOs and researchers (e.g., better screening of researchers, better working relationship between researchers and CEOs). In columns 3, 4, 7 and 8, I include CEO's-inventors' home countries pairwise linguistic and genetic distances as proxies for their ease of interaction and cultural proximity (Spolaore and Wacziarg, 2016). The CEO's bilateral trust coefficients remain statistically significant across all of these robustness checks in both bilateral trust subsamples. More importantly, they are similar to Table 3's estimates in magnitude, suggesting that the reported CEO's bilateral trust effect is not spuriously driven by favoritism or other confounding factors.

Furthermore, as trust and trustworthiness are correlated, one may concern that the CEO's trust effect instead captures the impact of her trustworthiness. I exploit the differences between (i) the baseline $bitrust_{dc}$ that measures CEO d's bilateral trust towards inventors from country c, and (ii) a new variable $invbitrust_{cd}$ that measures inventors from country c's trust towards CEO's d,[88] and find that in a specification based on equation 6 that includes both directions of bilateral trust as explanatory variables, the coefficient on $bitrust_{dc}$ is large and statistically significant while the coefficient on $invbitrust_{cd}$ is zero (Table A12, column 3). Given the variables' high correlation, I further employ specifications in which I partition the sample into deciles of $invbitrust_{cd}$ ($bitrust_{dc}$) and compare observations within the same decile by introducing a full set of decile dummies. That

[87] Consistent with the view that the bilateral trust effect is expectedly weaker towards US-based inventors, Table A10, which estimates equation 6 using an alternative bilateral trust sample constructed from only US-based inventors, yields a smaller CEO's bilateral trust coefficient of 2%, statistically significant at 10% level.

[88] $invbitrust_{cd} = \sum_e w_{de} \times ethbitrust_{ce}$ 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. Note that $invbitrust_{cd}$ measures inventors from country c's perception of CEO d's trustworthiness, not their perception of CEO d's trust towards them. The latter, as discussed in subsection 3.2, aligns more closely with $bitrust_{dc}$ instead.

is, I estimate the effect of $bitrust_{dc}$ ($invbitrust_{cd}$) among observations with very similar $invbitrust_{cd}$ ($bitrust_{dc}$). The resulting coefficients show that $bitrust_{dc}$ is still strongly associated with patent outcome (column 4) while the same is not true for $invbitrust_{cd}$ (column 5). The evidence suggests that it is the CEO's trust toward the inventors that is the main driver of the CEO's trust effect.

6 Evidence of mechanism

6.1 Framework for separating different mechanisms

Alternative mechanisms. Section 2 presents a model in which a CEO's trust in a researcher's type improves the latter's incentives to undertake high-risk explorations, which results in more innovation. Yet there exist other competing mechanisms that can also explain this relationship between CEO's trust and firm's innovation. First, trust could lead to greater delegation by the CEO, which induces more effort from the researcher and therefore improves R&D outcomes (Aghion and Tirole, 1997; Acemoglu et al., 2007; Bloom et al., 2012).[89] 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 her policies, the researcher is more likely to cooperate and exert effort if he trusts that the CEO will honor the promised rewards for success.[90, 91] In both of these frameworks, greater effort by the researcher improves the expected outcome of all R&D projects and therefore increases all types of innovation. On the other hand, greater risk taking likely produces more high-quality patents but not necessarily more low-quality ones. This suggests that it is possible to distinguish between the different mechanisms by examining the patent quality distribution, as detailed below.

Estimation of mechanism. I develop a formal framework to compare section 2's risk-taking mechanism that CEO's trust increases innovation by encouraging able researchers to choose risky projects (i.e., explore instead of exploit), against alternative mechanisms of trust inducing more effort by those researchers. The framework identifies the different mechanisms by exploiting their potentially different predictions regarding the outcome *quality* distribution of R&D projects, using patent citation counts and the likes as measures of quality.

First, I establish that the effect of CEO's trust does not work through increasing the scale of R&D, but rather the choice of projects and their eventual outcomes. This is suggested by

[89] Aghion and Tirole (1997) and Acemoglu et al. (2007) model higher trust as greater preference congruence between the principal and the agent, which leads to greater delegation by the principal. Separately, Bloom et al. (2012) consider trust as the principal's belief in the agent to behave in the "correct" way, and find that trust is empirically associated with both greater decentralization and better firm's performance.

[90] Therefore, it is the researcher's trust towards the CEO, or relatedly the CEO's trustworthiness, that matters for cooperation and the game's outcomes. This is inconsistent with the evidence presented in subsection 5.2 that CEO's trust towards the researcher, not the other direction of trust, is the main driver of CEO's trust effect on innovation.

[91] Additionally, Aghion et al. (2013) show both theoretically and empirically that greater monitoring enables more innovation, also through reducing career risks and allowing more risk taking. However, as trust reduces monitoring incentive, they are more likely substitutes than competing explanation of the other's effect on innovation.

the regression of (future) R&D expenditure on CEO's trust specified as in equation 5, which consistently yields statistically insignificant estimates close to zero (Table A15). That is, the number of independent R&D projects the firm runs (i.e., N) is not influenced by CEO's trust.

Let us assume that a project's outcome quality x, measured by a patent's forward citation counts, follow a distribution $F_T(\cdot)$ indexed by the CEO's trust T. Note that x is observable only when the project is patented, that is, when $x \geq 0$. It further assume that better quality patents are always rarer (i.e., $F'_T(x)$ is decreasing on $[0, \infty)$ $\forall T$).[92]

I parameterize this family of distributions as $F_T(x) = F_0(\frac{x - \bar{x} - b(T)}{a(T)} + \bar{x}) \overset{def}{\equiv} F(\frac{x - \tilde{b}(T)}{a(T)})$, in which $a(T)$ represents the change in project's outcome quality variance and $b(T)$ the shift in project's outcome quality mean induced by CEO's trust.[93] The risk-taking mechanism suggests that CEO's trust increases patented innovations through $a(T)$ (i.e., $a'(T) \geq 0$), while alternative mechanisms work through $b(T)$ (i.e., $b'(T) \geq 0$). As higher T implies higher number of observed patent counts $N(1 - F_T(0)) = N(1 - F(\frac{-\tilde{b}(T)}{a(T)}))$ under both types of mechanisms, it is not possible to distinguish between the two by just examining the effect of CEO's trust on total patent count.

The solution to this problem comes from considering patents within a specific low quality range $[c_1, c_2]$. Given the aforementioned assumptions regarding $F_T(.)$, it follows that:

Proposition 3 *Higher $b(T)$ increases the count of patents within the quality range $[c_1, c_2] \subset [0, \infty)$.*

That is, alternative mechanisms that work through $b(T)$ (i.e., mean shifting) increase not only the total patent counts but also the number of patents within any arbitrary patent quality range (see appendix D.1 for detailed proof). The same prediction does not hold for the baseline risk-taking mechanism that works through $a(T)$ instead. On the contrary, under certain mild conditions, it can be shown that higher $a(T)$ *decreases* the count of patents within the quality range $[c_1, c_2] \subset [0, c]$ for small enough c (see appendix D.2 for details).[94]

These results imply that it is possible to identify the two types of mechanisms by examining patent counts in low patent quality ranges. Specifically, when one consider patents in increasing brackets of quality, the effect of CEO's trust on the corresponding patent counts increases from negative/zero to positive under the risk-taking mechanism. In contrast, the alternative mechanisms predict similar effects of CEO's trust on patent counts in different quality brackets. This will serve as a simple test of the mechanism.[95]

[92] This assumption is consistent with the empirical patent quality distribution, as measured by forward citations.

[93] That is, $\tilde{b}(T) \overset{def}{\equiv} \bar{x} + b(T)$ and $F(.) \overset{def}{\equiv} F_0(.)$. Note that $a(0) = 1$, $b(0) = 0$, and $\bar{x} = \mathbb{E}_{F_0}(x)$.

[94] Figure 6 illustrates these results by showing a baseline distribution (in dotted red line) with its mean-preserving spread counterpart (in solid blue line) in the top figure and its mean-shifting counterpart (in solid green line) in the bottom one. The solid vertical line at zero represents the patent quality threshold and the dashed vertical line corresponds to a quality threshold c. One can only observe patented projects in the half-plane to the right of the patent threshold. Proposition 3 implies that the area between $[0, c]$ is always higher under the higher-mean distribution (see bottom figure) compared to the baseline distribution, while the same is not necessarily true under the higher-risk distribution (see top figure).

[95] Furthermore, one can also identify separately $a(T)$ and $b(T)$ from considering the trust effect on different patent

6.2 Effect on patent quality distribution via exploration

I apply subsection 6.1's methodology to identify between the risk-taking mechanism, by which CEO's trust increases innovation through encouraging able researchers to choose risky instead of safe R&D projects (i.e., exploration instead of exploitation), versus suggested alternative mechanisms of delegation and/or cooperation. The method considers trust effects patents in low quality quantiles.

I follow the literature on innovation and patenting in measuring patents' quality by their forward citation counts.[96] 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 $q \in [1, 10]$.[97]

Figure 7 documents how CEO's trust effect vary by patent quality decile by plotting the coefficients estimated from equation 5 using $\text{asinh}(pat^1_{ft})$ to $\text{asinh}(pat^{10}_{ft})$ as the outcome variables. The upward-sloping pattern indicates that CEO's trust has larger positive effect on higher-quality patents. On the other hand, its effect on patents below-median in quality is not statistically different from zero. As discussed in subsection 6.1, these results are consistent with the exploration channel, and reject alternative channels such as delegation or cooperation.[98] Furthermore, using Table 3's bilateral-trust specification (equation 6) also gives similar result that CEO's trust effect is the largest on patents in the top quality quartile, while its effect on the bottom quartile is either small or zero (see Table A13).[99]

Table 5 considers various other patent quality measures and estimates equation 5 using quality-weighted patent counts as the outcome variable (Squicciarini et al., 2013). Column 1 uses standard forward citation counts as the quality weights. Column 2 uses the number of backward citations to scientific literature. Columns 3 to 5 use patent scope, generality index, and originality index, which measure the range of technology fields covered by the patent, its forward citations, and its backward citations respectively.[100] Column 6 considers only granted patents. Across these different quality-weighted patent counts, the coefficients on CEO's trust are positive and statistically significant, with magnitudes larger than or similar to the baseline effect. The large effect on citations to scientific

quality quantiles. It is thus possible to structurally estimate the effects of trust via the two types of mechanisms (e.g., by assuming $a(T) = aT$, $b(T) = bT$, and $F \sim \mathcal{N}(\bar{x}, \sigma)$). This is a topic that I will return to in future research.

[96] Hall et al. (2005) show that one more citation per patent (around the median) is associated with 3% higher in market value for the firm. Trajtenberg (1990), Harhoff et al. (1999), and Moser et al. (2015) also find that patent's forward citation counts is correlated with patent quality.

[97] The bottom three deciles contain mostly patents with zero forward citations.

[98] This resonates 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.

[99] As patents are already divided into smaller cells of firm by country by year in this specification, I only further classify them by quality into 4 quartiles instead of 10 deciles. Similar results hold in both bilateral trust subsamples.

[100] Trajtenberg et al. (1997) first proposed the generality and originality indices, arguing that a patent is likely more general purposed if it benefits different fields and more original if it relies on different knowledge sources.

literature in column 2 is especially interesting, as it suggests that CEO's trust encourages researchers to explore directions that are closer to scientific frontiers and therefore could result in inventions of significantly higher quality (Cassiman et al., 2008; Branstetter, 2005). Furthermore, column 7 directly shows that CEO's trust improves not only the absolute forward citation counts, but also the average citation counts per patent, and this effect is of sizable magnitude (4.4%, statistically significant at 5% level).[101] The same results also hold in both bilateral trust subsamples, which similarly report largest effects on forward citations, citations to scientific literature, and patent scope (see Table A14). Together, Tables 5 and A14 provide further evidence that CEO's trust increases both the quantity and the quality of innovation, as is expected under more exploration.

6.3 Effect increases with researcher quality pool

Section 2's model predicts that CEO's trust always increases total innovation. However, as trust induces innovation through encouraging good researchers to explore, its effect is expected to be larger among firms with better researcher pool quality and vice versa. As data on the full sample of researchers in each firm are not available, I construct a proxy for research quality as the residuals from regressing patents 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 time space with similar observable characteristics (including R&D expenditure and CEO's trust), and one firm produces more patents than the other, then it is likely that the former has better researchers than the latter.

Table 6 interacts CEO's trust measure with firm-level proxy for researcher pool quality during the pre-transition period and finds that consistent with the model's implication, CEO's trust effect significantly increases with researcher quality. This finding is robust to averaging the quality proxy over different pre-transition windows (columns 1 to 3) and using different level of industry fixed effects in computing this proxy. Column 4 further shows that CEO's trust effect is sizable and statistically significant only among firms whose existing researcher pool quality is in the top two quintiles, consistent with the pattern plotted in Figure A4. Furthermore, the same pattern holds for CEO's trust effect on firm's R&D efficiency, as measured by patent output over R&D expenditure (column 6), as well as firm's future performance, as measured by future sales, employment, and total factor productivity (TFP) (Table A16). These results suggest that trust is effective to not only innovation but also real performance only when it is not grossly misplaced.

6.4 Evidence of effect on "corporate trust culture"

One concern is how a CEO's personal characteristics could affect a researcher's choices in large public firms, given the likely multiple layers between them.[102] On one hand, direct interactions

[101]The dependent variable in column 7 is the inverses hyperbolic sine of average forward citation counts of patents filed by firm f in year $t+1$, which is set to zero if firm f files zero patents in year $t+1$.

[102]Despite this concern, 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 result suggests that CEOs can influence innovation activities even firms where they are hierarchically distant from the inventors.

between the CEO and the researcher are not necessary for the mechanism, as the former's trust impacts the latter's choices through her influence on policies, which are observed and even anticipated by the researcher (based on his perception of her trust attitude). On the other hand, in reality it is unlikely that the CEO makes direct decisions regarding a specific researcher, so one would expect her trust to also have an effect on the beliefs and choices of those in below levels in order for it to influence the choices of the researcher. In this subsection, I explore whether CEO's trust attitude is transmitted within the firm.

To measure "firm's trust attitude," I use Sull's (2018) dataset of employee sentiments covering over 500 US large public firms. This dataset is constructed from the text analysis of almost one million online employee reviews on Glassdoor.com, one of the largest career intelligence sites worldwide, between 2008 and 2017.[103] It covers a large set of topics related to corporate culture and contains the number of instances each topic appears in a review with positive or negative sentiment.[104] 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."

I extend my firm and CEO data to 2016 and match them with review-level sentiment data by firm and year. I then aggregate each topic's sentiment measure by CEO term and standardize the resulting measures by their standard deviations.[105] This results in Table 7's sample of 393 observations at firm by CEO term level, covering 277 firms. To examine the relationship between CEO's trust attitude and corporate trust culture, I regress the described aggregated corporate-trust-culture sentiment measure on CEO's inherited trust, controlling for period-average firm's and CEO's characteristics and 3-digit industry fixed effects (column 2) or even firm fixed effects (column 3). The coefficients reports a strong association between CEO's trust and corporate trust culture, which is unlikely to be driven by firm-CEO matching as suggested by column (3). This relationship is robust to adding additional controls for CEO's approval rate by the same sets of reviewers (column 4) and CEO's other cultural traits as studied in Table 2 (columns 5 and 6). Even though these results should be taken with great caution,[106] they do provide suggestive evidence that CEO's trust attitude affects how those in below levels view and work with one another.[107]

[103] 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.

[104] These topics are also selected based on O'Reilly et al.'s (1991, 2014) 7 dimensions of corporate culture. For example, "corporate trust culture" is a topic 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.

[105] I only keep the CEO terms for which there are at least 120 reviews, to avoid the results being driven by a few idiosyncratic reviews.

[106] The caveats include: (i) the firm by CEO term subsample used in this analysis is small and only partly overlaps with the baseline sample, and (ii) the corporate-trust-culture and other culture measures are indirectly constructed from online reviews by only a subsample of firms' employees.

[107] This resonates with Graham et al.'s (2018) finding that corporate culture is primarily set by the current CEO.

7 Interpretation and discussions

7.1 Innovating or patenting?

Using patents to measure innovation raises the concern that a CEO's trust attitude may be correlated with her preference for patenting instead of having a true impact on innovation. The direction this correlation is ambiguous. On one hand, a more trusting CEO may count on her employees to keep trade secrets and therefore chooses to patent less. If so, the baseline estimates do not capture the full extent of CEO's trust effect on innovation. On the other hand, a more trusting CEO could have better confidence in the patent system and thus higher propensity to patent. To assess if the observed effect is driven by this, I construct measures of CEO's confidence in the government and in the scientific community as proxies for her confidence in the patent system.[108] Controlling for either of these measures in equation 5 does not significantly alter the CEO's trust coefficient, suggesting that the latter is unlikely to be confounded by CEO's confidence in the patent system and relevant institutions (Table A8, columns 5 and 6).[109] Furthermore, results from the bilateral trust subsamples (Table 3) provide another strong piece of evidence, for in this specification CEO's propensity to patent is fully absorbed by CEO fixed effects.[110] Together, the evidence indicate that the estimates from using patents as the outcome variable do capture the effect of CEO's trust on true innovation, not just its effect on patenting propensity.

7.2 Timing of CEO's trust effect

Does the effect of CEO's trust increase or decrease over time? Again, there is not a clear prediction of how the effect should evolve. On one hand, it takes time for a new CEO to implement hard policies or transmit soft culture, and for R&D to materialize into innovation, so one should expect larger effect over time. On the other hand, the theory suggests that CEO's prior belief, or inherited trust, should become less important as she updates her belief after each period. Therefore, whether CEO's trust effect becomes larger or smaller remains an empirical question. Figure A5 plots CEO's trust coefficients by the duration of CEO's tenure in the firm.[111] It may seem surprising that there

[108] These measures are calculated in the same way as CEO's inherited trust measure using answers to relevant questions in the GSS. Confidence in the government is the average of confidence in the federal government, US Supreme Court, and Congress. On their own, only CEO's trust in the scientific community is positively and significantly associated with patenting.

[109] The resulting CEO's trust estimate (standard error) is 0.069 (0.017) with control for CEO's confidence in the government, and is 0.063 (0.018) with control for CEO's confidence in the scientific community. I do not include both controls in the same regression as they are highly correlated (correlation of 0.76).

[110] Even if CEOs may have different levels of confidence in the patent systems of different countries, it is unlikely to be an issue for Table 3's results. This is because the countries in which firms would file for patent protection are not necessarily the home countries of inventors, which is especially true for the subsample of US-based inventors in which patents are mostly file in the US.

[111] Specifically, Figure A5 plots the coefficients $\hat{\beta_k}$ for $k \in [1, 9]$ from estimating: $\text{asinh}(pat_{fd,t+1}) = \sum_{k=1}^{9} (trust_{fdt} \times tenure_{dk} \times successor_d) + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \theta_E + \omega_t + \varepsilon_{fdt}$ using the transition-event sample, in which (i) $tenure_{dk}$ is an indicator equal to 1 if the CEO d starts working in firm f in year $t-k+1$, and (ii) $sucessor_d$ is an indicator equal to 1 if CEO d is the successor in transition E.

is a rather immediate effect, but note that the patent outcome variable is one-year forward. That is, CEO's trust has largest effect on patents filed in her third year in the firm. As researchers could anticipate future policy and culture changes following a CEO transition, it is likely that they adjust their project choices accordingly immediately after the transition', even before those changes materialize. In addition, since Hall et al. (1986) it has been shown that patent applications are often timed quite closely to R&D, and in a few exceptions such as pharmaceuticals, I observe no effect of CEO's trust on firm's patents (Table 9, column 5). Finally, the slight declining trend is suggestive of the presence of CEO's belief updating over time as implied by the model, even though the coefficients are not statistically different from one another.

7.3 Heterogenous effects by CEO and firm

Table 8 investigates how CEO's trust effect varies with CEO background. Column 1 interacts the CEO's inherited trust with her highest education level.[112] While both CEO's inherited trust and education level positively impact innovation, their interaction term is negative, indicating that inherited trust and education are substitutes. To better understand what kind of knowledge reduces the effect of prior belief, column 2 to 4 interacts CEO's trust with dummies indicating if the CEO has at least a master degree (column 2), a doctorate (column 3), and a postgraduate degree that is not an MBA (column 4). The interaction terms in columns 2 and 3 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 negative interaction term is largest in magnitude and statistically significant in column 4, suggesting that it is technical knowledge that reduces the effect of trust. Similarly, column 6 reports a negative interaction term between CEO's trust and a dummy indicating if she has prior R&D experience. 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.[113]

Table 9 reports some additional results on heterogeneous effects by firm size and industry. First, interaction terms between CEO's trust and second-order polynomial of firm's size decile (with respect to its 3-digit industry) suggest that the effect is largest among median-size firms. This possibly reflects the observation that it is more difficult for CEOs to have considerable impact on researchers in very large firm (while R&D and innovation may be less relevant for very small ones). Second, CEO's trust effect is considerable larger in ICT and electronic sectors (10.5%, statistically significant at 5% level). 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 where the firm is smaller.[114] This effect in the remaining sectors, however, is also positive and statistically significant, although of smaller magnitude (4.7%, statistically significant at 5% level). Put different, the effect of CEO's

[112] Education level below college degree is coded to -1, college degree – 0, master degrees – 1, and doctorate – 2.

[113] In the context of cross-country venture capital investment, Bottazzi et al. (2016) similar finds that education and work experience reduce the effect of bilateral trust on investment.

[114] The average firm in ICT is about half the size (as measured by employment) of the average firms in the remaining sectors. Yet together they file about over half of all the patents in the sample.

trust on innovation is ubiquitous across different industry sectors.

7.4 CEO's practice: qualitative insights

This paper's ensemble of quantitative evidence on the effect of CEO trust on patents may lead to questions on how exactly CEOs influence innovation processes within the firm. Channels highlighted in my model include the management of researchers in terms of recruitment, retention, and incentives. While it remains a major challenge to run large-scale surveys with quantitative questions on top managers' practices,[115] one can still get some qualitative insights from a recent survey on leadership and innovation among senior managers worldwide.[116] It is interesting to note that 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 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.[117]

Top managers' views also corroborate this paper's insights. When asked about processes of great impact on improving innovation performance, the second most agreed answer is about promoting risk taking that encourages innovation.[118] Shortermism and fear of failure are also ranked among the top of inhibitors of innovation. While almost all respondents agree that people and corporate culture are the most important determinants of innovation, top managers' top worry is not having the right talent, yet 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) recommends fostering an "innovation culture based on trust," in which people trust that it is safe to pursue risky ideas and paths. While one should be cautious of the methodological rigor of a qualitative, open-end survey, the qualitative insights suggest that trust has in practice been considered as an important driver of corporate innovation.

8 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

[115] An exception is Bandiera et al.'s (2017) data on CEO's time use and practices. Even in the recent literature on management surveys since Bloom and Van Reenen (2007), in most cases one can only obtain information from lower-level staffs.

[116] The survey was conducted by *The McKinsey Quarterly* (Barsh et al., 2007, 2008) in September 2007, covering 722 executives at the senior vice president level and above and 736 lower-level executives around the world.

[117] Regarding personnel decisions, there is a broad range of variation, as my model predicted: 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.

[118] The only slightly more popular answer is "Making innovation a core part of the leadership agenda."

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."[119] 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 association between CEO's trust and firm innovation, measured by patent quantity and quality. I measure a CEO's inherited trust based on her ethnic origins as inferred from her 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% increase in average patent quality. I further use 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 results are unlikely to be 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 thorugh her tolerance of failure. The model further predicts that (i) CEO trust's effect on innovation is driven by high-quality patents, and that (ii) it 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 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 (Bertrand and Schoar, 2003).

The current set of results leave out a few important questions to future work. First, while the main mechanism works through tolerance of failure, we do not have a direct measure of tolerance. Second, it may be fruitful to model the match between CEOs and firms, and control for it explicitly in trying to estimate the effect of CEO's trust on firms. Third, it would be interesting to better understand in which context does excessive trust lead to suboptimal innovation and performance.

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

References

Acemoglu, Daron, Philippe Aghion, Claire Lelarge, John Van Reenen, and Fabrizio Zilibotti, "Technology, Information, and the Decentralization of the Firm," *The Quarterly Journal of Economics*, 2007, *122* (4), 1759–1799. 4, 23

Aghion, Philippe and Jean Tirole, "Formal and Real Authority in Organizations," *Journal of Political Economy*, 1997, *105* (1), 1–29. 4, 23

_ and Peter Howitt, "A Model of Growth through Creative Destruction," *Econometrica*, 1992, *60* (2), 323–51. 5

_ , John Van Reenen, and Luigi Zingales, "Innovation and Institutional Ownership," *American Economic Review*, 2013, *103* (1), 277–304. 2, 23

Ahern, Kenneth, Daniele Daminelli, and Cesare Fracassi, "Lost in Translation? The Effect of Cultural Values on Mergers around the World," *Journal of Financial Economics*, 2015, *117* (1), 165–189. 4

Alesina, Alberto and George-Marios Angeletos, "Fairness and Redistribution," *American Economic Review*, 2005, *95* (4), 960–980. 19

Algan, Yann and Pierre Cahuc, "Inherited Trust and Growth," *American Economic Review*, December 2010, *100* (5), 2060–92. 1, 3, 4, 11

_ and _ , "Trust and Growth," *Annual Review of Economics*, 2013, *5* (1), 521–549. 1, 12, 18

_ and _ , "Trust, Growth, and Well-Being: New Evidence and Policy Implications," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 2, Amsterdam: Elsevier, 2014, pp. 49–120. 1, 4, 12, 18

Angrist, Joshua and Jörn-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton, New Jersey: Princeton University Press, 2009. 13

Arrow, Kenneth, "Economic Welfare and the Allocation of Resources for Invention," in National Bureau of Economic Research, ed., *The Rate and Direction of Inventive Activity: Economic and Social Factors*, Princeton, New Jersey: Princeton University Press, 1962, pp. 609–626. 1

_ , "Gifts and Exchanges," *Philosophy and Public Affairs*, 1972, *1* (4), 343–362. 1

_ , *The Limits of Organizations*, New York: Norton, 1974. 1, 5

Azoulay, Pierre, Joshua Graff Zivin, and Gustavo Manso, "Incentives and Creativity: Evidence from the Academic Life Sciences," *RAND Journal of Economics*, 2011, *42* (3), 527–554. 2, 8, 25

Baker, George, Robert Gibbons, and Kevin Murphy, "Informal Authority in Organizations," *Journal of Law, Economics, and Organization*, 1999, *15* (1), 56–73. 23

_ , _ , and _ , "Relational Contracts and the Theory of the Firm," *The Quarterly Journal of Economics*, 2002, *117* (1), 39–84. 23

Bandiera, Oriana, Luigi Guiso, Andrea Prat, and Raffaella Sadun, "Matching Firms, Managers, and Incentives," *Journal of Labor Economics*, 2015, *33* (3), 623–681. 3

— , Stephen Hansen, Andrea Prat, and Raffaella Sadun, "CEO Behavior and Firm Performance," 2017. Working Paper. 3, 30

Banfield, Edward, *The Moral Basis of a Backward Society*, New York: Free, 1958. 1

Barro, Robert and Rachel McCleary, "Religion and Economic Growth across Countries," *American Sociological Review*, 2003, *68* (5), 760–781. 4

— and — , *Religion and Economy*, Princeton, New Jersey: Princeton University Press, 2018. 4

Barsh, Joanna, Marla Capozzi, and Jonathan Davidson, "How Companies Approach Innovation: A McKinsey Global Survey," *McKinsey Quarterly*, 2007. 30

— , — , and — , "Leadership and Innovation," *McKinsey Quarterly*, 2008. 30

Becker, Sascha and Ludger Woessmann, "Was Weber Wrong? A Human Capital Theory of Protestant Economic History," *The Quarterly Journal of Economics*, 2009, *124* (2), 531–596. 4

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen, "Who Becomes an Inventor in America? The Importance of Exposure to Innovation," 2018. Working Paper. 19

Bennedsen, Morten, Francisco Pérez-González, and Daniel Wolfenzon, "Do CEOs Matter?," 2010. Working Paper. 3, 18, 79

Bennis, Warren and Burt Nanus, *Leaders: Strategies for Taking Charge*, New York: Harper Business, 1997. 31

Bertrand, Marianne, "CEOs," *Annual Review of Economics*, 2009, *1* (1), 121–150. 3, 18

— and Antoinette Schoar, "Managing with Style: The Effect of Managers on Firm Policies," *The Quarterly Journal of Economics*, 2003, *118* (4), 1169–1208. 3, 31

Bisin, Alberto and Thierry Verdier, ""Beyond the Melting Pot": Cultural Transmission, Marriage, and the Evolution of Ethnic and Religious Traits," *The Quarterly Journal of Economics*, 2000, *115* (3), 955–988. 3, 12

— and — , "The Economics of Cultural Transmission and the Dynamics of Preferences," *Journal of Economic Theory*, April 2001, *97* (2), 298–319. 3, 12

Bloom, Nicholas and John Van Reenen, "Patents, Real Options and Firm Performance," *Economic Journal*, 2002, *112* (478), C97–C116. 10

— and — , "Measuring and Explaining Management Practices Across Firms and Countries," *The Quarterly Journal of Economics*, 2007, *122* (4), 1351–1408. 30

— , Raffaella Sadun, and John Van Reenen, "The Organization of Firms Across Countries," *The Quarterly Journal of Economics*, 2012, *127* (4), 1663–1705. 2, 4, 14, 23

Bottazzi, Laura, Marco Da Rin, and Thomas Hellmann, "The Importance of Trust for Investment: Evidence from Venture Capital," *The Review of Financial Studies*, 2016, *29* (9), 2283–2318. 4, 14, 29

Branstetter, Lee, "Exploring the Link Between Academic Science and Industrial Innovation," *Annals of Economics and Statistics*, 2005, (79-80), 119–142. 26, 77

Butler, Jeffrey, Paola Giuliano, and Luigi Guiso, "The Right Amount of Trust," *Journal of* *the European Economic Association*, 2016, *14* (5), 1155–1180. 2

Campbell, John, "Household Finance," *Journal of Finance*, 2006, *61* (4), 1553–1604. 19

Card, David and Stefano DellaVigna, "What do Editors Maximize? Evidence from Four Leading Economics Journals," 2017. Working Paper. 15

Caselli, Francesco, "Accounting for Cross-Country Income Differences," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 1A, Amsterdam: Elsevier, 2005, pp. 679–741. 5

Cassiman, Bruno, Reinhilde Veugelers, and Pluvia Zuniga, "In Search of Performance Effects of (In)direct Industry Science Links," *Industrial and Corporate Change*, 2008, *17* (4), 611–646. 26, 77

Chuang, Yating and Laura Schechter, "Stability of Experimental and Survey Measures of Risk, Time, and Social Preferences: A Review and Some New Results," *Journal of Development Economics*, 2015, *117* (C), 151–170. 13

Cohen, Wesley, "Fifty Years of Empirical Studies of Innovative Activity and Performance," in Bronwyn Hall and Nathan Rosenberg, eds., *Handbook of The Economics of Innovation*, Vol. 1, Amsterdam: North-Holland, 2010, pp. 129–213. 5

Coleman, James, *Foundations of Social Theory*, Cambridge, Massachusetts: Harvard University Press, 1990. 1

David, Faith Noble Theo Vurdubakis Knights and Hugh Willmott, "Chasing Shadows: Control, Virtuality and the Production of Trust," *Organization Studies*, 2001, *22* (2), 311–336. 5

DeBacker, Jason, Bradley Heim, and Anh N. Tran, "Importing Corruption Culture from Overseas: Evidence from Corporate Tax Evasion in the United States," *Journal of Financial Economics*, 2015, *117* (1), 122–138. 1, 3

Dechezleprêtre, Antoine, Elias Einiö, Ralf Martin, Kieu-Trang Nguyen, and John Van Reenen, "Do Tax Incentives for Research Increase Innovation: An RDD for R&D," 2018. Working Paper. 3, 5, 75, 76, 77

Do, Quoc-Anh, Kieu-Trang Nguyen, and Anh N. Tran, "One Mandarin Benefits the Whole Clan: Hometown Favoritism in an Authoritarian Regime," *American Economic Journal: Applied Economics*, 2017, *9* (4), 1–29. 22

Doepke, Matthias and Fabrizio Zilibotti, "Culture, Entrepreneurship, and Growth," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 2, Amsterdam: Elsevier, 2014, pp. 1–48. 5

Durlauf, Steven, Paul Johnson, and Jonathan Temple, "Growth Econometrics," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 1A, Amsterdam: Elsevier, 2005, pp. 555–677. 5

Ederer, Florian and Gustavo Manso, "Incentives for Innovation: Bankruptcy, Corporate Governance, and Compensation Systems," in Robert Litan, ed., *Handbook on Law, Innovation and Growth*, Edward Elgar Publishing, 2011, chapter 5. 2, 6

— **and** — , "Is Pay for Performance Detrimental to Innovation?," *Management Science*, 2013, *59* (7), 1496–1513. 2, 31

Eriksson, Katherine and Zachary Ward, "The Ethnic Segregation of Immigrants in the United States from 1850 to 1940," 2018. Working Paper. 12

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde, "Global Evidence on Economic Preferences," 2018. Working Paper. 19, 65

— **,** — **,** — **, David Huffman, and Uwe Sunde**, "The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences," 2016. 13, 82

Fee, Edward, Charles Hadlock, and Joshua Pierce, "Managers with and without Style: Evidence Using Exogenous Variation," *The Review of Financial Studies*, 2013, *26* (3), 567–601. 18, 79

Fernández, Raquel, "Does Culture Matter?," in Jess Benhabib, Alberto Bisin, and Matthew O. Jackson, eds., *Handbook of Social Economics*, Vol. 1A, Amsterdam: North-Holland, 2011, pp. 481–510. 12

— **and Alessandra Fogli**, "Culture: An Empirical Investigation of Beliefs, Work, and Fertility," *American Economic Journal: Macroeconomics*, 2009, *1* (1), 146–77. 3

Foley, Fritz and William Kerr, "Ethnic Innovation and U.S. Multinational Firm Activity," *Management Science*, 2013, *59* (7), 1529–1544. 20

Fukuyama, Francis, *Trust: The Social Virtues and the Creation of Prosperity*, New York: Free, 1995. 1, 23

Gambetta, Diego, "Can We Trust Trust?," in Diego Gambetta, ed., *Trust: Making and Breaking Cooperative Relations*, Oxford: University of Oxford, 1988, pp. 213–237. 1, 2, 6, 82

Giannetti, Mariassunta and Yishay Yafeh, "Do Cultural Differences Between Contracting Parties Matter? Evidence from Syndicated Bank Loans," *Management Science*, 2012, *58* (2), 365–383. 4

Gibbons, Robert and Robert Kaplan, "Formal Measures in Informal Management: Can a Balanced Scorecard Change a Culture?," *American Economic Review: Paper & Proceedings*, 2015, *105* (5), 447–51. 5

Giuliano, Paola, "Living Arrangements in Western Europe: Does Cultural Origin Matter?," *Journal of the European Economic Association*, 2007, *5* (5), 927–952. 3, 13

— **and Antonio Spilimbergo**, "Growing Up in a Recession: Beliefs and the Macroeconomy," *Review of Economic Studies*, 2013, *81* (2), 787–817. 19

Glaeser, Edward, David Laibson, Jose Scheinkman, and Christine Soutter, "Measuring Trust," *The Quarterly Journal of Economics*, 2000, *115* (3), 811–846. 13, 82, 83

González-Uribe, Juanita and Moqi Groen-Xu, "CEO Contract Horizon and Innovation," 2017. Working Paper. 2, 26

Gorodnichenko, Yuriy and Gerard Roland, "Culture, Institutions, and the Wealth of Nations," *The Review of Economics and Statistics*, 2017, *99* (3), 402–416. 4

Gow, Ian, Steven Kaplan, David Larcker, and Anastasia Zakolyukina, "CEO Personality and Firm Policies," 2016. Working Paper. 3

Graham, John, Jillian Grennan, Campbell Harvey, and Shivaram Rajgopal, "Corporate Culture: Evidence from the Field," 2018. Working Paper. 5, 27

Grennan, Jillian, "A Corporate Culture Channel: How Increased Shareholder Governance Reduces Firm Value," 2014. Working Paper. 5, 27

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, *American Economic Review*, June 2004, *94* (3), 526–556. 1

_ , _ , and _ , "Does Culture Affect Economic Outcomes?," *Journal of Economic Perspectives*, June 2006, *20* (2), 23–48. 1, 3, 4, 11

_ , _ , and _ , "Alfred Marshall Lecture: Social Capital as Good Culture," *Journal of the European Economic Association*, 2008, *6* (2-3), 295–320. 1

_ , _ , and _ , "Trusting the Stock Market," *The Journal of Finance*, 2008, *63* (6), 2557–2600. 2, 6

_ , _ , and _ , "Cultural Biases in Economic Exchange?," *The Quarterly Journal of Economics*, 2009, *124* (3), 1095–1131. 1, 4, 14

_ , _ , and _ , "The Value of Corporate Culture," *Journal of Financial Economics*, 2015, *117* (1), 60–76. 1, 5

_ , _ , and _ , "Long-Term Persistence," *Journal of the European Economic Association*, 2016, *14* (6), 1401–1436. 3, 12

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, "Market Value and Patent Citations," *RAND Journal of Economics*, 2005, *36* (1), 16–38. 10, 25, 76

_ , Christian Helmers, Mark Rogers, and Vania Sena, "The Choice between Formal and Informal Intellectual Property: A Review," *Journal of Economic Literature*, 2014, *52* (2), 375–423. 2, 10

Hall, Browyn, Zvi Griliches, and Jerry Hausman, "Patents and R&D: Is There a Lag?," *International Economic Review*, 1986, *27* (2), 265–284. 29

Hall, Robert and Charles Jones, "Why do Some Countries Produce So Much More Output Per Worker than Others?," *The Quarterly Journal of Economics*, 1999, *114* (1), 83–116. 4

Harhoff, Dietmar, Francis Narin, Frederic Schererm, and Katrin Vopel, "Citation Frequency and the Value of Patented Inventions," *Review of Economics and Statistics*, 1999, *81* (3), 511–515. 25, 76

Hofstede, Gerrt, Geert Jan Hofstede, and Michael Minkov, *Cultures and Organizations: Software of the Mind*, London: McGraw-Hill, 1991. 5

Howell, Sabrina, "Financing Innovation: Evidence from R&D Grants," *American Economic Review*, April 2017, *107* (4), 1136–64. 5

Kaplan, Steven and Morten Sørensen, "Are CEOs Different? Characteristics of Top Managers," 2017. 3

— , **Mark Klebanov, and Morten Sørensen**, "Which CEO Characteristics and Abilities Matter?," *The Journal of Finance*, 2012, *67* (3), 973–1007. 3

Kerr, William and William Lincoln, "The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention," *Journal of Labor Economics*, 2010, *28* (3), 473–508. 3, 12

Klein Woolthuis, Rosalinde, Bas Hillebrand, and Bart Nooteboom, "Trust, Contract and Relationship Development," *Organization Studies*, 06 2005, *26*, 813–840. 2, 5

Knack, Stephen and Philip Keefer, "Does Social Capital Have an Economic Payoff? A Cross-Country Investigation," *The Quarterly Journal of Economics*, 1997, *112* (4), 1251–1288. 1, 3

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, "Technological Innovation, Resource Allocation, and Growth," *The Quarterly Journal of Economics*, 2017, *132* (2), 665–712. 76

La Porta, Rafael, Florencio Lopez de Silanes, Andrei Shleifer, and Robert Vishny, "Trust in Large Organizations," *American Economic Review*, 1997, *87* (2), 333–38. 1, 3

Lambert, Richard, "Executive Effort and Selection of Risky Projects," *RAND Journal of Economics*, 1986, *17* (1), 77–88. 2

Lerner, Josh, "The Importance of Patent Scope: An Empirical Analysis," *RAND Journal of Economics*, 1994, *25* (2), 319–333. 77

Liu, Xiaoding, "Cultural Origins and CEO Incentive Contracts," 2013. Working Paper. 19

— , "Corruption Culture and Corporate Misconduct," *Journal of Financial Economics*, 2016, *122* (2), 307–327. 1, 3, 12

Macchiavello, Rocco, "Development Uncorked: Reputation Acquisition in the New Market for Chilean Wines in the UK," 2010. Working Paper. 13

Malmendier, Ulrike and Geoffrey Tate, "CEO Overconfidence and Corporate Investment," *Journal of Finance*, 2005, *60* (6), 2661–2700. 3

— **and** — , "Superstar CEOs," *The Quarterly Journal of Economics*, 2009, *124* (4), 1593–1638. 3

Manso, Gustavo, "Motivating Innovation," *Journal of Finance*, 2011, *66* (5), 1823–1860. 2, 8

March, James, "Exploration and Exploitation in Organizational Learning," *Organization Science*, 1991, *2* (1), 71–87. 2, 6

Martinez, Elizabeth, Nancy Beaulieu, Robert Gibbons, Peter Pronovost, and Thomas Wang, "Organizational Culture and Performance," *American Economic Review: Papers & Proceedings*, 2015, *105* (5), 331–335. 5

Moser, Petra, Joerg Ohmstedt, and Paul Rhode, "Patent Citations and the Size of the Inventive Step: Evidence from Hybrid Corn," 2015. Working Paper. 25, 76

Nguyen, Bang Dang and Kasper Nielsen, "The Value of Independent Directors: Evidence from Sudden Deaths," *Journal of Financial Economics*, 2010, *98* (3), 550–567. 79

Nooteboom, Bart and Erik Stam, *Micro-foundations for Innovation Policy*, Amsterdam: Amsterdam University Press, 2008. 5

Nunn, Nathan, "Culture and the Historical Process," *Economic History of Developing Regions*, 2012, *27* (1), 108–126. 4

Olley, Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1996, *64* (6), 1263–97. 71

O'Reilly, Charles, David Caldwell, Jennifer Chatman, and Bernadette Doerr, "The Promise and Problems of Organizational Culture: CEO Personality, Culture, and Firm Performance," *Group & Organization Management*, 2014, *39* (6), 595–625. 5, 27

O'Reilly, Charles, Jennifer Chatman, and David Caldwell, "People and Organizational Culture: A Profile Comparison Approach to Assessing Person-Organzation Fit," *Academy of Management Journal*, 1991, *34* (3), 487–516. 5, 27

Pan, Yihui, Stephan Siegel, and Tracy Yue Wang, "Corporate Risk Culture," *Journal of Financial and Quantitative Analysis*, 2017, *52* (06), 2327–2367. 19

_ , _ , and _ , "The Cultural Origin of CEOs' Attitudes Towards Uncertainty: Evidence from Corporate Acquisitions," 2018. Working Paper. 12

Putnam, Robert, *Bowling Alone: The Collapse and Revival of American Community*, New York: Simon and Schuster, 2000. 1

_ , Robert Leonardi, and Raffaella Nanetti, *Making Democracy Work*, Princeton, New Jersey: Princeton University Press, 1993. 1, 23

Sapienza, Paola, Anna Toldra-Simats, and Luigi Zingales, "Understanding Trust," *Economic Journal*, 2013, *123* (12), 1313–1332. 82, 83

Schein, Edgar, *Organization Culture and Leadership*, San Francisco, California: Jossey-Bass Publishers, 1985. 5

Schmoch, Ulrich, "Concept of a Technology Classification for Country Comparisons," in "in" 2008. Final Report to the World Intellectual Property Organisation (WIPO). 77

Smith, Matthew, Danny Yagan, Owen Zidar, and Eric Zwick, "Capitalists in the 21st Century," 2017. Working Paper. 3

Spenkuch, Jörg, "Religion and Work: Micro Evidence from Contemporary Germany," *Journal of Economic Behavior & Organization*, 2017, *135* (C), 193–214. 19

Spolaore, Enrico and Romain Wacziarg, "Ancestry, Language and Culture," in Victor Ginsburgh and Shlomo Weber, eds., *The Palgrave Handbook of Economics and Language*, London: Palgrave Macmillan, 2016, pp. 174–211. 22, 49, 66

Squicciarini, Mariagrazia, Helene Dernis, and Chiara Criscuolo, "Measuring Patent Quality: Indicators of Technological and Economic Value," 2013. OECD Working Paper. 11, 25, 77

Sull, Donald, "Measuring Corporate Culture Using Glassdoor Reviews," MIT Organizational Economics Lunch Seminar 2018. 5, 27, 52

Tabellini, Guido, "The Scope of Cooperation: Values and Incentives*," *The Quarterly Journal of Economics*, 2008, *123* (3), 905–950. 3, 12

_ , "Culture and Institutions: Economic Development in the Regions of Europe," *Journal of the European Economic Association*, 2010, *8* (4), 677–716. 1, 4

Tian, Xuan and Tracy Yue Wang, "Tolerance for Failure and Corporate Innovation," *Review of Financial Studies*, 2014, *27* (1), 211–255. 8

Tibshirani, Robert, "Regression Shrinkage and Selection via the Lasso," *Journal of the Royal Statistical Society*, 1996, *58* (1), 267–288. 17

Tirole, Jean, "A Theory of Collective Reputations (with applications to the persistence of corruption and to firm quality)," *Review of Economic Studies*, 1996, *63* (1), 1–22. 13

Trajtenberg, Manuel, "A Penny for Your Quotes: Patent Citations and the Value of Innovation," *RAND Journal of Economics*, 1990, *21* (1), 172–187. 10, 25, 76

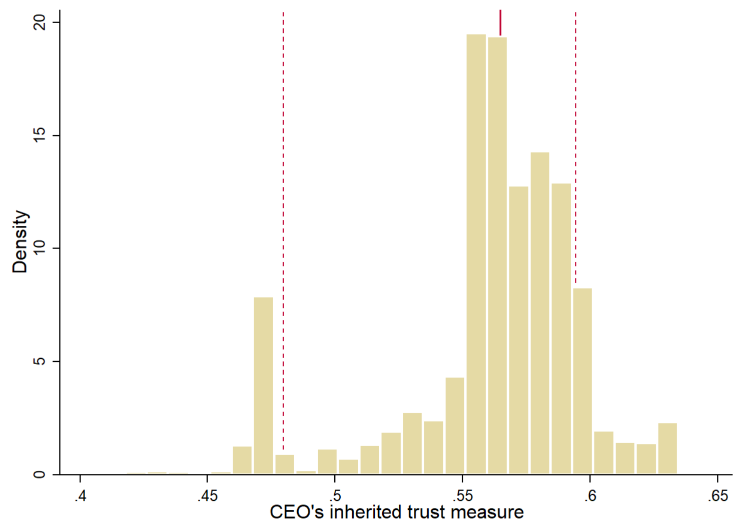
_ **, Rebecca Henderson, and Adam Jaffe**, "University Versus Corporate Patents: A Window On The Basicness Of Invention," *Economics of Innovation and New Technology*, 1997, *5* (1), 19–50. 25, 77

Van den Steen, Eric, "On the Origin of Shared Beliefs (and Corporate Culture)," *RAND Journal of Economics*, 2010, *41* (4), 617–648. 5

Weber, Max, *The Protestant Ethic and the Spirit of Capitalism*, London: Allen & Unwin, 1905. 19

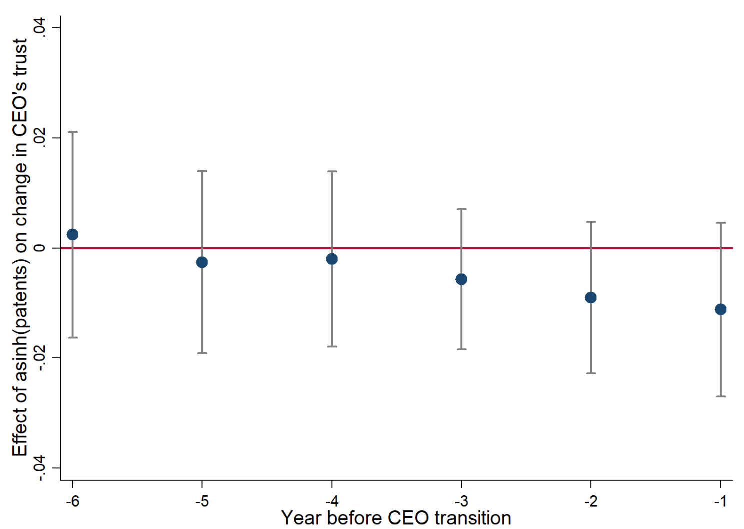
Xu, Guo, "How Does Collective Reputation Affect Hiring? Selection and Sorting in an Online Labour Market," 2015. Working Paper. 13

Figure 1: Distribution of CEO's Inherited Trust Measure



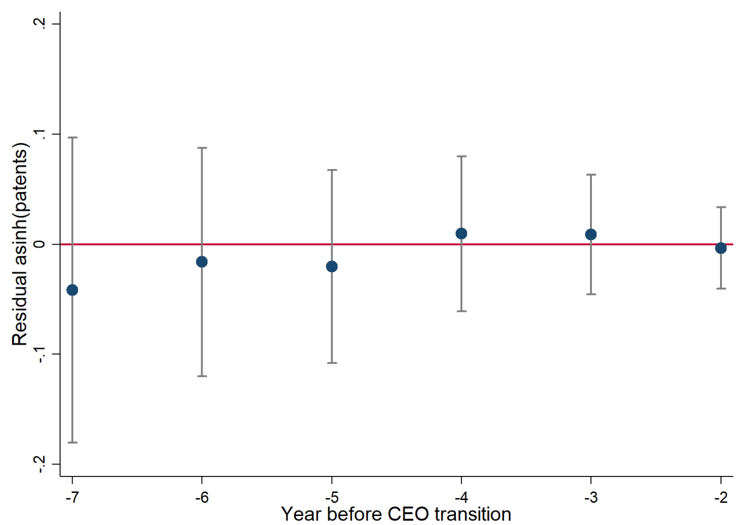
Notes: This figure shows the 1st-99th percentile distribution of CEO's GSS-based inherited generalized trust measure as described in subsection 3.2 for 5,753 CEOs in the baseline sample. The solid vertical line corresponds to the 50th percentile of the distribution. The dashed vertical lines correspond to the 10th and 90th percentiles of the distribution.

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



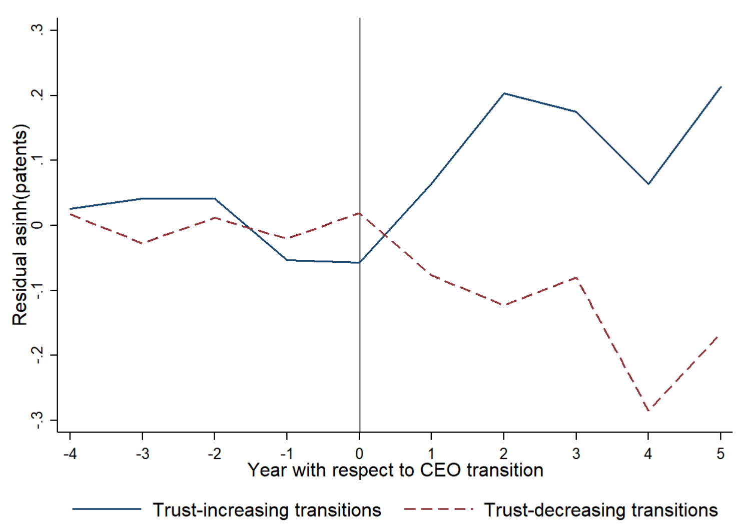
Notes: This figure plots the coefficients $\hat{\gamma}_k$ for $k \in [-6, -1]$ from estimating: $\Delta trust_{fdt} = \sum_{k=-7}^{-1} \gamma_k (\text{asinh}(pat_{fdt}) \times event_{t-k}) + \beta trust_{fdt} + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \omega_t + \varepsilon_{fdt}$, in which (i) $\Delta trust_{fdt}$ is the difference between CEO d's and her successor's trust measures, (ii) $event_{t-k}$ is an indicator equal to 1 if the transition happens in year $t-k$, and (iii) $\mathbf{X}_{ft}$ additionally includes a full set of firm's SIC3 industry dummies. Estimates are shown with their 95% confidence intervals. Standard errors are clustered by SIC3 industry.

Figure 3: Pre-Trend in Patents



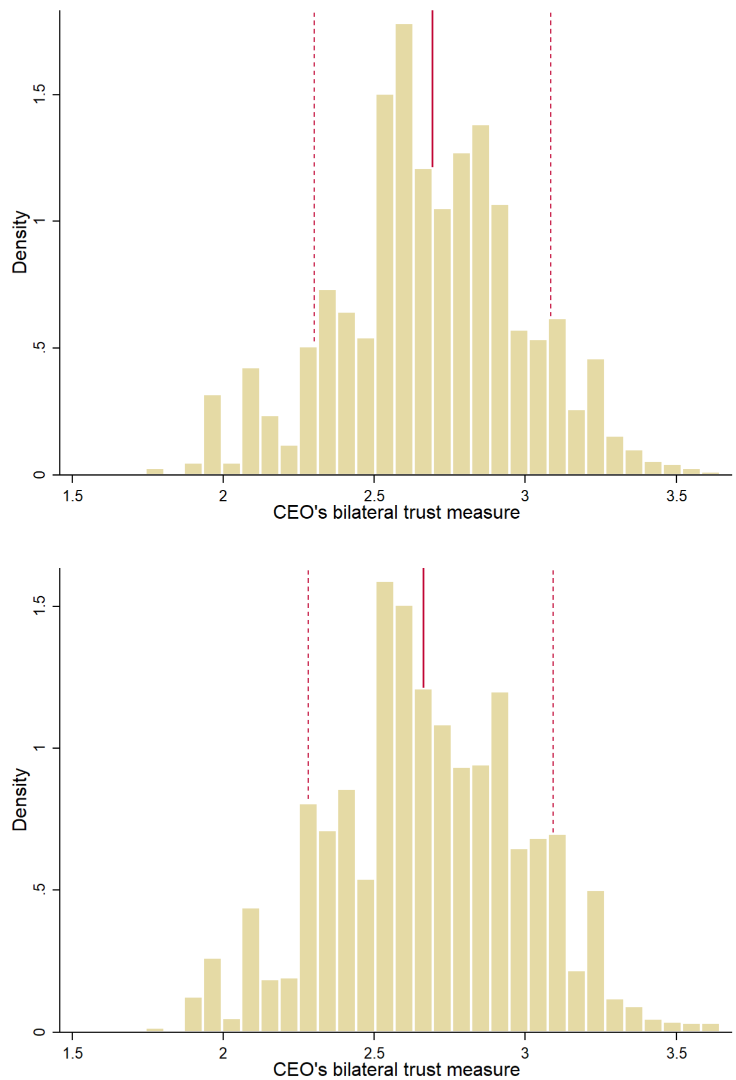
Notes: This figure plots the coefficients $\hat{\gamma}_k$ for $k \in [-7, -2]$ relative to $\hat{\gamma}_{-1}$ from estimating: $\text{asinh}(pat_{fdt}) = \sum_{k=-7}^{-1} \gamma_k event_{t-k} + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \theta_f + \omega_t + \varepsilon_{fdt}$, in which $event_{t-k}$ is an indicator equal to 1 if the next CEO transition happens in year $t-k$. Estimates are shown with their 95% confidence intervals. Standard errors are clustered by firm.

Figure 4: Patents by Change in CEO's Trust (Matched Sample)



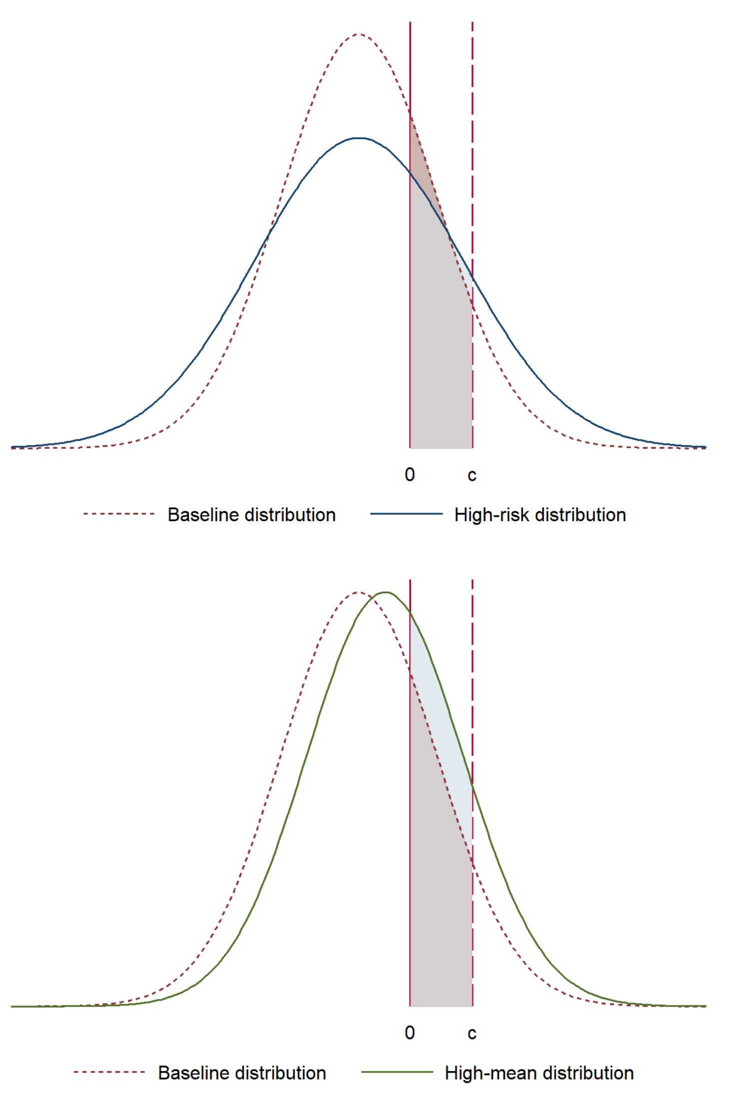
Notes: This figure plots firms' average residual patent application counts (after partialling out the covariates) by year with respect to CEO transition year (i.e., year 0). Among the sample of CEO transitions in which both predecessor's and successor's tenures are at least 5 years, each transition in which the new CEOs are *more* trusting than their predecessors (i.e., trust-increasing transition) is matched to a transition in which the new CEOs are *less* trusting than their predecessors (i.e., trust-decreasing transition) based on their average pre-transition residual patent counts. 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.

Figure 5: Distribution of CEO's Bilateral Trust towards Researchers



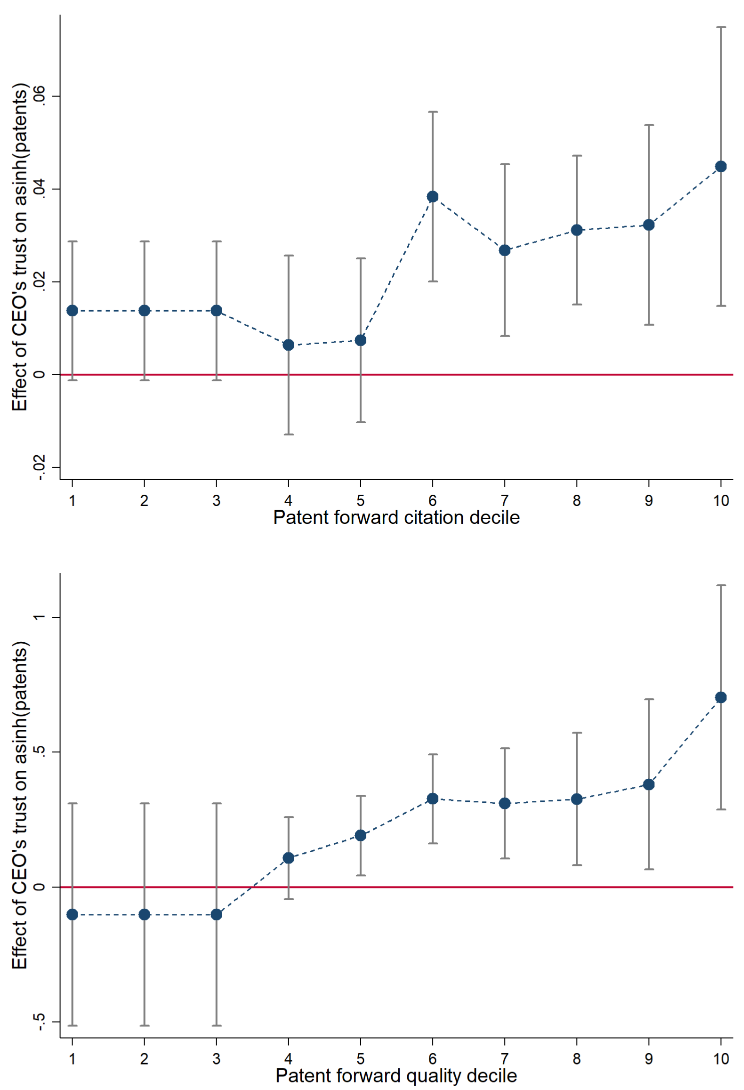
Notes: This figure shows the distribution of CEO's bilateral trust measure as described in subsection 3.2 for CEO-inventor country pairs in the baseline bilateral samples. The upper plot corresponds to the bilateral trust sample in which an inventor's country is inferred from his patent-listed address for non-US-based inventors. The lower plot 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 50th percentile of the distribution. The dashed vertical lines correspond to the 10th and 90th percentiles of the distribution.

Figure 6: Project Outcome Distributions under Different Mechanisms



Notes: The top figure illustrates the spread of project outcome distributions under more exploration; the bottom figure the rightward shift under greater effort. The dotted red line (both figures) corresponds to the baseline project outcome 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 a quality threshold c.

Figure 7: CEO's Trust Effect by Patent Quality Decile



Notes: This figure plots the effects of CEO's trust on firm's patent counts in different quality deciles estimated using equation (5), using as the dependent variable the inverse hyperbolic sine of patent counts in the upper plot and winsorized patent counts in the lower plot. A patent's quality decile is computed based on its forward citation counts 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 1: Baseline Effect of CEO's Trust on Firm's Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**asinh(Future patent applications)**						
CEO's trust (baseline)	0.059***	0.063***	0.063***	0.066***			
	(0.018)	(0.017)	(0.019)	(0.019)			
CEO's trust (LASSO)					0.067***		
					(0.021)		
CEO's trust (full GSS)						0.041**	
						(0.018)	
CEO's trust (WVS)							0.031**
							(0.013)
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
Industry $\times$ Year FEs				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 reports the baseline effect of CEO's inherited trust on firm's patents using equation (5). 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 counts in year $t+1$. The explanatory variable is CEO d's trust measures, constructed from: (i) CEO's ethnic origins and GSS trust question, considering only respondents in highly prestigious occupations (subsection 3.2) (columns 1-4); (ii) all commonly observable characteristics of CEOs and GSS respondents, including ethnic origin, age, gender, education, and birth cohort, using LASSO (column 5); (iii) CEO's ethnic origins and GSS trust question, considering the full sample of respondents (column 6); and (iv) CEO's ethnic origins and WVS trust question (column 7). All trust measures are standardized by the standard deviation of GSS-based inherited trust measure at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sale), 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 2: Controlling For Confounding Variables

Panel A. Controlling for home countries' level of development

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**asinh(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 grad (%)		-0.001				-0.000
		(0.000)				(0.001)
Governance quality (pct)			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 countries' macroeconomic characteristics using equation (5). 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 counts in year $t+1$. The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sale), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. CEO's home country controls include year t's ln(GDP), ln(population), and GDP growth rate (column 1), population share of high school graduates (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. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Panel B. Controlling for other cultural traits

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	**asinh(Future patent applications)**				
CEO's trust	0.063***	0.052**	0.068***	0.053**	0.053**
	(0.018)	(0.019)	(0.019)	(0.021)	(0.023)
College grad (%)	0.073			0.198**	0.143
	(0.100)			(0.093)	(0.115)
Work ethic (z-score)		0.017		0.022	0.023
		(0.015)		(0.016)	(0.015)
Risk preference (z-score)			-0.038	-0.033	-0.033
			(0.023)	(0.025)	(0.029)
GDP growth (%)					0.005*
					(0.003)
ln(US trade volume)					0.001
					(0.009)
Firm & Year FEs	X	X	X	X	X
Baseline controls	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598

Notes: This panel controls for CEO's other inherited cultural traits using equation (5). 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 counts in year $t+1$. The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sale), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (1) controls for the share of college graduates 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?"*. Column (3) controls for CEO's inherited risk preference, proxied by the share of GSS respondents in CEO's ethnic groups who have stock market or mutual fund investments. Column (4) controls for all of those variables. Column (5) further controls for CEO's home countries' GDP growth rate and ln(US exports + US imports). Standard errors are clustered by CEO's main ethnicity.

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

Table 3: CEO's Trust Effect in Bilateral Trust Samples

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**asinh(Future patent applications)**					
Sample: Based on inventors'	Non-US addresses			Addresses and last names		
CEO's bilateral trust	0.052**	0.051**	0.034*	0.026**	0.025**	0.013**
	(0.023)	(0.024)	(0.021)	(0.011)	(0.011)	(0.006)
Firm × Year FEs	X	X		X	X	
CEO FEs	X		X	X		X
Inventor country FEs	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	56,942	56,942	56,942
Firm × Inv. country's	3,481	3,481	3,481	8,554	8,554	8,554
Firms	730	730	730	1,263	1,263	1,263

Notes: This table reports the effect of CEO's bilateral trust towards a country on patents by inventors from that country using equation (6). 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)-(3), and additionally from his last name for US-based inventors in columns (4)-(6). 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 counts by inventors from country c 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 4: Bilateral Trust Effect with Country Pairwise Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**asinh(Future patent applications)**							
Sample: Based on inventors'	Non-US addresses				Addresses and last names			
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: This table controls for other CEO-inventor country pairwise characteristics besides bilateral trust using equation (6). 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)-(4), and additionally from his last name for US-based inventors in columns (5)-(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 counts by inventors from country c in year $t+1$. 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 (columns 5 and 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 5: CEO's Trust Effect on Quality-Weighted Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent var:	**asinh(Future quality-weighted patents)**							
Quality measure:	Forward cites	Backward NPL cites	Tech. scope	Generality	Originality	Granted all	Granted USPTO	Average cites
CEO's trust	0.100***	0.103***	0.061**	0.053***	0.050***	0.049***	0.056***	0.044**
	(0.031)	(0.031)	(0.025)	(0.015)	(0.015)	(0.016)	(0.014)	(0.020)
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	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598	3,598	3,598	3,598

Notes: This table reports CEO's trust effect on quality-weighted patents using equation (5). 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 counts in year $t+1$, weighted by: forward citations (column 1); backward citations to non-patent (i.e., scientific) literature (column 2); patent technological scope (column 3); generality index (i.e., technological diversity of forward citations) (column 4); originality index (i.e., technological diversity of backward citations) (column 5); granted patents (column 6); and granted USPTO patents (column 7). The dependent variable in column 8 is the inverse hyperbolic sine of firm f's average forward citations per patent in year $t+1$ (or zero if firm f has zero patent applications in year $t+1$). The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sale), 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 6: CEO's Trust Effect by Pre-Transition Researcher Pool Quality

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**asinh(Future patent applications)**					**asinh(R&D efficiency)**
	All patents				High quality	
CEO's trust	0.066***	0.066***	0.067***		0.057***	0.039***
	(0.018)	(0.018)	(0.019)		(0.015)	(0.013)
Trust × Proxy for pre-transition researcher quality	0.040**	0.034*	0.021		0.039**	0.025**
	(0.018)	(0.018)	(0.017)		(0.019)	(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)		
Pre-transition window	-1 to 0	-2 to 0	All yrs	-1 to 0	-1 to 0	-1 to 0
Firm & Year FEs	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X
Observations	19,506	19,508	19,547	19,506	19,506	19,506
Events	2,278	2,279	2,285	2,278	2,278	2,278

Notes: This table explores the heterogeneous effects of CEO's trust on firm's patents by pre-transition researcher pool quality using equation (5) and the sample constructed from CEO transition events. 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 (subsection 3.2). Firm-level proxy for researcher pool quality is computed from averaging the residuals from regressing patents on observable firm and CEO characteristics, controlling for SIC2 industry and year fixed effects (subsection 6.3) over different pre-transition windows. The dependent variable is the inverse hyperbolic sine of firm f's (i) patent application counts (columns 1 to 4), (ii) high quality (i.e., above median) patent application counts (column 5), and (iii) R&D efficiency, calculated as patent application counts over lagged R&D expenditure (column 6), in year $t+1$. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sale), asinh(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.

Table 7: CEO's Trust Effect on "Corporate Trust Culture"

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Corporate trust culture**					
CEO's trust	0.179***	0.193***	0.452*	0.234***	0.427**	0.755**
	(0.062)	(0.072)	(0.258)	(0.073)	(0.174)	(0.327)
CEO approval (%)				1.584***	1.540**	0.893
				(0.588)	(0.591)	(0.920)
College grad (%)					-0.687	-1.397
					(1.100)	(1.653)
Work ethic					-0.254*	-0.256*
					(0.143)	(0.152)
Risk preference					-0.286	-0.693*
					(0.246)	(0.362)
Industry (SIC3) FEs	X	X		X	X	
Baseline controls		X	X	X	X	X
Firm FEs			X			X
Observations	393	393	393	393	393	393
Firms	277	277	277	277	277	277
Industries (SIC3)	90	90	90	90	90	90

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 explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). 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. Baseline controls include (i) firm's average age, average age squared, ln(average total assets), ln(average sale), 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 2's notes. Standard errors are clustered by SIC3 industry.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table 8: Heterogeneous Effects by CEO's Background

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	**asinh(Future patent applications)**				
CEO's trust	0.085***	0.082***	0.072***	0.097***	0.063***
	(0.017)	(0.019)	(0.016)	(0.020)	(0.018)
Education level	0.159				
	(0.113)				
Trust × Education level	-0.028				
	(0.022)				
Postgraduate degree dummy		0.176			
		(0.149)			
Trust × P.G. degree		-0.030			
		(0.029)			
Doctorate dummy			0.308		
			(0.299)		
Trust × Doctorate			-0.056		
			(0.058)		
Non-MBA P.G. degree dummy				0.702***	
				(0.230)	
Trust × Non-MBA P.G. degree				-0.135***	
				(0.044)	
R&D experience dummy					0.536
					(0.704)
Trust ×R&D experience					-0.135
					(0.148)
Firm & Year FEs	X	X	X	X	X
Baseline controls	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384
Firms	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 education and experience using equation (5). 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 counts in year $t+1$. The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sale), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (1) interacts CEO's trust measure with her highest education level (-1 – no degree, 0 – Bachelor degree, 1 – Masters degree, 2 – Doctor degree). Columns (2)-(4) interact CEO's trust measure with a dummy indicating if (i) she has a masters or doctorate (column 2), (ii) she has a doctorate (column 3), or (iii) she has a masters or doctorate but not an MBA degree (column 4). Column (5) interacts CEO's trust measure with a dummy indicating if she has prior R&D experience. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table 9: Heterogeneous Effects by Firm's Characteristics

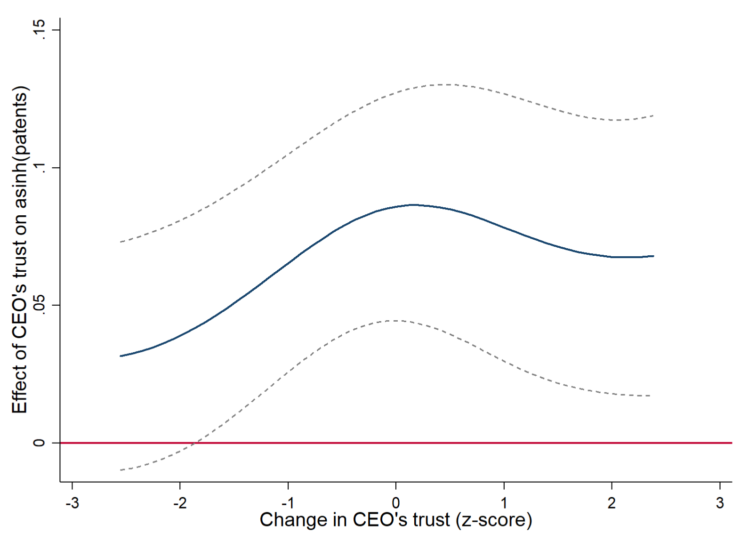
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**asinh(Future patent applications)**					
Sample:	By asset size	By employment size	IT/ Electr.	Non-IT/ Electr.	Pharma/ Chem.	Non-Pharma/Chem.
CEO's trust			0.105**	0.047**	0.019	0.062***
			(0.041)	(0.019)	(0.063)	(0.020)
Trust × Size quintile 1	0.020	0.011				
	(0.033)	(0.036)				
Trust × Size quintile 2	0.014	0.049				
	(0.032)	(0.031)				
Trust × Size quintile 3	0.132***	0.141***				
	(0.043)	(0.028)				
Trust × Size quintile 4	0.084**	0.045				
	(0.039)	(0.035)				
Trust × Size quintile 5	0.077***	0.075**				
	(0.022)	(0.031)				
Firm & Year FEs	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X
Observations	29,384	28,713	6,958	22,426	3,310	26,074
Firms	3,598	3,577	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 (5). 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 counts in year $t+1$. The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sale), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Columns (1) and (2) interact CEO's trust measure with firm's size quintile dummies, computed with respect to firm's 3-digit industry × year cohort using total assets or employment as firm size measure. Columns (3) corresponds to the subsample of firms in ICT and electronic industries (i.e., computer and data processing services (SIC 737), computer and office equipment (SIC 357), electronic and other equipment (SIC 36)) and column (4) – the remaining subsample. Column (5) corresponds to the subsample of firms in pharmaceutical and chemical industries (i.e., chemicals and allied products (SIC 28)) and column (6) – the remaining subsample. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Figure A1: Patents by Change in CEO's Trust (Non-Matched Sample)

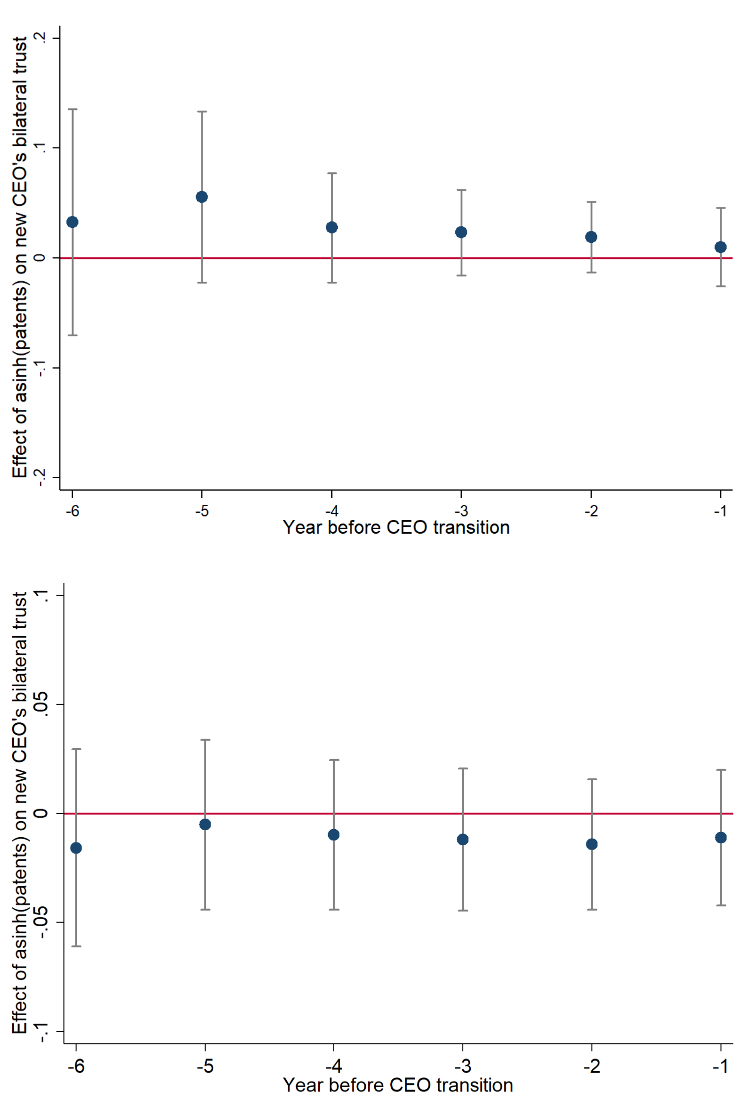
Notes: This figure plots firms' average residual patent application counts (after partialling out the covariates) by year with respect to CEO transition year (i.e., year 0). The solid blue line groups together all CEO transitions in which the new CEOs are *more* trusting than their predecessors (i.e., 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. The sample includes CEO transitions in which both predecessor's and successor's tenures are at least 5 years.

Figure A2: CEO's Trust Effect by Change in CEO's Trust



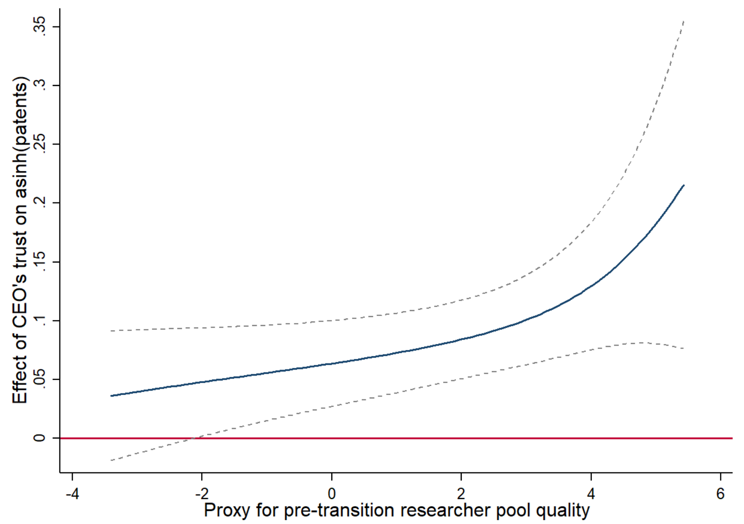
Notes: This figure plots semi-parametric estimates of the CEO's trust coefficient on firm's patents as a function of the change in CEO's trust after the corresponding transition (the X-axis variable). The semiparametric estimation is based on equation (5), using a Gaussian kernel function of the X-axis variable and a bandwidth of 20% of the range. The dashed lines indicate the 95% confidence intervals for the CEO's trust coefficients. Standard errors are clustered by CEO's main ethnicity.

Figure A3: Pre-Change Patents and New CEO's Bilateral Trust



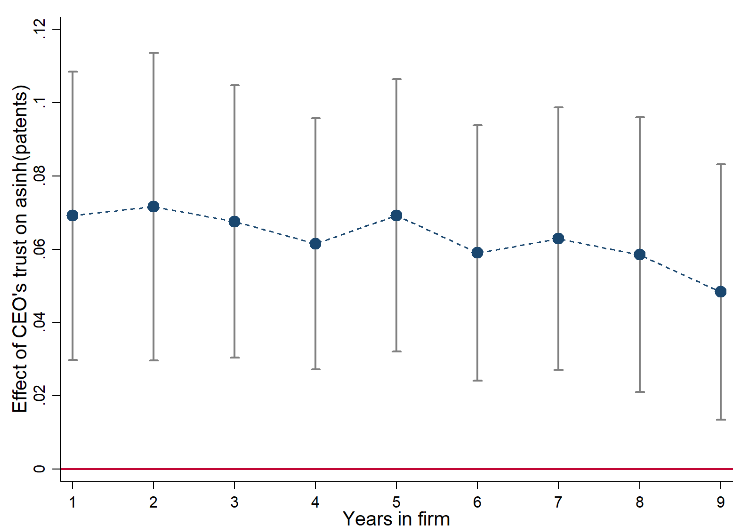
Notes: This figure plots the coefficients $\hat{\gamma}_k$ for $k \in [-6,-1]$ from estimating: $\Delta bitrust_{fdct} = \sum_{k=-7}^{-1} \gamma_k(\text{asinh}(pat_{fdct}) \times event_{t-k}) + \beta bitrust_{fdct} + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \theta_f + \kappa_c + \omega_t + \varepsilon_{fdct}$, in which (i) $\Delta bitrust_{fdct}$ is the difference between CEO d's and her successor's bilateral trust measures towards individuals from country c, and (ii) $event_{t-k}$ is an indicator equal to 1 if the transition happens in year $t-k$. Estimates are shown with their 95% confidence intervals. Standard errors are clustered by firm. The upper plot corresponds to the bilateral trust sample in which an inventor's country is inferred from his patent-listed address for non-US-based inventors. The lower plot corresponds to the bilateral trust sample in which an inventor's country is additionally inferred from his last name for US-based inventors.

Figure A4: CEO's Trust Effect by Pre-Transition Researcher Pool Quality



Notes: This figure plots semi-parametric estimates of the CEO's trust coefficient on firm's patents as a function of pre-transition researcher pool quality (the X-axis variable). Firm-level proxy for researcher pool quality is computed from the residuals from regressing patents on observable firm and CEO characteristics, controlling for SIC2 industry and year fixed effects (subsection 6.3) over a 2-year pre-transition window. The semiparametric estimation is based on equation (5), using a Gaussian kernel function of the X-axis variable and a bandwidth of 20% of the range. The dashed lines indicate the 95% confidence intervals for the CEO's trust coefficients. Standard errors are clustered by CEO's main ethnicity.

Figure A5: CEO's Trust Effect by Tenure in Firm



Notes: This figure plots the coefficients $\hat{\beta}_k$ for $k \in [1, 9]$ from estimating: $\text{asinh}(pat_{fd,t+1}) = \sum_{k=1}^{9} (trust_{fdt} \times tenure_{dk} \times successor_d) + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \theta_E + \omega_t + \varepsilon_{fdt}$ using the transition-event sample, in which (i) $tenure_{dk}$ is an indicator equal to 1 if the CEO d starts working in firm f in year $t - k + 1$, and (ii) $sucessor_d$ is an indicator equal to 1 if CEO d is the successor in transition E.

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 3.2). 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 3.2) for (i) 5,753 CEOs in the baseline sample, and (ii) 7,027 name-matched CEOs.

Table A3: Baseline Sample' 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)		
Inherited generalized trust (full WVS)	0.37	(0.08)	0.36	(0.08)		
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	0.26	(0.44)	0.26	(0.44)	0.28	(0.45)
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)
asinh(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)
asinh(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: Based on inventors'	**Non-US addresses**		**Addresses/last names**	
# 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	0.26	(0.44)	0.25	(0.44)
Has prior R&D experience	0.03	(0.16)	0.02	(0.15)
# CEOs	960		1,654	

Panel B. Firm's characteristics

Sample: Based on inventors'	**Non-US addresses**		**Addresses/last names**	
# 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)
asinh(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)
asinh(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 asinh(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 counts (after partialling out the covariates) in the 5 years before and after CEO transitions, separately for trust-increasing and trust-decreasing transitions as described in the notes to Figure 4. 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: Robustness Checks for CEO's Trust Effect on Firm's Patents

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	asinh(Future patent applications)							
Specification:	Baseline	Alt. clusterings		Alt. samples				Poisson
CEO's trust	0.063***	0.063***	0.063***	0.063***	0.061***	0.075***	0.087***	0.168**
	(0.019)	(0.022)	(0.022)	(0.019)	(0.020)	(0.020)	(0.026)	(0.069)
Sample excluding				Singletons	Female CEOs	Interim CEOs	Transition years	
Clustering scheme		Firm	Two-way					Robust
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	29,195	28,523	28,909	26,202	17,536
Firms	3,598	3,598	3,598	3,409	3,550	3,558	3,552	1,915

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Future patent applications							
Forward:	1-year						2-year	3-year
Transformation:	asinh(.)			log(1+.)	win.	raw	asinh(.)	
Specification:	Additional controls			Alt. transformations			Alt. forwards	
CEO's trust	0.066***	0.063***	0.060***	0.053***	1.462**	4.464***	0.046*	0.039*
	(0.019)	(0.019)	(0.018)	(0.015)	(0.584)	(1.293)	(0.027)	(0.023)
log(employment)	0.101***							
	(0.012)							
asinh(R&D stock)		0.015*						
		(0.008)						
asinh(R&D exp.)			0.092***					
			(0.011)					
Dep. var. mean					*13.28*	*18.02*		
Firm & Year FEs	X	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X	X
Observations	28,506	29,384	29,384	29,384	29,384	29,384	29,384	29,384
Firms	3,548	3,598	3,598	3,598	3,598	3,598	3,598	3,598

Panel C.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**asinh(Future patent applications)**					**D(asinh(pat))**
CEO's trust	0.070***	0.071***		0.041	0.035	
	(0.018)	(0.019)		(0.028)	(0.025)	
Trust × Change in trust		0.013				
		(0.012)				
Post-transition			-0.056***			
			(0.018)			
Post-transition × Trust-increasing			0.087***			
			(0.021)			
Predecessor CEO's trust						-0.016***
						(0.005)
Event sample				Trust increasing	Trust decreasing	
Event & Year FEs	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X
Observations	20,389	20,389	19,504	9,764	9,740	2,444
Events	2,446	2,446	2,343	1,191	1,152	2,444

Notes: This table report the robustness checks for the baseline effect of CEO's inherited trust on firm's patents using equation (5). **Panel A:** Column (1) reports the baseline specification in which (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 counts 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 (subsection 3.2); (iv) baseline controls include firm's age, age squared, ln(total assets), ln(sale), and CEO's age, age squared, gender, education dummies, tenure in firm; and (v) standard errors are clustered by CEO's main ethnicity. Column (2) clusters standard errors by firm. Column (3) clusters standard errors two-way by CEO's main ethnicity and firm. Column (4) excludes singletons; column (5) female CEOs; column (6) interim CEOs; column (7) CEO transition years. Column (8) estimates a semi-log Poisson count model with winsorized $pat_{f,t+1}$ as the dependent variable. **Panel B:** Column (1) additionally controls for ln(employment); column (2) asinh(R&D stock); column (3) asinh(R&D expenditure). Columns (4)-(6) use $ln(1 + pat_{f,t+1})$, winsorized $pat_{f,t+1}$, and raw $pat_{f,t+1}$ as the dependent variable. Columns (7)-(8) use $asinh(pat_{f,t+2})$ and $asinh(pat_{f,t+3})$ as the dependent variable. **Panel C:** This panel employs a sample constructed from CEO transition events and event fixed effects (instead of firm fixed effects). 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 successor and predecessor CEOs' 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) and (5) employ subsamples of trust-increasing and trust-decreasing CEO transition events. Column (6) reports $\hat{\beta}$ from estimating: $\Delta\,\text{asinh}(pat_E) = \beta trust_E^{pre} + \Delta\mathbf{X}_E + \Delta\mathbf{Z}_E + \varepsilon_E$, in which (i) each observation E is a CEO transition event, (ii) $\Delta\,\text{asinh}(pat_E)$, $\Delta\mathbf{X}_E$, 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 predecessor CEO.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A7: CEO's Retirement and Death Events

Panel A. Including all years in each event

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent var:	**asinh(Next period's patent applications)**						**D(.)**
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)	
Predecessor 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:	**asinh(Next period's patent applications)**						**D(.)**
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)	
Predecessor 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)-(6) estimate equation (5). Each subsample includes all firm f × year t × 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)-(3)'s subsamples include transitions in which the predecessor CEO retired at 65, between 64 and 66, or between 63 or 67 respectively. Columns (4)-(5)'s subsamples include transitions in which the predecessor 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 counts in year $t+1$. The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sale), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (7) estimates $\Delta\,\text{asinh}(pat_E) = \beta trust_E^{pre} + \Delta\mathbf{X}_E + \Delta\mathbf{Z}_E + \varepsilon_E$, 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) to (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 A8: Alternative Measures of Other Cultural Traits

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**asinh(Future patent applications)**					
CEO's trust	0.067***	0.059***	0.063***	0.073***	0.069***	0.063***
	(0.022)	(0.020)	(0.018)	(0.023)	(0.017)	(0.018)
Self-reported upper class	-0.131					
	(0.196)					
Occupation prestige		0.015				
		(0.015)				
Alt. work ethic			0.008			
			(0.021)			
Alt. risk preference				-0.027		
				(0.026)		
Confidence in government					0.011	
					(0.013)	
Confidence in science						0.032*
						(0.017)
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 table explores alternative GSS-based measures of CEO's other inherited cultural traits as additional controls in equation (5). 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 counts in year $t+1$. The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sale), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (1) controls for the share of self-reported upper class in CEO's ethnic groups. Column (2) controls for average GSS occupational prestige score among those in CEO's ethnic groups. Column (3) controls for CEO's inherited work ethic, derived from the GSS question: *"If you were to get enough money to live as comfortably as you would like for the rest of your life, would you continue to work or would you stop working?"*. Column (4) controls for CEO's inherited risk preference, proxied by the share of GSS respondents in CEO's ethnic groups who consider job security as the least important feature of a job. Columns (5) and (6) control for CEO's inherited confidence in the government and in the scientific community, 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 (2)-(6) are standardized by their standard deviations at ethnicity level. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A9: Global Preference Survey's Trust and Other Cultural Traits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:				**asinh(Future patent applications)**			
CEO's trust (GPS)	0.040**	0.039***	0.036**	0.041**	0.046***	0.041**	0.043***
	(0.015)	(0.014)	(0.015)	(0.016)	(0.013)	(0.016)	(0.013)
Risk preference		0.003					0.019
		(0.017)					(0.027)
Patience			0.010				-0.016
			(0.014)				(0.026)
Positive reciprocity				-0.005			0.003
				(0.018)			(0.033)
Negative reciprocity					-0.023***		-0.031***
					(0.007)		(0.010)
Altruism						-0.003	0.004
						(0.014)	(0.028)
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 described in subsection 3.2 but using the Global Preference Survey (GPS) (Falk et al., 2018). 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 counts in year $t+1$. The explanatory variable is CEO d's GPS-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(sale), 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. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A10: CEO's Trust Effect in US-Only Bilateral Trust Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**asinh(Future patent applications)**						
Sample:	Based on last names of US-based inventors						
CEO's bilateral trust	0.019*	0.019*	0.011	0.005	0.017	0.018	0.020*
	(0.011)	(0.011)	(0.007)	(0.012)	(0.012)	(0.011)	(0.011)
Common language dummy					0.017		
					(0.024)		
Geographical distance (1000km)						-0.008	
						(0.010)	
Genetic distance (z-score)							-0.019
							(0.049)
Excl. same-country pairs				X			
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
CEO × Year FEs		X					
Inv. country × Year FEs		X					
Firm × Inv. country's FEs			X				
Year FEs			X				
Observations	53,967	53,967	53,967	49,497	52,769	52,769	51,334
Firm × Inv. country's	8,240	8,240	8,240	7,661	8,051	8,051	7,828
Firms	1,186	1,186	1,186	970	997	997	997

Notes: This table reports the effect of CEO's bilateral trust towards a country on patents by inventors from that country using equation (6). 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 counts by inventors from country c in year $t+1$. Column (4) excludes same-country CEO-inventor country pairs. Columns (5) to (7) control for CEO-inventor country pairwise distances, including: (i) whether the countries share a common language (column 5), (ii) weighted geographical distance between the countries (column 6), and (iii) weighted genetic distance between the countries' populations (column 7) (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 A11: Margins of CEO's Bilateral Trust Effect

Panel A. Bilateral trust sample based on inventors' non-US addresses

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**asinh(Future patent applications)**					
	By firms in bilateral trust sample		By inventor groups			
Sample:			Both margins		Intensive margin	
CEO's generalized trust	0.101***	0.126***				
	(0.037)	(0.027)				
CEO's bilateral trust			0.047*	0.037*	0.053	0.072
			(0.024)	(0.020)	(0.049)	(0.049)
Observations	7,356	6,915	22,450	22,450	9,065	9,065
Firm × Inv. country's			3,383	3,383	1,673	1,673
Firms	724	724	700	700	437	437

Panel B. Bilateral trust sample based on inventors' addresses and last names

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**asinh(Future patent applications)**					
	By firms in bilateral trust sample		By inventor groups			
Sample:			Both margins		Intensive margin	
CEO's generalized trust	0.071**	0.095***				
	(0.031)	(0.028)				
CEO's bilateral trust			0.025**	0.015**	0.031**	0.020**
			(0.011)	(0.007)	(0.013)	(0.009)
Firm & Year FEs	X	X				
Baseline controls		X				
Firm × Year FEs			X		X	
CEO FEs			X	X	X	X
Inventor country FEs			X		X	
Firm × Inv. country FEs				X		X
Year FEs				X		X
Observations	12,764	11,931	53,967	53,967	38,467	38,467
Firm × Inv. country's			8,240	8,240	6,418	6,418
Firms	1,256	1,256	1,186	1,186	925	925
	724	724	700	700	437	437

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, columns (1) and (2) report 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 (5) (i.e., observation unit is firm f × year t × its current CEO d, see notes to Table 1 for further details). Columns (3)-(6) report CEO's bilateral trust effect on inventors' patents using equation (6) (i.e., observation unit is firm f × year t × its current CEO d × country c, see notes to Table 3 for further details). Columns (3) and (4) employ all observations such that firm f has patents by inventors from country c during 2000-2012. The resulting coefficients capture both intensive and extensive margins of CEO's bilateral trust effect. Columns (5) and (6) employ only observations such that firm f has patents by inventors from country c before CEO d assumes position. The resulting coefficients capture only the intensive margin of CEO's bilateral trust effect. Standard errors are clustered by CEO's main ethnicity in columns (1) and (3) and by CEO's main ethnicity × inventor country in columns (3)-(6).
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A12: Directions of CEO-Inventor Bilateral Trust

Panel A. Bilateral trust sample based on inventors' non-US addresses

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	**asinh(Future patent applications)**				
CEO-toward-inventors bilateral trust	0.102***		0.100**	0.138***	
	(0.025)		(0.044)	(0.052)	
Inventors-toward-CEO bilateral trust		0.076**	0.003		-0.016
		(0.032)	(0.047)		(0.055)
Observations	12,863	12,863	12,863	12,863	12,863
Firm × Inventor country's	2,009	2,009	2,009	2,009	2,009
Firms	580	580	580	580	580

Panel B. Bilateral trust sample based on inventors' addresses and last names

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	**asinh(Future patent applications)**				
CEO-toward-inventors bilateral trust	0.041**		0.030	0.049*	
	(0.016)		(0.026)	(0.028)	
Inventors-toward-CEO bilateral trust		0.037***	0.013		0.029
		(0.014)	(0.023)		(0.026)
Firm × Year FEs	X	X	X	X	X
CEO FEs	X	X	X	X	X
Inventor country FEs	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
Firm × Inventor country's	5,005	5,005	5,005	5,005	5,005
Firms	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 (6). 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 counts by inventors from country c in year $t+1$. Decile dummies in columns (4) and (5) 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 A13: Bilateral Trust Effect by Patent Quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**asinh(Future patents in each quality quartile)**							
Sample:	Based on non-US addresses				Based on addresses/last names			
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 (6). 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)-(4), and additionally from his last name for US-based inventors in columns (5)-(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 counts 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 counts 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 A14: Bilateral Trust Effect on Quality-Weighted Patents

Panel A. Bilateral trust sample based on inventors' non-US addresses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**asinh(Future quality-weighted patents)**						
Quality measure:	Forward cites	Backward NPL cites	Tech scope	Generality	Originality	Granted all	Granted USPTO
CEO's bilateral trust	0.095**	0.053*	0.100***	0.023	0.032*	0.040*	0.038*
	(0.039)	(0.032)	(0.034)	(0.015)	(0.018)	(0.021)	(0.020)
Observations	23,284	23,284	23,284	23,284	23,284	23,284	23,284
Firm × Inv. country's	3,481	3,481	3,481	3,481	3,481	3,481	3,481
Firms	730	730	730	730	730	730	730

Panel B. Bilateral trust sample based on inventors' addresses and last names

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**asinh(Future quality-weighted patents)**						
Quality measure:	Forward cites	Backward NPL cites	Tech scope	Generality	Originality	Granted all	Granted USPTO
CEO's bilateral trust	0.051***	0.046***	0.051***	0.020**	0.022**	0.023**	0.027**
	(0.018)	(0.016)	(0.016)	(0.008)	(0.009)	(0.010)	(0.011)
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	X
Observations	56,942	56,942	56,942	56,942	56,942	56,942	56,942
Firm × Inv. country's	8,554	8,554	8,554	8,554	8,554	8,554	8,554
Firms	1,263	1,263	1,263	1,263	1,263	1,263	1,263

Notes: This table reports CEO's bilateral trust effect on quality-weighted patents using equation (6). 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 Panel A, and additionally from his last name for US-based inventors in Panel B. 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 counts by inventors from country c in year $t+1$, weighted by: forward citations (column 1); backward citations to non-patent (i.e., scientific) literature (column 2); patent technological scope (column 3); generality index (i.e., technological diversity of forward citations) (column 4); originality index (i.e., technological diversity of backward citations) (column 5); granted patents (column 6); and USPTO patents (column 7). Standard errors are clustered by CEO's main ethnicity × inventor country.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A15: Effect of CEO's Trust on R&D

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**asinh(R&D expenditure)**			**asinh(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 (5). 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 $t+km$ for $k \in [1,3]$. The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sale), 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 A16: Effect of CEO's Trust on Firm Future Performance

Panel A.

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Future	**ln(sales)**	**ln(employment)**	**ln(capital)**	**TFP (KL)**	**TFP (KLM)**
CEO's trust	-0.036**	-0.032**	-0.022	0.006	0.000
	(0.017)	(0.013)	(0.025)	(0.013)	(0.026)
Trust × Proxy for pre-tran-	0.048***	0.034***	-0.000	0.015	0.031
sition researcher quality	(0.014)	(0.010)	(0.013)	(0.011)	(0.018)
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
Events	2,237	2,224	2,149	2,177	1,421

Panel B.

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Future	**ln(sales)**	**ln(employment)**	**ln(capital)**	**TFP (KL)**	**TFP (KLM)**
Trust × Quality quintile 1	-0.153***	-0.154***	-0.068	0.007	-0.008
	(0.040)	(0.035)	(0.047)	(0.036)	(0.041)
Trust × Quality quintile 2	-0.119**	-0.044	-0.063*	-0.046	-0.076
	(0.046)	(0.030)	(0.036)	(0.030)	(0.052)
Trust × Quality quintile 3	0.039	0.002	0.006	0.035	-0.005
	(0.058)	(0.043)	(0.049)	(0.060)	(0.106)
Trust × Quality quintile 4	0.058**	0.069**	0.104**	-0.008	-0.026
	(0.024)	(0.026)	(0.051)	(0.032)	(0.052)
Trust × Quality quintile 5	0.034	-0.000	-0.056	0.051*	0.117***
	(0.045)	(0.027)	(0.050)	(0.027)	(0.041)
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
Events	2,237	2,224	2,149	2,177	1,421

Notes:
This table explores the heterogeneous effects of CEO's trust on firm's patents by pre-transition researcher pool quality using equation (5) and the sample constructed from CEO transition events. 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 (subsection 3.2). Firm-level proxy for researcher pool quality is computed from averaging the residuals from regressing patents on observable firm and CEO characteristics, controlling for SIC2 industry and year fixed effects (subsection 6.3) over a 2-year pre-transition window. The dependent variable is 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); and TFP computed from sales, employment, capital, and material following Olley and Pakes (1996) (column 5). Baseline controls include (i) firm's age, age squared, asinh(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 Theory appendices

A.1 Proof of Proposition 1

Recall from subsection 2.1 that in period 1, the manager sets b^L and b^M to zero and chooses b^H to maximize her expected payoff from hiring a good researcher:

$$\int_0^{\bar{\pi}(D)} \left[s^M + V_2^P\right] d\pi + \int_{\bar{\pi}(D)}^1 \left\{\pi \left[s^H - b^H + V_2^P\right] + (1-\pi)\left[s^L + DV_2^P\right]\right\} d\pi \tag{A1}$$

where $\bar{\pi}(D) = \frac{c+(1-D)V_2^A}{b^H+(1-D)V_2^A}$. To further reduce notation burden, I omit the outcome superscript H from b^H and the period subscript 2 from V_2^P and V_2^A for the rest of this subsection.

Expression (A1)'s first order condition with respect to b is:

$$\begin{aligned} \frac{\partial\bar{\pi}}{\partial b}\left[s^M + V^P\right] - \frac{\partial\bar{\pi}}{\partial b}\bar{\pi}\left[s^H - b + V^P\right] - \frac{\partial\bar{\pi}}{\partial b}(1-\bar{\pi})(s^L + DV^P) - \int_{\bar{\pi}}^1 \pi d\pi &= 0 && \text{(A2)} \\ \iff \left(-\frac{\partial\bar{\pi}}{\partial b}\right)\left\{\bar{\pi}\left[s^H - b - s^L + (1-D)V^P\right] - \left[s^M - s^L + (1-D)V^P\right]\right\} - \int_{\bar{\pi}}^1 \pi d\pi &= 0 && \text{(A3)} \end{aligned}$$

where $\left(-\frac{\partial\bar{\pi}}{\partial b}\right) = \frac{c+(1-D)V^A}{(b+(1-D)V^A)^2}$ 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) $\left[s^H - b - s^L + (1-D)V^P\right]$, and (iv) $\int_{\bar{\pi}}^1 \pi d\pi$ are decreasing in b. In addition, (v) $\bar{\pi}\left[s^H - b - s^L + (1-D)V^P\right] - \left[s^M - s^L + (1-D)V^P\right]$ is non-negative as any value of b that makes (v) negative cannot be the manager's optimal choice. The first order condition therefore is also decreasing in b in the relevant range of b. This implies that for a given set of parameters (i.e., s^L, s^M, s^H, c, D, and corresponding V^P, V^A), equation (A3) has a unique solution b^* that maximizes the manager's expected payoff in equation (A1), which induces the good researcher to explore when π is above threshold $\bar{\pi}^* = \frac{c+(1-D)V^A}{b^*+(1-D)V^A}$.

Comparative static of $\bar{\pi}^*$ with respect to $(1-D)V^P$. As equation (A3) is decreasing in b and $(1-D)V^P$, its unique solution b^* is also decreasing in $(1-D)V^P$. It then follows that $\bar{\pi}^*$ is increasing in $(1-D)V^P$ (as $\bar{\pi}^*$ is decreasing in b^*).

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

$$\begin{aligned} b = \frac{c+(1-D)V^A}{\bar{\pi}} - (1-D)V^A &= \frac{c}{\bar{\pi}} + \left(\frac{1}{\bar{\pi}} - 1\right)(1-D)V^A, && \text{(A4)} \\ \frac{\partial\bar{\pi}}{\partial b} = \frac{c+(1-D)V^A}{(b+(1-D)V^A)^2} &= \frac{\bar{\pi}^2}{c+(1-D)V^A}. && \text{(A5)} \end{aligned}$$

Next, let's also rewrite the first order condition with respect to b (equation A3) in terms of $\bar{\pi}$:

$$\begin{aligned} \frac{\bar{\pi}^2}{c+(1-D)V^A}\left\{\bar{\pi}\left[\Delta_{HL} - \frac{c}{\bar{\pi}} - \left(\frac{1}{\bar{\pi}} - 1\right)(1-D)V^A\right] - \Delta_{ML}\right\} - \frac{1-\bar{\pi}^2}{2} &= 0 && \text{(A6)} \\ \iff \bar{\pi}\Delta_{HL} - \Delta_{ML} - \left[\left(\frac{1}{\bar{\pi}^2} - 1\right)\frac{c+(1-D)V^A}{2} + c + (1-\bar{\pi})(1-D)V^A\right] &= 0 && \text{(A7)} \end{aligned}$$

where $\Delta_{HL} = s^H - s^L + (1-D)V^P$ and $\Delta_{ML} = s^M - s^L + (1-D)V^P$, both are positive. As equation (A7) is increasing in $\bar{\pi}$, it has a unique solution $\bar{\pi}^*$. Furthermore, as equation (A7) is decreasing in $(1-D)V^A$, this unique solution $\bar{\pi}^*$ is increasing in $(1-D)V^A$.

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

A.2 No credible commitment to tolerance of failure

This subsection considers the case when the manager cannot credibly commit to being tolerant of failure, the key decision that drives the model's results. In this setting, her decision whether to tolerate period 1's bad outcome is based on her updated belief at the end of period 1, with the aim to maximize her 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 manager's updated belief after observing period 1's bad outcome is:

$$\theta^U = \frac{\theta^P(1-\bar{\pi})^2}{2(1-\theta^P) + \theta^P(1-\bar{\pi})^2}. \tag{A8}$$

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

$$\frac{\theta^P(1-\bar{\pi})^2}{2(1-\theta^P) + \theta^P(1-\bar{\pi})^2} V_2^P + \frac{2(1-\theta^P)}{2(1-\theta^P) + \theta^P(1-\bar{\pi})^2} s^L > 0 \tag{A9}$$

$$\iff \theta^P > \frac{-2s^L}{(1-\bar{\pi})^2 V_2^P - 2s^L} \equiv \bar{\theta}_{post}(\bar{\pi}). \tag{A10}$$

In an equilibrium in which the manager 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 manager 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 4 *When the manager cannot credibly commit to being tolerant of failure, the game's equilibrium depends on her prior belief θ^P.*
(i) If $\theta^P > \bar{\theta}_{post}(\bar{\pi}^*(0))$, the manager 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 manager 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 manager tolerates failure (i.e., $D = 1$) as in (i), and one in which she does not (i.e., $D = 0$) as in (ii).

Comparison with the baseline model. Recall from subsection 2.1 that in the baseline model when the manager can credibly commit to tolerance of failure, she chooses so (i.e., $D = 1$) when her prior belief θ^P is above threshold $\bar{\theta}$ (equation 2):

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

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 A10). The intuition is that the manager'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 her *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 manager does not tolerate period 1's bad outcome (i.e., $D = 0$), even though it is *ex ante* optimal for her to do so (i.e., $D = 1$) (Proposition 4).[120] Furthermore, if it is also the case that $\bar{\theta} < \bar{\theta}_{post}(\bar{\pi}^*(1))$,[121] then for $\theta^P \in (\bar{\theta}, \bar{\theta}_{post}(\bar{\pi}^*(1)))$, this non-tolerant equilibrium is the unique equilibrium, and the manager cannot at all implement the *ex ante* desirable policy of tolerance of failure. These problems are alleviated only if the manager can credibly commit to her *ex ante* decision, as in the baseline model, or if she is high trusting with $\theta^P > \bar{\theta}_{post}$. This result implies that trust acts as a substitute for commitment.

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

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

B Data construction

B.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.[122] 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,[123] 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.[124] This patent-to-firm linkage is based on a matching procedure implemented by the OECD and is available as part of Orbis.[125] 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 (SIC2 between 60 and 67), as these sectors make up a considerable share of the firm sample but traditionally do not patent their innovations. This resulting sample includes 4,345 firms during the study period between 2000 and 2011 (Table A3), which yields in 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 (see appendix B.3).

[122]BoardEx and Compustat data were retrieved through the Wharton Research Data Services (WRDS) in May 2017.

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

[124]I accessed Orbis platform through the LSE Library Services. The linkage between firms and patents provided by Orbis was retrieved in July 2017.

[125]The matching is done based on the names and addresses of patent applicants on patent records, which data 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.

B.2 Patent and inventor data

My patent data are drawn 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 nearly 70 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). PATSTAT data cover close to the population of all worldwide patents between 1900 and 2015 and contain comprehensive information on patent application and publication dates, applicants and inventors, patent family, technology classification, and backward and forward citations.

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 is 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.[126] Over 2000-2012, 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 yield similar results (e.g., Table 5, Table A14).

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.[127] 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. The most well-known patent quality measure is forward citation counts (i.e., the number of future citations a given patent receives), which has been shown to be positively 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 counts to compute: (i) a patent's quality decile

[126] 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 small share of patents are filed jointly by at least two firms (Dechezleprêtre et al., 2018).

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

relative to its technology field by application year cohort (e.g., Figure 7, Table A13),[128] (ii) firm's quality-adjusted patent counts, and (iii) firm's average patent quality. Given that forward citations take time to accumulate, I restrict my sample to patents filed before 2012 to allow for observation windows of at least 5 years.

Besides forward citations, I also employ a range of alternative patent quality measures (Squicciarini et al., 2013), as listed below.

- First, 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).

- Second, 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).

- Third, the generality index, defined as one minus the technology-class Herfindahl–Hirschman Index (HHI) (at IPC4 level) of a patent's forward citations, measures the range of technology fields and industries influenced by the patent (Trajtenberg et al., 1997).

- Fourth, the originality index, defined as one minus the technology-class HHI (at IPC4 level) of a patent's backward citations, captures the breath of technology fields on which the patent relies, thereby reflecting its knowledge diversification (Trajtenberg et al., 1997).

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 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 the 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 these labs, based on their patent contributions, are (in order) Germany, Great Britain, India, Canada, Japan, China, France, Israel, Switzerland, and Italy.[129] As it is possible for one patent to have inventors based in different countries, 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

[128] 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.

[129] Eurobarometer bilateral trust measure is available for 7 out of these 10 countries.

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.4, and further manually clean the remaining unmatched ones (as described in appendix B.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 count be probabilistically mapped to multiple countries of origin.

B.3 CEO biographical data

I identify a firm's CEO in BoardEx from her 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 3.2). I first map CEOs' last names to ethnic origins using the census-based last name-ethnic origin mapping detailed in appendix B.4. 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,[130] and manually search for the origins of unmatched CEO last names that appear with high frequency. 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 are no significant differences between these name-matched 83% and the remaining non-matched 17% across all observable characteristics.

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. 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

[130] For example, compound last names including "Van" are likely Dutch, "Von" German, or "Les" French, etc. Further details are available upon request.

positions are those whose title contains either one of the following words (or their derivations): "research," "innovation," "scientific," or "technology."

Table A7 employ special subsamples of CEO retirement and death events. 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, as observed in BoardEx. 65 is the official Social Security retirement age and the traditional retirement age used 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 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 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).

B.4 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 or 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 they 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 census 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' 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' 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 in computing CEO's inherited generalized trust measure,[131] and other measures of inherited cultural traits. In 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 and slightly reduces the precision of the key estimates.

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

[131] $w_{de} = w_{se}$ if CEO d's last name is s.

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 convert countries to GSS ethnic origins and add 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-Eurobarometer origin mapping. To compute CEOs' bilateral trust measure, I construct the mapping between last names and countries of origin covered in the Eurobarometer in similar steps to above. 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.

C Trust measurement error and bias

C.1 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.[132]

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 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

[132] 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.

trust games in Glaeser et al. (2000) at around 0.50,[133] 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.[134] 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 C.1, 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.

C.2 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 $\hat{\beta}_{TE} = \frac{\text{Cov}(M.Y_{ft}, M.TEth_{ct})}{\text{Var}(M.TEth_{ct})}$, given the linear de-mean operator $M.X_{it} = X_{it} - \mathbb{E}_t(X_{it}|i)$. Also observe that:

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

[133]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

[134]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.

In case of independent survey measurement error ϵ_{dt}, 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 (see also 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, 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.[135] Consequently, the estimator $\hat{\beta}_{TE}$ likely underestimates the true effect of individual CEO's trust on innovation.

[135] 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.

D Framework for separating mechanisms

D.1 Proof of Proposition 3

As the count of patents within quality range $[c_1, c_2]$ is $N\left[F(\frac{c_2-\tilde{b}(T)}{a(T)}) - F(\frac{c_1-\tilde{b}(T)}{a(T)})\right] \stackrel{def}{\equiv} Y(a(T), b(T))$, the effects of changes in a and b on patent counts within quality range $[c_1, c_2]$ are:

$$\frac{\partial Y}{\partial a} = N\left[f\left(\frac{c_2-\tilde{b}}{a}\right)\left(-\frac{c_2-\tilde{b}}{a^2}\right) - f\left(\frac{c_1-\tilde{b}}{a}\right)\left(-\frac{c_1-\tilde{b}}{a^2}\right)\right], \tag{A11}$$

$$\frac{\partial Y}{\partial b} = N\left[f\left(\frac{c_2-\tilde{b}}{a}\right)\left(\frac{-1}{a}\right) - f\left(\frac{c_1-\tilde{b}}{a}\right)\left(\frac{-1}{a}\right)\right]. \tag{A12}$$

Recall the assumptions from subsection 6.1 that better quality patents are always rarer (i.e., $F_T'(x)$ is decreasing on $[0, \infty)$ $\forall T$). This assumption implies that $f\left(\frac{c_2-\tilde{b}}{a}\right) < f\left(\frac{c_1-\tilde{b}}{a}\right)$ as $c_1 < c_2$. As a result, $\frac{\partial Y}{\partial b}$ in expression (A12) is always positive, indicating that higher $b(T)$ increases the count of patents within the quality range $[c_1, c_2] \subset [0, \infty)$.

D.2 Patent quality under mean-preserving spread

Unlike expression (A12) which is always positive, expression (A11) does not have an unambiguous sign: while $f\left(\frac{c-\tilde{b}}{a}\right)$ is decreasing in c over the $[c_1, c_2]$ interval as shown in appendix D.1, $c - \tilde{b}$ is increasing. It is thus possible to identify the mechanism at work (i.e., through $a(T)$ or $b(T)$) under conditions that warranty $\frac{\partial Y}{\partial a} < 0$, namely, for ranges of c where $f\left(\frac{c-\tilde{b}}{a}\right)\left(\frac{c-\tilde{b}}{a^2}\right)$ 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, $f\left(\frac{c-\tilde{b}}{a}\right)$ decreases less fast than $c - \tilde{b}$ increases. The following proposition illustrates a special case:

Proposition 5 *Consider a normal distribution $\mathcal{N}(\bar{x}, \sigma)$ with density f, and $b = 0$ (i.e., no mean-shifting mechanism at work). Higher $a(T)$ decreases the count of patents of quality within any range $[c_1, c_2] \subset [0, a\sigma + \bar{x}]$.*

Proof. The proposition's statement is equivalent to $\frac{\partial Y}{\partial a}$ in expression (A12) being negative, itself equivalent to $f\left(\frac{c-\tilde{b}}{a}\right)\left(\frac{c-\tilde{b}}{a^2}\right)$ being increasing in c over the $[c_1, c_2]$ interval. This happens when its derivative with respect to c: $\frac{1}{a^2}\left[\frac{1}{a}f'\left(\frac{c-\tilde{b}}{a}\right)\left(c-\tilde{b}\right) + f\left(\frac{c-\tilde{b}}{a}\right)\right]$, is nonnegative.

In case f is a normal distribution density, this derivative being nonnegative is equivalent to $-\frac{1}{a^2\sigma^2}(c-\tilde{b})^2 + 1 \geq 0 \Leftrightarrow |c - \tilde{b}| = |c - \bar{x} - b| \leq a\sigma$. Let $b = 0$, this condition is equivalent to $c \in [0, a\sigma + \bar{x}]$. ∎