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

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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 US public firms and 700,000 patents during 2000-2011. To identify the effect of CEO's trust, I exploit (i) variation in generalized trust across CEOs' ethnic origins, inferred from their last names using de-anonymized historical censuses, and (ii) 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, Exploration, CEO, Corporate culture, Cultural transmission.

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

—Arrow (1972)

1 Introduction

Arrow (1974, c.1, p.23) emphasized trust as "an important lubricant of a social system," as it is impossible to fully contract upon all possible states of nature.[1] This insight is especially relevant in the context of research and innovation, where 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 simple 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, which are associated with 700,000 patents and over one million inventors. I infer a CEO's ethnic origin from his last name using de-anonymized historical US censuses, then measure his inherited generalized trust as the average trust among US residents of the same ethnic origin. Similarly, I compute a CEO's bilateral trust directed towards researchers in different ethnic groups based on average bilateral trust between the corresponding country pairs (highlighted in Guiso et al., 2009).

In the first empirical design, I exploit CEO turnovers to estimate the effect of CEO's trust on patent counts and future citations. In the second one, I estimate how a CEO's bilateral trust towards different ethnic groups affects patents filed by inventors in different overseas R&D labs within multinational firms, and by inventors of different ethnic origins in the same US firm, in each

[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 influence on the accumulation and allocation of factors of production. 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 innovation 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; Graham et al., 2018 among others), therefore their trust is of first order importance in studying the firm's trust towards researchers.

case controlling for CEO and other stringent fixed effects. I further examine trust's effect on the distribution of patent quality to differentiate risk-taking from possible alternative mechanisms.

To model the process of research, I build on Arrow's (1962) insight that research is inherently uncertain, and by nature it is very 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 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 her, 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 she 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 her period 1's outcome.

In this setting, the CEO's trust in the researcher is modeled as his prior belief about her 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's (2011) and Aghion et al.'s (2013), which 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, as well

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

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

[5] My choice to model trust as a belief, similarly to Guiso et al. (2008b), 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."

[6] More broadly, this paper relates to the literature on contractual and financial arrangements to incentivize innovation (see survey 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.

as the role of trust as substitute for the CEO's commitment capacity.[7]

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,[8] are extracted from PATSTAT, a worldwide patent database covering over 60 major patent offices, including the US Patent and Trademark Office (USPTO) and its counterparts in Europe (EPO) and Japan (JPO). 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 management 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). I propose 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's performance.[9]

Building on the literature on transmitted and inherited cultural values that highlights the role of cultural origin in shaping an individual's cultural traits,[10] I measure a CEO's trust based on his ethnic origins as inferred from his last name and measures of inherited trust among descendants of US immigrants. First, I construct a probabilistic mapping between CEOs' last names and ethnic origins from four de-anonymized US censuses, which contain the names and ancestry of the US population between 1910 and 1940.[11] Second, I compute an ethnic-specific measure of trust for 36 different ethnic origins most common in the US using responses to the trust question in the US General Social Survey (GSS), considering only respondents in highly prestigious occupations

[7] 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).

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

[9] 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).

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

[11] The inference of ethnic origin from last names was pioneered by Kerr and Lincoln (2010).

that are comparable to the CEO sample.[12] Each CEO's inherited trust measure is the weighted average of ethnic-specific trust based on her likely ethnic composition. Although this inherited trust measure is not perfect, it captures an important component of CEO's individual trust, and likely produces unbiased estimates of the latter's true effect.

To assess the role of generalized trust, the first empirical strategy uses firm fixed effects to exploit changes in CEOs and subsequent changes in patenting within the same firm over time, controlling for CEO observable characteristics. The identifying condition is supported by the empirical evidence that both timing of CEO change and the new CEO's trust are not related to the firm's past patenting activities or performance. I find that one standard deviation increase in CEO's inherited generalized trust, equivalent to the difference between Greek and English averages, is associated with over 6% increase in the number of patents filed. For the average firm in my sample, the additional patents are worth close to $7 million annually. This result is robust to controlling for a large set of country of origin characteristics and ethnic of origin socioeconomic conditions and cultural traits.

To separate the role of trust from other CEO's unobservable characteristics such as management style or ability, the second empirical strategy exploits within-CEO variation in CEO's bilateral trust towards different ethnic groups and the corresponding variation in patents by inventors from those different ethnicities, using CEO fixed effects. I calculate bilateral trust measures for directed pairs of CEO's and inventors' countries of origin using Eurobarometer data.[13] 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 difference in bilateral trust towards an inventor country of origin is positively associated with 3-5% difference in patents by inventors from the corresponding R&D lab or ethnicity, after controlling for a broad range of time-variant fixed effects at the firm-by-year, CEO, and inventor country levels. These results are robust to adding even more stringent firm-by-inventor country fixed effects (i.e., using variation in changes in bilateral trust following CEO changes), and accounting for possible alternative explanations such as favoritism or better information flows and coordination between CEOs and researchers.

[12] This approach follows Guiso et al. (2006), Algan and Cahuc (2013, 2014), and the related literature.

[13] 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.

To distinguish (i) the proposed mechanism that trust induces innovation via encouraging risk-taking and exploration from (ii) other mechanisms in which trust induces more effort by researchers,[14] I develop a framework to identify the mechanisms via their different implications on trust's effect on the distribution of patent quality. Using future citation count 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 or average patent value by 4-6%. In addition, I find that trust is most effective in inducing innovation in firms with likely high researcher quality, and only among those firms does trust have a positive impact on firm's future performance.

These results on the effect of CEO's trust on firm's innovation provide a possible micro-foundation for the macro relationship between long-term economic outcomes and trust, as evidenced in Guiso et al. (2006), Tabellini (2010), and Algan and Cahuc (2010), among others.[15] 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 in the long run.[16] This mechanism helps explain the macroeconomic differences not only in development levels but also in growth rates across countries.[17] Separately, this paper extends the empirical literature of more traditional determinants of R&D and patents by highlighting the role of cultural factors, as distinct from government policies such as tax credits and grants (e.g., Howell, 2017; Dechezleprêtre et al., 2018, and the Cohen, 2010 survey).

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, using data from Sull (2018). The dataset covers many dimensions of employees' sentiments based on

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

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

[16] 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.

[17] 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.

O'Reilly et al. (1991, 2014) across 500 large US public firms between 2008 and 2017 (similar to Grennan, 2014). In specifications with CEO controls and industry fixed effects, or 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. I also find suggestive evidence that this cultural transmission happens via the CEO's selection of top management team. In that regard, this paper also provides new findings supporting the role of corporate culture in determining corporate outcomes,[18] and shows a channel through which corporate culture can be influenced: by an injection of culture from the top (as suggested by Van den Steen, 2010).

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).[19] 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 a model of trust and innovation, which readers more interested in the empirical contributions of this paper can skip. 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 A conceptual framework

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 of good type with probability θ, or bad type with probability $1-\theta$. In this setting, a bad researcher represents one who lacks ability or willingness to take the appropriate courses of actions. The CEO knows neither the researcher's type nor θ. In each

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

[19] 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 et al., 2001; Klein Woolthuis et al., 2005).

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 $1-\pi$.[20] 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 observes the researcher's output at the end of each period, but not her action.[21]

CEO. The CEO asks the researcher to carry out R&D at the beginning of period 1 without knowing her type. Simultaneously, he decides on an outcome-contingent contract that maps period 1's potential outcome s^i to (b_1^i, D^i), $i \in \{L, M, H\}$ where b^i is a bonus on top of 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.[22]

Trust. Although the CEO does not observe θ, he has his own prior subjective belief that the researcher is good with probability θ^P, which reflects his trust towards the researcher. A more trusting CEO has a higher subjective θ^P than a less trusting one.[23] This model focuses on studying how this key parameter of CEO's trust affects the players' strategies and the game's outcome.[24]

Payoffs and restrictions. After each period $t \in \{1, 2\}$ with realized outcome $i \in \{L, M, H\}$, the researcher gets $w + b_t^i - c$ (if she chooses exploration) or $w + b_t^i$ (otherwise), and the CEO gets $s^i - b_t^i$.[25] If the researcher is fired at the end of period 1, both players' payoffs in period 2

[20] 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).

[21] 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.

[22] Alternatively, the contract can be designed as a mapping (specified at the beginning of period 1) between each potential outcome of the game (i, j) to (b^{ij}, D^i) where $i, j \in \{L, M, H\}$ denote the game's outcomes in periods 1 and 2 respectively. This set up is equivalent to the baseline set up under the assumption of credible commitment.

[23] 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.

[24] In this framework, the researcher's trust does not matter, hence is omitted. This modeling choice is guided by the empirics, as in subsection 5.2.

[25] 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

is zero.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 her for bad outcome. To satisfy the players' participation constraints, I also restrict the parameters such that the CEO's expected payoff from hiring a good researcher is positive. It then follows that $D^i = 1$ for $i \in \{H, M\}$, as these outcomes fully reveal that the research is the good type. However, if period 1's outcome is L, the CEO cannot tell if the researcher is bad or if she is good but unlucky. His choice of D^L (i.e., whether to tolerate the researcher's failure) depends on his assessment of which is more likely to be the case, and this assessment depends on his prior subjective belief θ^P.

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 his 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 V_2^A a good researcher's period-2 expected payoff, both are positive under the players' participation constraints.[26]

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:

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

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

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

not discount future payoff. Introducing risk aversion or time discounting does not affect the model's key insights.

[26] 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 $\pi_2 > c/b_2^*$.

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

The proof is detailed in appendix 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. When failure is not tolerated and termination implies a large loss in future payoff, a good researcher requires higher probability of success to undertake exploration. Similarly, the CEO also prefers a good researcher to take less exploration risk in period 1 for the same fear of losing his future payoff from a relationship with such good researcher when exploration fails. That is, tolerance of failure enables a good researcher to take risk and explore more often, thereby produces more instances of successful innovation.[27]

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.[28]

CEO's tolerance of failure: rehire versus fire. Let $V_1^P(D)$ denote the CEO's period-1 expected payoff from hiring a good researcher under policy $D \in \{0,1\}$. It can be shown that $V_1^P(1) > V_1^P(0) > 0$.[29] The CEO chooses to tolerate failure (i.e., $D^L = 1$) if it maximizes his total expected payoff:

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

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

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 her being of the bad type. As the benefit of incentivizing optimal exploration then outweighs the benefits of screening out bad

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

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

[29] 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, $V_1^P(1) > V_1^P(0)$.

researchers, he chooses to tolerate failure to avoid mistakenly screening out good researchers in period 2, and also to induce more exploration by good researchers in period 1.[30]

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

2.2 The right amount of trust

While more trust induces more innovation, what is a CEO's "right amount of trust" that optimizes his payoff?[31] When the CEO can credibly commit to his policy of tolerance of failure D^L, an objective CEO (one who holds the correct belief of the probability of the good type $\theta^P = \theta$) always chooses the optimal policy. However, a CEO with too high or too low trust may not, if his level of trust θ^P is on the wrong side of $\bar{\theta}$, compared with θ. For instance, when the researcher pool is too bad to tolerate failure ($\theta < \bar{\theta}$), but the CEO is over-trusting ($\theta^P > \bar{\theta}$), his tolerance of failure leads to costly excessive innovation. In contrast, when the researcher pool is good ($\theta > \bar{\theta}$) but the CEO is under-trusting ($\theta^P < \bar{\theta}$), his intolerance of failure leads to inefficiently low level of innovation.[32]

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

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

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

[32] Consistent with this insight, subsection 6.3 shows 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 literature on innovation in using patent and citation counts as measures for innovation (e.g., Trajtenberg, 1990; Hall et al., 2005).[33] My patent data come from PATSTAT, the largest available worldwide patent database which covers patents from the 1900s up to 2016. It brings together over 80 million patent documents from over 60 patent offices and has complete coverage of patents from all major offices, including the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO), and the Japan Patent Office (JPO).[34] I assign patents to firms using the matching procedure implemented by the EPO and the OECD and made available via Bureau van Dijk's ORBIS platform.[35]

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 count, such as backward citations to scientific literature, patent scope, exploratiVeness, etc. (details in appendix B.2). In addition, PATSTAT also provides information on the inventors of each patent, including their names and addresses, as recorded on patent documents. 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), and 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 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

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

[34] 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).

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

(Squicciarini et al., 2013). As a result, I focus 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 and employment history. 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, and employment history (details in appendix B.3).

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

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

where $ethtrust_e$ is the average trust measure among US descendants of immigrants from country e,[36] and w_{de} is the probability that CEO d is a US descendant of immigrants from that country.

I follow the literature on inherited trust (e.g., Guiso et al., 2006; Algan and Cahuc, 2010) in computing $ethtrust_e$ using individual-level data on trust attitude and ethnic origins from the US General Social Survey (GSS), a representative survey of social attitudes among US residents conducted between 1972 and 2014, 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?"*.[37] His ethnic origin is captured by the question *"From what countries or part of the world did your ancestors come?"*, which covers 36 most common ethnic origins in the US, including all major European countries in addition to Canada, Mexico, China, and India.[38] To better match the CEO sample,

[36] More precisely, this includes all US residents who are first-generation immigrants or their descendants.

[37] Following the literature, I construct a trust indicator equal to 1 if the answer is "Most people can be trusted," and 0 if the answer is "Can't be too careful" or "Other, depends." This grouping makes a clear separation between high trusting individuals as opposed to moderate or low trusting ones (Algan and Cahuc, 2010). The use of GSS-like trust questions to measure trust has been experimentally validated in trust game settings (Berg et al., 1995) by Fehr et al. (2002), Sapienza et al. (2013), and Falk et al. (2016). As robustness checks, I also compute alternative $ethtrust_e$ measures using other trust questions in the GSS and other surveys (see Tables A9 and A10 for details).

[38] 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" (4.4%), "American only" (2.8%), "Other Asian" (0.4%), "Other European" (0.3%), and "Other" (0.9%), which together cover less than 9% of total respondents.

I only consider respondents in highly prestigious occupations.[39] The baseline $ethtrust_e$ measure is then the average trust attitude of selected GSS respondents whose self-reported ethnic origin is e (Table A1). Finally, I use LASSO to construct an alternative trust measure that also takes into account other 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). These censuses contain individual-level data on birthplace and ancestry of the whole US population during 1910-1940, merged with individual names obtained from the Minnesota Population Center. Across four censuses there are 80 million individuals with foreign birthplaces or ancestry, sharing among them five million unique last names. I only consider 75,000 last names with at least 100 observations and allow each last name to be mapped to multiple ethnic origins with probabilities proportional to their numbers of observations. Separately, I also compile lists of most common last names in 50 different countries from multiple sources and use these lists to cross-check and supplement the baseline census-based mapping (details in appendix C.1).[40]

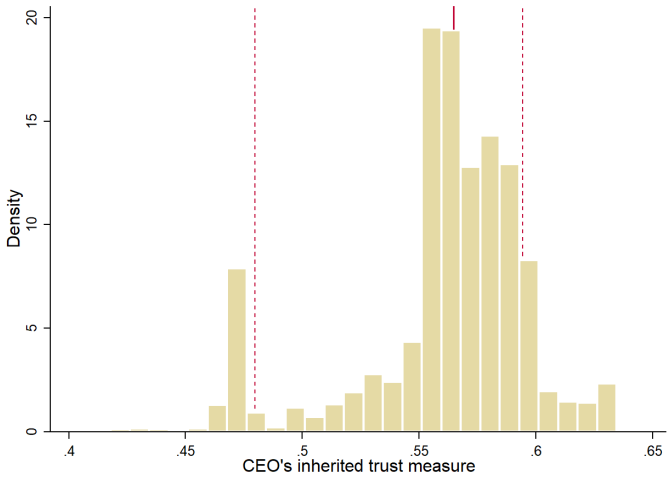
83% of the CEO sample could be mapped to their ethnic origins based on their last names. Panel A of Table A3 shows that there is no significant difference between these 83% and the remaining 17% across all observable characteristics. Three most common ethnic origins among CEOs are Irish, German, and English, which together account for about half of the CEO sample (Table A2), very similar to the ethnic origin distribution among GSS respondents in prestigious occupations. The average CEO's inherited trust measure is 0.56, considerably higher than the average GSS trust measure of 0.38,[41] but again comparable to that of 0.51 among those in 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.

[39] Specifically, I only consider respondents whose GSS occupation prestige score is in the top 25% (i.e., 50 or above). This covers most respondents in management occupations. The ordinary and Spearman rank correlations between $ethtrust_e$ computed from this sample and that computed from all GSS respondents are 0.85 and 0.75, respectively.

[40] One may worry that this last name-based mapping only captures an individual's patrilineage. However, given the documented high level of ethnic segregation (Eriksson and Ward, 2018) and high intra-ethnic marriage rate in the US during the 1940s, this is unlikely a first order concern. (The majority of the CEOs in my sample were born in the 1940s or 1950s.) Separately, Dohmen et al. (2012) provide evidence of positive assortative mating based on trust and risk attitudes in a representative sample of German population. Similarly, Pan et al. (2018) find that uncertainty avoidance measures constructed from CEOs' last names and from their mothers' maiden names are highly correlated. Finally, as 98% of my CEO sample are male, name changing due to marriage is not a concern.

[41] This is consistent with Fehr and List's (2004) experimental findings that CEOs exhibit more trusting behavior, use punishment less often, and consequently reach substantially higher efficiency levels than undergraduate students.

Figure 1: Distribution of CEO's Inherited Trust Measure



Notes: This figure shows the 1^{st}-99^{th} 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 50^{th} percentile of the distribution. The dashed vertical lines correspond to the 10^{th} and 90^{th} percentiles.

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

Ideally, one would like to observe each CEO's individual trust attitude, yet 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 errors.[42] While the inherited trust measure misses (i) the individual-specific component of trust, it smoothes out (ii) those individual-level measurement errors. In appendix D.1, I develop a framework to assess the relative sizes of (i) and (ii) using parameters from the literature. The results suggest that the baseline inherited trust measure is better than an individual-level survey-based trust measure and about 80% as precise as an individual-level game-based measure.[43] 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 D.2).[44]

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

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

where $ethbitrust_{ec}$ is a measure for how much a person from country of origin e trusts a person from country of origin c. This country-pair-level bilateral trust measure ($ethbitrust_{ec}$) comes from the Eurobarometer surveys' question *"I would like to ask you a question about how much trust you have in people from various countries. For each, please tell me whether you have a lot of trust, some trust, not very much trust, or no trust at all."*[45] The surveys cover respondents from 16 EU countries and ask about their trust attitude towards 28 countries, including some non-EU countries such as Russia, Japan, and China.[46] 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

[42] 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).

[43] 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 option is highly infeasible, especially among CEOs.

[44] 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).

[45] 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 $ethbitrust_{ec}$.

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

ethnic origins are among the 16 surveyed countries, which make up 45% of the CEO name-matched sample (details in appendix C.1).

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 industry and those whose headquarters are outside of the US. I only consider firms with at least one name-matched CEO, which cover 92% of the firm sample, 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 (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, over this 12-year period, each firm has on average 1.7 name-matched CEOs and about two thirds of the firms have more than one CEOs. 98% of the CEOs are male, each CEO has an average tenure of 7 years, and very few CEOs have ever been the chief executive of more than one firm in the sample.[47]

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:

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

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 $t+1$.[48] As patent distribution is skewed, I use its inverse hyperbolic sine transformation $\text{arsinh}(pat_{fd,t+1})$ as the main outcome variable instead of raw patent counts.[49] The main explanatory variable $trust_d$ is CEO d's inherited trust measure

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

[48] Results are robust to using further-forward patent application counts in year $t+2$ or $t+3$ (Table A7).

[49] The inverse hyperbolic sine transformation $\text{arsinh}(x) = \ln\left(x + \sqrt{1+x^2}\right)$ takes value 0 at $x = 0$ and approximates $\ln x + \ln 2 + O(\frac{1}{x \ln x})$ for large x. It has been promoted as a substitute for $\ln(1+x)$ by David Card (e.g., Card and DellaVigna, 2017), because one can still interpret changes in $\text{arsinh}(x)$ as close approximates of percentage changes in x for sufficiently large x thanks to its similarity with $\ln x$, while the function's behavior around $x = 0$ approximates $\ln(1+x) + O(x^2)$. Results are robust to (i) using $\ln(1+pat_{f,t+1})$, winsorized, or raw $pat_{f,t+1}$ as the outcome variable, and (ii) estimating a semi-log Poisson count model with $pat_{f,t+1}$ as the outcome variable, instead of OLS (Table A7).

(details in subsection 3.2), normalized by its standard deviation.[50] The specification includes a full set of firm fixed effects θ_f, which controls for all firm-level time-invariant characteristics that correlate with either firms' innovation capability or selection of CEO. In addition, equation 5 also controls for firm's time-variant characteristics $\mathbf{X}_{ft}$ (i.e., firm's age, ln(assets), ln(sales)), 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 (to account for macro-level cyclicality in innovation).[51] Standard errors are clustered by CEO's main ethnic origin in case there are idiosyncratic factors that are specific to an ethnicity.[52]

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's trust on firm f's patents. That is, the effect captured by β_1 is unlikely the result of reverse causality or confounded by firm f's time-variant unobservable characteristics that affect both the firm's choice of CEO and its innovation outputs (e.g., changes in firm's strategy driven by the board).

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 2A). Similar, Figure A1 shows that change in CEO's trust also does not correlate with firm's other pre-change characteristics, such as R&D expenditure, employment, sales, or total assets. Furthermore, Figure 2B plots the average patent application counts by the number of years before the transition for the full sample of firms. The flat pre-trend in patents indicates that the timing of the CEO transition is not driven by a trend in patenting,

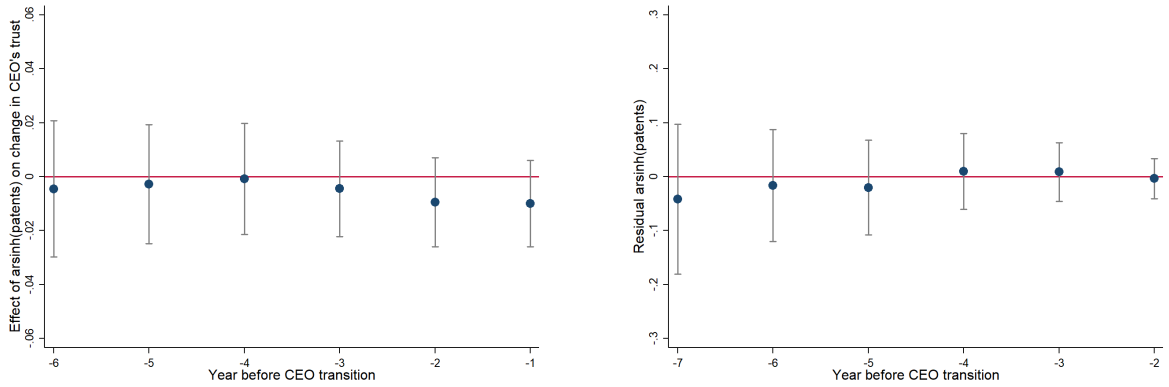
[50] Inherited trust's standard deviation at ethnicity level is 0.11, equal to the difference between Greek and English average inherited trust levels.

[51] Additionally controlling for (i) employment and R&D stocks or flows, or (ii) industry-by-year fixed effects yields quantitatively similar results (Table A7).

[52] I follow Abadie et al.'s (2017) advice to cluster at the level of the source of variation in treatment. CEO d's main ethnic origin is $e_d^* = \text{argmax}_e(w_{de})$. Average $w_{de_d^*}$ among CEOs is 71%. Results are robust to (i) clustering standard errors by firm, and (ii) clustering two-way by CEO's main ethnic origin and firm (Table A7).

suggesting that reverse causation is unlikely a concern in this setting.

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



A. Common trend B. Pre-trend

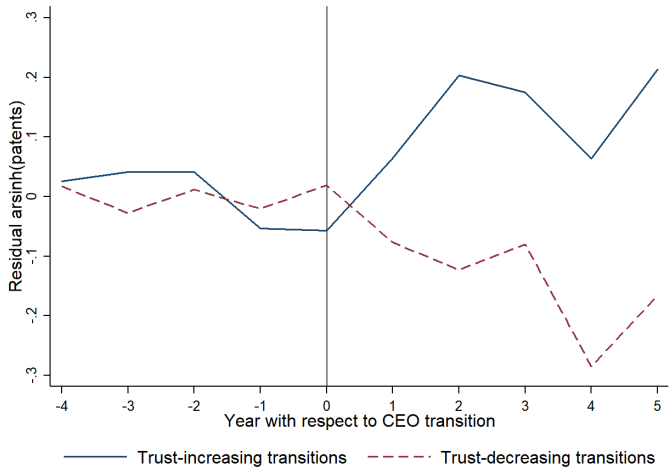
Notes: **Subfigure A** plots the coefficients $\hat{\gamma}_k$ for $k \in [-6, -1]$ from estimating: $\Delta trust_d = \sum_{k=-7}^{-1} \gamma_k(\text{arsinh}(pat_{fdt}) \times event_{t-k}) + \beta trust_d + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \mu_{s_{(f)}k} + \omega_t + \varepsilon_{fdt}$, in which (i) $\Delta trust_d$ 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) μ_{sk} is a full set of firm f's 3-digit SIC industry $s \times$ year k (i.e., year with respect to CEO transition) fixed effects. **Subfigure B** plots the coefficients $\hat{\gamma}_k$ for $k \in [-7, -2]$ relative to $\hat{\gamma}_{-1}$ from estimating: $\text{arsinh}(pat_{fdt}) = \sum_{k=-7}^{-1} \gamma_k event_{t-k} + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \theta_f + \omega_t + \varepsilon_{fdt}$, in which $event_{t-k}$ is an indicator equal to 1 if the next CEO transition happens in year $t-k$. Standard errors are clustered by firm. Estimates are shown with their 95% confidence intervals.

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

Figure 3's event-study graph, which plots firms' patent application counts by year with respect to CEO transition year (year 0), visually summarizes the paper's key empirical finding. The solid blue line groups together all CEO transitions in which the new CEOs are *more* trusting than their predecessors (trust-increasing transitions), and the dotted red line corresponds to those in which the new CEOs are *less* trusting (trust-decreasing transitions). The two lines exhibit similar pre-trends in the years before CEO transitions, but diverge visibly post-CEO change. Firms that experience an increase in CEO's trust after the transition also experience increases in patenting in post-transition years (the upward-sloping solid line) and vice versa (the downward-sloping dotted line).[53] 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

[53] In Figure 3, each trust-increasing transition is matched to a trust-decreasing one based on their average pre-transition residual patent counts to address possible mean reversion. However, not implementing this matching procedure yields an event-study graph with very similar pattern (Figure A2). This further supports the common trend identification assumption, as the patent pre-trends in this figure are not guaranteed to coincide by construction.

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



Notes: This figure plots firms' average residual patent application counts (after partialling out (i) firm and CEO controls, and (ii) firm's industry and year fixed effects) by year with respect to CEO transition year (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.

different from zero (by matching), the difference in their post-transition patents is large, positive, and statistically significant at 5% level.[54]

Baseline CEO's trust effect. Table 1 then estimates equation 5, which exploits changes in CEOs and subsequent changes in patenting within the same firm over time, using the full baseline sample described in subsection 3.3. Given evidence of common trend, the coefficient on CEO's trust captures its effect on firm's forward patent counts. I first report two basic specifications without any firm or CEO controls (column 1) or including only CEO controls (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

[54]It may seem surprising that there is a rather immediate effect that peaks in years 2 and 3. However, since Hall et al. (1986) it has been shown that patent applications are often timed quite closely to R&D. Indeed, I find that CEO's trust effect is largest in industries with short lag between R&D and patents, such as ICT (Table 10, column 5), and close to zero in industries with long R&D horizon, such as pharmaceuticals (Table 10, column 7).

standard deviation increase in CEO's trust is associated with 6.3% increase in firm's patent filing, statistically significant at 1% level. For the average baseline firm, this equals 1.1 additional patents annually, or $6.8 million in monetary value,[55] and is not the result of increases in R&D investments (Table A6). Furthermore, Figure A3, which plots the CEO's trust estimates as a function of the change in CEO's trust, shows that this economically substantial impact is driven by both positive and negative changes in CEO's trust, consistent with the pattern shown in Figure 3.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**arsinh(Future patent applications)**							
Specification:	Without controls		Baseline	Add. FEs	Alt. trust measures			Patent period
CEO's trust (baseline)	0.059***	0.063***	0.063***	0.066***				0.103***
	(0.018)	(0.017)	(0.019)	(0.019)				(0.025)
CEO's trust (LASSO)					0.067***			
					(0.021)			
CEO's trust (full GSS)						0.041**		
						(0.018)		
CEO's trust (WVS)							0.030**	
							(0.011)	
Firm & Year FEs	X	X	X	X	X	X	X	X
CEO controls		X	X	X	X	X	X	X
Firm controls			X	X	X	X	X	X
Industry × Year FEs				X				
Observations	29,384	29,384	29,384	29,384	29,384	29,384	29,384	14,881
Firms	3,598	3,598	3,598	3,598	3,598	3,598	3,598	2,068

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 × 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 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, considering only upper middle class respondents (column 7). Column (8)'s patent-period subsample includes all year t's that are within the first and last years that firm f patents during the study period. 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(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Columns 5 to 7 employ alternative measures of trust. In column 5, I use LASSO to predict individual trust attitude from not only ethnic origin but also all other demographic variables commonly available in both BoardEx and GSS, including age, gender, education, and birth cohort.[56]

[55] Estimates of individual patent value (computed from firms' excess stock returns on patent grant dates) come from Kogan et al. (2017). For the average baseline firm, a patent is worth on average $6.1 million.

[56] 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

This augmented measure yields a larger CEO's trust coefficient, but not by much, suggesting that the baseline trust measure already captures most of the meaningful variations in individual trust across observable demographic characteristics. Column 6's trust measure is constructed from the trust answers of *all* GSS respondents, and column 7's the trust answers of upper middle class WVS respondents in each ethnicity's home country. As both measures are not as close to the US CEO population as the baseline, they expectedly yield smaller, yet still positive and statistically significant, estimates of the CEO's trust effect.[57]

Finally, column 8 focuses on the subsample of patenting firms in between the years of their first and last observed patent applications during the study period. This results in a much larger CEO's trust coefficient, consistent with the intensive margin being the dominant force. Indeed, Panels B and D of Table A7 directly shows that the CEO's trust effect works mostly through the intensive margin, while there is limited evidence of an extensive margin effect.[58]

Exogenous CEO transitions. Table A8 focuses on a special subsample of CEO transitions for which the common trend condition is better warranted: transitions following CEO's retirements or deaths (e.g., Fee et al., 2013; Bennedsen et al., 2010). As the need to replace the existing CEO arises exogenously, the timing of the transition is likely exogenous to firm's other decisions. Even when subsequent CEO appointment is endogenous to firm's underlying characteristics, under the assumption that they do not change in the event of an exogenous transition, firm fixed effects sufficiently address firm's endogenous new CEO selection. I focus on CEO natural retirements around the age of 65 in columns 1 to 3.[59] Column 6 further includes CEO's 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.[60] In line with the literature on CEO's impact on firm's performance (see survey by Bertrand, 2009), although

to predict CEOs' trust attitude. It is worth noting that all ethnic origin dummies are retained in the selected model.

[57]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.

[58]Column 9 of Panel B shows that higher CEO's trust does not increase the probability of a firm patenting in a given year. However, conditional on firm's patenting, CEO's trust is positively associated with the number of patents being filed by the firm (column 5). Similarly, columns 5 and 6 of Panel D show that the CEO's trust effect is present only among firms having patented before the respective CEO transitions. Among those firms, however, higher CEO's trust does increase the probability that they continue to patent after the transitions (column 6).

[59]65 is the official Social Security retirement age (as used in Fee et al., 2013). In the data, I also observe a spike in CEO's leaving executive positions for good around age 65.

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

estimated from small samples of specific events, those results indicate that CEO's trust strongly affects firm's innovation.

Potential confounding factors. The same literature raises the concern that some of CEO's characteristics may correlate with CEO's trust, and also 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. Second, I exploit within-CEO variation in bilateral trust to control for all CEO observable and unobservable characteristics with CEO fixed effects (in subsection 5). Although the latter provides better identification of the effect of CEO's trust, the former is nevertheless insightful as it sheds some light on other factors by CEO's origins that may also influence firm's innovation.

Given firms' inclination to trade with, have business in, or hire from their CEOs' home countries and the potential spillovers from these linkages, Panel A of Table 2 controls for a range of macroeconomic variables measuring CEO's home countries' level of development and technological capabilities. These controls include country-by-year-level GDP, population, and GDP growth (column 1), high school graduation rate (column 2), governance quality index (column 3), total trade volume with the US (column 4), and total patent applications (column 5), all of which have been shown to be related to country-level trust measure (see surveys by Algan and Cahuc, 2013, 2014). Among them, only GDP growth and trade volume with the US have statistically significant relationships with firm's patenting (column 6). More importantly, across Panel A, the magnitude and precision of the CEO's trust estimate is not affected by any of those factors.

In Panel B, I examine if the CEO's trust effect is driven by other cultural traits instead of trust attitude. First, a CEO's ethnic group's socioeconomic characteristics could impact his skill accumulation, via investments in human capital or exposure to skills (e.g., Bell et al., 2018). Given the strong correlations among self-perceived class, occupational prestige, earnings, and education, in column 1, I use an ethnicity's high-income share as a summary statistics for its socioeconomic characteristics.[61] The related literatures on culture and on CEOs have also pointed to some salient cultural values that have economic significance at both macro and microeconomic levels. 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,

[61] Alternatively controlling for ethnicity-level occupation prestige or education gives similar results (Table A9).

Table 2: Controlling For Potential Confounding Variables

Panel A. Controlling for home countries' level of development

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

Notes: This panel controls for CEO's home countries' macroeconomic characteristics 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(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. CEO's home country controls include ln(GDP), ln(population), and GDP growth rate (column 1), 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. Each time-varying home-country variable h_{dt} is calculated as $h_{dt} = \sum_e w_{de} \times h_{et}$ where h_{et} is the value of h in the home country of ethnicity e in year t and w_{de} is as explained in subsection 3.2 (details in appendix C.2). Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

2017); (ii) risk preference, which affects firm's financing decisions and individual's entrepreneurial activities (e.g., Kihlstrom and Laffont, 1979; Pan et al., 2017); and (iii) time preference, which is strongly correlated with both national and individual education, income, and saving behaviors (e.g., Falk et al., 2018).[62] 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.[63] Columns 3 and 4's measures of risk and time preferences come from

[62] Using their Global Preference Survey data, Falk et al. (2018) find that patience explains 40% of the country-level variation in income and is an even more robust predictor of development compared to trust.

[63] Relatedly, Alesina and Angeletos (2005) and Giuliano and Spilimbergo (2013) show that individuals' answer to the same question is correlated with their preference for redistribution. Separately, column 6 of Table A9 directly

Panel B. Controlling for other cultural traits

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

Notes: This panel controls for CEO's other inherited cultural traits using equation (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(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (1) controls for the share of respondents earning at least $25,000 annually (i.e., GSS's highest income bracket) in CEO's ethnic groups. Column (2) controls for CEO's inherited work ethic, derived from the GSS question: *"Some people say that people get ahead by their own hard work; others say that lucky breaks or help from other people are more important. Which do you think is most important?"*. Columns (3) and (4) control for CEO's inherited risk preference (column 3) and time preference (i.e., patience, column 4), as measured by the Global Preference Survey (Falk et al., 2018). Column (5) controls for all of those variables. Column (6) further controls for CEO's home countries' GDP growth rate and ln(US exports + US imports). Further details on variable construction are available in appendix C.2. Standard errors are clustered by CEO's main ethnicity. *** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Falk et al.'s (2018) Global Preference Survey (GPS), an experimentally-validated survey dataset covering 80,000 individuals in 76 countries.[64] Finally, column 5 pools together all the cultural trait controls and column 6 adds the home country controls that are statistically significant in Panel A. As in Panel A, controlling for a multitude of other cultural traits does not significantly alter the magnitude or precision of the CEO's trust estimate, suggesting that it is unlikely confounded by other factors related to the CEO's ethnic origins.[65]

controls for the share of Protestants in CEO's ethnic groups, which yields comparable CEO's trust estimate.

[64] Table A10 presents further tests using GPS' trust and other cultural trait measures, including positive reciprocity, negative reciprocity, and altruism.

[65] In addition, controlling for CEO's confidence in the scientific community or the government as proxies for his confidence in the patent system does not affect the CEO's trust coefficient (Table A9), suggesting that this effect is unlikely driven by differential patenting propensity.

5 Within-CEO effect of CEO's bilateral trust

5.1 Within-CEO empirical strategy

Despite the evidence discussed so far, there remain other CEO personal characteristics that one cannot observe, measure, or directly control for, such as ability, management style, or preference for innovation. Those characteristics can correlate with CEO's trust and have direct effects on firm's innovation at the same time. As a result, equation 5's β_1 may confound the effect of CEO's trust with that of other unobserved characteristics. To address this concern, I exploit within-CEO variation in CEO's bilateral trust towards different groups of inventors and the corresponding variation in patenting among those different inventor groups. Such within-CEO variation allows me to include a full set of CEO fixed effects in the following equation:

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

Each observation is a combination of firm f by year t by its CEO d by inventors' country c. The outcome variable $pat_{fdc,t+1}$ is firm f's total patent counts by inventors from country c in year $t+1$. The main explanatory variable $bitrust_{dc}$ measures how much CEO d trusts individuals from country c (details in subsection 3.2). Besides the crucial CEO fixed effects (ω_d), equation 6 also controls for inventor country fixed effects (κ_c) that absorb all inventor country's baseline characteristics (e.g., development level, institution quality, technological comparative advantage, inventor pool quality), and for firms' time-variant characteristics with firm-by-year fixed effects (θ_{ft}). Given these stringent sets of fixed effects, any remaining variations would have to be at the firm-inventor country pair or CEO-inventor country pair levels. To control for potential confounding factors by those variations, I additionally include firm-by-inventor country fixed effects or an array of CEO-inventor country pairwise controls in the robustness checks. The coefficient β_2 then captures the effect of CEO's bilateral trust toward individuals in a country on corresponding patent counts by inventors from that country. Standard errors are clustered by CEO's main ethnicity-inventor country pair.[66]

To construct the outcome variable pat_{fct}, I use information on patent inventors' addresses or last names to allocate patents to different inventor countries or origins (e.g., Foley and Kerr, 2013, details in appendix B.2). For non-US-based inventors, I assign the corresponding patents to the countries where the inventors reside, which likely coincide with where firms' R&D labs are located.

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

About 30% of the patents in my sample are by those overseas R&D labs of US-based multinational firms, most of which are in Europe, Japan, and China. For the remaining US-based inventors, I infer their ethnic origins from their last names, then assign the corresponding patents to their inventors' countries of origin accordingly.[67] The variable pat_{fct} is the sum of all patents filed by firm f in year t that are assigned to country c.

The baseline 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.[68] If a firm-inventor country pair satisfies this condition, then it is included in the baseline sample even in the years when the pair has zero patent to avoid biases arising from selection into patenting over time. Therefore, β_2 captures both the intensive and the extensive margins of CEO's bilateral trust effect on inventors' patenting. Using the address-based approach to identify inventors' countries results 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 (Table A4). Figure 4 shows the distribution of the CEO's bilateral trust measure in these subsamples.

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

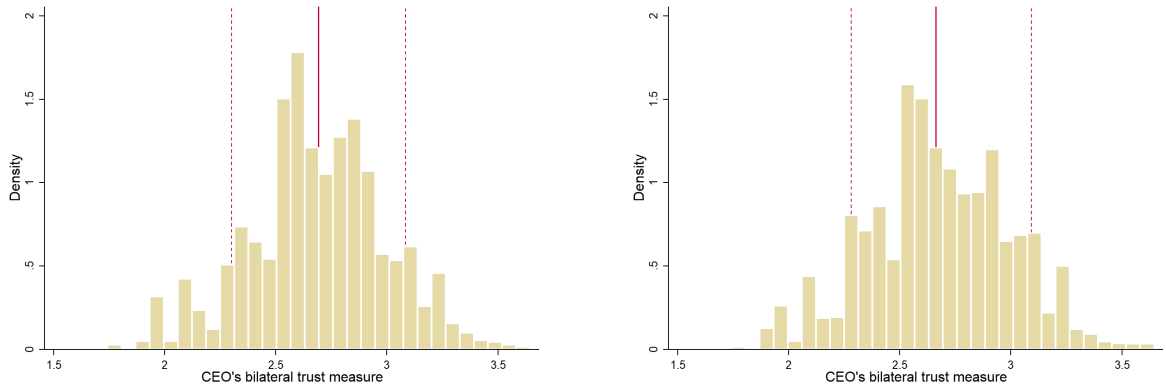
Table 3 reports the effect of CEO's bilateral trust towards individuals in a country on corresponding patent counts by inventors from that country, estimated using equation 6. Columns 1 to 4 consider the bilateral trust sample constructed from only non-US-based inventors and columns 5 to 8 use both non-US- and US-based inventors. The baseline bilateral-trust specification (equation 6) is reported in columns 1 and 5. In addition, I fully interact the sets of firm, CEO, and inventor country dummies with year dummies in columns 2 and 6. Columns 3 and 7 further include firm-by-inventor country fixed effects to control for specific characteristics of each R&D lab or group in the firm that are not already captured by firm or inventor country fixed effects.[69] Finally, columns

[67] Similar to CEOs, over 80% of all inventors could be mapped to their ethnic origins based on their last names. When a patent has multiple inventors (i) living in different countries (which happens rarely) or (ii) having different countries of origin, I allocate a proportional fraction of the patent to each of those countries.

[68] 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.

[69] This within-R&D lab/group specification mirrors equation 5's within-firm specification. That is, it exploits (i) changes in CEO's bilateral trust towards different R&D labs or groups in the same firm following a change in CEO and (ii) subsequent changes in patenting by the corresponding R&D labs or groups, after controlling for other CEO

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



A. Non-US-based inventors

B. All inventors

Notes: This figure shows the distribution of CEO's bilateral trust measure as described in subsection 3.2 for CEO-inventor country pairs in the baseline bilateral samples. Subfigure A corresponds to the bilateral trust sample in which an inventor's country is inferred from his patent-listed address for non-US-based inventors. Subfigure B corresponds to the bilateral trust sample in which an inventor's country is additionally inferred from his last name for US-based inventors. The solid vertical line corresponds to the 50^{th} percentile of the distribution. The dashed vertical lines correspond to the 10^{th} and 90^{th} percentiles.

4 and 8 focus on the subsamples between the first and last years of patenting by the corresponding R&D lab or group during the study period.

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 (columns 2 and 3) or further refining the sample (column 4). Columns 5 to 8 exhibit similar pattern across the different specifications. One would expect that the effect of CEO's bilateral trust is smaller in this sample (3% compared to 5% in the other sample) for two reasons. First, as the differences among US-based inventors from different home countries are less salient, CEOs' bilateral trust towards those inventors are less heterogenous.[70] Second, from an organizational perspective, CEOs would be more likely to implement differentiating policies towards

characteristics with CEO fixed effects. Similar to Figure 2A, Figure A4 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.

[70] Relatedly, the Eurobarometer bilateral trust measure is also likely a better proxy for CEO's bilateral trust towards non-US-based inventors, who are actual residences in the surveyed countries, than that towards US-based ones.

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

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	arsinh(Future patent applications)							
Sample:	Non-US-based inventors				All inventors			
CEO's bilateral trust	0.052**	0.051**	0.034*	0.082**	0.026**	0.025**	0.013**	0.046***
	(0.023)	(0.024)	(0.021)	(0.038)	(0.011)	(0.011)	(0.006)	(0.017)
Firm × Year FEs	X	X		X	X	X		X
CEO FEs	X		X	X	X		X	X
Inventor country FEs	X			X	X			X
CEO × Year FEs		X				X		
Inv. country × Year FEs		X				X		
Firm × Inv. country FEs			X				X	
Year FEs			X				X	
Observations	23,284	23,284	23,284	11,835	56,942	56,942	56,942	32,834
Firm × Inv. country's	3,481	3,481	3,481	2,597	8,554	8,554	8,554	6,674
Firms	730	730	730	625	1,263	1,263	1,263	1,085

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 (i) firm f has patents by inventors from country c during 2000-2012 (columns 1-3 and 5-7), and (ii) year t is within the first and last years (during the study period) that firm f has patents by inventors from country c (i.e., patent-period subsample) (columns 4 and 8). 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 $t+1$. Standard errors are clustered by CEO's main ethnicity × inventor country.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

R&D labs in different countries than towards different groups of US-based. On the other hand, this sample covers a much larger share of the patent pool, which results in a larger estimation sample and more precisely-estimated coefficients.[71] Together, results from both samples complement each other in showing that CEO's trust positively impacts on firm's innovation.[72]

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 A12, columns 5 and 6). Even though the CEO's trust coefficients are less precisely estimated in

[71] Consistent with the view that the bilateral trust effect is expectedly weaker towards US-based inventors, Table A11 shows that estimating equation 6 using an alternative bilateral trust sample constructed from only US-based inventors yields an even smaller CEO's bilateral trust coefficient of 2%, statistically significant at 10% level.

[72] It is worth noting that the within-in firm effects of CEO's generalized trust on firm's patents are also statistically positive among the subsamples of firms included in these bilateral trust samples (Table A12, column 1). That is, the bilateral trust effect reported in Table 3 reflects more than just a reallocation of innovation outputs among different R&D labs or groups within the same firm.

these subsamples, they are of similar, if not larger, magnitude compared to the combined effects in the full sample. On the other hand, evidence of an extensive margin effect is much less robust (columns 7 and 8). These results suggest that CEO's trust work largely through the intensive margin by improving the innovation outputs of existing R&D labs and researchers, as suggested by the model in Section 2.

Other potential explanations. Table 4 controls for potential confounding factors at CEO-inventor country pair level. An immediate concern is that CEOs may differentially favor inventors

Table 4: Bilateral Trust Effect with Country Pairwise Controls

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

Notes: 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.

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 spillover of favoritism (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 or 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 (see Spolaore and Wacziarg, 2016 for details). The CEO's bilateral trust coefficients remain statistically significant across all of these robustness checks in both bilateral trust 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, information, coordination, or other similar confounding factors.

Furthermore, as trust and trustworthiness are correlated, one may worry that the CEO's trust effect instead captures the impact of his trustworthiness. I explore this difference by considering two explanatory variables together, (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,[73] When both are included, the coefficient on $bitrust_{dc}$ is large and statistically significant while the coefficient on $invbitrust_{cd}$ is practically zero (Table A13, column 3). Given the two variables' high correlation, I further relax the linearity of this specification by estimating the effect of $bitrust_{dc}$ ($invbitrust_{cd}$) while controlling more flexibly for $invbitrust_{cd}$ ($bitrust_{dc}$). I do so by partitioning the sample into deciles of $invbitrust_{cd}$ ($bitrust_{dc}$) and introducing a full set of decile dummies, so as to 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's conceptual framework proposes that a CEO's trust in a researcher's being of the good type improves the latter's incentives to undertake high-risk ex-

[73] $invbitrust_{cd} = \sum_e w_{de} \times ethbitrust_{ce}$ 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 trust towards CEO d's, not their perception of CEO d's trust towards them.

plorations, resulting in more innovations. Yet there exist alternative mechanisms through which CEO's trust could impact firm's innovation. First, trust could lead to greater delegation by the CEO, which induces more effort from the researcher and thereby improves R&D outcomes (Aghion and Tirole, 1997; Acemoglu et al., 2007; Bloom et al., 2012).[74] Second, trust, as catalyst for co-operation (Putnam et al., 1993; Fukuyama, 1995), could also have an essential role in sustaining informal relational contracts (Baker et al., 1999, 2002). That is, when the CEO cannot credibly commit to his policies, the researcher is more likely to cooperate and exert effort if she trusts that the CEO will honor the promised rewards for success.[75] In these other mechanisms, greater effort by the researcher improves the expected outcome of all R&D projects and thereby 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 formalized below.

Estimation of mechanism. First, I establish that the effect of CEO's trust does not work through increasing the scale of R&D, as suggested by the statistically insignificant, close-to-zero estimates that result from regressing (future) R&D expenditure on CEO's trust (Table A6). That is, CEO's trust does not influence the number of independent R&D projects run by the firm (denoted N), but rather the types of projects being chosen (as in the risk-taking mechanism) and/or their realized outcomes (as in effort-inducing mechanisms).

Let us assume that a project's realized quality x, measured by a patent's forward citation count, follows a distribution $F_T(\cdot)$ indexed by CEO's trust T. Note that x is observable only when the project is patented, say, when $x \geq 0$. It is further assumed that better quality patents are always rarer (i.e., $f_T(x)$ is decreasing on $[0, \infty)\ \forall\ T$). This assumption is consistent with the empirical distribution of patent quality, as measured by forward citations (Figure A5).

I parameterize this family of distributions as $F_T(x) = F(\frac{x-\mu(T)}{\sigma(T)})$, in which $\mu(T)$ represents project quality mean and $\sigma^2(T)$ project quality variance, both are functions of CEO's trust T.[76]

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

[75] In this framework, it is the researcher's trust towards the CEO that should matter for cooperation and the game's outcomes. This is inconsistent with the empirical evidence that the trust effect is driven by the CEO's trust towards the researcher, not the other way round (Table A13).

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

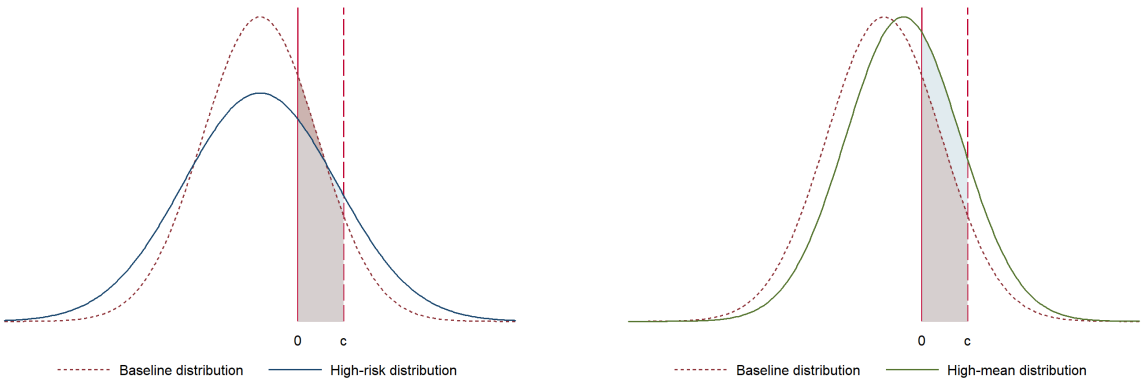
The risk-taking mechanism suggests that CEO's trust increases patented innovations through $\sigma(T)$ (i.e., $\sigma'(T) \geq 0$), while alternative effort-inducing mechanisms work through $\mu(T)$ (i.e., $\mu'(T) \geq 0$). When patenting is sufficiently difficult, so that the average project is not good enough for patenting ($\mathbb{E}_{F_T}(x) < 0$), a higher T implies higher number of observed patent counts $N\left[1 - F_T(0)\right] = N\left[1 - F(\frac{-\mu(T)}{\sigma(T)})\right]$ under both types of mechanisms, hence it is not possible to distinguish between the two by examining the effect of CEO's trust on total patent counts.

However, the mechanisms differ in their impacts on the number of patents within a specific low quality range $[c_1, c_2]$. Under the assumption that $f_T(x)$ is decreasing on $[0, \infty)\ \forall\ T$, it follows that:

Proposition 3 *Higher $\mu(T)$ increases the number of patents within any quality range $[c_1, c_2] \subset [0, \infty)$. The same is not true for higher $\sigma(T)$.*

That is, any effort-inducing or other mean-shifting mechanism that works through $\mu(T)$ increases not only total patent counts but also the number of patents within any arbitrary patent quality range (proof in appendix E.1), as illustrated by the larger area between $[0, c]$ under the mean-shifted distribution in subfigure 5B. However, the same prediction does not hold for the proposed

Figure 5: Project Quality Distributions under Different Mechanisms



A. Risk-taking mechanism

B. Mean-shifting mechanism

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

risk-taking mechanism that works through $\sigma(T)$ instead. On the contrary, under certain mild

conditions, it can be shown that higher $\sigma(T)$ *decreases* the count of patents within the quality range $[c_1, c_2] \subset [0, c]$ for small enough c (details in appendix E.2), as illustrated in subfigure 5A.

These results imply that it is possible to identify between the two types of mechanisms by examining the numbers of patents in low quality ranges. Specifically, when one consider patents in brackets of increasing 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 effort-inducing mechanisms predict positive effects of CEO's trust on patent counts across different quality brackets. This will serve as a simple test of the mechanism.

6.2 Effect on patent quality distribution via exploration

I follow the literature on innovation in measuring patents' quality by their forward citation counts.[77] 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 $q \in [1, 10]$.[78]

Figure 6 reports how CEO's trust effect vary by patent quality decile by plotting the coefficients estimated from equation 5 using $\text{arsinh}(pat^1_{ft})$ to $\text{arsinh}(pat^{10}_{ft})$ (subfigure 6A) or winsorized pat^1_{ft} to pat^{10}_{ft} (subfigure 6B) as the outcome variables. The upward-sloping patterns in both subfigures indicate that CEO's trust has larger positive effect on higher-quality patents. On the other hand, its effect on patents below-median in quality is not statistically different from zero. Similarly, Table A14, which employs equation 6's bilateral trust specification, shows that CEO's bilateral trust also has the largest effects on patents in the top quality quartile, while its effects on lower-quality-quartile patents are small and statistically insignificant.[79] These results from both specifications all point towards risk taking as the key driver of the CEO's trust effect, as they are inconsistent with alternative mean-shifting mechanisms such as delegation, cooperation, or coordination.[80]

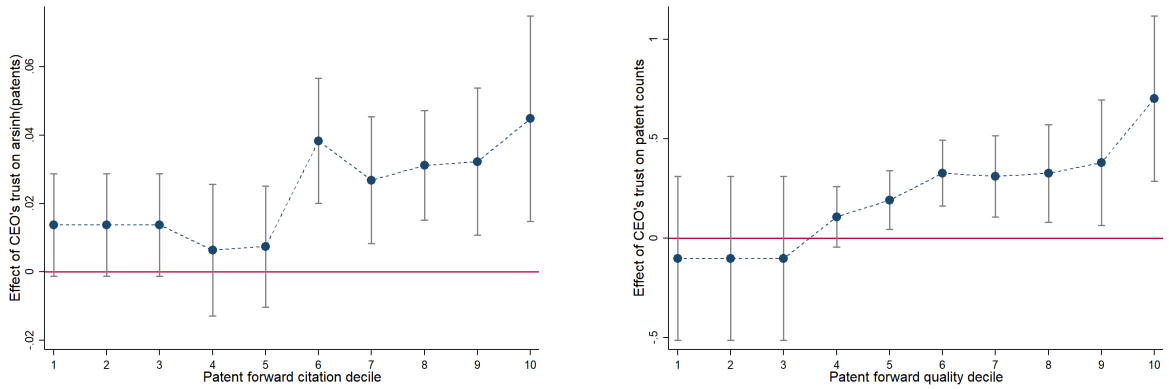
[77] Hall et al. (2005) and Kogan et al. (2017) show that a patent's impact on the firm's market value is highly correlated with its forward citation count. Trajtenberg (1990), Harhoff et al. (1999), and Moser et al. (2015) also find that patent's forward citation count is correlated with patent quality.

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

[79] 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.

[80] 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

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



A. IHS patent counts

B. Winsorized patent counts

Notes: This figure plots the effects of CEO's trust on firm's patent counts in different quality deciles estimated using equation (5), using as the dependent variable the inverse hyperbolic sine of patent counts in subfigure A and winsorized patent counts in subfigure B. A patent's quality decile is computed based on its forward citation count with respect to its technology field × year cohort. Estimates are shown with their 95% confidence intervals. Standard errors are clustered by CEO's main ethnicity.

Table 5 considers various other patent quality measures and estimates equation 5 using quality-weighted patent counts as the outcome variable. These measures include forward citation count (column 1), number of backward citations to scientific literature (column 2), the range of technology covered by the patents (column 3), explorative patent and granted patent indicators (columns 4 and 5), and Kogan et al.'s (2017) estimated patent value (column 6).[81] Across these different quality-weighted patent counts, the coefficients on CEO's trust are positive and statistically significant, with magnitudes larger than or at least similar to the baseline effect, consistent with the pattern that CEO's trust has larger effect on high-quality patents. The large effect on citations to scientific literature (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). Relatedly, columns 4 and 7 show that CEO's trust induces proportionally more explorative patents, i.e., those building on knowledge that is new to the firm.[82] This leads to improvements in not only the absolute forward

early failure and rewarding long-term success.

[81] Kogan et al. (2017) compute a patent's monetary value to a firm from the firm's excess stock return on the patent's grant date. Their data cover USPTO patents granted in 2011 or earlier, and therefore are comprehensive only for patents filed in 2008 or earlier.

[82] A patent is considered explorative if at least 90% of its citations are outside of the firm's existing knowledge stock, which includes all patents and works developed and cited by the firm in the past. About 25% of patents in my sample are explorative. This patent exploratiVeness measure (Benner and Tushman, 2002) has been used in many

Table 5: CEO's Trust Effect on Quality-Weighted Patents

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	arsinh(Future quality-weighted patents)						**Share**	**arsinh**	**arsinh**
Quality measure:	Forward cites	Backward NPL cites	Tech. scope	Explora-tive pat.	Granted USPTO	Patent value	**(Explor. pat.)**	**(Avg. cites)**	**(Avg. value)**
CEO's trust	0.100***	0.103***	0.061**	0.065***	0.056***	0.113***	0.011**	0.044**	0.060**
	(0.031)	(0.031)	(0.025)	(0.014)	(0.014)	(0.041)	(0.004)	(0.020)	(0.024)
Firm & Year FEs	X	X	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384	20,218	29,384	29,384	20,218
Firms	3,598	3,598	3,598	3,598	3,598	3,168	3,598	3,598	3,168

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); explorative patents (i.e., patents mostly citing knowledge that is new to the firm) (column 4); granted USPTO patents (column 5); and patent value (i.e., firm f's excess stock return on patent grant date as estimated by Kogan et al., 2017) (column 6). The dependent variable in column (7) is the share of explorative patents; column (8) the inverse hyperbolic sine of the average forward citations per patent; and column (9) the inverse hyperbolic sine of the average patent value; all computed among patents filed by firm f's in year $t+1$ (or set to zero if firm f has no patent application in year $t+1$). The explanatory variable is CEO d's GSS-based inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

citation counts (column 1) or total patent value (column 6), but also the average citation count per patent (column 8) and the average patent value (column 9). These CEO's trust effects on average patent quality are also of sizable magnitude, at 4-6%, statistically significant at 5% level. Together, Tables 5 and A15 (with similar results from the bilateral-trust specification) 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 pool quality

Section 2's model also points out that while higher CEO's trust increases total innovation, this may not always be optimal. As trust induces innovation through encouraging *good* researchers to explore more often, at the cost of not screening out the bad ones, its effect is expected to be limited among firms with few good researchers. Furthermore, CEO's trust could even have a negative impact on firm's performance when it is grossly misplaced.

As data on the full pool of researchers in each firm are not available, I construct a proxy for

recent innovation studies such as Brav et al. (2018) and Fitzgerald et al. (2019).

researcher 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 year with similar observable characteristics (including R&D expenditure and CEO's trust), and one firm happens to produce more patents than the other, then it is likely due to the former's having better researchers than the latter. Using this firm-level proxy for researcher pool

Table 6: CEO's Trust Effect by Pre-Transition Researcher Pool Quality

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	arsinh(Future patent applications)					**arsinh(R&D**
	All patents				High quality	**efficiency)**
CEO's trust	0.066***	0.066***	0.067***		0.057***	0.039***
	(0.018)	(0.018)	(0.019)		(0.015)	(0.013)
Trust × Researcher quality	0.040**	0.034*	0.021		0.039**	0.025**
(proxy, pre-transition period)	(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 2-digit SIC 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(sales), arsinh(R&D expenditure), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (4) interacts CEO's trust measure with researcher pool quality quintile dummies (computed based on firm-level proxy for pre-transition researcher pool quality). The remaining columns interact CEO's trust measure with firm-level proxy for pre-transition pool quality. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

quality, Table 6 finds that consistent with the model's implication, CEO's trust effect significantly increases with existing researcher quality, as plotted in Figure A6A. 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. 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 and Figure A6B), as well as firm's future performance, as measured by future sales, employment, and total factor productivity (Table A16). These results suggest that trust is most effective at enhancing firm's innovation and real performance only when it is well matched to a trustworthy environment.

6.4 Evidence of effect on "corporate trust culture"

One may ask how a CEO's personal characteristics could affect a researcher's project choices in large public firms, given the likely multiple layers between them.[83] On the one hand, CEOs yield great influence on firms' policies, which are observed or even anticipated by researchers even when there is no direct interaction between them. On the other hand, CEOs' beliefs and preferences can also trickle down the different layers in firms to directly impact researchers' behaviors. This subsection reports some evidence of this transmission of CEO's trust within the firm.

To measure "firm's trust attitude," I use Sull's (2018) dataset of employee sentiments that covers over 500 US large public firms. The dataset is constructed from the text analysis of close to one million online employee reviews on Glassdoor.com, one of the largest career intelligence sites worldwide, between 2008 and 2017.[84] 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.[85] 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 individual employee's trust sentiment by CEO term and standardize

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

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

[85] 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.

the resulting corporate trust culture measure by its standard deviation.[86] This results in Table 7's sample of 394 observations at firm-by-CEO term level, covering 276 firms. To examine the relationship between CEO's trust and corporate trust culture, I regress the aggregated corporate trust culture measure on CEO's inherited trust, controlling for period-average firm's and CEO's characteristics and 3-digit SIC industry fixed effects (column 2) or even firm fixed effects (column 5). The coefficients report a strong association between CEO's trust and corporate trust culture, which is unlikely driven by firm's time-invariant characteristics as suggested by column 5. This relationship is robust to adding additional controls for CEO's approval rate by the same sets of reviewers (columns 3 and 6) and CEO's other cultural traits as in Table 2 (columns 4 and 7).

Table 7: CEO's Trust and "Corporate Trust Culture"

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

Notes: This table presents the effect of CEO's trust on measures of corporate culture computed from online employee reviews (Sull, 2018). Sample includes all firm f × CEO d observations over the 2008-2017 period. The dependent variable measures firm f's "corporate trust culture" (i.e., the extent to which employees trust one another) during CEO d's term. The explanatory variable is CEO d's inherited trust measure, standardized by its standard deviation at ethnicity level (subsection 3.2). Baseline controls include (i) firm's average age, average age squared, ln(average total assets), ln(average sales), and (ii) CEO's average age, average age squared, gender, education dummies, average tenure in firm (controls are averaged over CEO d's term in firm f). CEO approval rate is computed from online employee reviews. Additional controls for CEO's other cultural traits are as explained in Table 2's notes. Standard errors are clustered by 3-digit SIC industry.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table 8 further suggests that such cultural transmission may be reinforced by the selection

[86] Following Grennan (2014), I only keep the CEO terms for which there are at least 100 meaningful reviews (25^{th} percentile in terms of review counts), to avoid the results being driven by a few idiosyncratic reviews. All results are robust to using different review count cutoffs.

of directors. Column 7 shows that the average inherited trust measure among firm's directors improves under a more trusting CEO. This is driven by both the facts that (i) new directors being hired under a more trusting CEO, especially those remaining until the end of the CEO's tenure, are also more trusting (columns 1-2 and 4-5), and (ii) directors leaving the board under this more trusting CEO are the less trusting ones (columns 3 and 6). These findings resonate with Van den Steen's (2010) theory that screening, self-sorting, and manager-directed learning is the source of shared beliefs and values (i.e., corporate culture) in an organization, and Graham et al.'s (2018) survey-based insight that corporate culture is primarily set by the current CEO. Although Tables 7 and 8's results should be taken with caution,[87] they nonetheless provide meaningful evidence that CEO's trust attitude has non-negligible impacts on firm's corporate culture.

Table 8: CEO's Trust and Director Selection

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

Notes: This table reports the association between CEO's trust and directors' trust. Columns (1)-(3): Samples include observations of director r × firm f × year t × its current CEO d over the baseline 2000-2011 period, separately for newly appointed directors (i.e., new directors, column 1), newly appointed directors who stay on the board until the end of the CEO's term (i.e., staying directors, column 2), and directors who leave the board the following year and before the end of the CEO's term (i.e., leaving directors, column 3). The dependent variable is director r's inherited trust measure (subsection 3.2). Columns (4)-(7): Samples include observations of firm f × year t × its current CEO d. The dependent variable is the average inherited trust measure of all new directors (column 4), all staying directors (column 5), all leaving directors (column 6), and all directors (column 7). Directors who ever serve as the firm's CEO are always excluded. The explanatory variable is CEO d's inherited trust measure. Baseline controls include (i) CEO's age, age squared, gender, education dummies, tenure in firm, and (ii) firm's age, age squared. Standard errors are clustered by CEO's main ethnicity.

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

[87] First, Table 7's firm-by-CEO term sample is small and only partly overlaps with the baseline sample. Second, the measure of corporate trust culture are indirectly constructed from online reviews by only a subsample of firms' employees.

7 Further quantitative evidence and qualitative insights

7.1 CEO's prior exposure matters to trust effect

Table 9 investigates how CEO's trust effect varies with his prior exposure, including his knowledge and experience regarding R&D. Columns 1 to 3 interact CEO's trust with dummies indicating if the CEO has at least a master degree (column 1), a doctorate (column 2), and a postgraduate degree that is not an MBA (column 3). The coefficients in columns 1 and 2 suggest that CEO's trust effect is halved if the CEO has some postgraduate education and eliminated if the CEO has a doctorate. Most interestingly, the difference is largest in magnitude and statistically significant in column 3, suggesting that it is technical knowledge that reduces the effect of trust. Similarly, columns 4 and 5 report smaller or zero CEO's trust effect among CEOs with prior experience in R&D (column 4) or in the firm (column 5). 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.[88]

Finally, the last two columns compare between CEOs who were born and/or education abroad and those likely US-born and/or educated.[89] Not surprisingly, the CEO's trust coefficients are considerably larger among CEOs who are first-generation immigrants to the US, for whom ethnic-specific inherited trust is likely a more significant component of their individual trust.

7.2 Evidence of CEO's trust effect across firm sizes and industries

Table 10 reports some additional results on heterogeneous effects by firm size and industry. First, interaction terms between CEO's trust and firm's size quintile dummies (with respect to its 3-digit SIC industry) suggest that the effect is largest among medium-size firms (columns 1 and 2). This possibly reflects the observation that it is more difficult for CEOs to have considerable impact on researchers in very large firms, while R&D and innovation may be less relevant for very small ones, unless they already are patenting firms (columns 3 and 4). Second, CEO's trust effect is significantly larger in ICT and electronic sectors (10.5%, column 5), while it is not statistically

[88] Relatedly, Figure A7 shows a slight declining trend in CEO's trust coefficients over the CEO's tenure in the firm, again consistent with the model's prediction that CEO's prior belief, or inherited trust, becomes less important as he updates his belief after each period. Relatedly, in the context of cross-country venture capital investment, Bottazzi et al. (2016) find that education and work experience reduce the effect of bilateral trust on investment.

[89] Based on CEOs' birthplace data from Marquis Who's Who, I manually identify precisely 49 foreign-born CEOs. The rest of the CEOs are classified as likely US-born, although in many cases their birthplace information is not available. This type of measurement error can only create a downward bias in the difference between foreign-born and US-born CEOs' trust effects.

Table 9: CEO's Trust Effect and Prior Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**arsinh(Future patent applications)**						
CEO's background:	Education			Experience		First generation	
D variable:	Postgrad. degree	Doctorate degree	Non-MBA P.G. degree	Prior R&D experience	Above 3 yrs in firm	Born/educated abroad	Born abroad
A: Trust × D = 0	0.082***	0.072***	0.092***	0.064***	0.077***	0.059***	0.061***
	(0.019)	(0.016)	(0.023)	(0.017)	0.025)	(0.020)	(0.019)
B: Trust × D = 1	0.052**	0.017	-0.004	0.007	0.054**	0.116*	0.276**
	(0.025)	(0.059)	(0.038)	(0.130)	(0.025)	(0.064)	(0.111)
Difference: B - A	-0.030	-0.056	-0.096*	-0.057	-0.024	0.057	0.215*
	(0.029)	(0.058)	(0.049)	(0.120)	(0.032)	(0.068)	(0.108)
Firm & Year FEs	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X
Observations	29,384	29,384	29,384	29,384	29,384	29,384	29,384
Firms	3,598	3,598	3,598	3,598	3,598	3,598	3,598

Notes: This table explores the heterogeneous effects of CEO's trust on firm's patents by CEO's background, 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(sales), and (ii) CEO's age, age squared, gender, education dummies (excluded in columns 1-3), tenure in firm (excluded in column 5). Each column interacts CEO's trust measure with a dummy indicating if (i) he has a masters or doctorate degree (column 1), (ii) he has a doctorate degree (column 2), (iii) he has a non-MBA masters or a doctorate degree (column 3), (iv) he has prior R&D experience (column 4), (v) he has been in firm f for more than three years (column 5), (vi) he was born or educated abroad (column 6), or (vii) he was born abroad (column 7). Standard errors are clustered by CEO's main ethnicity.

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

different from zero among chemical and pharmaceutical firms (column 7). This is consistent with the argument that CEO's trust effect should be more visible where the lag between R&D and patents is shorter, and also where firms are smaller.[90] Nonetheless, CEO's trust also has positive and statistically significant effect on innovation in other remaining industries, although of smaller magnitude (4.7%, column 6), suggesting that it is not driven by just ICT and electronic firms but ubiquitous across industries.

7.3 Qualitative insights on CEO's practice

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,

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

Table 10: CEO's Trust Effect across Firm Sizes and Industries

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

Notes: This table explores the heterogeneous effects of CEO's trust on firm's patents by firm size and industry using equation (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(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Columns (1)-(4) interact CEO's trust measure with firm's size quintile dummies, computed with respect to firm's 3-digit SIC industry × year cohort using total assets (columns 1 and 3) or employment (columns 2 and 4) as firm size measure. Columns (1) and (2) use the full baseline sample; columns (3) and (4) use the patent-period subsample (details in Table 1's notes). Columns (5) corresponds to the subsample of firms in ICT and electronic industries (i.e., computer and data processing services (SIC3 code 737), computer and office equipment (SIC3 code 357), electronic and other equipment (SIC2 code 36)) and column (6) the remaining subsample. Column (7) corresponds to the subsample of firms in pharmaceutical and chemical industries (i.e., chemicals and allied products (SIC2 code 28)) and column (8) the remaining subsample. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

and incentives. While it remains a major challenge to run large-scale surveys with quantitative questions on top managers' practices,[91] one can still get some qualitative insights from a recent *McKinsey* survey on leadership and innovation among senior managers worldwide.[92] 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

[91] 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.

[92] The survey was conducted by *McKinsey Global Institute* (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.

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.[93]

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.[94] 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 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."[95] The anecdote highlights this paper's message on the role of such trusting CEOs in inculcating a corporate culture of tolerance of failure, which can lead to more innovation.

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

[93] 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.

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

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

increase in annual patent counts and 4-6% increase in average patent quality or value. 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 findings are unlikely driven by confounding factors such as CEO's country of origin or individual characteristics.

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

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

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 directly observe individual researchers' contracts or tenures. Second, it is important to better understand in which context excessive trust would lead to suboptimal innovation and performance. Third, while this paper focuses on the within-firm effect of CEO's trust, it would be interesting to further examine its implications on the sorting of researchers across firms.

References

Abadie, Alberto, Susan Atheys, Guido Imbens, and Jeffrey Wooldridge, "When Should You Adjust Standard Errors for Clustering?," 2017. Working Paper. 17

Abowd, John, Francis Kramarz, and David Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–334. 16

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. 5, 31

Aghion, Philippe and Jean Tirole, "Formal and Real Authority in Organizations," *Journal of Political Economy*, 1997, *105* (1), 1–29. 5, 31

_ **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

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. 23

Algan, Yann and Pierre Cahuc, "Inherited Trust and Growth," *American Economic Review*, December 2010, *100* (5), 2060–92. 1, 3, 5, 12

_ **and** _ , "Trust and Growth," *Annual Review of Economics*, 2013, *5* (1), 521–549. 1, 4, 14, 22

_ **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, 5, 14, 22

Angrist, Joshua and Jörn-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton, New Jersey: Princeton University Press, 2009. 15, 84

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, 2

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

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

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, 9, 33

Baker, George, Robert Gibbons, and Kevin Murphy, "Informal Authority in Organizations," *Journal of Law, Economics, and Organization*, 1999, *15* (1), 56–73. 31

_ **,** _ **, and** _ , "Relational Contracts and the Theory of the Firm," *The Quarterly Journal of Economics*, 2002, *117* (1), 39–84. 31

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, 42

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. 5

_ **and** _ , *Religion and Economy*, Princeton, New Jersey: Princeton University Press, 2018. 5

Barsh, Joanna, Marla Capozzi, and Jonathan Davidson, "How Companies Approach Innovation: A McKinsey Global Survey," *McKinsey Quarterly*, 2007. 42

_ **,** _ **, and** _ , "Leadership and Innovation," *McKinsey Quarterly*, 2008. 42, 43

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. 5

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. 22

Bennedsen, Morten, Francisco Pérez-González, and Daniel Wolfenzon, "Do CEOs Matter?," 2010. Working Paper. 3, 21, 77

Benner, Mary and Michael Tushman, "Process Management and Technological Innovation: A Longitudinal Study of the Photography and Paint Industries," *Administrative Science Quarterly*, 2002, *47* (4), 676–707. 34

Bennis, Warren and Burt Nanus, *Leaders: Strategies for Taking Charge*, New York: Harper Business, 1997. 43

Berg, Joyce, John Dickhaut, and Kevin McCabe, "Trust, Reciprocity, and Social History," *Games and Economic Behavior*, 1995, *10* (1), 122–142. 12

Bertrand, Marianne, "CEOs," *Annual Review of Economics*, 2009, *1* (1), 121–150. 3, 21

_ **and Antoinette Schoar**, "Managing with Style: The Effect of Managers on Firm Policies," *The Quarterly Journal of Economics*, 2003, *118* (4), 1169–1208. 3, 16

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, 14

_ **and** _ , "The Economics of Cultural Transmission and the Dynamics of Preferences," *Journal of Economic Theory*, April 2001, *97* (2), 298–319. 3, 14

Bloom, Nicholas and John Van Reenen, "Measuring and Explaining Management Practices Across Firms and Countries," *The Quarterly Journal of Economics*, 2007, *122* (4), 1351–1408. 42

_ **, Raffaella Sadun, and John Van Reenen**, "The Organization of Firms Across Countries," *The Quarterly Journal of Economics*, 2012, *127* (4), 1663–1705. 4, 5, 15, 31

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, 15, 40

Branstetter, Lee, "Exploring the Link Between Academic Science and Industrial Innovation," *Annals of Economics and Statistics*, 2005, *79-80*, 119–142. 34, 75

Brav, Alon, Wei Jiang, Song Ma, and Xuan Tian, "How does hedge fund activism reshape corporate innovation?," *Journal of Financial Economics*, 2018, *130* (2), 237–264. 35

Butler, Jeffrey, Paola Giuliano, and Luigi Guiso, "The Right Amount of Trust," *Journal of the European Economic Association*, 2016, *14* (5), 1155–1180. 10

Card, David and Stefano DellaVigna, "What do Editors Maximize? Evidence from Four Leading Economics Journals," 2017. Working Paper. 16

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. 34, 75

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. 15

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

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. 5, 11, 73, 74, 75

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. 29, 52, 54

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

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde, "The Intergenerational Transmission of Risk and Trust Attitudes," *Review of Economic Studies*, 2012, *79* (2), 645–677. 13, 14

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, 7

_ **and** _ , "Is Pay for Performance Detrimental to Innovation?," *Management Science*, 2013, *59* (7), 1496–1513. 2, 43

Eriksson, Katherine and Zachary Ward, "The Ethnic Segregation of Immigrants in the United States from 1850 to 1940," 2018. Working Paper. 13

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde, "Global Evidence on Economic Preferences," 2018. Working Paper. 23, 24, 63

_ , _ , _ , **David Huffman, and Uwe Sunde**, "The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences," 2016. Working Paper. 12, 15, 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. 21, 77

Fehr, Ernst and John List, "The Hidden Costs and Returns of Incentives—Trust and Trustworthiness among CEOs," *Journal of the European Economic Association*, 09 2004, *2* (5), 743–771. 13

_ , **Urs Fischbacher, Bernhard von Rosenbladt, Jürgen Schupp, and Gert G. Wagner**, "A Nation-Wide Laboratory ? Examining trust and trustworthiness by integrating behavioral experiments into representative surveys," *Schmollers Jahrbuch - Zeitschrift für Wirtschafts und Sozialwissenschaften*, 2002, *122* (4), 519–542. 12

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. 14

_ **and Alessandra Fogli**, "Culture: An Empirical Investigation of Beliefs, Work, and Fertility," *American Economic Journal: Macroeconomics*, 2009, *1* (1), 146–77. 3, 14

Fitzgerald, Tristan, Benjamin Balsmeier, Lee Fleming, and Gustavo Manso, "Innovation Search Strategy and Predictable Returns," 2019. Working Paper. 35

Foley, Fritz and William Kerr, "Ethnic Innovation and U.S. Multinational Firm Activity," *Management Science*, 2013, *59* (7), 1529–1544. 25

Fukuyama, Francis, *Trust: The Social Virtues and the Creation of Prosperity*, New York: Free, 1995. 1, 31

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, 7, 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. 6

Giuliano, Paola, "Living Arrangements in Western Europe: Does Cultural Origin Matter?," *Journal of the European Economic Association*, 2007, *5* (5), 927–952. 3, 14

_ **and Antonio Spilimbergo**, "Growing Up in a Recession: Beliefs and the Macroeconomy," *Review of Economic Studies*, 2013, *81* (2), 787–817. 23

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

González-Uribe, Juanita and Moqi Groen-Xu, "CEO Contract Horizon and Innovation," 2017. Working Paper. 2, 37

Gorodnichenko, Yuriy and Gerard Roland, "Culture, Institutions, and the Wealth of Nations," *The Review of Economics and Statistics*, 2017, *99* (3), 402–416. 5

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. 1, 6, 39

Grennan, Jillian, "A Corporate Culture Channel: How Increased Shareholder Governance Reduces Firm Value," 2014. Working Paper. 6, 37, 38

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, "The Role of Social Capital in Financial Development," *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, 4, 5, 12

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

_ **,** _ **, and** _ , "Trusting the Stock Market," *The Journal of Finance*, 2008, *63* (6), 2557–2600. 2, 7

_ **,** _ **, and** _ , "Cultural Biases in Economic Exchange?," *The Quarterly Journal of Economics*, 2009, *124* (3), 1095–1131. 1, 4, 15

_ **,** _ **, and** _ , "The Value of Corporate Culture," *Journal of Financial Economics*, 2015, *117* (1), 60–76. 1, 6

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

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, "Market Value and Patent Citations," *RAND Journal of Economics*, 2005, *36* (1), 16–38. 11, 33, 74

_ **, 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. 3, 11

Hall, Browyn, Zvi Griliches, and Jerry Hausman, "Patents and R&D: Is There a Lag?," *International Economic Review*, 1986, *27* (2), 265–284. 19

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. 5

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. 33, 74

Hofstede, Gerrt, Geert Jan Hofstede, and Michael Minkov, *Cultures and Organizations:*

Software of the Mind, London: McGraw-Hill, 1991. 6

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. Working Paper. 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, 13

Kihlstrom, Richard and Jean-Jacques Laffont, "A General Equilibrium Entrepreneurial Theory of Firm Formation Based on Risk Aversion," *Journal of Political Economy*, 1979, *87* (4), 719–48. 23

Klein Woolthuis, Rosalinde, Bas Hillebrand, and Bart Nooteboom, "Trust, Contract and Relationship Development," *Organization Studies*, 06 2005, *26*, 813–840. 3, 6

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

Knights, David, Faith Noble, Theo Vurdubakis, and Hugh Willmott, "Chasing Shadows: Control, Virtuality and the Production of Trust," *Organization Studies*, 2001, *22* (2), 311–336. 6

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. 20, 33, 34, 35, 74, 75

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

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. 75

Liu, Xiaoding, "Cultural Origins and CEO Incentive Contracts," 2013. Working Paper. 22

_ , "Corruption Culture and Corporate Misconduct," *Journal of Financial Economics*, 2016, *122* (2), 307–327. 1, 3, 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, 9

March, James, "Exploration and Exploitation in Organizational Learning," *Organization Science*, 1991, *2* (1), 71–87. 2, 7

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. 6

Moser, Petra, Joerg Ohmstedt, and Paul Rhode, "Patent Citations and the Size of the Inventive Step: Evidence from Hybrid Corn," 2015. Working Paper. 33, 74

Nguyen, Bang Dang and Kasper Nielsen, "The Value of Independent Directors: Evidence from Sudden Deaths," *Journal of Financial Economics*, 2010, *98* (3), 550–567. 77

Nooteboom, Bart and Erik Stam, *Micro-foundations for Innovation Policy*, Amsterdam: Amsterdam University Press, 2008. 6

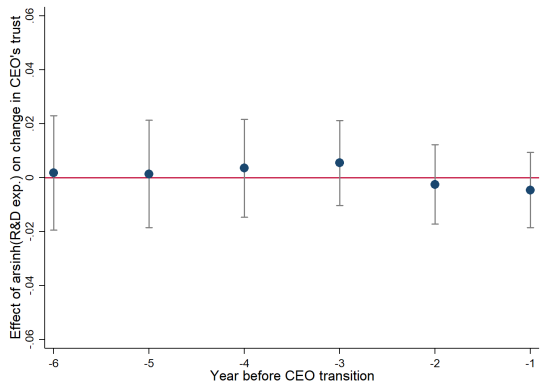
Nunn, Nathan, "Culture and the Historical Process," *Economic History of Developing Regions*, 2012, *27* (1), 108–126. 5

Olley, Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1996, *64* (6), 1263–97. 69

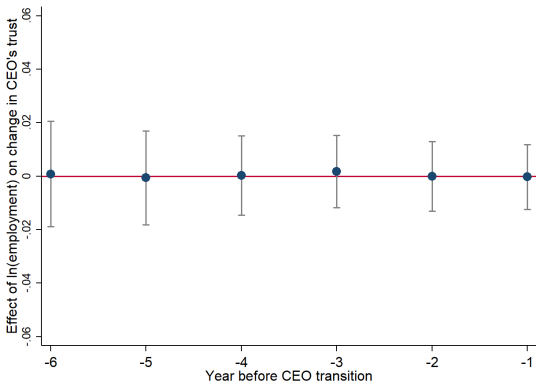
O'Reilly, Charles, David Caldwell, Jennifer Chatman, and Bernadette Doerr, "The Promise and Problems of Organizational Culture: CEO Personality, Culture, and Firm Perfor-

mance," *Group & Organization Management*, 2014, *39* (6), 595–625. 6, 37
_ **, 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. 6, 37
Pan, Yihui, Stephan Siegel, and Tracy Yue Wang, "Corporate Risk Culture," *Journal of Financial and Quantitative Analysis*, 2017, *52* (06), 2327–2367. 23
_ **,** _ **, and** _ , "The Cultural Origin of CEOs' Attitudes Towards Uncertainty: Evidence from Corporate Acquisitions," *The Review of Financial Studies*, 2018, *forthcoming*. 13
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, 31
Sapienza, Paola, Anna Toldra-Simats, and Luigi Zingales, "Understanding Trust," *Economic Journal*, 2013, *123* (12), 1313–1332. 12, 82, 83
Schein, Edgar, *Organization Culture and Leadership*, San Francisco, California: Jossey-Bass Publishers, 1985. 6
Schmoch, Ulrich, "Concept of a Technology Classification for Country Comparisons," in "Final Report to the World Intellectual Property Organisation (WIPO)" 2008. 75
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. 22
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. 29, 30, 64
Squicciarini, Mariagrazia, Helene Dernis, and Chiara Criscuolo, "Measuring Patent Quality: Indicators of Technological and Economic Value," 2013. OECD Working Paper. 12, 75
Sull, Donald, "Measuring Corporate Culture Using Glassdoor Reviews," MIT Organizational Economics Lunch Seminar 2018. 5, 37, 38
Tabellini, Guido, "The Scope of Cooperation: Values and Incentives*," *The Quarterly Journal of Economics*, 2008, *123* (3), 905–950. 3, 14
_ , "Culture and Institutions: Economic Development in the Regions of Europe," *Journal of the European Economic Association*, 2010, *8* (4), 677–716. 1, 5
Tian, Xuan and Tracy Yue Wang, "Tolerance for Failure and Corporate Innovation," *Review of Financial Studies*, 2014, *27* (1), 211–255. 9
Tibshirani, Robert, "Regression Shrinkage and Selection via the Lasso," *Journal of the Royal Statistical Society*, 1996, *58* (1), 267–288. 20
Trajtenberg, Manuel, "A Penny for Your Quotes: Patent Citations and the Value of Innovation," *RAND Journal of Economics*, 1990, *21* (1), 172–187. 11, 33, 74
Van den Steen, Eric, "On the Origin of Shared Beliefs (and Corporate Culture)," *RAND Journal of Economics*, 2010, *41* (4), 617–648. 6, 39
Weber, Max, *The Protestant Ethic and the Spirit of Capitalism*, London: Allen & Unwin, 1905. 22

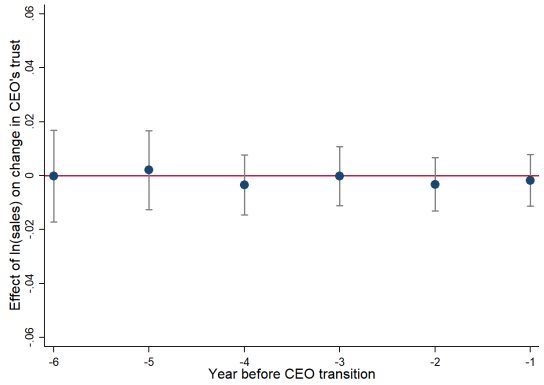
Figure A1: Pre-Change Firm Performance and Change in CEO's Trust



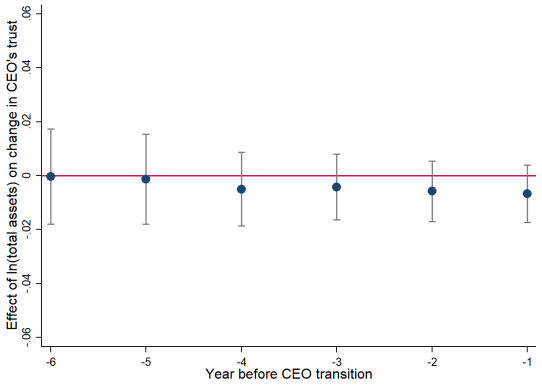
A. Common trend in R&D expenditure



B. Common trend in employment



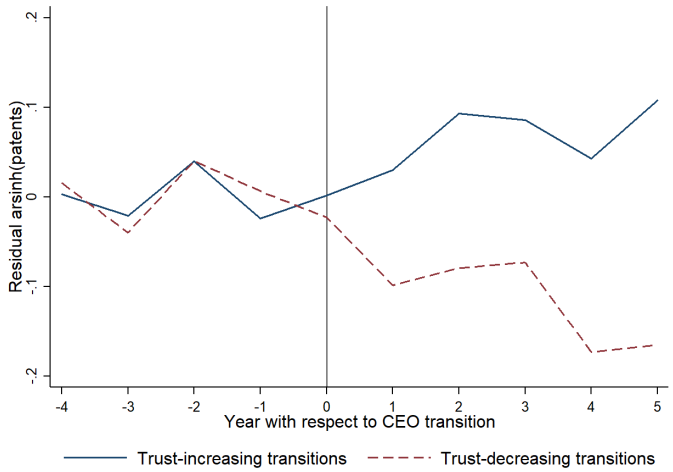
C. Common trend in sales



D. Common trend in total assets

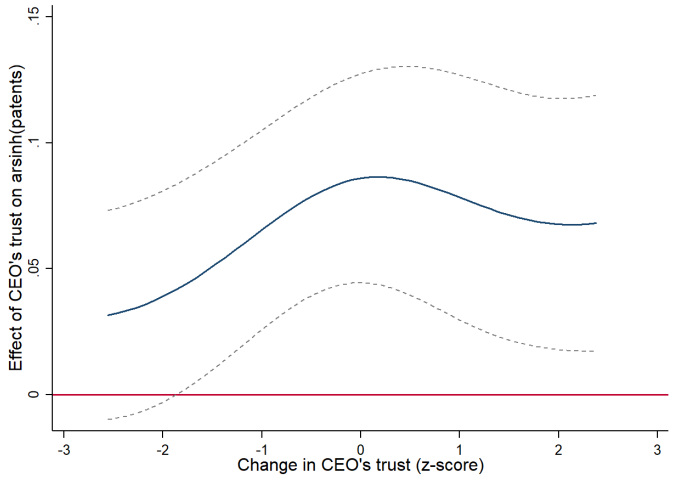
Notes: This figure plots the coefficients $\hat{\gamma}_k$ for $k \in [-6, -1]$ from estimating: $\Delta trust_d = \sum_{k=-7}^{-1} \gamma_k (perfmeasure_{fdt} \times event_{t-k}) + \beta trust_d + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \mu_{s_{(f)}k} + \omega_t + \varepsilon_{fdt}$, in which (i) $\Delta trust_d$ 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 $t-k$, (iii) μ_{sk} is a full set of firm f's 3-digit SIC industry $s \times$ year k (i.e., year with respect to CEO transition) fixed effects, and (iv) $perfmeasure$ is arsinh(R&D expenditure) in subfigure A, ln(employment) in subfigure B, ln(sales) in subfigure C, and ln(total assets) in subfigure D. Standard errors are clustered by firm. Estimates are shown with their 95% confidence intervals.

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



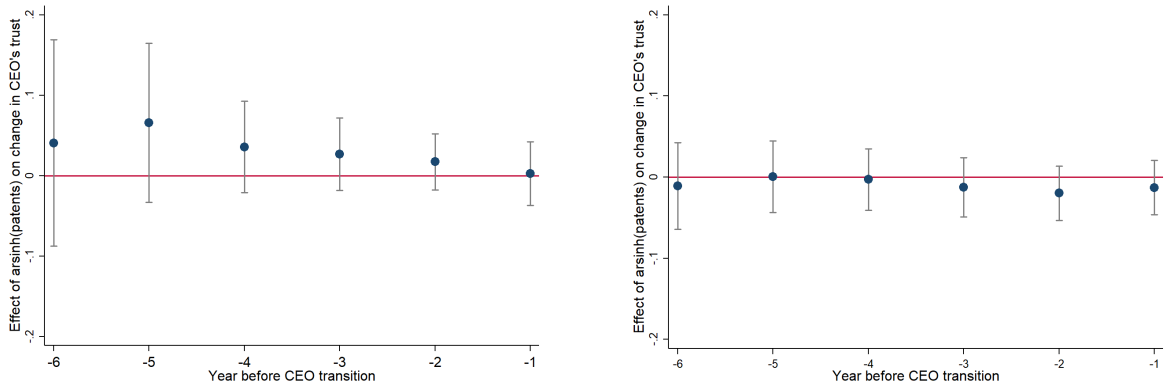
Notes: This figure plots firms' average residual patent application counts (after partialling out (i) firm and CEO controls, and (ii) firm's 3-digit SIC industry and year fixed effects) by year with respect to CEO transition year (i.e., year 0). The sample includes CEO transitions in which both predecessor's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

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



Notes: This figure plots semi-parametric estimates of the CEO's trust coefficient on firm's patents as a function of the change in CEO's trust after the corresponding transition (i.e., $\Delta trust_E$, the X-axis variable), namely $\frac{\partial \text{arsinh}(pat_{fd,t+1})}{\partial trust_d}(\Delta trust_E)$. The point estimate at each value of $\Delta trust_E$ is obtained from the benchmark regression in equation 5, weighted by a Gaussian kernel function of $\Delta trust_E$ around that particular value with a bandwidth equal to 20% of the range (see Do et al., 2017 for details of this method). Standard errors are clustered by CEO's main ethnicity. The dashed lines indicate the 95% confidence intervals for the CEO's trust coefficients.

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

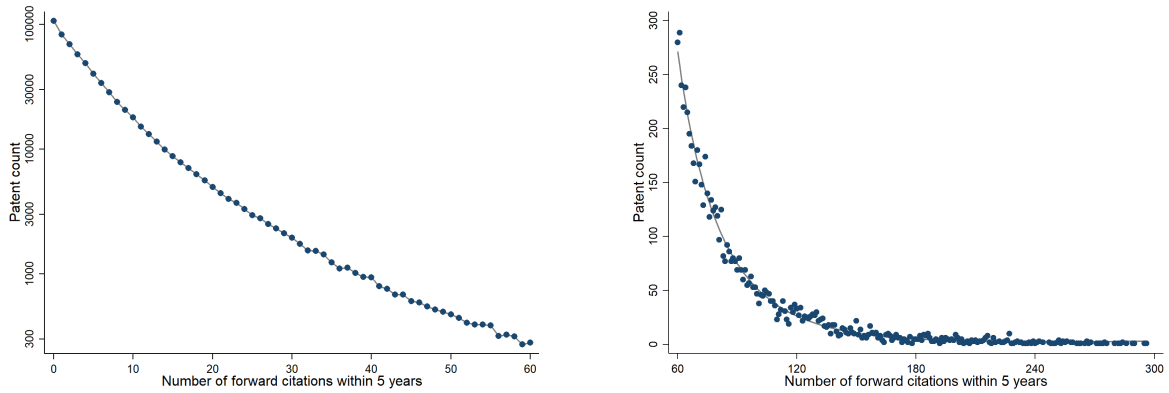


A. Non-US-based inventors

B. All inventors

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

Figure A5: Distribution of Patent's Forward Citation Count

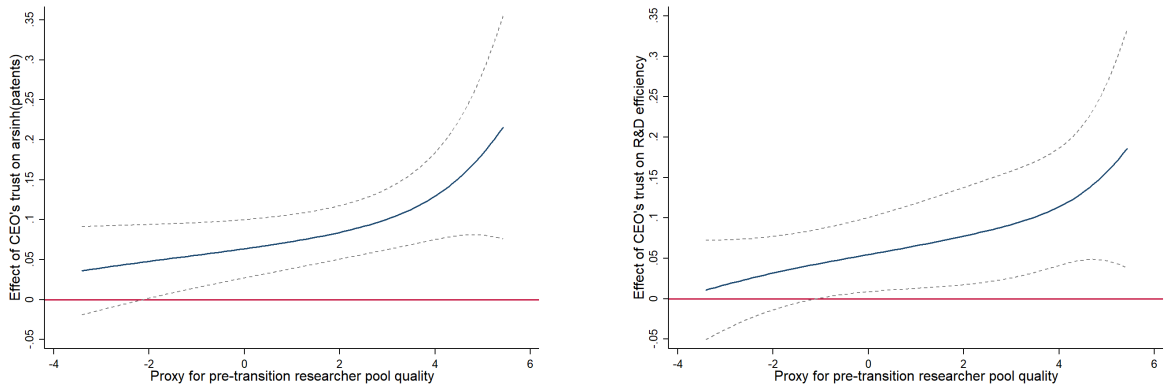


A. 0^{th}-99^{th} percentile

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

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

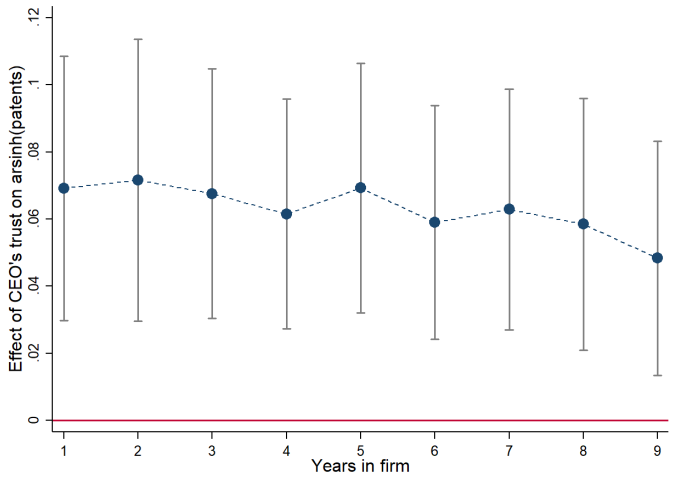
Figure A6: CEO's Trust Effect by Pre-Transition Researcher Pool Quality



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

Notes: This figure plots semi-parametric estimates of the CEO's trust coefficient on firm's patents as a function of pre-transition researcher pool quality (i.e., $prequal_E$, the X-axis variable). Proxy for $prequal_E$ is computed from the residuals from regressing patents on observable firm and CEO characteristics, controlling for 2-digit SIC industry and year fixed effects (subsection 6.3) over the (-1, 0) 2-year pre-transition window. The point estimate at each value of $prequal_E$ is obtained from the benchmark regression in equation 5, weighted by a Gaussian kernel function of $prequal_E$ around that particular value with a bandwidth equal to 20% of the range (see Do et al., 2017 for details of this method). Standard errors are clustered by CEO's main ethnicity. Subfigure A reports CEO's trust effect on firm's future patents, namely $\frac{\partial \text{arsinh}(pat_{fd,t+1})}{\partial trust_d}(prequal_E)$. Subfigure B reports CEO's trust effect on firm's future R&D efficiency, namely $\frac{\partial \text{arsinh}(rdprod_{fd,t+1})}{\partial trust_d}(prequal_E)$, in which $rdprod_{fd,t+1}$ is calculated as patent application counts in year $t+1$ over lagged R&D expenditure in year t. The dashed lines indicate the 95% confidence intervals for the CEO's trust coefficients.

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



Notes: This figure plots the coefficients $\hat{\beta}_k$ for $k \in [1,9]$ from estimating: $\text{arsinh}(pat_{fd,t+1}) = \sum_{k=1}^{9} \beta_k (trust_d \times tenure_{dk} \times successor_d) + \mathbf{X}_{ft} + \mathbf{Z}_{dt} + \theta_E + \omega_t + \varepsilon_{fdt}$ 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	0.28	(0.45)	0.29	(0.45)	0.31	(0.46)
Has prior R&D experience	0.02	(0.14)	0.02	(0.13)	0.02	(0.14)
Age when becoming CEO	50.1	(8.5)	50.3	(8.7)	49.9	(8.9)
Prior tenure in firm (yrs)	6.44	(8.18)	6.59	(8.36)	6.70	(8.57)
Tenure as CEO (yrs)	7.23	(6.14)	7.23	(6.32)	7.22	(6.11)
# CEOs	5,753		7,027		1,466	

Panel B. Firm's characteristics

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

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

Table A4: Bilateral Trust Samples' Descriptive Statistics

Panel A. CEO's characteristics

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

Panel B. Firm's characteristics

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

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

Table A5: Average Patents Before and After CEO Transitions

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

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

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

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

Notes: This table reports the baseline effect of CEO's inherited trust on R&D expenditure and stock using equation (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 $t+k$ 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(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

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

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	**Future patent applications**								
Transformation:	arsinh(.)								win.
Specification:	Baseline	Alt. clusterings		Alt. weights		Additional controls			Poisson
CEO's trust	0.063***	0.063***	0.063***	0.069***		0.066***	0.063***	0.060***	0.168**
	(0.019)	(0.022)	(0.022)	(0.020)		(0.019)	(0.019)	(0.018)	(0.069)
CEO's trust *(main eth. origin)*					0.056*** (0.019)				
ln(employment)						0.101*** (0.012)			
arsinh(R&D stock)							0.015* (0.008)		
arsinh(R&D exp.)								0.092*** (0.011)	
Clustering scheme		Firm	Two-way						Robust
Firm & Year FEs	X	X	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X	X	X
Weighted				X	X				
Observations	29,384	29,384	29,384	29,384	29,384	28,506	29,384	29,384	17,536
Firms	3,598	3,598	3,598	3,598	3,598	3,548	3,598	3,598	1,915

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	**Future patent applications**								
Transformation:	arsinh(.)			arsinh(.)	ln(.)	ln(1+.)	win.	raw	$\mathbb{1}_{.>0}$
Specification:	Alt. samples			Patenting samples		Alt. transformations			
CEO's trust	0.063***	0.061***	0.075***	0.086***	0.099***	0.053***	1.462**	4.464***	0.009
	(0.019)	(0.020)	(0.020)	(0.025)	(0.020)	(0.015)	(0.584)	(1.293)	(0.006)
Dep. var. mean							*13.28*	*18.02*	*0.383*
Sample including	Single-tons	Female CEOs	Interim CEOs						
Sample excluding				Patent firms	Patent years				
Firm & Year FEs	X	X	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X	X	X
Observations	29,195	28,523	28,909	19,146	11,265	29,384	29,384	29,384	29,384
Firms	3,409	3,550	3,558	2,266	1,982	3,598	3,598	3,598	3,598

Panel C.

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

Panel D.

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

Notes: This table reports 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(sales), 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) weights each observation by the precision of CEO d's last name-ethnic origin mapping, measured as $\sum_e w_{de}^2$. Column (5) measures CEO d's inherited trust based on his main ethnic origin (i.e., $trust_d = ethtrust_{e_d^*}$) and weights each observation by the weight of that ethnic origin in CEO d's last name-ethnic origin mapping (i.e., $w_{de_d^*}$). Column (6) additionally controls for ln(employment); column (7) arsinh(R&D stock); column (8) arsinh(R&D expenditure). Column (9) estimates a semi-log Poisson count model with winsorized $pat_{f,t+1}$ as the dependent variable. **Panel B:** Column (1) excludes singletons; column (2) female CEOs; column (3) interim CEOs. Column (4) includes only firms f that patent during 2000-2012; column (5) firms f that patent in year $t+1$ (i.e., $pat_{f,t+1} > 0$). Columns (6)-(9) use $ln(1+pat_{f,t+1})$, winsorized $pat_{f,t+1}$, raw $pat_{f,t+1}$, and a dummy indicating if firm f patents in year $t+1$ (i.e., $\mathbb{1}_{pat_{f,t+1}>0}$) as the dependent variable. **Panel C:** Column (1) uses $arsinh(pat_{f,t})$ as the dependent variable. Column (2) uses $arsinh(pat_{f,t+1})$ as the dependent variable and excludes the last year of CEO d's tenure. Columns (3)-(5) use $arsinh(pat_{f,t+2})$ as the dependent variable. Columns (4)-(5) exclude the last year and the last 2 years of CEO d's tenure. Columns (6)-(9) use $arsinh(pat_{f,t+3})$ as the dependent variable. Columns (7)-(9) exclude the last year, the last 2 years, and the last 3 years of CEO d's tenure. T denotes the last year of CEO d's tenure in firm f. **Panel D:** 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)-(6) employ subsamples of firms having zero patent (column 4) or having patented (columns 5-6) in the pre-transition period. Column (6) uses a dummy indicating if firm f patents in year $t+1$ (i.e., $\mathbb{1}_{pat_{f,t+1}>0}$) as the dependent variable. Column (7) reports $\hat{\beta}$ from estimating: $\Delta \operatorname{arsinh}(pat_E) = \beta trust_E^{pre} + \Delta \mathbf{X}_E + \Delta \mathbf{Z}_E + \varepsilon_E$, in which (i) each observation E is a CEO transition event, (ii) $\Delta \operatorname{arsinh}(pat_E)$, $\Delta \mathbf{X}_E$, and $\Delta \mathbf{Z}_E$ are the differences between post- and pre-transition average patents, firm's, and CEO's characteristics respectively, and (iii) $trust_E^{pre}$ is the trust measure of the predecessor CEO.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A8: CEO's Retirement and Death Events

Panel A. Including all years in each event

Dependent var:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	arsinh(Future patent applications)						**D(arsinh(pat))**
Sample:	Retired 64-65	Retired 64-66	Retired 63-67	Died transition yr	Died transition yr+1	Retired or died	Retired or died
CEO's trust	0.281***	0.104**	0.083*	0.410	0.400	0.095**	
	(0.095)	(0.042)	(0.047)	(0.308)	(0.279)	(0.045)	
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

Dependent var:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	arsinh(Future patent applications)						**D(arsinh(pat))**
Sample:	Retired 64-65	Retired 64-66	Retired 63-67	Died transition yr	Died transition yr+1	Retired or died	Retired or died
CEO's trust	0.328***	0.137**	0.124**	0.736**	0.780***	0.142**	
	(0.103)	(0.060)	(0.056)	(0.363)	(0.300)	(0.054)	
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 $f \times$ year $t \times$ its current CEO d observations that correspond to the predecessor's and successor's terms of the relevant transitions (Panel A) and that are not the transition years (Panel B). Columns (1)-(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(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (7) estimates $\Delta \operatorname{arsinh}(pat_E) = \beta trust_E^{pre} + \Delta \mathbf{X}_E + \Delta \mathbf{Z}_E + \varepsilon_E$, 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 A9: Other Measures of Trust and Other Cultural Traits

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	arsinh(Future patent applications)							
	Alt. trust measures		Socioeconomic characteristics				Confidence	
CEO's trust	0.063***	0.058***	0.059***	0.060***	0.063***	0.052**	0.062***	0.082***
	(0.021)	(0.021)	(0.020)	(0.019)	(0.018)	(0.024)	(0.018)	(0.022)
Occupation prestige			0.015					
			(0.015)					
Average schooling years				0.014				
				(0.015)				
College graduates (share)					0.073			
					(0.100)			
Protestants (share)						0.033		
						(0.054)		
Confidence in science							0.018	
							(0.032)	
Confidence in Congress								0.039*
								(0.021)
Confidence in Federal Govt.								-0.036
								(0.035)
Confidence in Supreme Court								0.019
								(0.023)
Firm & Year FEs	X	X	X	X	X	X	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 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 × 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(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Columns (1) and (2) employ alternative trust questions in the GSS to construct CEO's inherited trust measure. Column (1) uses the "distrust" question *"Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair?"*. Column (2) uses the question *"Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves?"*. Columns (3)-(6) control for (i) average GSS occupational prestige score (column 3), (ii) average years of schooling (column 4), (iii) share of college graduates (column 5), and (iv) share of Protestants (column 6), among respondents in CEO's ethnic groups. Columns (7) and (8) control for CEO's inherited confidence in the scientific community (column 7) and three branches of the government (column 8), 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 (3), (6), (7), and (8) are standardized by their standard deviations at ethnicity level. Further details on variable construction are available in appendix C.2. Standard errors are clustered by CEO's main ethnicity.

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

Table A10: Global Preference Survey's Trust and Other Cultural Traits

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

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

Panel B. Using GSS-based (i.e., baseline) CEO's inherited trust measure

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

Notes: This table employs inherited trust measure and other cultural trait measures constructed in the same way as 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 in Panel A is CEO d's GPS-based inherited trust measure, and in Panel B his GSS-based (i.e., baseline) inherited trust measure; each standardized by its respective standard deviation at ethnicity level. Baseline controls include (i) firm's age, age squared, ln(total assets), ln(sales), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Column (1) reports the baseline effect of CEO's GPS-based inherited trust. Column (2) controls for CEO's inherited risk preference; column (2) patience; column (3) positive reciprocity; column (4) negative reciprocity; column (5) altruism. Column (6) controls for all those variables. Further details on variable construction are available in appendix C.2. Standard errors are clustered by CEO's main ethnicity.

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

Table A11: CEO's Trust Effect in US-Based Inventor Bilateral Trust Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**arsinh(Future patent applications)**						
Sample:	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 A12: Margins of CEO's Bilateral Trust Effect

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

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

Panel B. All inventor bilateral trust sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**Future patent application**							
Sample:	Generalized	Bilateral trust sample						
	trust sample	Full sample			Intensive margin		Extensive margin	
Transformation:	arsinh(.)	arsinh(.)	ln(.)	$\mathbb{1}_{>0}$	arsinh(.)	$\mathbb{1}_{>0}$	arsinh(.)	$\mathbb{1}_{.>0}$
CEO's generalized trust	0.095***							
	(0.028)							
CEO's bilateral trust		0.026**	0.063***	0.009**	0.026*	0.006	0.010	0.011
		(0.011)	(0.022)	(0.004)	(0.015)	(0.005)	(0.014)	(0.007)
Firm & Year FEs	X							
Baseline controls	X							
Firm × Year FEs		X	X	X	X	X	X	X
CEO FEs		X	X	X	X	X	X	X
Inventor country FEs		X	X	X	X	X	X	X
Observations	11,931	56,942	34,479	56,942	33,058	33,058	23,884	23,884
Firm × Inv. country's		8,554	7,405	8,554	5,718	5,718	3,389	3,389
Firms	1,256	1,263	1,083	1,263	990	990	990	990

Notes: This table reports CEO's generalized and bilateral trust effects on patents among the samples of firms included in bilateral trust analyses. In Panel A, an inventor's country is inferred from his patent-listed address for non-US-based inventors; in Panel B, an inventor's country is additionally inferred from his last name for US-based inventors. In each panel, column (1) 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 Table 1's notes for further details). Columns (2)-(8) 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 Table 3's notes for further details). Columns (2) and (4) employ all observations such that firm f has patents by inventors from country c during 2000-2012. Column (3) includes only observations such that firm f has patents by inventors from country c in year $t+1$ (i.e., $pat_{fc,t+1} > 0$). Columns (5) and (6) employ only observations such that firm f has patents by inventors from country c *before* CEO d assumes position. Columns (7) and (8) employ only observations such that firm f has patents by inventors from country c *after* CEO d assumes position. The dependent variable in columns (4), (6), and (8) is a dummy indicating if firm f has patents by inventors from country c in year $t+1$ (i.e., $\mathbb{1}_{pat_{fc,t+1}>0}$). Standard errors are clustered by CEO's main ethnicity in columns (1) and by CEO's main ethnicity × inventor country in columns (2)-(8).
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table A13: Directions of CEO-Inventor Bilateral Trust

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

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	**arsinh(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)
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	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. All inventor bilateral trust sample

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	**arsinh(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 A14: Bilateral Trust Effect by Patent Quality

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

Notes: This table reports the heterogenous effects of CEO's bilateral trust on patents in different quality quartiles using equation (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 count with respect to its technology field × year cohort. Standard errors are clustered by CEO's main ethnicity × inventor country.

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

Table A15: Bilateral Trust Effect on Quality-Weighted Patents

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

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	arsinh(Future quality-weighted patents)					**arsinh**
Quality measure:	Forward cites	Backward NPL cites	Tech scope	Granted all	Granted USPTO	**(Average cites)**
CEO's bilateral trust	0.095**	0.053*	0.100***	0.040*	0.038*	0.063**
	(0.039)	(0.032)	(0.034)	(0.021)	(0.020)	(0.025)
Firm × Year FEs	X	X	X	X	X	X
CEO FEs	X	X	X	X	X	X
Inventor country FEs	X	X	X	X	X	X
Observations	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
Firms	730	730	730	730	730	730

Panel B. All inventor bilateral trust sample

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	arsinh(Future quality-weighted patents)					**arsinh**
Quality measure:	Forward cites	Backward NPL cites	Tech scope	Granted all	Granted USPTO	**(Average cites)**
CEO's bilateral trust	0.051***	0.046***	0.051***	0.023**	0.027**	0.032***
	(0.018)	(0.016)	(0.016)	(0.010)	(0.011)	(0.011)
Firm × Year FEs	X	X	X	X	X	X
CEO FEs	X	X	X	X	X	X
Inventor country FEs	X	X	X	X	X	X
Observations	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
Firms	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); granted patents (column 4); and USPTO patents (column 5). The dependent variable in column (6) is the inverse hyperbolic sine of the average forward citations per patent among patents filed by inventors from country c (in firm f) in year $t+1$ (or zero if inventors from country c in firm f have no patent application in year $t+1$). Standard errors are clustered by CEO's main ethnicity × inventor country.

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

Table 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 × Researcher quality	0.048***	0.034***	-0.000	0.015	0.031
(proxy, pre-transition period)	(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 2-digit SIC industry and year fixed effects (subsection 6.3) over the (-1, 0) 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, arsinh(R&D expenditure), and (ii) CEO's age, age squared, gender, education dummies, tenure in firm. Panel A interacts CEO's trust measure with firm-level proxy for pre-transition pool quality. Panel B interacts CEO's trust measure with researcher pool quality quintile dummies (computed based on firm-level proxy for pre-transition researcher pool quality). Standard errors are clustered by CEO's main ethnicity.
*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

A Conceptual framework 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:

$$\frac{\partial \bar{\pi}}{\partial b}\left[s^M + V^P\right] - \frac{\partial \bar{\pi}}{\partial b}\bar{\pi}\left[s^H - b + V^P\right] - \frac{\partial \bar{\pi}}{\partial b}(1-\bar{\pi})(s^L + DV^P) - \int_{\bar{\pi}}^1 \pi d\pi = 0 \tag{A2}$$

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

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 $\bar{\pi}$:

$$b = \frac{c+(1-D)V^A}{\bar{\pi}} - (1-D)V^A = \frac{c}{\bar{\pi}} + \left(\frac{1}{\bar{\pi}} - 1\right)(1-D)V^A, \tag{A4}$$

$$\frac{\partial \bar{\pi}}{\partial b} = \frac{c+(1-D)V^A}{(b+(1-D)V^A)^2} = \frac{\bar{\pi}^2}{c+(1-D)V^A}. \tag{A5}$$

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

$$\frac{\bar{\pi}^2}{c+(1-D)V^A}\left\{\bar{\pi}\left[\Delta_{HL} - \frac{c}{\bar{\pi}} - \left(\frac{1}{\bar{\pi}} - 1\right)(1-D)V^A\right] - \Delta_{ML}\right\} - \frac{1-\bar{\pi}^2}{2} = 0 \tag{A6}$$

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

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

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

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

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

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

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

Comparison with the baseline model. Recall from subsection 2.1 that in the baseline model when the CEO can credibly commit to tolerance of failure, he chooses so (i.e., $D = 1$) when his prior belief θ^P is above threshold $\bar{\theta}$ (equation 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 CEO's *ex ante* cutoff $\bar{\theta}$ takes into consideration $V_1^P(1) - V_1^P(0)$, the gain from optimal exploration in period 1 under $D = 1$, and therefore $\bar{\theta}$ is lower than his *ex post* cutoff $\bar{\theta}_{post}(\bar{\pi}^*(0))$, which does not internalize this gain.

As a result, for $\theta^P \in (\bar{\theta}, \bar{\theta}_{post}(\bar{\pi}^*(0)))$, without the capacity to commit, there always exists an equilibrium in which the CEO does not tolerate period 1's bad outcome (i.e., $D = 0$), even though it is *ex ante* optimal for him to do so (i.e., $D = 1$) (Proposition 4).[96] Furthermore, if it is also the case that $\bar{\theta} < \bar{\theta}_{post}(\bar{\pi}^*(1))$,[97] then for $\theta^P \in (\bar{\theta}, \bar{\theta}_{post}(\bar{\pi}^*(1)))$, this non-tolerant equilibrium is the unique equilibrium, and the CEO cannot at all implement the *ex ante* desirable policy of tolerance of failure. These problems are alleviated only if the CEO can credibly commit to his *ex ante* decision, as in the baseline model, or if he is high trusting with $\theta^P > \bar{\theta}_{post}$. This result implies that trust acts as a substitute for commitment.

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

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

B Data and sample 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.[98] 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,[99] 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.[100] This patent-to-firm linkage is based on a matching procedure implemented by the EPO and the OECD and is available as part of Orbis.[101] The matching between BoardEx-Compustat and Orbis firms is done via ISIN/CUSIP. I also manually check all cases in which (i) the matching is not one to one, or (ii) the company names in BoardEx/Compustat and Orbis do not match. In addition, I use Orbis' manual search function to look for BoardEx-Compustat firms that cannot be identified in Orbis using ISIN/CUSIP. This results in a close to full match (above 99%) and allows me identify all patent applications owned by the matched firms. As Orbis also contains information on firm's ownership structure, I additionally identify patent applications by subsidiaries that are above 50% owned by one of these firms.

Sample restriction. Finally, I exclude all firms in finance, insurance, and real estate (2-digit SIC codes between 60 and 67), as these industries make up a considerable share of the firm sample but traditionally do not patent their innovations. This results in a sample of 4,345 firms between 2000 and 2011 (Table A3), which yields a final baseline sample of 3,598 firms after conditioning on firms having at least one CEO (i) whose ethnic origins could be inferred from her last name, and (ii) whose data on gender, age, and education are non-missing (see appendix B.3).

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

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

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

[101] The matching is done based on the names and addresses of patent applicants on patent records, which are available from PATSTAT. In an UK setting, Dechezleprêtre et al. (2018) find that the matching quality is excellent with about 95% of UK and EPO patents being matched to their owning companies.

B.2 Patent and inventor data

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

Baseline patent counts. Each patent application to a patent office is uniquely identified in both PATSTAT and Orbis by its unique EPODOC application number. In addition to this identifier, PATSTAT reports a unique patent family indicator (DOCDB) which is the same for all patent applications (in different countries) related to the same invention. For the purpose of measuring innovation (i.e., to avoid double-counting inventions that are protected in several countries), I count all patent applications in the same family, irrespective of where they are filed, as one patent and assign this patent to its earliest application year. I only consider patents applications classified as "patent of invention" in PATSTAT, which are equivalent to USPTO's utility patents. The number of patent families filed by a firm (or a group of inventors in a firm) is my primary measure of innovation.[102] Between 2000 and 2012, 2,230 out of 3,598 baseline firms filed at least one patent, and together owned 1.8 million patent applications in 700,000 patent families over this period. In addition, I also construct alternative measures of innovation counting only patent families filed to or granted by the USPTO, which yields similar results (e.g., Table 5, Table A15).

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

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

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

al., 2017). In this paper, I use forward citation count to compute: (i) a patent's quality decile relative to its technology field by application year cohort (e.g., Figure 6, Table A14),[104] (ii) firm's quality-adjusted patent counts, and (iii) firm's average patent quality (e.g., Table 5, Table A15). Given that forward citations take time to accumulate, I restrict my sample to patents filed before 2012 to allow for sufficient time window to observe patents' forward citations.

Besides forward citations, I also employ a range of alternative patent quality measures, 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 share of "new citations" (i.e., citations to patents or works that have not been developed or cited by the firm in the past) by a patent measures the extent to which it is built on knowledge that is new to the firm. A patent is considered explorative if at least 90% of its citations are new, which cutoff corresponds to the 25% percentile in new citation share among the patents in my sample.
- Fourth, the value of a patent, computed by Kogan et al. (2017), measures a patent's monetary value to a firm from the firm's excess stock return on the patent's grant date. The data cover USPTO patents granted in 2011 or earlier, and therefore are comprehensive only for patents filed in 2008 or earlier.

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 these inventors are based in the same country, consistent with the interpretation that the patents are by overseas R&D labs of multinational firms. The 10 most common locations of those labs, based on their patent contributions, are (in order) Germany, Great Britain, India, Canada, Japan, China, France, Israel, Switzerland, and Italy.[105]

[104] 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.

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

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 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 C.1, 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 his position title, that is, if (i) it includes either one of the following phrases: *"CEO," "Chief Executive,"* or *"Principal Executive,"* and (ii) the phrase is not preceded by terms such as deputy, vice, division, group, regional, emeritus, etc. I verify if each firm has one CEO at a point in time, unless there are co/joint-CEOs, and manually check all exceptions. CEO transitions are inferred from the start and end dates of each CEO position.

CEOs' trust measures are computed from their ethnic origins as inferred from their last names (see subsection 3.2). I first map CEOs' last names to ethnic origins using the census-based last name-ethnic origin mapping detailed in appendix C.1. 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,[106] 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 is no significant difference 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

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

an MBA degree. I further supplement this classification with relevant information contained in CEOs' titles, such as "Doctor," "JD," or "MBA." The education variable is equal to the highest degree level a CEO has attained, and CEOs with no education information are dropped. BoardEx also provides data on CEOs' educational institutions, which allow me to identify if they have been educated abroad or in the US. Third, I use information on CEOs' employment history to impute their tenure in the respective firms, and to identify whether they have held an R&D related position prior to becoming the CEO. R&D-related positions are those whose title contains either one of the following words (or their derivations): "research," "innovation," "scientific," or "technology."

Table A8 employ special subsamples of CEO's 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 commonly-used retirement age in the related literature (e.g, Fee et al., 2013). In the data, I also observe a spike in CEO's leaving executive positions for good around 65. CEO's deaths are identified from CEO's year of death as provided by BoardEx. They could be unexpected or the result of long-term health decline. Given that there are very few CEO's deaths while still in position in my sample (only 34 cases), I do not further narrow them down to only sudden deaths as is the standard in the related literature (Nguyen and Nielsen, 2010; Bennedsen et al., 2010).

C Inherited trust and other cultural trait measures

C.1 Mapping last names to ethnic origins

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

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

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

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

While this mapping may seem coarse, the fact that the GSS's ethnic classification is designed to cover the most common ethnicities in the US implies that a large share (at least 80%) of foreign-

origin individuals in the censuses could be mapped to a GSS ethnic origin under the first step. On the other hand, the remaining ones still need to be accounted for systematically, as dropping them could introduce unwanted selection into the final last name-ethnic origin mapping. The exact correspondence between the census' country of origin and the GSS's ethnic origin classifications is available upon request.

79 million foreign-born individuals in the censuses share among them five million unique last names, the majority of which appear fewer than 10 times. To improve precision, I first filter out aberrant observations by dropping ethnic origins that occur less than 10% of the times for a given last name. I then consider only 75,000 last names that appear for at least 100 times in the remaining sample, which constitute 66% of this sample. The probabilistic mapping between last names and GSS ethnic origins is constructed from the resulting sample. Specifically, I compute w_{se}, the probability that a person with last name s is of ethnicity e as $w_{se} = \frac{n_{se}}{N_s}$, in which n_{se} is the number of individuals with last name s from ethnic origin e, and N_s is the total number of individuals with last name s in the sample. For example, based on this mapping, the last name Johnson is 78% Swedish and 22% Norwegian; the last name Smith is 32% English, 26% German, 24% Irish, and 18% Canadian.

This last name-GSS ethnic origin mapping is used to compute $trust_d$, the baseline CEO's inherited generalized trust measure, [107] as well as most other inherited cultural trait measures (details in appendix C.2). 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. Separately, dropping Canada as a possible ethnic origin also does not change the paper's key findings.

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

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

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

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

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

C.2 Other cultural trait and home-country variables

Similar to $trust_d$ (details in subsection 3.2), each other inherited cultural trait variable $trait_d$ is computed as $trait_d = \sum_e w_{de} \times ethtrait_e$, where $ethtrait_e$ is ethnicity e's average cultural trait measure and w_{de} is the probability that CEO d is of ethnicity e.

GSS-based variables. For those, (i) e runs over the GSS ethnic origins, (ii) $ethtrait_e$ is derived from GSS data, and (iii) w_{de} comes from the aforementioned last name-GSS ethnic origin mapping.

WVS-based variables. For those, (i) e runs over the WVS countries, (ii) $ethtrait_e$ is derived from WVS data, and (iii) w_{de} comes from the aforementioned last name-WVS country mapping.

GPS-based variables. For those, (i) e runs over the GSS ethnic origins, (ii) $ethtrait_e$ is derived from GPS data, and (iii) w_{de} comes from the aforementioned last name-GSS ethnic origin mapping.

Home-country macroeconomic variables. Each time-varying home-country variable h_{dt} is computed as $h_{dt} = \sum_e w_{de} \times h_{et}$ where (i) e runs over the GSS ethnic origins, (ii) h_{et} is the value of h in the home country of ethnicity e in year t, and (iii) w_{de} comes from the aforementioned last name-GSS ethnic origin mapping.

Sources and Constructions of Cultural Trait and Home-Country Variables

Variable	Appears (only) in	Source	Respondent sample	Lastname mapping
Baseline General Social Survey trust	Throughout paper	GSS	GSS respondents in prestigious occupations	Lastname-GSS
Full-sample GSS trust	Table 1, col. 6	GSS	All GSS respondents	Lastname-GSS
Alternative trust: Fair	Table A9, col. 1	GSS	GSS respondents in prestigious occupations	Lastname-GSS
Alternative trust: Helpful	Table A9, col. 2	GSS	GSS respondents in prestigious occupations	Lastname-GSS
Work ethic[(1)]	Table 2B, col. 2	GSS	GSS respondents in prestigious occupations	Lastname-GSS
High-income share[(1)]	Table 2B, col. 1	GSS	All GSS respondents	Lastname-GSS
Average occupation prestige	Table A9, col. 3	GSS	All GSS respondents	Lastname-GSS
Average schooling years	Table A9, col. 4	GSS	All GSS respondents	Lastname-GSS
College graduate share	Table A9, col. 5	GSS	All GSS respondents	Lastname-GSS
Protestant share	Table A9, col. 6	GSS	All GSS respondents	Lastname-GSS
Confidence in science	Table A9, col. 7	GSS	GSS respondents in prestigious occupations	Lastname-GSS
Confidence in Congress; Federal Government; Supreme Court	Table A9, col. 8	GSS	GSS respondents in prestigious occupations	Lastname-GSS
World Value Survey trust	Table 2, col. 7	WVS	Upper-middle-class WVS respondents[(2)]	Lastname-WVS
Global Preference Survey trust	Table A10, Panel A	GPS	High-skilled GPS respondents[(3)]	Lastname-GSS[(4)]
Risk preference[(1)]	Table 2B, col. 3; Table A10, col. 2	GPS	High-skilled GPS respondents[(3)]	Lastname-GSS[(4)]
Patience[(1)]	Table 2B, col. 4; Table A10, col. 3	GPS	High-skilled GPS respondents[(3)]	Lastname-GSS[(4)]
Positive reciprocity	Table A10, col. 4	GPS	High-skilled GPS respondents[(3)]	Lastname-GSS[(4)]
Negative reciprocity	Table A10, col. 5	GPS	High-skilled GPS respondents[(3)]	Lastname-GSS[(4)]
Altruism	Table A10, col. 6	GPS	High-skilled GPS respondents[(3)]	Lastname-GSS[(4)]
Home-country GPD (growth); population	Table 2A, col. 1	World Development Indicators		Lastname-GSS[(5)]
Home-country high-school graduate share	Table 2A, col. 2	Barro and Lee (2010)		Lastname-GSS[(5)]
Home-country governance quality	Table 2A, col. 3	World Governance Indicators		Lastname-GSS[(5)]
Home-country US trade volumne	Table 2A, col. 4	US Comtrade		Lastname-GSS[(5)]
Home-country patent applications	Table 2A, col. 5	PATSTAT		Lastname-GSS[(5)]

[(1)] These variables also appear together in Table 7, columns 4 and 7.
[(2)] Constructing WVS-based trust measure from *all* WVS respondents' answers yields quantitatively similar results.
[(3)] Constructing GPS-based cultural trait measures from *all* GPS respondents' answers yields quantitatively similar results.
[(4)] GPS data are collected for 76 countries, which cover most of the 36 GSS ethnic origins. Alternatively using country-level last name-GPS country mapping to construct GPS-based cultural trait measures yields quantitatively similar results.
[(5)] Home-country macroeconomic variables are available at country level and cover most of the 36 GSS ethnic origins. Alternatively using country-level last name-country mapping (similar to the last name-WVS country mapping) to construct these variables yields quantitatively similar results.

D Trust measurement error and bias

D.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.[108]

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

[108] 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,[109] 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.[110] 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 D.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.

D.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 $\hat{\beta}_{TE} = \frac{\text{Cov}(M.Y_{ft}, M.TEth_{ct})}{\text{Var}(M.TEth_{ct})}$, with the firm-demeaning linear operator $M.X_{ft} = X_{ft} - \mathbb{E}_t(X_{ft}|f)$ for each firm f. Also observe that:

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

[109] 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.

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

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

The bias' sign is that of $-\text{Cov}(\mathbb{E}(\epsilon_{dt}|c), TEth_{ct})$, or the opposite of the covariance across countries between ethnic-based inherited trust, and individual survey measurement errors. It is likely negative if, for example, high-trust countries' respondents tend to push their answers higher than the true level of trust, and low-trust countries' respondents tend to lower theirs. There is a technical reason to expect this pattern: Surveyed trust TS_i is a yes-no answer, which naturally exaggerates the variation in the individual trust component T_i. For example, two individuals' beliefs at 60% and 40% will map into two opposite answers of value 1 and 0, respectively.[111] Consequently, the estimator $\hat{\beta}_{TE}$ likely underestimates the true effect of individual CEO's trust on innovation.

[111] 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.

E Framework for separating different mechanisms

E.1 Proof of Proposition 3

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

$$\frac{\partial Y}{\partial \mu} = N\left[f\left(\frac{c_2-\mu}{\sigma}\right)\left(\frac{-1}{\sigma}\right) - f\left(\frac{c_1-\mu}{\sigma}\right)\left(\frac{-1}{\sigma}\right)\right], \tag{A11}$$

$$\frac{\partial Y}{\partial \sigma} = N\left[f\left(\frac{c_2-\mu}{\sigma}\right)\left(-\frac{c_2-\mu}{\sigma^2}\right) - f\left(\frac{c_1-\mu}{\sigma}\right)\left(-\frac{c_1-\mu}{\sigma^2}\right)\right]. \tag{A12}$$

Recall the assumptions from subsection 6.1 that better quality patents are always rarer (i.e., $f'(x)$ is decreasing on $[0, \infty)\ \forall\ T$). This assumption implies that $f\left(\frac{c_2-\mu}{\sigma}\right) < f\left(\frac{c_1-\mu}{\sigma}\right)$ as $c_1 < c_2$. As a result, $\frac{\partial Y}{\partial \mu}$ in expression (A11) is positive, indicating that higher $\mu(T)$ increases the number of patents within any quality range $[c_1, c_2] \subset [0, \infty)$. On the other hand, expression (A12) does not have an unambiguous sign: while $f\left(\frac{c-\mu}{\sigma}\right)$ is decreasing in c over the $[c_1, c_2]$ interval, $c-\mu$ is always increasing in c.

E.2 Patent quality under mean-preserving spread

Proposition 3 suggests that it is possible to identify the mechanism at work (i.e., through $\mu(T)$ or $\sigma(T)$) under conditions that warranty $\frac{\partial Y}{\partial \sigma} < 0$, namely, for ranges of c where $f\left(\frac{c-b}{\sigma}\right)\left(\frac{c-\mu}{\sigma^2}\right)$ is increasing in c. This condition is quite easy to satisfy for small c, at least among distributions in the exponential family, such that when c is small, $f\left(\frac{c-\mu}{\sigma}\right)$ decreases less fast than $c-\mu$ increases. The following proposition illustrates a special case:

Proposition 5 *Let's consider the family of normal distribution* $\frac{x-\mu(T)}{\sigma(T)} \sim \mathcal{N}(0,1)$ *and assume that* $\mu'(T) = 0$ *(i.e., no mean-shifting mechanism at work). Higher* $\sigma(T)$ *decreases the count of patents of quality within any range* $[c_1, c_2] \subset [0, \mu + \sigma(T)]$.

The proposition's statement is equivalent to $\frac{\partial Y}{\partial \sigma}$ in expression (A12) being negative, itself equivalent to $f\left(\frac{c-\mu}{\sigma}\right)\left(\frac{c-\mu}{\sigma^2}\right)$ being increasing in c over the $[c_1, c_2]$ interval. This happens when its derivative with respect to c: $\frac{1}{\sigma^2}\left[\frac{1}{\sigma}f'\left(\frac{c-\mu}{\sigma}\right)(c-\mu) + f\left(\frac{c-\mu}{\sigma}\right)\right]$, is nonnegative. When f is a standard normal distribution density, it is equivalent to $-\frac{1}{\sigma^2}(c-\mu)^2 + 1 \geq 0 \Leftrightarrow |c-\mu| \leq \sigma$, satisfied over $c \in [0, \mu + \sigma(T)]$.