The Human Factor in AI: Evidence on CEO Big Five Traits and Firm AI Patenting*

Yilun Lu

University of Texas at Arlington

College of Business

August 8, 2025

Abstract

This study investigates how CEO personality traits influence firm-level artificial intelligence (AI) innovation, focusing specifically on the Big Five personality dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Utilizing a comprehensive dataset spanning from 2001 to 2023, I document that CEO conscientiousness consistently suppresses AI innovation, while CEOs exhibiting higher levels of agreeableness and neuroticism significantly foster greater AI innovation outcomes. Importantly, the positive effects of agreeableness and neuroticism are not driven by an early-tenure burst of collaboration or anxiety-fueled experimentation, nor does the negative effect of conscientiousness fade as routines solidify.

Keywords: CEO personality traits, Big Five traits, Artificial intelligence, AI innovation, Firm innovation

JEL classification: G30, O30, D91, M12

*I am grateful to Joseph Harrison for providing the CEO personality traits data and Michael Woeppel for valuable guidance on the patent data.

1. Introduction

General purpose technologies (GPTs) such as electricity, semiconductors, and the Internet have repeatedly upended competitive landscapes and ignited long-run growth cycles (Bresnahan and Trajtenberg, 1995). Artificial intelligence (AI) is widely viewed as the most recent GPT because it combines near unlimited scalability with continuous improvements in prediction, recognition, and decision support algorithms (Cockburn et al., 2019; Goldfarb et al., 2023). Capital market research already shows that AI inventions command sizeable valuation premia (Chen et al., 2024) and can reshape firm growth paths (Babina et al. 2024). Yet the diffusion of AI is far from automatic: unlike earlier GPT waves that relied primarily on physical assets, modern AI systems depend critically on human judgment to source data, tune models, and integrate outputs into products.

A substantial body of research underscores the influence of CEO personality traits on various corporate outcomes, including acquisitive deal making (Aabo et al., 2023), strategic risk taking (Benischke et al., 2019), sustainability performance (Venugopal et al., 2023), and firm innovation (Galasso and Simcoe, 2011; Hirshleifer et al., 2012; You et al., 2020). However, prior studies that focus on CEO personality and firm innovation almost exclusively examine general R&D or patenting. Whether and how CEO traits matter specifically for AI innovation remains unexplored, representing a critical omission given the distinctive features of AI. To address this gap, I link text-based measures of CEO Big Five traits (Harrison et al., 2020) to three complementary proxies of AI innovation: the quantity of AI-related patents (AIPAT), their quality measured through forward citations (AICITAT), and the stock market-implied value of these patents (AIMV). The results are striking. Among the Big Five CEO personality traits, I find that only three traits affect firms' entry into the AI revolution. Higher CEO conscientiousness consistently reduces AI innovation, whereas greater agreeableness and neuroticism increase it.

These effects persist even after CEOs have led the firm for five or more years. In highly competitive industries, the negative impact of conscientiousness and the positive impact of agreeableness intensify, while the neuroticism premium largely evaporates. According to Chen et al. (2024), investors place higher valuations on AI innovations compared to conventional innovations, noting that AI patents command a 9% valuation premium and generate approximately 26% more forward citations than non-AI patents within the same patent classification and industry group. These distinct valuation characteristics suggest that factors driving AI innovation could significantly differ from those influencing general innovation, thus making this research imperative.

This study aims to make several important contributions by showing that who leads the firm shapes how it participates in the AI revolution. First, I integrate GPT economics with upper echelons theory, demonstrating that leadership psychology is a significant driver of technological diffusion. Second, whereas prior research on AI has primarily focused on its direct impacts on corporate processes, customer interactions, operational efficiencies (Huang and Rust, 2018; Loureiro et al., 2021), or stock market outcomes (Zhang et al., 2024), this paper is among the first to systematically explore the drivers behind firms' AI innovation, offering a foundational understanding of managerial determinants specific to AI. Third, the findings translate directly into actionable guidance for boards, investors, and policymakers. Boards that hope to compete on AI should scrutinize leadership psychology as carefully as financial incentives: moving from a highly conscientious to a more agreeable or neurotic chief executive is beneficial for firm AI innovation. Asset managers can incorporate these trait effects when valuing intangible growth options, since firms led by “AI-friendly” personalities systematically generate intellectual property that commands a valuation premium. For policymakers, the results highlight an often

overlooked lever for national AI competitiveness: leadership supply. Initiatives that broaden the pipeline of technologically curious, collaborative executives can accelerate the diffusion of general-purpose AI technologies.

The remainder of the paper proceeds as follows. Section 2 reviews the literature on CEO personality and innovation and develops hypotheses for each Big Five trait in the context of AI. Section 3 describes sample construction, variable definitions, and the empirical design. Section 4 presents the main results, a battery of robustness and endogeneity checks, and analyses of moderating factors. Section 5 discusses the implications of the findings and concludes.

2. Literature Review and Hypothesis Development

McCrae and John (1992) integrate extensive lexical and psychometric evidence to delineate five comprehensive and independent dimensions of personality—Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (OCEAN). Collectively, these dimensions provide a robust framework for analyzing individual differences in decision-making behaviors within financial contexts. The OCEAN framework has gained prominence in psychological research, particularly within studies examining leadership traits and their organizational implications (Judge et al., 2002).

Openness to experience encompasses a broad and deep engagement with cognitive and sensory experiences, highlighting curiosity, aesthetic appreciation, and preference for novelty. Beyond intellectual dimensions, openness also includes emotional sensitivity and the ability to embrace diverse experiences (McCrae and John, 1992). This trait manifests positively in workplace settings, particularly regarding leadership effectiveness and adaptive behaviors during organizational transitions (Judge et al., 1999; Judge et al., 2002). Bono and Judge (2004) highlight that open leaders excel in intellectual stimulation and inspiring motivation, displaying imagination, challenging established norms, and crafting visionary organizational futures.

Research indicates that CEOs who score high on openness foster corporate cultures emphasizing innovation and strategic adaptability (Nadkarni and Herrmann, 2010; O'Reilly et al., 2014). Extending these insights specifically to the context of AI, CEOs exhibiting openness may similarly champion the adoption and advancement of AI-driven initiatives, due to their receptiveness to innovative ideas and technologies.

H1: Greater CEO openness to experience is positively associated with firm AI innovation.

Conscientiousness is characterized by disciplined self-regulation, cautiousness, reliability, and deliberate decision-making (McCrae & John, 1992). Highly conscientious individuals typically demonstrate controlled behavior and aversion to risks (Goldberg, 1990). Consistent with these traits, conscientiousness negatively impacts adaptability and strategic flexibility, often constraining leaders from embracing innovative opportunities and impeding their openness to change (LePine et al., 2000; Nadkarni and Herrmann, 2010). Conscientious leaders tend to resist innovation, adhere rigidly to established protocols, and focus excessively on detail-oriented tasks at the expense of broader strategic objectives (Hogan and Hogan, 2001; Judge et al., 2009). Specifically, conscientious CEOs display narrower cognitive perspectives and selective information processing, potentially undermining innovation initiatives (Nadkarni and Herrmann, 2010). Le et al. (2011) further caution that excessive conscientiousness can lead to organizational rigidity and hinder adaptive behaviors critical for innovation. Given these established insights, conscientious CEOs might similarly exhibit reluctance in embracing transformative AI innovations.

H2: CEO conscientiousness is negatively associated with firm AI innovation.

Extraversion describes individuals with high levels of sociability, positive emotional expression, and assertiveness. These individuals typically exhibit high energy, enthusiasm, and proactive social engagement, contrasted with introverts who are typically reserved and contemplative (McCrae and John, 1992). Although extraverted individuals might sometimes display overly bold and assertive behaviors that inflate self-assessment and dominance (Hogan & Hogan, 2001; Judge et al., 2009; McCrae & John, 1992), these traits can positively drive ambitious organizational objectives and proactive strategic moves (Judge et al., 2002; Bono and Judge, 2004). Extraverted CEOs often demonstrate enhanced flexibility and a greater propensity to initiate strategic shifts (Nadkarni and Herrmann, 2010). Such CEOs typically invest more heavily in uncertain but potentially rewarding endeavors such as research and development or acquisitions (Malhotra et al., 2018; Benischke et al., 2019). Extending these findings, it is plausible that extraverted CEOs may proactively pursue AI initiatives, viewing these projects as opportunities to assert competitive leadership and strategic advantage.

H3: CEO extraversion is positively associated with firm AI innovation.

Agreeableness encompasses traits such as altruism, cooperation, and trustworthiness, reflecting a predisposition toward harmonious interpersonal interactions. In contrast, antagonism manifests as skepticism, hostility, and self-interest (McCrae and John, 1992). Agreeable leaders tend to cultivate cooperative work environments and demonstrate positive interpersonal dynamics (Barrick et al., 2002). This collaborative orientation reflects a core belief in the value of hard work, a perspective that is positively linked to career advancement (Holland et al., 1993). However, agreeableness may sometimes foster environments less oriented toward aggressive competition or innovation-driven results, given agreeable individuals' modesty and collaborative

orientation, traits not consistently associated with forceful leadership or dynamic organizational performance (O'Reilly et al., 2014; Goldberg, 2013). Harrison et al. (2020) suggest that agreeableness poses evaluative challenges, complicating accurate assessments of its organizational impact. Indeed, empirical investigations by Kaplan et al. (2012) report no significant association between agreeableness-related traits and subsequent performance in CEOs of private equity-funded firms. Similarly, Aabo et al. (2024) predict a negative relationship between CEO agreeableness and strategic flexibility but find no significant support for this link. Extending these mixed results to AI innovation contexts, I test the null hypothesis that there is no significant relationship between CEO agreeableness and firm AI innovation.

H4: CEO agreeableness is not significantly associated with firm AI innovation.

Neuroticism involves a persistent tendency to experience negative emotions such as anxiety, depression, irritability, and self-consciousness. High levels of neuroticism correlate with emotional instability, whereas lower levels correspond to calmness and emotional resilience (McCrae and John, 1992). Traditionally, neuroticism is linked to risk aversion and negative emotional reactions; however, contemporary research argues it may have beneficial implications within creative and innovative contexts. Nettle (2006) proposes that neuroticism enhances anticipatory capacities, facilitating achievement-driven behavior in highly competitive environments, especially when complemented by high intelligence. Particularly relevant to rapidly evolving technological landscapes, neurotic CEOs, driven by anxiety about competitive threats or technological obsolescence, might proactively engage with emerging technologies such as AI to preempt competitive disadvantages and safeguard their firm's strategic positioning.

H5: CEO neuroticism is positively associated with firm AI innovation.

3. Empirical Design

3.1. Sample Construction and Data Source

The data utilized in this study span fiscal years from 2001 to 2023, comprising a total of 5,356 firm-year observations. The sample period starts from 2001 due to the availability of updated CEO personality traits data from Harrison et al. (2019), which begins in that year. I obtain institutional ownership data from FactSet 13F and all other firm characteristics from Compustat. CEO education data come from BoardEx, while other CEO control variables such as age, gender, tenure, salary, bonus, and incentives are collected from ExecuComp.

Patent data come from Stoffman et al. (2022) and are merged with The Artificial Intelligence Patent Dataset (AIPD), initially released by the United States Patent and Trademark Office (USPTO) in 2021 (Giczy et al., 2022) and later updated by Pairolero et al. (2025). The study period concludes in 2023, coinciding with the latest available preprocessed patent citation data from the USPTO (Stoffman et al., 2022) and the updated AIPD data, both ending in 2023.

Following standard practices, I exclude financial institutions identified by four-digit Standard Industrial Classification (SIC) codes ranging from 6000 to 6999, owing to their distinct accounting and financial attributes. Firms from utility industries (SIC codes 4900–4999) are also excluded due to their unique regulatory and operational characteristics.

The AIPD employs machine learning models to classify patents across eight distinct AI technological components: natural language processing (ai_score_nlp), AI hardware (ai_score_hardware), machine learning (ai_score_ml), computer vision (ai_score_vision), speech (ai_score_speech), knowledge processing (ai_score_kr), evolutionary computation (ai_score_evo), and planning and control (ai_score_planning). For each AI component, the dataset provides a prediction score between 0.0 and 1.0, indicating the probability that a patent

pertains to that specific AI technology. I label a patent as AI-related if it surpasses a threshold of 50 percent probability in at least one of these eight AI categories.

3.2. AI Innovation Measure

3.2.1. AI Patents Count and Citation Weighted AI Patent Count

Using patent data might incur certain selection biases. Many inventions never satisfy the substantive or procedural requirements of the USPTO, and firms sometimes elect trade secrecy or other appropriation strategies in lieu of formal patent protection (Hall, Jaffe, and Trajtenberg, 2001). Consequently, patent data might capture only a subset of true inventive output. Despite these drawbacks, patents constitute the most systematic and publicly accessible indicator of firm-level technological advances (Griliches, 1990). Unlike R&D expenditures, which capture only monetary inputs and do not account for qualitative factors such as managerial effort, project prioritization and internal incentive schemes, patent measures more directly reflect realized inventive outcomes and therefore reduce concerns about measurement error (Ben-Nasr et al., 2021). Indeed, recent studies increasingly endorse patents as credible signals of innovation intensity and originality (Graham and Hegde, 2015; Sunder et al., 2017; Stoffman et al. 2022).

In line with Ben-Nasr et al. (2021), Hall et al. (2001), and Zhang et al. (2024), I construct two firm-year measures of AI innovation based on patenting activity. The first metric, $AIPAT_{i,t}$, captures the AI-related patents granted to firm *i* in year *t* and prior years:

$$AIPAT_{i,t} = \underbrace{PAT_{i,t}}_{current\ grants} + 0.8\,PAT_{i,t-1} + 0.6\,PAT_{i,t-2} + 0.4\,PAT_{i,t-3} + 0.2\,PAT_{i,t-4} \quad (1)$$

where $PAT_{i,t-k}$ is the number of AI-related patents granted to firm *i* in year *t-k*. This weighted sum places greater emphasis on more recent inventions and yields a smoother measure of a firm's patenting momentum. However, a shortcoming of this measure is that it is a simple count of the number of patent and falls short of capturing the importance of the innovation. To capture the value of these inventions, I next form a citation-weighted counterpart:

$$AICITAT_{i,t} = \underbrace{CITAT_{i,t}}_{\substack{citations\ to \\ patents\ granted \\ in\ year\ t}} + 0.8\ CITAT_{i,t-1} + 0.6\ CITAT_{i,t-2} + 0.4\ CITAT_{i,t-3} + 0.2\ CITAT_{i,t-4} \quad (2)$$

where $CITAT_{i,t-k}$ denotes the number of forward citations received by AI patents granted in year *t-k*. To mitigate skewness and improve interpretability, both the weighted patent-count and the citation-weighted patent count are converted into log-levels by taking the natural logarithm of one plus each series.

3.2.2. Stock Market Value of AI Patents

Following Kogan et al. (2017) and Stoffman et al. (2022), I construct a stock market value of AI-related innovations (AIMV) at the firm-year level. In essence, stock price reactions to patent grant announcements reveal investors' assessment of an innovation's value to the firm. Unlike simple patent counts or citation-based indices, this market-driven measure reflects the anticipated economic impact of a patent.

The idiosyncratic stock return *R* of firm *i* on the grant date of patent *j* comes from two components: (i) the percent value impact of the patent (as a fraction of firm *i*'s market capitalization), denoted by R_j, and (ii) a noise term ε_j capturing unrelated price movements. Intuitively, if a patent is very valuable, the firm's stock should jump by γ_j% upon grant approval;

if the stock move R_j is smaller or mixed with noise, investors only partially learn the patent's value.

$$R_j = \gamma_j + \varepsilon_j \tag{3}$$

To extract the dollar value of patent *j*, I scale the return impact by the firm's market capitalization and adjust for two factors: multiple simultaneous patent grants and the probability of patent success.

$$\zeta_j = (1 - \Theta)^{-1} \frac{1}{N_{t_j}} E[\gamma_j | R_j] \, M_j \tag{4}$$

where ζ_j is the estimated economic value of patent *j*, M_j is the market capitalization of firm *i* on the day before the patent announcement, $E[\gamma_j | R_j]$ is the expected value of the patent's payoff given the observed stock return signal R_j, and Θ denotes the unconditional grant probability. The factor $\frac{1}{N_{t_j}}$ apportions the stock return impact across multiple patents if the firm receives more than one grant on the same day.

To compute $E[\gamma_j | R_j]$, a Bayesian model updating framework is adopted. I assume that the patent's value fraction γ_j is distributed as truncated normal $\mathcal{N}^+(0, \sigma^2_{\gamma,i,t_j})$ (limited to $\gamma_j \geq 0$), and the noise term is distributed as $\varepsilon_j \sim \mathcal{N}\left(0, \sigma^2_{\varepsilon,i,t_j}\right)$. These distribution parameters are allowed to vary by firm *i* and time t_j to reflect differences in innovation volatility and market uncertainty. Under these assumptions, the conditional expectation can be derived in closed form as:

$$E[\gamma_j|R_j] = \Lambda_{i,t_j} R_j + \sqrt{\Lambda_{i,t_j}}\sigma_{\varepsilon,i,t_j} \frac{\phi\left(-\sqrt{\Lambda_{i,t_j}}\frac{R_j}{\sigma_{\varepsilon,i,t_j}}\right)}{1-\Phi\left(-\sqrt{\Lambda_{i,t_j}}\frac{R_j}{\sigma_{\varepsilon,i,t_j}}\right)} \tag{5}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal probability density and cumulative distribution functions, respectively, and Λ_{i,t_j} is the signal-to-noise ratio defined as:

$$\Lambda_{i,t_j} = \frac{\sigma^2_{\gamma,i,t_j}}{\sigma^2_{\gamma,i,t_j} + \sigma^2_{\varepsilon,i,t_j}} \tag{6}$$

The remaining estimation procedure of the parameters σ^2_{γ,i,t_j} and $\sigma^2_{\varepsilon,i,t_j}$ follows exactly Stoffman et al. (2022), with the signal-to-noise ratio varying over time but remaining constant across firms (i.e., $\Lambda_{i,t_j} = \Lambda_{t_j}$).

AIMV is defined as the natural logarithm of one plus the total CPI-adjusted dollar value of AI-related patent grants received by firm *i* in year *t*:

$$AIMV_{i,t} = \ln\left(1 + \sum_{j \epsilon P_{i,t}} \zeta_j^{CPI}\right) \tag{7}$$

where ζ_j^{CPI} is ζ_j deflated to 1982 million dollars using the CPI, and $j \epsilon P_{i,t}$ denotes all AI-related patents granted to firm *i* in year *t*.

3.3. Big Five Personality Traits

To capture CEOs' underlying dispositions, I adopt the validated, language-based measure of the Big Five personality traits developed by Harrison et al. (2019). This approach focuses exclusively on the unscripted Q&A segments of quarterly earnings calls—where questions from analysts are unpredictable and thus more likely to elicit authentic CEO responses (Malhotra et al., 2018; Green et al., 2019). Transcripts of the unscripted Q&A segments of quarterly earnings calls are sourced from LexisNexis Full Disclosure Wire, and only those CEOs appearing in at least three calls and speaking a minimum of 1,000 words per call are retained. The optimized models are applied to the full corpus to produce, for each CEO, five continuous trait estimates on a scale from one (extremely low) to seven (extremely high).

Note that Harrison et al. (2019, 2020) adopt a dynamic approach to quantifying CEO personality, whereas the traditional literature in personnel psychology treats Big Five traits as stable, time-invariant dispositions. For example, Judge et al. (2002) conceptualize these traits as enduring antecedents of leadership effectiveness, while earlier work by Judge and Bono (2000) links static trait measures to transformational leadership behaviors. To reconcile these perspectives, I calculate executive-level mean values of the trait estimates from Harrison et al. (2019) to construct invariant trait measures. This aggregated, time-invariant metric enables a clear separation of inherent personality dispositions from their temporal fluctuations.

3.4. Control Variables

To isolate the effect of CEO personality traits on firm AI innovation, I control for various CEO and firm characteristics identified in prior literature as influential determinants of corporate innovation. Firm-specific control variables include firm size (natural log of total assets), profitability measures (ROA), and book leverage (ratio of total debt to total assets). I also capture strategic investment intensity through capital expenditure and the ratio of property, plant, and

equipment to total assets. Industry competition is proxied by the Herfindahl Hirschman Index (HHI), and ownership structure is measured by institutional ownership, defined as the proportion of shares held by institutions.

Following You et al. (2020), I include several CEO specific controls that cover demographics (age; education; gender), experience (tenure), and compensation. Specifically, CEO age is measured as the natural log of CEO age. CEO education is an indicator variable taking the value of 1 if the CEO holds a master's or doctoral degree and 0 otherwise. CEO gender is an indicator variable taking the value of 1 if the CEO is female and 0 otherwise. CEO tenure is operationalized as the natural log of one plus the number of months the CEO has held the position. Compensation structure is represented by two variables: salary and bonus, measured as the proportion of these components relative to total compensation, and CEO incentives, calculated as the ratio of stock options (both exercisable and unexercisable) and restricted stock holdings to total compensation.

4. Results

4.1. Descriptive Statistics

Table 1, Panel A presents an overview of the distribution by year and industry. Observations per year peak at 317 in 2009 and gradually decline afterward. The reduced number of observations in recent years is primarily due to limited availability of updated CEO characteristics rather than constraints on AI patent data. This is consistent with trends reported by Sunder et al. (2017). A further reason for the drop in observations particularly in 2022 and 2023 is that the updated, time-variant CEO trait data provided by Harrison et al. (2019) only covers executives up to 2021. Consequently, new CEOs appointed after 2021 are not represented when extending the sample through 2023. From an industry perspective, my sample primarily

comprises firms from business equipment (1,672 firm-years, 31%), manufacturing (1,137 firm-years, 21%), and health (658 firm-years, 12%). These sectors tend to be highly active in AI patenting, aligning with previous findings that companies operating in high-tech, pharmaceutical, and resource-intensive industries are generally more innovative than firms in other sectors (Grullon et al., 2012).

Table 1 Panel B reports descriptive statistics for the main variables in my analysis, with detailed definitions presented in Appendix A. The average logged AI patent count (AIPAT) is 2.873, indicating considerable variation (standard deviation of 2.050), consistent with substantial heterogeneity in AI innovation intensity. The forward citation-weighted AI patent count (AICITAT) averages at 4.676, revealing an even greater variation, highlighting that patent quality varies substantially across firms. The AI innovation market value (AIMV) has a mean of 2.012 and exhibits pronounced skewness, with median at zero, underscoring that a significant number of firms do not produce AI innovations with substantial immediate market value, while a subset achieves notable breakthroughs. CEO personality characteristics, captured by the Big Five traits, also display meaningful variations. On average, CEOs in my sample exhibit high levels of agreeableness (mean 4.565), extraversion (mean 4.512), and conscientiousness (mean 4.282), moderate openness (mean 4.178), and relatively low neuroticism (mean 2.900). The results are in line with Harrison et al. (2019) and Aabo et al. (2024).

Figure 1 illustrates the variation of CEO Big-Five personality traits across different industries based on the Fama-French 12 industry classifications (excluding Finance and Utilities). Openness is highest in telecommunication (median just below 5) and shows the largest upper tail in business equipment, indicating a subset of especially exploratory leaders. Conscientiousness peaks in energy, telecommunication and shops, while business equipment

posts the lowest median values. Extraversion exhibits limited variation, with interquartile ranges below 0.5 points, although median values are elevated in shops and health. Agreeableness clusters tightly around 4.5 across sectors but displays noticeably lower medians in energy and telecommunication. Neuroticism remains low overall (median ≈ 3), yet dispersion widens in energy. Taken together, these clear sectoral differences illustrated in Figure 1 underscore the necessity of incorporating industry fixed effects in the regression analysis.

Turning to the time-series dynamics, Figure 2, Panel A shows that both AIMV and AIPAT rise monotonically, with AIMV approximately doubling from 2001 to 2023. A prominent kink appears in 2012 and 2016, coinciding with the 2012 ImageNet deep-learning breakthrough that triggered a wave of corporate AI adoption. This pattern aligns with Babina et al. (2024), who document an increased demand for AI-skilled employees, evidenced by rising AI-related job postings and employee resumes highlighting AI skills during this timeframe. Panel B of Figure 2 documents that the increase in AI innovation displays an intuitive distribution across industries. Business Equipment and Health sectors dominate AI patent production, reflecting their strategic emphasis on leveraging AI. However, untabulated results confirm that nearly all sectors experienced notable growth in AI innovation post-2016, supporting the argument that AI increasingly functions as a general-purpose technology (Goldfarb et al., 2023).

4.2. Baseline Regression Results

Table 2 presents results from the baseline regressions examining the relationship between CEO personality traits and firm-level AI innovation, measured through three distinct proxies: AI patent count (Column 1), citation-weighted AI patent count (Column 2), and stock market value of AI patents (Column 3). The results highlight three key CEO personality traits as significant determinants of AI innovation: conscientiousness, agreeableness, and neuroticism. CEO

conscientiousness negatively impacts innovation, significant at the 1% level across all measures. A coefficient of -0.468 in Column 1 implies that a one-standard-deviation increase in conscientiousness (0.721, Table 1) corresponds to approximately a 28.6% (computed as $e^{-0.468*0.721} - 1$) reduction in AI patent quantity. Similarly, Columns 2 and 3 show that a one-standard-deviation increase in conscientiousness leads to reductions of 33% and 24.3% in citation-weighted patent output and patent market value, respectively. These results indicate substantial economic significance.

Conversely, CEO agreeableness and neuroticism exhibit strong positive associations with AI innovation. A one-standard-deviation increase in agreeableness boosts patent quantity by roughly 16% and patent quality by 26%, while neuroticism enhances the same outcomes by approximately 13% and 29%, respectively. Both traits also significantly elevate the stock market value of AI patents. The positive coefficients suggest that agreeable CEOs may foster collaborative environments, effectively leveraging team-based knowledge networks. Neurotic CEOs, driven by anxiety over competition and technological obsolescence, appear more likely to proactively invest in innovative AI technologies.

Interestingly, the effects of CEO openness and extraversion are not statistically significant. Despite the intuitive expectation that openness promotes innovation through creative thinking and exploration of novel ideas, my results show no meaningful relation to AI patenting outcomes. Similarly, extraversion, associated with social dominance and charisma, also shows no discernible impact. These null results imply that these traits alone may be insufficient drivers of innovation within a broader multi-industry AI context.

Regarding control variables, firm size and capital expenditures positively relate to innovation outcomes, while high leverage and asset tangibility negatively affect innovation,

consistent with constraints arising from financial structure and asset rigidity. Additionally, female CEOs significantly enhance the market value of AI innovations, underscoring the potential benefits of executive diversity for innovation. Finally, compensation structure matters: a higher salary and bonus share curbs innovation, whereas equity-based incentives marginally increase patent value, emphasizing the importance of aligning managerial pay with long-run technological goals.

4.3. Endogeneity Concerns

4.3.1. Control for Time-Varying Industry Effects

Table 3 addresses the possibility that the baseline results are spuriously driven by industry-level shocks that evolve over time. Following Ren et al. (2021), I augment the benchmark specification with a full set of two-way fixed effects that interact the Fama-French industry codes with calendar year dummies, thereby purging the estimates of any time-varying heterogeneity common to firms operating in the same industry. The significant CEO personality traits (conscientiousness, agreeableness, and neuroticism) from the baseline regressions retain their statistical and economic significance under these stringent controls. The magnitudes of coefficients are only modestly attenuated relative to Table 2, and all three traits retain significance at the 5 % level (most at the 1 % level). These findings confirm that the documented relationships are not an artefact of contemporaneous industry trends, but instead reflect robust links between CEO personality and firm-level AI innovation.

4.3.2. Difference-in-Differences Analysis

Table 4 presents the results from the difference-in-differences (DID) analysis examining how CEO trait transitions influence firm-level AI innovation. Following Huang and Kisgen

(2013), I utilize a DID framework centered around CEO turnover events. Specifically, the analysis examines the innovation outcomes in a three-year window before and after CEO transitions, comparing firms experiencing transitions from low to high trait CEOs (treatment group) with those maintaining stable CEO traits (control group). I estimate the following DID model.

$$AI_Innovation_{it} = \beta_0 + \beta_1(Transition_i * Post_t) + \beta_2 Transition_i + \beta_3 Post_t + \gamma \boldsymbol{X}_{it} + Firm\ FE + Year\ FE + \varepsilon_{it} \quad (8)$$

where $AI_Innovation_{it}$ represents three distinct innovation outcomes for firm *i* at time *t*: (1) AI patent count, (2) citation weighted AI patent count, and (3) stock market value of AI related patents. The main variable of interest is the interaction term $Transition_i * Post_t$, capturing the effect of transitioning from a low-trait CEO (bottom tercile) to a high-trait CEO (top tercile) on AI innovation, compared to firms experiencing no significant trait transition (low-trait to low-trait). The dummy variable $Transition_i$ equals one for treated firms and zero otherwise, while $Post_t$ equals one for the years following the CEO transition. Firm and year fixed effects control for time-invariant firm characteristics and macroeconomic shocks, respectively, while $\boldsymbol{X}_{it}$ represents a full vector of controls used in the baseline regressions.

The estimated results are reported in Columns 1 to 3 of Table 4. Consistent with the baseline evidence, greater conscientiousness is innovation-suppressing: when a highly methodical CEO replaces a less conscientious one, AI patent output falls by roughly 23 to 38 percent ($\approx e^{\beta_1} - 1$). Higher agreeableness and neuroticism propels AI innovation.

I further consider the second case: the treatment group includes firms that change from high-trait CEOs to low-trait CEOs, and control groups are firms with low-trait CEOs before and after the transition. The estimated results are reported in Columns 4–6. Every focal trait flips sign exactly as expected. Conscientiousness, which negatively impacts AI innovation in Columns 1–3, now enters with a positive and statistically significant coefficient. There are also stronger economic magnitudes, as the absolute values of the coefficients on conscientiousness in Columns 4–6 are much larger than those in Columns 1–3. This asymmetry suggests that the beneficial impact of shifting to a less conscientious CEO (relaxing rigid managerial controls) on AI innovation is substantially stronger than the detrimental impact of moving toward a highly conscientious CEO. In contrast, while agreeableness and neuroticism also reverse signs as anticipated, their magnitudes remain more balanced across transitions.

4.3.3. Reverse Causality

A primary concern in studies examining CEO personality traits and firm outcomes is the issue of reverse causality. Specifically, innovative firms may preferentially hire CEOs with certain personality traits perceived to enhance innovative potential, such as agreeableness or neuroticism. In this context, my earlier results linking CEO traits with firm-level AI innovation might suffer from such reverse causality if firms deliberately select CEOs to match existing innovation strategies.

To address this concern directly, Table 5 presents analyses employing a time-variant measure of CEO personality traits. I utilize the CEO personality traits from the earliest available year for each CEO within the original Harrison et al. (2019) dataset, which concludes in 2021. Evidently, CEO traits in the earliest year could not have resulted from a firm's AI innovation in

any of the subsequent years. Thus, if I find that CEO traits in the earliest year are related to firm AI innovation, it is much more likely that causality runs from CEO traits to AI innovation than vice versa.

Results in Table 5 confirm the baseline findings, emphasizing conscientiousness, agreeableness, and neuroticism as robust determinants of AI innovation outcomes. CEO conscientiousness measured at the earliest year consistently exhibits a negative and highly significant impact on all three innovation proxies. A one-unit increase in early measured conscientiousness corresponds to decreases in AI innovation, with coefficients of -0.393, -0.559, and -0.507 across these innovation metrics, respectively. Conversely, agreeableness and neuroticism measured at the earliest year demonstrate positive and statistically significant relationships with innovation outcomes. A one-unit increase in agreeableness is linked with increases in AI patent output and quality, with respective coefficients of 0.232 (AIPAT) and 0.184 (AICITAT), as well as enhanced market value of AI patents (0.159). Similarly, early-measured neuroticism positively impacts AI innovation, with robust coefficients of 0.371 (AIPAT) and 0.701 (AICITAT), albeit slightly weaker effects on AIMV (0.257).

4.4. CEO tenure and AI innovation

Upper echelons theory recognizes that a chief executive's influence on firm strategy is not static but evolves through identifiable "seasons" of tenure. Hambrick and Fukutomi (1991) argue that new CEOs initially enter a "response to mandate" phase marked by limited knowledge and low internal power. To overcome this legitimacy deficit, CEOs tend to pursue high-variance innovation projects, as they have strong incentives to signal competence quickly while routines are still malleable. Finance evidence confirms that this "honeymoon of experimentation" generates a measurable spike in real corporate actions. Pan et al. (2016) suggest that early-tenure

CEOs treat capital allocation as an adaptive search process, making them more likely to pay attention to the quality of investments and less likely to overinvest.

To address the concern that the observed relationships between CEO personality traits and AI innovation may reflect dynamics associated with tenure length rather than the traits themselves, I re-examine the baseline regressions using progressively longer-tenured CEO subsamples (Table 6). If the positive effects of agreeableness and neuroticism were driven by an early-tenure burst of collaboration or anxiety-fuelled experimentation, and if the negative effect of conscientiousness faded as routines solidify, coefficients should drift toward zero (or even reverse) once the CEO has steered the firm for four or five years. However, results from the subsample analyses consistently show that the negative effect of conscientiousness and the positive effects of agreeableness and neuroticism remain robust, statistically significant, and economically meaningful even for CEOs with tenure of five years or more. The persistence of these patterns after the typical assimilation window eliminates concerns that tenure-related dynamics, rather than enduring personality, drive AI patenting outcomes.

4.5. Moderating effects of industry competition

Product market competition fundamentally shapes firms' innovation incentives and managers' decision latitude. Moderate competition spurs innovation, as firms seek to innovate to "escape competition" when rival pressure intensifies (Aghion et al., 2005). However, extremely high competition can also undermine innovation by eroding profit margins and available slack resources. Aghion et al. (2005) document an inverted-U relationship between competition and innovation, showing that competition initially encourages innovation among neck-and-neck firms, but beyond a point, further competition discourages innovation, especially among laggard

firms. Moreover, a fiercely competitive environment imposes short-term performance pressure on firms. In high-competition industries, managers must focus on efficiency and immediate survival rather than indulging personal strategic preferences (Chen and Steinwender, 2021). This implies that in highly competitive settings, firms will tend to converge on similar strategic behaviors, such as racing to innovate or cutting costs to survive, potentially leaving less room for CEO personality to make a distinctive impact on AI innovation outcomes. I thus examine this moderating role of industry competition on CEO personality traits by introducing interaction terms between traits and an indicator variable, IndComp, defined as one if the industry Herfindahl–Hirschman Index is below the 25th percentile in a given year.

In Table 7, Column 1 of each panel reports the full-sample regression that contains the interaction terms. Across all three innovation measures CEO conscientiousness is again negative, whereas agreeableness and neuroticism are positive; however, both conscientiousness and agreeableness display significant interactions with IndComp while neuroticism does not. This indicates that the distinctive influence of a neurotic personality is washed out under high competition. When splitting the sample by competition intensity, coefficients on neuroticism reported in Column 2 (low-competition industries) remain consistently significant at the 1% level, considerably stronger than those in Column 3 (high-competition industries), corroborating the interaction findings. By comparison, coefficients on conscientiousness become more negative, and coefficients on agreeableness become more positive in Column 3 relative to Column 2, consistent with their significant interaction terms in Column 1 and suggesting stronger influences of CEO conscientiousness and agreeableness traits on AI innovation in highly competitive industries. Altogether, these findings suggest that industry competition does

not uniformly weaken the influence of CEO personality; rather, it functions as a contextual filter that intensifies some personality-driven effects while diminishing others.

5. Conclusion

This paper provides novel insights into the intersection of leadership psychology and technological innovation, specifically addressing how CEO Big Five personality traits influence firm-level AI innovation. Using a comprehensive sample from 2001 to 2023, I identify distinct and economically significant patterns connecting CEO conscientiousness, agreeableness, and neuroticism to AI innovation outputs. My findings robustly demonstrate that conscientious CEOs systematically exhibit reduced AI innovation, whereas CEOs high in agreeableness and neuroticism significantly enhance firms' AI innovation efforts. These relationships persist beyond potential tenure-related effects and remain resilient across various endogeneity checks, including the DID analyses around CEO transitions and reverse causality tests employing the original time-variant personality traits sample.

Further examination reveals that industry competition substantially moderates these personality effects. In highly competitive sectors, the negative impact of conscientiousness on AI innovation intensifies, suggesting that excessive managerial discipline becomes increasingly counterproductive under pressure-driven environments. At the same time, the positive influence of agreeableness grows stronger, underscoring the value of cooperative leadership in dynamic competitive landscapes. Interestingly, the neuroticism premium largely dissipates under heightened competitive pressure, possibly reflecting reduced managerial discretion in highly constrained strategic environments.

These findings carry important implications for boards, investors, and policymakers. Boards aiming to lead or sustain AI-driven innovation should weigh CEO personality alongside

conventional financial and strategic factors, emphasizing the recruitment of leaders with collaborative and adaptive psychological profiles. Investors can better evaluate firm innovation prospects by factoring CEO personality traits into assessments of intangible asset valuation, particularly in innovation-intensive industries. For policymakers focused on enhancing national technological competitiveness, nurturing a diverse pipeline of adaptable and collaborative executives could provide a substantial strategic advantage in diffusing AI technologies across industries.

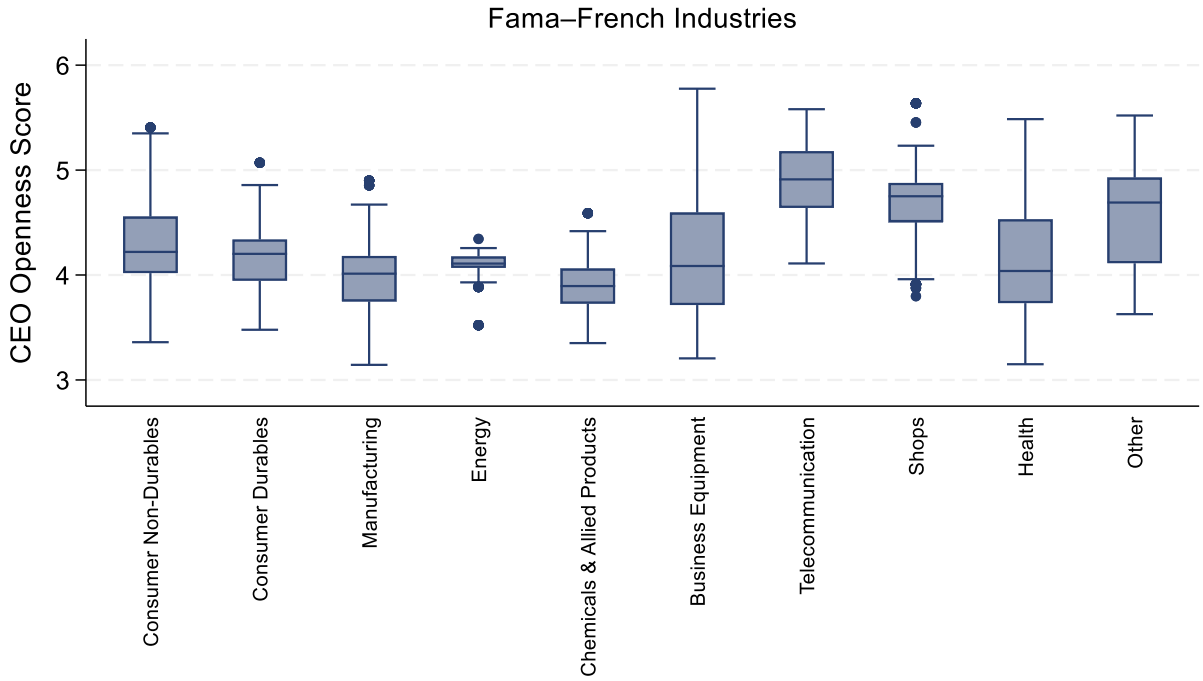
Table 1
Descriptive statistics.

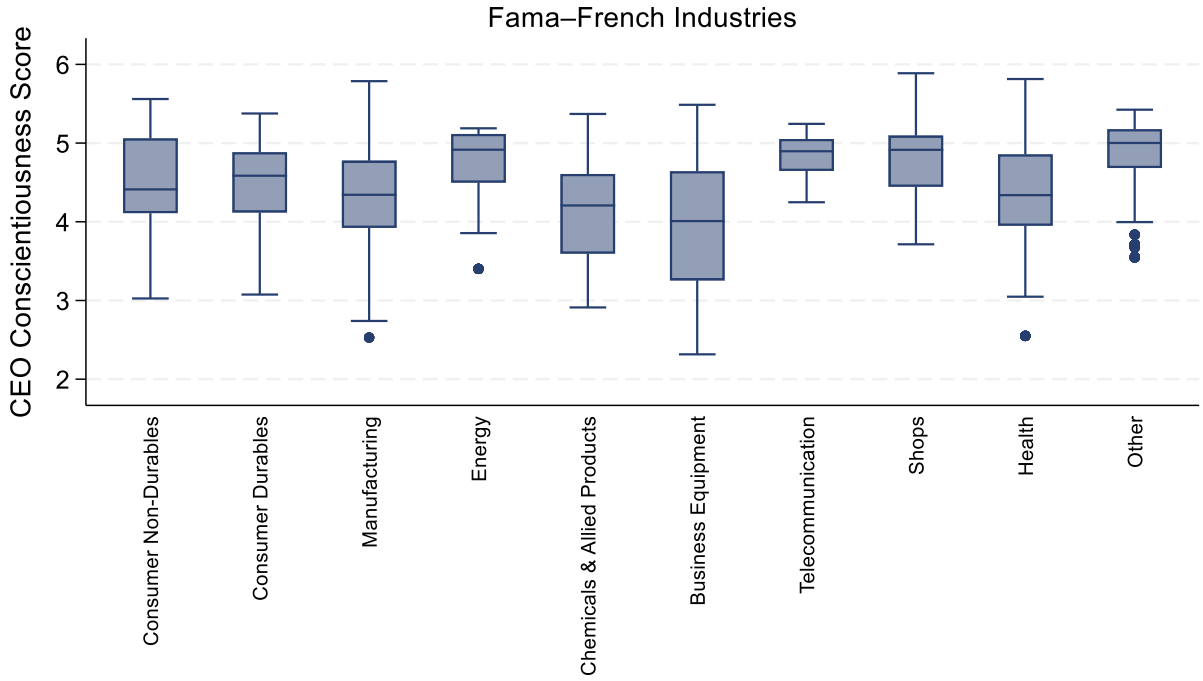
Panel A: Sample distribution			
Year	# of observations	Industry	# of observations
2001	210	Consumer non-durables	367
2002	238	Consumer durables	309
2003	253	Manufacturing	1,137
2004	251	Energy	153
2005	242	Chemicals	267
2006	243	Business equipment	1,672
2007	272	Telecommunication	112
2008	293	Shops	296
2009	317	Health	658
2010	299	Other	385
2011	316	Total	5,356
2012	304		
2013	299		
2014	297		
2015	258		
2016	237		
2017	217		
2018	203		
2019	177		

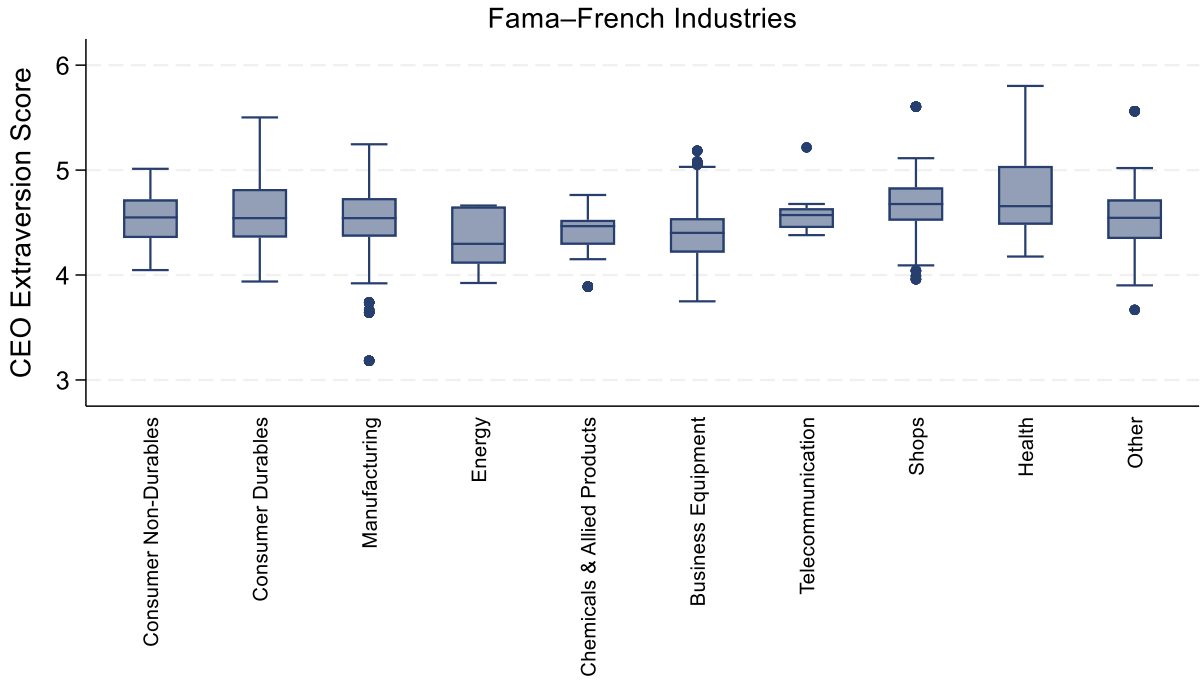
2020	154
2021	121
2022	96
2023	59

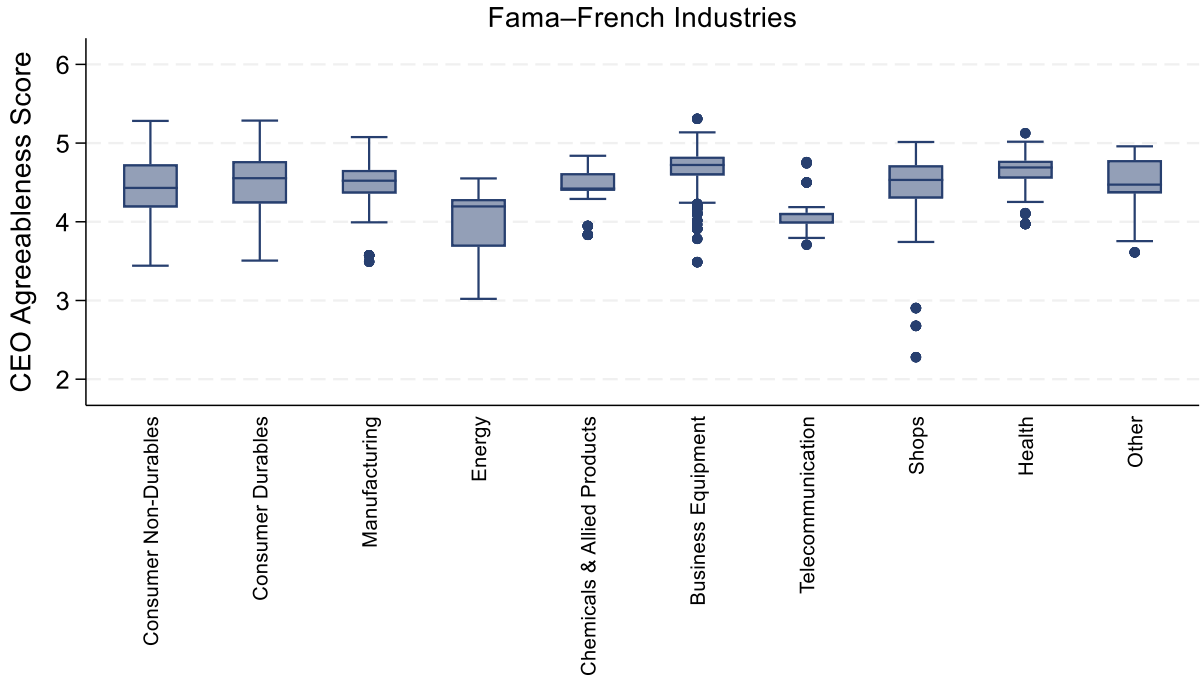
Panel B: Summary statistics

	Mean	**Std. Dev.**	**10th**	**25th**	**Median**	**75th**	**90th**
Innovation Variables							
AIPAT	2.873	2.050	0	1.099	2.845	4.299	5.583
AICITAT	4.676	2.927	0	2.595	5.029	6.790	8.300
AIMV	2.012	2.546	0	0	0	3.756	5.944
CEO Characteristics							
CEO openness	4.178	0.487	3.543	3.830	4.123	4.531	4.841
CEO conscientiousness	4.282	0.721	3.152	3.792	4.428	4.870	5.100
CEO extraversion	4.512	0.306	4.119	4.316	4.498	4.702	4.902
CEO agreeableness	4.565	0.300	4.157	4.416	4.620	4.776	4.888
CEO neuroticism	2.900	0.302	2.562	2.688	2.850	3.055	3.300
CEO age	53.665	7.230	44.000	49.000	54.000	59.000	63.000
CEO gender	0.040	0.196	0.000	0.000	0.000	0.000	0.000
CEO education	0.719	0.449	0.000	0.000	1.000	1.000	1.000
CEO tenure	121.158	85.934	41.002	64.033	100.435	149.290	224.690
CEO salary and bonus	0.295	0.240	0.081	0.124	0.214	0.386	0.650
CEO incentives	1.831	3.563	0.000	0.186	0.641	1.866	4.185
Firm Characteristics							
Size	7.646	1.715	5.473	6.369	7.591	8.843	9.966
ROA	0.032	0.129	-0.083	0.011	0.053	0.092	0.139
CapEx	0.037	0.031	0.010	0.017	0.028	0.047	0.076
PPE	0.190	0.158	0.045	0.077	0.139	0.249	0.405
Book Leverage	0.504	0.246	0.181	0.321	0.497	0.653	0.813
HHI	0.256	0.203	0.070	0.119	0.188	0.316	0.569
IO	0.760	0.189	0.502	0.677	0.807	0.899	0.952


Fama–French Industries
CEO Openness Score
6
5
4
3
Consumer Non-Durables
Consumer Durables
Manufacturing
Energy
Chemicals & Allied Products
Business Equipment
Telecommunication
Shops
Health
Other


Fama–French Industries
CEO Conscientiousness Score
6
5
4
3
2
Consumer Non-Durables
Consumer Durables
Manufacturing
Energy
Chemicals & Allied Products
Business Equipment
Telecommunication
Shops
Health
Other


Fama–French Industries
CEO Extraversion Score
6
5
4
3
Consumer Non-Durables
Consumer Durables
Manufacturing
Energy
Chemicals & Allied Products
Business Equipment
Telecommunication
Shops
Health
Other


Fama–French Industries
CEO Agreeableness Score
6
5
4
3
2
Consumer Non-Durables
Consumer Durables
Manufacturing
Energy
Chemicals & Allied Products
Business Equipment
Telecommunication
Shops
Health
Other

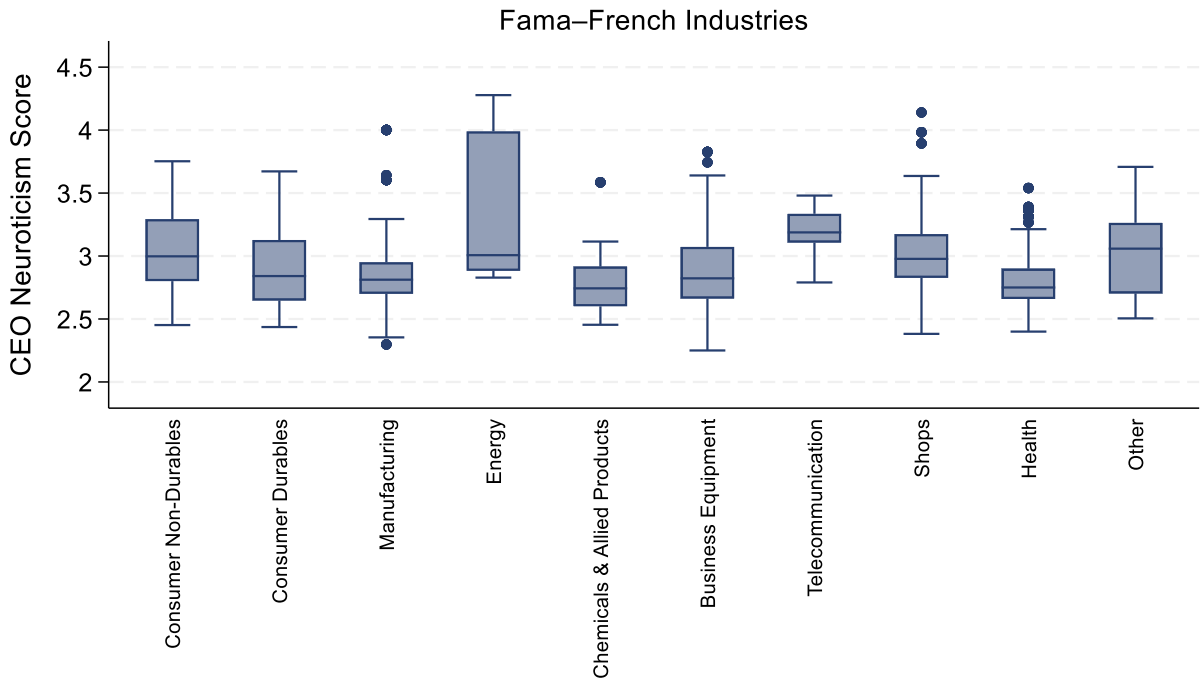


Fig.1. CEO Big Five Trait Scores by Industry Sector.

This figure reports the median, minimum, maximum, and standard deviation of CEO Big Five Trait Scores for the Fama-French 12 industries (excluding Finance and Utilities).

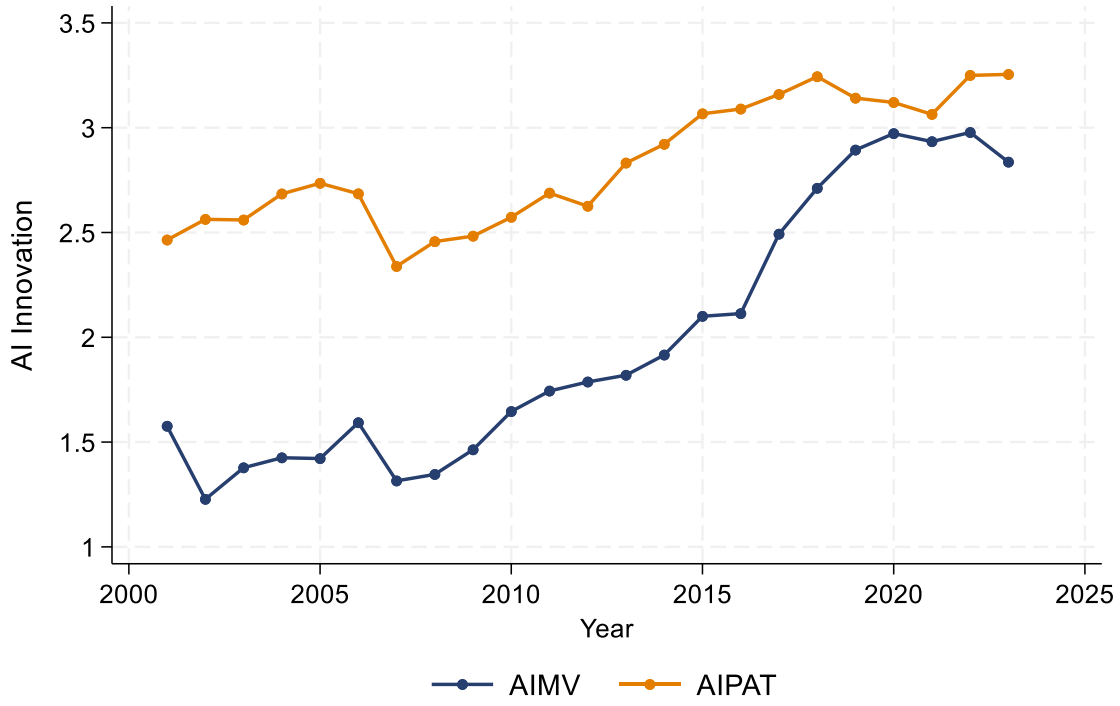


Fig.2. Panel A: Time Series of AI Innovation.

Panel A shows the annual mean value of the two measures of AI Innovation (AIMV / AIPAT) for all sample firms between 2001 and 2023.

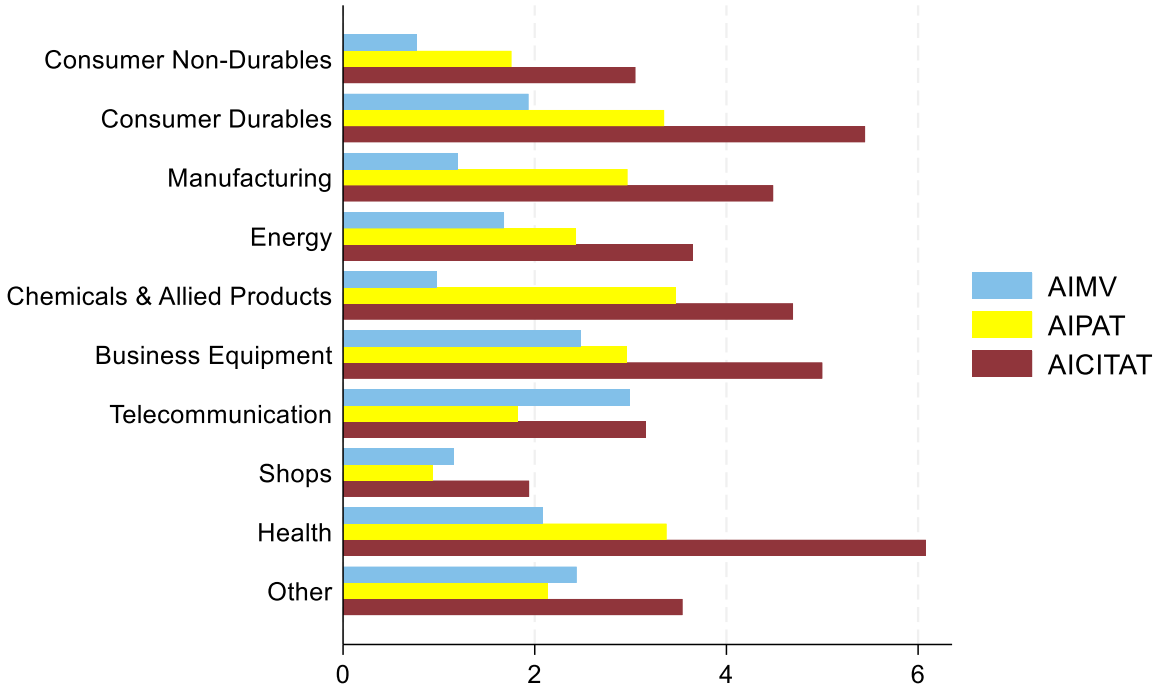


Fig.2. Panel B: AI Innovation by Industry Sector.

Panel B displays the average AI innovation intensity for each of the 12 Fama–French industries (excluding Finance and Utilities), pooled across the full sample period.

Table 2

Relation between CEO personality traits and patenting activities.

Standard errors are clustered at the year level and t- statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) AIPAT	(2) AICITAT	(3) AIMV
CEO openness	-0.124	-0.265	0.072
	(-1.647)	(-1.700)	(0.553)
CEO conscientiousness	-0.468***	-0.556***	-0.387***
	(-11.919)	(-7.122)	(-5.330)
CEO extraversion	-0.064	0.053	-0.079
	(-0.719)	(0.358)	(-0.621)

CEO agreeableness	0.492***	0.770***	0.422**
	(4.998)	(3.852)	(2.483)
CEO neuroticism	0.412***	0.833***	0.435***
	(5.605)	(4.484)	(3.323)
Log(CEO age)	0.043	-0.101	-0.209
	(0.252)	(-0.388)	(-1.257)
CEO gender	0.087	0.051	0.258***
	(1.223)	(0.365)	(3.231)
CEO education	-0.035*	-0.119***	-0.056
	(-1.782)	(-4.619)	(-1.565)
Log(1+ tenure)	-0.103***	-0.047	-0.163***
	(-4.981)	(-1.066)	(-6.847)
CEO salary and bonus	-0.344***	-0.801***	-0.278**
	(-3.026)	(-5.221)	(-2.437)
CEO incentives	-0.057**	-0.030	0.041*
	(-2.727)	(-0.981)	(1.970)
Size	0.679***	0.744***	0.979***
	(51.233)	(40.627)	(53.635)
ROA	-0.015	-0.080	0.347
	(-0.070)	(-0.299)	(1.565)
CapEx	3.773***	6.885***	7.494***
	(3.353)	(3.822)	(6.180)
PPE	-2.864***	-4.238***	-4.520***
	(-12.280)	(-10.896)	(-20.208)
Book Leverage	-0.262**	-0.301*	-0.490***
	(-2.263)	(-1.827)	(-4.799)
HHI	0.465***	0.565***	0.094
	(3.383)	(4.417)	(0.669)
IO	-0.762***	-1.025***	-1.332***
	(-3.324)	(-3.096)	(-5.498)
Constant	-1.599	-1.511	-3.604**
	(-1.268)	(-0.677)	(-2.352)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Observations	5,356	5,356	5,356
R^2 or Pseudo R^2	0.487	0.447	0.502

Table 3

Control of time-varying industry effects.

This table builds on the baseline model by including an additional control for time-varying industry effects (Columns 1-3). t- statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
VARIABLES	AIPAT	AICITAT	AIMV
CEO openness	-0.218**	-0.391**	-0.041
	(-2.026)	(-2.434)	(-0.323)
CEO conscientiousness	-0.416***	-0.501***	-0.343***
	(-5.620)	(-4.521)	(-3.939)
CEO extraversion	-0.114	0.013	-0.159
	(-1.086)	(0.081)	(-1.282)
CEO agreeableness	0.424***	0.633***	0.331**
	(3.636)	(3.627)	(2.414)
CEO neuroticism	0.395***	0.809***	0.473***
	(3.186)	(4.356)	(3.244)
Constant	-0.433	0.140	-2.100
	(-0.362)	(0.078)	(-1.493)
Controls	Yes	Yes	Yes
Industry FE	No	No	No
Year FE	No	No	No
Industry*Year FE	Yes	Yes	Yes
Observations	5,356	5,356	5,356
R-squared	0.529	0.485	0.553

Table 4

AI innovation around CEO transitions.

This table presents regression results examining how transitions in CEO personality traits influence firm innovation outcomes. Columns 1 to 3 focus on transitions from CEOs with low scores on a given trait to successors with high scores. Columns 4 to 6 analyze transitions in the opposite direction, from high to low scores. The "Post" variable captures firm innovation activity

during the three years following the CEO transition. All regressions include firm fixed effects, year fixed effects, and control variables. t- statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%, respectively.

	Transition from low to high			Transition from high to low		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	AIPAT	AICITAT	AIMV	AIPAT	AICITAT	AIMV
By CEO openness						
Transition*Post	0.323**	0.373**	0.048	-0.405*	-0.431	-0.025
	(2.520)	(2.005)	(0.180)	(-1.941)	(-1.301)	(-0.067)
By CEO conscientiousness						
Transition*Post	-0.267**	-0.298*	-0.484*	0.441*	1.111**	1.279***
	(-2.132)	(-1.653)	(-1.955)	(1.683)	(2.533)	(2.611)
By CEO extraversion						
Transition*Post	0.252	0.460**	0.535*	-0.408***	-0.539**	0.301
	(1.521)	(2.111)	(1.741)	(-2.732)	(-2.196)	(1.132)
By CEO agreeableness						
Transition*Post	0.312**	0.291*	0.922***	-1.044***	-1.266***	-0.714**
	(2.251)	(1.874)	(3.172)	(-5.237)	(-5.083)	(-2.031)
By CEO neuroticism						
Transition*Post	0.281*	0.372*	1.441**	-0.718*	-0.952*	-0.612*
	(1.720)	(1.753)	(2.014)	(-1.820)	(-1.691)	(-1.724)

Table 5

CEO personality traits and AI innovation (time-variant trait sample).

This table investigates potential reverse causality by utilizing CEO personality traits measured at their earliest available year, treating personality traits as time-variant measures from the original dataset by Harrison et al. (2019), which concludes in 2021. All regressions include industry fixed

effects, year fixed effects, and control variables. t- statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) AIPAT	(2) AICITAT	(3) AIMV
CEO openness (earliest year)	-0.067	0.026	0.184
	(-0.866)	(0.208)	(0.991)
CEO conscientiousness (earliest year)	-0.393***	-0.559***	-0.507***
	(-11.741)	(-10.198)	(-4.185)
CEO extraversion (earliest year)	0.112	0.015	0.217*
	(1.099)	(0.094)	(2.026)
CEO agreeableness (earliest year)	0.232***	0.184*	0.159*
	(2.880)	(1.893)	(1.739)
CEO neuroticism (earliest year)	0.371***	0.701***	0.257*
	(4.323)	(8.544)	(1.893)
Constant	0.362	2.917*	0.803
	(0.383)	(1.929)	(0.919)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,064	3,064	3,064
R-squared	0.478	0.444	0.486

Table 6

CEO tenures and AI innovation.

This table presents regression results examining the impact of CEO personality traits on firm-level AI innovation outcomes for subsets of CEOs based on tenure length. Panel A includes CEOs with tenures of at least three years, Panel B focuses on CEOs with tenures of at least four years, and Panel C covers CEOs with tenures of at least five years. Standard errors are clustered at the year level and t- statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
VARIABLES	AIPAT	AICITAT	AIMV
Panel A: CEO tenures ≥3 years			
CEO openness	-0.115	-0.236	0.052
	(-1.676)	(-1.520)	(0.419)
CEO conscientiousness	-0.459***	-0.547***	-0.412***
	(-11.283)	(-6.255)	(-5.252)
CEO extraversion	-0.102	0.018	-0.049
	(-1.100)	(0.109)	(-0.364)
CEO agreeableness	0.512***	0.841***	0.465**
	(4.912)	(3.961)	(2.347)
CEO neuroticism	0.378***	0.845***	0.469***
	(5.340)	(5.152)	(3.586)
Constant	-1.307	-1.929	-4.040**
	(-1.066)	(-0.836)	(-2.335)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4,981	4,981	4,981
R-squared	0.483	0.446	0.493

Panel B: CEO tenures ≥4 years			
CEO openness	-0.158**	-0.348**	0.084
	(-2.546)	(-2.345)	(0.598)
CEO conscientiousness	-0.393***	-0.433***	-0.416***
	(-11.275)	(-5.023)	(-4.688)
CEO extraversion	-0.187**	-0.035	-0.000
	(-2.124)	(-0.204)	(-0.003)
CEO agreeableness	0.487***	0.770***	0.555**
	(4.455)	(3.346)	(2.653)
CEO neuroticism	0.416***	0.890***	0.621***
	(4.940)	(0.297)	(4.208)
Constant	-1.460	-2.414	-4.651**
	(-0.895)	(-0.791)	(-2.222)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4,656	4,656	4,656
R-squared	0.494	0.452	0.502
Panel C: CEO tenures ≥5 years			
CEO openness	-0.215***	-0.308*	0.084
	(-3.106)	(-1.862)	(0.612)
CEO conscientiousness	-0.369***	-0.434***	-0.396***
	(-8.398)	(-4.458)	(-4.001)
CEO extraversion	-0.164*	-0.089	0.007
	(-1.793)	(-0.548)	(0.052)
CEO agreeableness	0.401***	0.608***	0.496**
	(4.759)	(3.310)	(2.730)
CEO neuroticism	0.434***	0.830***	0.438***

	(6.896)	(6.097)	(3.159)
Constant	-1.630	-2.178	-5.195***
	(-1.229)	(-0.840)	(-2.920)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4,204	4,204	4,204
R-squared	0.489	0.442	0.478

Table 7

The moderating effects of industry competition.

This table examines whether industry competition moderates the impact of CEO Big-Five personality traits on firm-level AI innovation. The dependent variables are the natural log of AI patent applications (Panel A), citation-weighted AI patents (Panel B), and market value of AI patents (Panel C). Industry competition (IndComp) equals one if a firm's industry Herfindahl–Hirschman Index (HHI) is below the 25th percentile of its annual distribution, indicating a highly competitive environment, and zero otherwise. Standard errors are clustered at the year level and t- statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%, respectively.

Panel A: AIPAT			
		IndComp=0	IndComp=1
VARIABLES	(1)	(2)	(3)
CEO openness	-0.166**	-0.112	1.097***
	(-2.572)	(-1.307)	(5.200)
CEO conscientiousness	-0.262***	-0.321***	-1.565***
	(-5.486)	(-4.970)	(-16.598)
CEO extraversion	-0.364***	-0.316***	0.274
	(-4.233)	(-3.971)	(1.712)

CEO agreeableness	0.252*	0.284*	0.983***
	(1.885)	(2.009)	(4.928)
CEO neuroticism	0.446***	0.600***	0.415*
	(3.620)	(4.352)	(1.832)
IndComp	-6.386***		
	(-4.644)		
CEO openness* IndComp	0.271		
	(1.417)		
CEO conscientiousness* IndComp	-0.932***		
	(-7.804)		
CEO extraversion* IndComp	0.950***		
	(5.170)		
CEO agreeableness* IndComp	0.963***		
	(4.804)		
CEO neuroticism* IndComp	0.239		
	(0.921)		
Constant	-0.204	-0.391	-6.509***
	(-0.135)	(-0.280)	(-4.415)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,356	4,073	1,283
R-squared	0.503	0.480	0.690
Panel B: AICITAT			
		IndComp=0	IndComp=1
VARIABLES	(1)	(2)	(3)
CEO openness	-0.377**	-0.350*	1.568***
	(-2.690)	(-1.869)	(5.777)

CEO conscientiousness	-0.286***	-0.291**	-2.269***
	(-3.022)	(-2.320)	(-21.255)
CEO extraversion	-0.356**	-0.336**	0.711***
	(-2.531)	(-2.389)	(2.823)
CEO agreeableness	0.483**	0.536**	1.717***
	(2.156)	(2.144)	(4.931)
CEO neuroticism	0.913***	1.182***	0.677**
	(3.886)	(4.450)	(2.418)
IndComp	-9.500***		
	(-4.157)		
CEO openness* IndComp	0.579**		
	(2.145)		
CEO conscientiousness* IndComp	-1.237***		
	(-8.261)		
CEO extraversion* IndComp	1.387***		
	(5.358)		
CEO agreeableness* IndComp	1.276***		
	(4.081)		
CEO neuroticism* IndComp	0.205		
	(0.514)		
Constant	0.256	-0.314	-9.137**
	(0.108)	(-0.136)	(-2.774)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,356	4,073	1,283
R-squared	0.461	0.445	0.642

Panel C: AIMV

		IndComp=0	IndComp=1
VARIABLES	(1)	(2)	(3)
CEO openness	0.069	0.255**	0.998**
	(0.621)	(2.413)	(2.583)
CEO conscientiousness	-0.178**	-0.299***	-1.472***
	(-2.190)	(-3.309)	(-7.782)
CEO extraversion	-0.240*	-0.287**	0.209
	(-1.846)	(-2.287)	(1.068)
CEO agreeableness	0.185	0.247	0.592**
	(1.017)	(1.377)	(2.292)
CEO neuroticism	0.427**	0.593***	0.612*
	(2.580)	(3.563)	(2.057)
IndComp	-2.481		
	(-1.210)		
CEO openness* IndComp	0.125		
	(0.469)		
CEO conscientiousness* IndComp	-0.931***		
	(-4.806)		
CEO extraversion* IndComp	0.336		
	(1.643)		
CEO agreeableness* IndComp	0.795**		
	(2.745)		
CEO neuroticism* IndComp	0.277		
	(0.753)		
Constant	-2.845	-4.072**	-3.576*
	(-1.475)	(-2.296)	(-1.891)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Year FE	Yes	Yes	Yes
Observations	5,356	4,073	1,283
R-squared	0.513	0.829	0.533

Appendix A.

Variable Descriptions.

Variables	Description	Source
Innovation Variables		
AIPAT	Natural log of one plus the time-decayed sum of AI-related patents granted to a firm in a year.	Stoffman et al. (2022)
AICITAT	Natural log of one plus the time-decayed sum of forward citations to AI-related patents granted to a firm in a year.	Stoffman et al. (2022); USPTO
AIMV	Natural log of one plus the CPI-adjusted dollar value of AI-related patents granted to a firm in a year.	Stoffman et al. (2022)
CEO Characteristics		
CEO openness	Continuous score (1 = extremely low to 7 = extremely high) capturing the CEO's openness via a validated text-analysis of unscripted earnings-call Q&A.	Harrison et al. (2019)
CEO conscientiousness	Continuous score (1 = extremely low to 7 = extremely high) capturing the CEO's conscientiousness via a validated text-analysis of unscripted earnings-call Q&A.	Harrison et al. (2019)
CEO extraversion	Continuous score (1 = extremely low to 7 = extremely high) capturing the CEO's extraversion via a validated text-analysis of unscripted earnings-call Q&A.	Harrison et al. (2019)
CEO agreeableness	Continuous score (1 = extremely low to 7 = extremely high) capturing the CEO's agreeableness via a	Harrison et al. (2019)

	validated text-analysis of unscripted earnings-call Q&A.	
CEO neuroticism	Continuous score (1 = extremely low to 7 = extremely high) capturing the CEO's neuroticism via a validated text-analysis of unscripted earnings-call Q&A.	Harrison et al. (2019)
CEO age	Age in years of the chief executive.	ExecuComp
CEO gender	Equals 1 for female CEOs; 0 for male.	ExecuComp
CEO education	Equals 1 if the CEO holds a master's or doctoral degree; 0 otherwise.	BoardEx
CEO tenure	Number of months since the CEO began the current appointment.	ExecuComp
CEO salary and bonus	(Annual salary + bonus)/total compensation.	ExecuComp
CEO incentives	(Unexercised options + restricted stock)/total compensation.	ExecuComp
Firm Characteristics		
Size	The natural log of a firm's total assets.	Compustat
ROA	NI/AT	Compustat
CapEx	CAPX/AT	Compustat
PPE	PPENT/AT	Compustat
Book Leverage	LT/AT	Compustat
HHI	The sum of squared market shares of all firms within a 4-digit SIC industry in year t, based on annual sales. It measures the level of industry concentration.	Compustat
IO	Average of the four quarterly institutional-ownership ratios in a year, where each quarterly ratio equals shares held by institutional investors divided by total shares outstanding.	FactSet 13F

References

Aabo, T., Hanousek Jr, J., Pantzalis, C., & Park, J. C. (2023). CEO personality traits and corporate value implication of acquisitions. Journal of Empirical Finance, 73, 86-106.

Aabo, T., Pantzalis, C., Park, J. C., Trigeorgis, L., & Wulff, J. N. (2024). CEO personality traits, strategic flexibility, and firm dynamics. Journal of Corporate Finance, 84, 102524.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and innovation: An inverted-U relationship. Quarterly Journal of Economics, 120(2), 701-748.

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics, 151, 103745.

Barrick, M. R., Stewart, G. L., & Piotrowski, M. (2002). Personality and job performance: Test of the mediating effects of motivation among sales representatives. Journal of Applied Psychology, 87(1), 43-51.

Benischke, M. H., Martin, G. P., & Glaser, L. (2019). CEO equity risk bearing and strategic risk taking: The moderating effect of CEO personality. Strategic Management Journal, 40(1), 153-177.

Ben-Nasr, H., Bouslimi, L., & Zhong, R. (2021). Do patented innovations reduce stock-price crash risk? International Review of Finance, 21(1), 3-36.

Bono, J. E., & Judge, T. A. (2004). Personality and transformational and transactional leadership: A meta-analysis. Journal of Applied Psychology, 89(5), 901-910.

Bresnahan, T. F., & Trajtenberg, M. (1995). General-purpose technologies “Engines of growth”? Journal of Econometrics, 65(1), 83-88.

Chen, C., & Steinwender, C. (2021). Import competition, heterogeneous preferences of managers, and productivity. Journal of International Economics, 133, 103533.

Chen, Wilbur X., Shi, T. T., & Srinivasan, S. (2024). The value of AI innovations. Harvard Business School Working Paper 24-069.

Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation (NBER Working Paper 24449). National Bureau of Economic Research.

Galasso, A., & Simcoe, T. S. (2011). CEO overconfidence and innovation. Management Science, 57(8), 1469-1484.

Giczy, A. V., Pairolero, N. A., & Toole, A. A. (2022). Identifying artificial intelligence invention: A novel AI patent dataset. Journal of Technology Transfer, 47(2), 476-505.

Goldfarb, A., Taska, B., & Teodoridis, F. (2023). Could machine learning be a general-purpose technology? A comparison of emerging technologies using data from online job postings. Research Policy, 52(1), 104653.

Goldberg, L. R. (2013). An alternative "description of personality": The Big-Five factor structure. In Personality and Personality Disorders (pp. 34-47). Routledge.

Grullon, G., Lyandres, E., & Zhdanov, A. (2012). Real options, volatility, and stock returns. Journal of Finance, 67(4), 1499-1537.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). The NBER patent-citation data file: Lessons, insights and methodological tools. (NBER Working Paper).

Hambrick, D. C., & Fukutomi, G. D. (1991). The seasons of a CEO's tenure. Academy of Management Review, 16(4), 719-742.

Harrison, J. S., Thurgood, G. R., Boivie, S., & Pfarrer, M. D. (2019). Measuring CEO personality: Developing, validating, and testing a linguistic tool. Strategic Management Journal, 40(8), 1316-1330.

Harrison, J. S., Thurgood, G. R., Boivie, S., & Pfarrer, M. D. (2020). Perception is reality: How CEOs' observed personality influences market perceptions of firm risk and shareholder returns. Academy of Management Journal, 63(4), 1166-1195.

Hirshleifer, D., Low, A., & Teoh, S. H. (2012). Are overconfident CEOs better innovators? Journal of Finance, 67(4), 1457-1498.

Hogan, R., & Hogan, J. (2001). Assessing leadership: A view from the dark side. International Journal of Selection and Assessment, 9(1-2), 40-51.

Holland, J. L., Johnston, J. A., Asama, N. F., & Polys, S. M. (1993). Validating and using the Career Beliefs Inventory. Journal of Career Development, 19(4), 233-244.

Huang, J., & Kisgen, D. J. (2013). Gender and corporate finance: Are male executives overconfident relative to female executives? Journal of Financial Economics, 108(3), 822-839.

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155-172.

Judge, T. A., & Bono, J. E. (2000). Five-factor model of personality and transformational leadership. Journal of Applied Psychology, 85(5), 751-765.

Judge, T. A., Bono, J. E., Ilies, R., & Gerhardt, M. W. (2002). Personality and leadership: A qualitative and quantitative review. Journal of Applied Psychology, 87(4), 765-780.

Judge, T. A., Erez, A., Bono, J. E., & Thoresen, C. J. (2002). Are measures of self-esteem, neuroticism, locus of control, and generalized self-efficacy indicators of a common core construct? Journal of Personality and Social Psychology, 83(3), 693-710.

Judge, T. A., Piccolo, R. F., & Kosalka, T. (2009). The bright and dark sides of leader traits: A review and theoretical extension of the leader-trait paradigm. Leadership Quarterly, 20(6), 855-875.

Judge, T. A., Thoresen, C. J., Pucik, V., & Welbourne, T. M. (1999). Managerial coping with organizational change: A dispositional perspective. Journal of Applied Psychology, 84(1), 107-122.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. Quarterly Journal of Economics, 132(2), 665-712.

Le, H., Oh, I. S., Robbins, S. B., Ilies, R., Holland, E., & Westrick, P. (2011). Too much of a good thing: Curvilinear relationships between personality traits and job performance. Journal of Applied Psychology, 96(1), 113-133.

LePine, J. A., Colquitt, J. A., & Erez, A. (2000). Adaptability to changing task contexts: Effects of general cognitive ability, conscientiousness, and openness to experience. Personnel Psychology, 53(3), 563-593.

Loureiro, S. M. C., Guerreiro, J., & Tussyadiah, I. (2021). Artificial intelligence in business: State of the art and future research agenda. Journal of Business Research, 129, 911-926.

Malhotra, S., Reus, T. H., Zhu, P., & Roelofsen, E. M. (2018). The acquisitive nature of extraverted CEOs. Administrative Science Quarterly, 63(2), 370-408.

McCrae, R. R., & John, O. P. (1992). An introduction to the Five-Factor model and its applications. Journal of Personality, 60(2), 175-215.

Nadkarni, S., & Herrmann, P. O. L. (2010). CEO personality, strategic flexibility, and firm performance: The case of the Indian business process outsourcing industry. Academy of Management Journal, 53(5), 1050-1073.

Nettle, D. (2006). The evolution of personality variation in humans and other animals. American Psychologist, 61(6), 622-631.

O'Reilly III, C. A., Caldwell, D. F., Chatman, J. A., & Doerr, B. (2014). The promise and problems of organizational culture: CEO personality, culture, and firm performance. Group & Organization Management, 39(6), 595-625.

Pairolero, N. A., Giczy, A. V., Torres, G., Islam Erana, T., Finlayson, M. A., & Toole, A. A. (2025). The artificial intelligence patent dataset (AIPD) 2023 update. Journal of Technology Transfer, 1-24.

Pan, Y., Wang, T. Y., & Weisbach, M. S. (2016). CEO investment cycles. Review of Financial Studies, 29(11), 2955-2999.

Ren, S., Cheng, Y., Hu, Y., & Yin, C. (2021). Feeling right at home: Hometown CEOs and firm innovation. Journal of Corporate Finance, 66, 101815.

Stoffman, N., Woeppel, M., & Yavuz, M. D. (2022). Small innovators: No risk, no return. Journal of Accounting and Economics, 74(1), 101492.

Sunder, J., Sunder, S. V., & Zhang, J. (2017). Pilot CEOs and corporate innovation. Journal of Financial Economics, 123(1), 209-224.

Venugopal, A., Nerur, S., Yasar, M., & Rasheed, A. A. (2023). CEO personality and corporate sustainability performance. Management Decision, 61(12), 3691-3716.

You, Y., Srinivasan, S., Pauwels, K., & Joshi, A. (2020). How CEO/CMO characteristics affect innovation and stock returns: Findings and future directions. Journal of the Academy of Marketing Science, 48, 1229-1253.

Zhang, J., Cui, C., Zheng, C., & Taylor, G. (2024). Artificial intelligence innovation and stock-price crash risk. Journal of Financial Research.