Crafting an AI Compass: The Influence of Global AI Standards on Firms*

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March 10, 2025

Abstract

We investigate the technical and ethical standardization of artificial intelligence (AI) and its corporate implications around the globe. We show that AI standards not only fuel AI investments but also broader capital and R&D spending. Standardization of machine learning methods, programming languages, protocols for big data, guidelines for data interchange, and interoperability of industrial data encourage investment. Conversely, frameworks for societal and privacy considerations in AI discourage investment. AI standards have a positive ripple effect on firm value, gradually amplifying as the standards mature and their impact on firms deepens.

Keywords: Artificial Intelligence, Standard Setting, Investment, Technology Diffusion, Machine Learning, Big Data, Ethical AI, AI Safety, Privacy, AI Regulation, RegTech
JEL Classification: D22, E22, O30, O32, O33, K20

Acknowledgements: We thank Yi Chen, Will Cong, Jess Cornaggia, Zhi Da, Umit Gurun, Sabrina Howell (discussant), Jingzhi Huang, Wei Jiang, Colin Mayer, Ye Li, Robert Seamans (discussant), D. Daniel Sokol, Laura Veldkamp (discussant), Jing Yang, and Yao Zeng for their useful feedback. We are grateful to Zachary Arnold for sharing the data on AI investments, patents and publications from the Emerging Technology Observatory (ETO). We are also grateful for the insightful comments from seminar participants at Pennsylvania State University and conference participants at the 2024 Next Generation of Antitrust, Data Privacy & Data Protection Scholars Conference, Asian Bureau of Finance and Economic Research 11^{th} Annual Conference, 4^{th} Annual Empirical Research Conference on Standardization Conference, 2024 AI and Platform Evolution Conference, and 2024 Columbia & RFS AI in Finance Conference. Please send correspondence to Mehmet Canayaz.

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1 Introduction

Technological standardization, i.e., the process of establishing universal rules and guidelines for firms, is the foundation upon which innovation is built (Tassey, 2017).[1] Once a standard is set, companies operating within its domain are compelled to align their activities accordingly (Lerner and Tirole, 2015; Baron and Schmidt, 2019).[2] This alignment contributes to substantial increases in productivity and GDP growth rates, often approaching double-digit percentages.[3] While academic research has contributed to our understanding of the economics tied to standard setting (Lerner and Tirole, 2006; Chiao et al., 2007; Simcoe, 2012; Lerner and Tirole, 2014), the influence of standards on business outcomes, particularly those related to critical technologies such as artificial intelligence (AI), have yet to be explored.

Unlike conventional standards that ensure device compatibility and performance, AI standards aim to promote the secure, ethical, and interoperable development of AI systems (Raimondo and Locascio, 2023). Their scope spans a wide range of industries, reflecting AI's role as a general-purpose technology (Agrawal et al., 2018; Cockburn et al., 2018). Standardizing AI, however, presents unique challenges, because AI systems make autonomous decisions and can exhibit unethical behavior or spiral out of control.[4] Nonetheless, developing AI standards that facilitate safety and profitability is essential before AI becomes widely adopted in business operations in unproductive ways or without adequate oversight.

This paper fills an important gap in the literature by investigating the implications of AI standards for firms. It provides the first analysis of how AI standards influence corporate activities, including AI-related research that pushes the knowledge frontier in the public domain, as well as AI-specific and broader firm investments in the private domain. To achieve this, we utilize a unique, hand-collected dataset of AI

[1] See https://bit.ly/4doYSPs for the International Organization for Standardization (ISO)'s definition of a standard.

[2] Although compliance is not compulsory, firms often comply with standards to gain market access, boost consumer confidence, reduce costs, etc. Standards are also informative for regulators, as they often develop formal regulations based on established standards. See https://www.iso.org/benefits-of-standards.html.

[3] The French Standardization Association (AFNOR) estimates that standardization boosts France's GDP growth by 25%. In the UK, standards contributed 13% to labor productivity growth from 1948 to 2002, while in Canada, standardization added 17% to labor productivity and 9% to real GDP growth from 1981 to 2004. See, e.g., https://bit.ly/3Cvj6a0.

[4] See https://bit.ly/4dkMLD6 and https://bit.ly/43WIFfJ for more on AI risks. A 2023 survey by the Centre for the Governance of AI found that 91% of respondents agreed on the need for prudent AI management (https://bit.ly/3Copos1).

standards, along with data on AI standardization committees that shed light on how expert consensus on AI rules and guidelines is achieved. We also introduce novel metrics that measure the relatedness between standards and AI as a scientific field, based on textual similarity with science textbooks and conceptual alignment with core AI concepts.

The establishment of AI standards carries important implications for firms. On the positive side, AI standards offer widely accepted frameworks for implementing AI, thereby reducing the economic uncertainty faced by firms and encouraging higher corporate investment. They also tackle the compatibility and interoperability of AI systems, ensuring that different AI systems can coordinate and exchange data efficiently. This accelerates the diffusion of AI technologies and induces more investment. On the flip side, AI standards that impose ethical and safety constraints can curb the effectiveness of AI, potentially leading to reduced investment. This is because such standards make the concept of ethical AI more tangible and enhance the enforceability of such constraints, thereby providing a framework for shaping future mandated governance structures.

To provide empirical evidence on how standardization of AI impacts businesses, we gather data on global AI standards. Our principal source is the report "US Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools," prepared by NIST following Executive Order 13859.[5] This document provides a strategic blueprint that guides US participation in global AI standardization and, in the process, identifies critical AI standardization committees within international organizations. After identifying these committees, we collect data on standards from each committee's respective website and enrich this data with additional textual analysis and interpretation.

To the best of our knowledge, our dataset is the first of its kind in the literature, offering exclusive insights into the creation and content of global AI standards.[6] It provides a comprehensive view of the key

[5]This report is publicly accessible and can be downloaded from the following URL: https://bit.ly/43ywOoz.

[6]The Searle Center at Northwestern University hosts a dataset on non-AI standards predating the sampling period of our paper. It can be accessed here: https://bit.ly/3THmMPt.

players in this domain, detailing which countries are pushing AI standardization efforts by leading committees within international organizations and which are contributing to the process by being members of these committees. Taking it a step further, it also breaks down the contents of AI standards through textual analysis, documenting a wide spectrum of AI categories to provide a deeper understanding of the subject matter. These components include but are not limited to machine learning (including language models), big data, data interchange, trustworthiness, and robotics, all of which likely have heterogeneous effects on corporate outcomes.

Our data documents that the standardization of AI is not monopolistic but rather a globally collaborative endeavor. This said, countries across the world do exercise their influence by securing key leadership roles within key committees, known as *secretariats*, or through active membership in these committees. The secretariat oversees the committee's technical and administrative processes. A country being the secretariat of a standard-setting committee is often regarded as having a strong influence on the shaping of global standards developed under that committee (Blind and von Laer, 2022), potentially through strategic agenda setting and information provision (Farrell and Simcoe, 2012), in favor of domestic firms. An excellent summary of how countries use leadership positions in standardization committees to favor local firms is provided by Neaher et al. (2021).[7]

To estimate the influence of AI standards on firms, we rely on the exogenous nature of United Nations Security Council (UNSC) membership rotations. This is motivated by the strong UN-ISO collaboration evidenced in the ISO report titled "ISO and the UN: Working Together for International Standardization."[8] Kuziemko and Werker (2006) show that countries rotating onto the UNSC see an increase in aid from permanent UNSC member nations, hinting at potential quid pro quo arrangements. In our setting, as the rotating UNSC members change, we observe significant changes in the number of AI standards

[7] Other well-known instances of government clout include assistance to local firms in standard essentiality (e.g., 5G). Qualcomm's "no license, no chip" policy generates over 75% of its pre-tax profits. See https://bit.ly/4afsUDS.

[8] Available for download from the ISO website: https://www.iso.org/files/live/sites/isoorg/files/store/en/PUB100432.pdf.

issued by committees under the secretariats of permanent UNSC members. This stems from the changing percentage of committee members more or less sympathetic to the permanent members' agendas as countries cycle through UNSC membership. These random shocks enable us to assess the local impact of AI standards on firms within permanent UNSC member nations through a two-stage least squares (2SLS) procedure.

Following the 2SLS strategy described above, we examine the influence of AI standards on corporate investment decisions. Our analysis begins with an examination of firms' research publications presented at leading AI conferences, using novel data from the Emerging Technology Observatory (ETO). This dataset encompasses public and private AI-innovator firms from around the globe and includes all of their AI publications, along with those categorized into computer vision, natural language processing, and robotics fields. Analyzing these research publications is crucial, as they not only serve as a proxy for firms' investments in AI technology but also advance the frontier of knowledge within the AI community. Our findings indicate that a one standard deviation increase in AI standards results in an increase of 0.21 standard deviations in firm-level overall AI research activity, 0.27 in computer vision research, 0.22 in natural language processing research, and 0.32 in robotics research.[9]

We extend the above analyses by employing a comprehensive country-year panel that includes data on AI-specific investments across 36 categories and AI-specific patent activity in 22 distinct fields. Our findings reveal that AI standards significantly promote increased investments and patent activity in numerous AI-related domains. Specifically, AI standards drive growth in areas such as robotics, manufacturing, cybersecurity, privacy, data analytics, software, facial recognition technology, and education. Additionally, we observe a surge in AI patent applications in domains such as banking, security, industrial manufacturing, machine learning, transportation, telecommunications, and computer vision following

[9]This finding is aligned with the existing research on how standards can facilitate innovation. Standards can boost innovation by codifying knowledge and providing a foundation for new technologies to emerge (Allen and Sriram, 2000). Research institutions use standards as input for innovation (Blind and Gauch, 2009). Also, seeking standards certification is associated with successful product innovation (Mirtsch et al., 2020).

the adoption of AI standards. Collectively, our results underscore the profound impact of AI standards on corporate investments in AI technology, benefiting both firms and the broader AI community.

AI standards can have substantial implications beyond AI innovators by boosting the productivity of machines and equipment, thereby increasing returns on investment in physical capital. For this reason, we also explore the influence of AI standards on the capital expenditures of firms. Our analysis reveals that a one standard deviation increase in AI standards results in a 0.11 standard deviation rise in capital expenditures and a 0.24 standard deviation increase in R&D expenditures, consistent with our earlier findings on AI investments. These findings hold true even when we randomly exclude up to 250 AI standards from our sample, underscoring that our results are not driven by a few selective standards and highlighting the broader relevance of AI standards for capital investment.

The above findings are robust to a rigorous placebo test where we use the percentage of rotating UNSC members as an instrument for the number of AI standards published by non-UNSC affiliated secretariats. In this test, we confirm that our placebo instrument, which captures variation in the number of AI standards unrelated to quid pro quo influence through the UNSC, is not helpful in identifying a meaningful effect on our main variables of interest.

Our definition of AI standards is based on NIST's assessment of the relevance of committees to AI. Specifically, we define AI standards as those published by committees that NIST has identified as crucial to AI standardization. Although NIST has considerable expertise in identifying committees that specialize in standards, we independently verify the AI relevance of the standards published by these committees, as well. To do so, we create two novel proxies for the relatedness of AI standards to AI as a field of science.

Our first AI relatedness measurement is based on the textual similarity of AI standards with the contents of popular science textbooks. This provides us with novel metrics for assessing both the time series and cross-sectional variation in AI relatedness. We demonstrate that during our main sampling period

(from 2017 to the end of 2022), the textual similarity between academic resources on AI and AI standards reached a maximum of 90%, indicating that the standards published by committees identified by NIST as AI-critical were indeed related to AI. Additionally, we observe that highly rated AI standards, in terms of AI relatedness, clearly cite artificial intelligence or closely related concepts such as machine learning or neural networks in their titles.

Building on these findings, we next create an AI relatedness score for each standard in our sample, determined by the proportion of terms in the standard that correspond to the vocabulary found in a popular AI textbook. We validate the robustness of this measurement through a stress test, where we compare the textual similarity of AI standards with other science textbooks containing false triggers (i.e., vocabulary similar to AI terminology but used in contexts not directly related to AI). We then present important evidence of effect heterogeneity showing that the estimated effects of AI standards increase as we examine standards in the top 50%, 25%, and 10% of the AI relatedness spectrum.

Our second AI relatedness measure is based on contextual similarity with core AI concepts. It categorizes AI standards into groups such as machine learning, data, safety, privacy, and automation, among others. Using this metric, we show that data standards, automation standards, interchange standards, and machinery & equipment standards have significantly positive effects on investment. In contrast, ethics & accountability standards exhibit a significant negative impact. Moreover, data standards have the strongest positive effect on language processing research, while automation, machinery & equipment, and interchange standards have the strongest effect on computer vision research.

Our findings remain robust when we change our identification strategy to use UNSC membership rates in AI committees instead of focusing on UNSC membership rates under countries' secretariats in total. The proportion of UNSC members within committees is based on their composition prior to UNSC rotation announcements, making it unlikely that future rotation expectations could confound membership in all AI committees and corporate outcomes. Importantly, committee-level rotations vary

in terms of importance, allowing us to examine cases where support from UNSC rotations might have a small or large influence over the publication of AI standards based on the percentage of necessary votes to publish a standard. Furthermore, our committee-level instrument also helps confirm that our conclusions hold even after excluding some AI committees, such as the most active ones.

Our committee analysis reveals that committees focused on data, automation, interoperability, and programming languages significantly enhance investment, while those addressing biometrics and AI guidance have adverse effects. These findings highlight the pivotal role of issuing committees in shaping corporate investment decisions, demonstrating that a blanket assessment of AI standards as either beneficial or detrimental is overly simplistic. The impact of AI standards depends on both their content and the issuing committee, as evidenced by the differing effects of standards issued by data interchange committees compared to interchange standards issued by all committees.

Our paper also looks into how AI standards influence firm value. Our estimates indicate that a surge of one standard deviation in AI standards can improve firm value by up to 0.14, 0.31 and 0.46 standard deviations in the first, second and third years respectively. This finding signifies that the ripple effects of AI standards extend beyond the initial near-term impacts, showcasing a significant compound effect.

To rationalize our empirical findings, we introduce a stylized model to study how a firm's investment is affected by the expected future publications of AI standards. A firm lives for an infinite horizon. In each period and within each domain of AI investment, it decides on the investment in two types of competing AI technologies. The investment is partially irreversible, in the sense that disinvestment is costly. The firm expects a future random (Poisson) arrival of the publication of AI standards, which could be either (i) technological standards that endorse one type of AI technology over another within an AI investment domain, or (ii) privacy/ethical standards that impose privacy-related or ethical constraints on the adoption of AI technologies. The firm also decides on capital expenditure investment in physical assets. Motivated by the insight that AI is a general purpose technology that can lead to the fourth industrial rev-

olution, i.e., Industry 4.0 (Peres et al., 2020), we argue that more AI-related investment incentivizes the firm to increase capital expenditure in physical assets by increasing the marginal productivity of such assets. Based on our theoretical framework, we make the following empirical predictions: more technological standards published are associated with more AI-related investment and capital expenditure post-publication, while more privacy/ethical standards published are associated with less AI-related investment and capital expenditure post-publication.

The remainder of the paper is organized as follows. Section 2 presents the literature review. Section 3 develops our testable hypotheses. Section 4 presents our data. Section 5 explains our empirical framework. In Section 6, we present our empirical findings in support of the theoretical predictions above. Section 7 concludes the article. To keep the main text concise, we provide additional material in the Appendix. Appendix Section A presents our theoretical framework and mathematical proofs. Appendix Section B includes further data descriptions. Key findings are detailed in Appendix Section C, such as effect heterogeneity based on our committee-level instrument, country-level AI investments and patents, a robustness check where we randomly exclude 250 AI standards and rerun the 2SLS regressions, and effect heterogeneity based on the level of uncertainty resolved with the publication of AI standards. Appendix Section D offers a detailed definition of AI, examples of AI standards, and their applications across different industry settings.

2 Literature Review

Our paper's main contribution is to the emerging literature in financial economics on AI. Some papers highlight the beneficial aspects of using AI technologies. Babina et al. (2024) find that AI-related investment increases firm growth and innovation. Howell et al. (2024) show that lending automation reduces racial disparities in credit access. Meanwhile, other research reveals the dark side of applying AI in financial activities. Dou et al. (2024) show that AI-powered trading strategies can lead to collusion among

traders. Researchers also argue that the adoption of AI can replace human labor (Acemoglu and Restrepo, 2018; Acemoglu et al., 2022). Other related work in this area includes data economy and privacy (Begenau et al., 2018; Cong et al., 2021b; Canayaz et al., 2022; Liu et al., 2023), AI and corporate disclosure (Cao et al., 2024), robo-advising (D'Acunto et al., 2019), as well as decision biases, reliability, and interoperability of AI algorithms (Wellman and Rajan, 2017; Agrawal et al., 2019a; Acemoglu, 2021).[10] We contribute to the literature with a unique perspective: to examine how AI standards affect firm's investment. In addition, we introduce a novel database on AI-specific research publications and investment, which enables us to examine the impact of AI standards on both AI-specific and broader investment.

A few recent papers discuss AI-related policies and regulations. Cuéllar et al. (2022) examine the impacts of potential AI regulations on managers' perceptions of AI ethical issues and their intentions to adopt AI technologies. Agrawal et al. (2019a) emphasize three aspects of AI economic policies: data privacy, international coordination, and AI liability. Clark and Hadfield (2019) argue that the evolving nature of AI technologies amplifies the importance to make regulations more agile and adaptive, which gives self-regulation (e.g., global AI standards) an advantage over government regulations.[11] While most studies in this field focus on hypothetical AI regulations, we contribute to this literature by examining actual AI standard publications, providing a unique contribution through the analysis of existing self-regulatory practices.

Our paper is also related to the literature on how standardization affects R&D investment by shaping the infrastructure of innovation. On the one hand, researchers argue that standards facilitate innovation and technology diffusion by codifying knowledge (Allen and Sriram, 2000; Blind and Gauch, 2009), increasing compatibility (Pelkmans, 2001; Lerner and Tirole, 2014; Baron and Schmidt, 2019), and ensuring minimum quality (Mirtsch et al., 2020). On the other hand, standardization hinders R&D investment

[10] See Agrawal et al. (2019b) on the economics of AI and Goldstein et al. (2021); Farboodi and Veldkamp (2022); Cong et al. (2021a) on big or unstructured data.

[11] Blind et al. (2017) show that standards boost innovation efficiency more than government regulations in uncertain markets, and Campello et al. (2024) examine how regulators learn about emerging technologies amid regulatory uncertainty.

by reducing an industry's degree of radical innovation (Foucart and Li, 2021) or increasing market concentration (Windrum, 2004). However, none of these studies examines AI standards; also, the majority of these papers are either theoretical or use survey data. Our work contributes to the literature by (1) being among the first to study standards about AI, and (2) examining the impact of AI standards using actual investment data.

Our work is also related to the literature on the economics of standard-setting organizations (SSOs). Lerner and Tirole (2006) and Chiao et al. (2007) study theoretical models with sponsors of technological standards (e.g., owners of technologies) strategically resorting to more or less independent SSOs to endorse their technologies.[12] Simcoe (2012) shows both theoretically and empirically that when SSO participants favor specific technologies, the conflicts of interests among SSO participants will lead to inefficient delay of the publication of standards.[13] We enrich the literature by being among the first to characterize the international collective effort within SSOs in the context of AI standard setting.

Finally, our observation that firms tend to postpone investments until uncertainty is resolved by the publication of standards echoes the literature on real options theory and investment under uncertainty (Dixit and Pindyck, 1994; Grenadier, 2002; Grenadier and Wang, 2007).

3 Theory

To illustrate how AI standards affect firm investment, we introduce a stylized model featuring investment under uncertainty. This section summarizes the structure of our model and its testable implications, and Appendix Section A contains additional details and proofs. In our model, a firm lives for an infinite horizon. In each period t, the firm faces decisions on the AI investment in multiple AI domains. Examples of AI domains include natural language processing, computer vision and robotics. Within each domain,

[12] They make the following theoretical predictions and verify with empirical evidence: (i) there is a negative relationship between the extent to which an SSO favors technology sponsors and the concession level required of sponsors and (ii) there is a positive correlation between the sponsor friendliness of the selected SSO and the quality of the standard.

[13] Baron and Gupta (2018) describe a database on 3GPP standardization, the key SSO in mobile telecommunications. Baron and Spulber (2018) provide data on technology standards and SSO membership, without focusing on AI.

the firm can invest in two types of competing AI technologies, type A and type B. Let $I_{AI,t}^{n,A}$ and $I_{AI,t}^{n,B}$ be the two types of AI-related investment in domain n in period t. In addition to AI investment, the firm also chooses $I_{K,t}$, which is the physical investment in period t (i.e., CapEx).

Both the investment in AI technologies and CapEx are partially irreversible, i.e., disinvestment is costly due to fire sales. Let the terms $CI_n(I_{AI,t}^{n,A})$, $CI_n(I_{AI,t}^{n,B})$, and $CI_n(I_{K,t})$ be the investment costs of $I_{AI,t}^{n,A}$, $I_{AI,t}^{n,B}$, and $I_{K,t}$ respectively. Given investment I in AI-domain n and type $i = A, B$, the cost of investment is $CI_n(I) = I$ if $I \geq 0$ (positive investment), and $CI_n(I) = C^n I$ if $I < 0$ (disinvestment), with $C^n \in (0,1)$. That is, only a fraction C^n of disinvestment amount can be salvaged. Similarly, the investment cost for physical investment K is that $CI_K(I) = I$ if $I \geq 0$, and $CI_K(I) = C^K I$ if $I < 0$, with $C^K \in (0,1)$.

The firm uses both physical capital (i.e., PP&E) and AI capital as inputs for production. Importantly, AI-related capital and PP&E enter the production function with a multiplicative structure. In other words, AI-related capital *complements* physical capital. This complementarity arises because AI is widely recognized as a general-purpose technology that could drive the fourth industrial revolution, known as Industry 4.0 (Peres et al., 2020). That is, it has the potential to enhance the productivity of machines and equipment, thereby boosting the return on investment in PP&E.

Formally, the firm's output in period t is $AI_t^{\alpha} K_t^{1-\alpha} D(1-\tilde{\tau}_t)$, where AI_t is the AI-related capital stock, K_t is the physical capital stock, D is the exogenous data input, $\tilde{\tau}_t \in [0,1)$ embodies the limitations on data privacy and ethical AI requirements, and $\alpha \in (0,1)$ represents the relative contribution of AI capital in production. The AI-related capital stock AI_t is defined as $AI_t = \sum_{n=1}^{N} \left(\tilde{s}_t^{n,A} F(AI_t^{n,A}) + \tilde{s}_t^{n,B} F(AI_t^{n,B}) \right)$, which is the AI-related capital aggregated across type-A and type-B investment within each domain n, and across all domains. The terms $AI_t^{n,A}$ and $AI_t^{n,B}$ are the two types of AI-related capital stock in domain n, while $\tilde{s}_t^{n,A}$ and $\tilde{s}_t^{n,B}$ stand for the productivity of the two types respectively. The function $F(\cdot)$ is increasing and concave. Assuming away depreciation, both the AI-related capital stock ($AI_t^{n,A}$, $AI_t^{n,B}$) and the physical capital stock (K_t) increase by the amount of corresponding investment. That is,

$AI_t^{n,i} = AI_{t-1}^{n,i} + I_{AI,t}^{n,i}$ for $i = A, B, n \in \{1, 2, ..., N\}$, and $K_t = K_{t-1} + I_{K,t}$.

Note that our setting incorporates both "AI innovators" (e.g., firms with AI research publications), who invest in AI to innovate on these technologies, and "AI consumers" (e.g., manufacturing and healthcare facilities), who invest in AI to adopt the technologies and facilitate their production and service. Lastly, the flow payoff in period t is discounted using a discount factor $\beta \in (0, 1)$. The initial capital stock is $AI_0^{n,i} = K_0 = 0$, for $i = A, B$, $n \in \{1, 2, ..., N\}$.

To summarize, the firm's investment problem in each period $j \geq 1$ is

$$\begin{aligned}
\max_{\{I_{AI,t}^{n,A}, I_{AI,t}^{n,B}, I_{K,t}\}_{t=j}^{\infty}} \mathbb{E} \sum_{t=j}^{\infty} \beta^{t-1} \Big\{ AI_t^{\alpha} K_t^{1-\alpha} D(1-\tilde{\tau}_t) - \sum_{n=1}^{N} \Big(CI_n(I_{AI,t}^{n,A}) + CI_n(I_{AI,t}^{n,B}) \Big) - CI_K(I_{K,t}) \Big\} \\
s.t. \text{ (AI factor) } AI_t = \sum_{n=1}^{N} \Big(\tilde{s}_t^{n,A} F(AI_t^{n,A}) + \tilde{s}_t^{n,B} F(AI_t^{n,B}) \Big) \\
\text{(capital dynamics) } AI_t^{n,i} = AI_{t-1}^{n,i} + I_{AI,t}^{n,i}, \text{ for } i = A, B, n \in \{1, 2, ..., N\}. \\
K_t = K_{t-1} + I_{K,t}. \\
\text{(costly disinvestment) } CI_n(I) = \begin{cases} I & \text{if } I \geq 0 \\ C^n I & \text{if } I < 0 \end{cases} \quad CI_K(I) = \begin{cases} I & \text{if } I \geq 0 \\ C^K I & \text{if } I < 0 \end{cases}
\end{aligned} \tag{1}$$

The firm operates under the anticipation of a stochastic event – the publication of AI standards, which alter the productivity of various AI technologies. However, how productivity varies after the standards are published depends crucially on the nature of the standards.

Suppose the standards published are *technological standards*, which typically specify the "best practices" for technologies. Such standards narrow down the variety of technologies by endorsing one technology over another (Lerner and Tirole, 2014). The endorsed technology within that domain then witnesses a quicker and broader adoption than the unendorsed counterpart, benefiting from positive network externalities—its value grows as more users adopt it, according to Tassey (2017). This leads to a bifurcation of productivity between the two technologies: the chosen technology sees a surge in pro-

ductivity following the standards' release, whereas the other suffers a decline in productivity. This division is further deepened by two additional factors that boost the favored technology's productivity: (i) standards often codify the details of the endorsed technology and provide a clear blueprint for the implementation, and (ii) standards enhance the interoperability of the endorsed technology by creating a compatible ecosystem that surrounds and supports this technology.

To characterize the bifurcation of productivity within domain n, we assume the productivity before the publication of standards is constant over time, that is, $\tilde{s}_t^{n,A} = \tilde{s}_t^{n,B} = s^n > 0$, for $t \leq T$, where T denotes the random publication period. There is a divergence in productivity between the two technologies after the publication. With probability $p^{n,A} \in (0,1)$, type-A is endorsed by the standard, so $(\tilde{s}_t^{n,A}, \tilde{s}_t^{n,B}) = (\bar{s}^n, \underline{s}^n)$ with $0 < \underline{s}^n < s^n < \bar{s}^n$, for all $t > T$; while with probability $p^{n,B} = 1 - p^{n,A}$, type-B is endorsed, so $(\tilde{s}_t^{n,A}, \tilde{s}_t^{n,B}) = (\underline{s}^n, \bar{s}^n)$, for all $t > T$.[14] In addition, publication of more technological standards imply that more domains in AI technology experiences the bifurcation.

The situation is very different if the published standards are *privacy* or *ethical standards*, which include the interpretability of AI algorithms and restrictions on data privacy. These restrictions shrink the firm's data pool and limit the scope of AI applications, as certain practices previously employed to maximize efficiency might no longer be permissible under new privacy and ethics rules. The publication of such standards play a crucial role in reinforcing the enforceability of such constraints, making these concepts more tangible and provide a framework for shaping future government policies.[15] To capture the constraining effects of privacy and ethical AI standards, we normalize the pre-publication level of $\tilde{\tau}_t = 0$ for all $t \leq T$ and the post-publication level to be $\tau \in (0,1)$. In addition, publication of more privacy/ethical standards imposes stricter restrictions, leading to a larger τ.

In this setting, there are several forces affecting how investment responses to the publication of stan-

[14] Note that we do not restrict $p^{n,A}$ to be 1/2; that is, we allow the firm to expect one technology to be more likely to be endorsed than the other.

[15] See Clark and Hadfield (2019): "There are numerous examples of cases in which public regulation has piggybacked on systems initially developed privately".

dards. First, the firm cannot predict which technology will be endorsed by technological standards or how restrictive privacy/ethical standards will be. Therefore, the option value of delaying its partially irreversible investment drives the firm to wait until the publication of standards resolves this uncertainty. This consideration tends to increase post-publication investment above pre-publication levels.

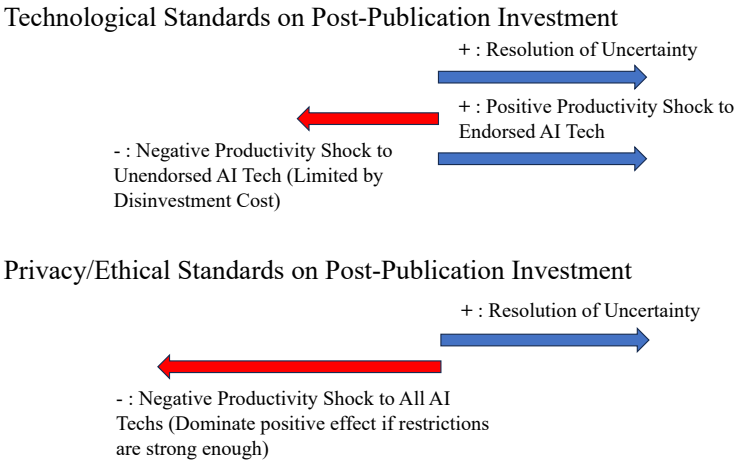
Second, beyond the uncertainty resolution effect, the publication of standards can lead to productivity shocks relative to pre-publication levels, affecting the optimal capital stock. This impact varies depending on whether the standards are privacy/ethical or technological, and for technological standards, whether the investment is in endorsed or unendorsed technology.

Whether the publication of standards boost or deter investment depends on the overall effect of the two forces. Privacy/ethical standards typically reduce productivity below pre-publication levels, leading to disinvestment to lower the capital stock. This counters the investment-boosting effect of uncertainty resolution. When even the most benign restrictions imposed by such standards are sufficiently strict, this investment-deterrence effect dominates the investment-boosting effect of uncertainty resolution, leading to strictly negative investments post-publication. Furthermore, the publication of more such standards lead to stronger restrictions, resulting in even larger post-publication disinvestment.

Technological standards, on the other hand, increase productivity for the endorsed AI technology. This results in positive post-publication investment, aligning with the uncertainty resolution effect. Conversely, productivity decreases for the unendorsed technology, which tends to induce disinvestment and opposes the uncertainty resolution effect. However, the overall effect on investment remains positive due to the partial irreversibility of investment, that is, there is no adjustment cost for positive investment but a cost for disinvestment. Thus, investment increases post-publication of technological standards. Furthermore, more technological standards publications resolve more uncertainties and generate positive productivity shocks in more AI domains, potentially boosting post-publication investment even further.

Exhibit 1 illustrates the varies forces discussed above. Based on our theoretical analysis, we make the

Exhibit 1. Intuition: Standards Publication and Investment



following empirical predictions.

Hypothesis 1. *(i) Both the firm's AI-related investment and CapEx are higher after the publication of standards, if a higher number of technological standards are published.*

(ii) Both the firm's AI-related investment and CapEx are lower after the publication of standards, if a higher number of privacy/ethical standards are published.

In the following sections, we empirically test Hypothesis 1. Additionally, in Appendix Section A, we provide proofs to the proposition on which Hypothesis 1 is based.[16] We also provide a numerical example to further validate the predictions of Hypothesis 1: both AI-related and physical investments increase with the publication of an additional technological standard, but decrease with the publication of an additional privacy/ethical standard. Moreover, there is a investment spike (drop) in the period immediately after the publication of technological (privacy/ethical) standards.[17] Note that AI-related investment and physical investment respond to standards publication in the *same* direction, because the AI capital and the physical capital are complements to each other in the production function.

[16] See Proposition 1 in Internet Appendix A.
[17] See Figures A2 and A3 in Internet Appendix A for the numerical examples.

4 Data Collection and Summary Statistics

This section describes the data used in our empirical analyses. Section 4.1 presents our data on AI standards and the relevance of AI standards to AI as a field of science. Section 4.2 describes our data on firm-level AI research and development activities. Section 4.3 details broader firm investment characteristics and presents summary statistics on our sample. Additional information on our country-level AI investments and AI patenting data can be found in Appendix Section C, which also provides detailed variable descriptions.

4.1 Data on AI Standards

We gather data on AI standards from a range of resources, with the primary one being the "US Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools" report produced by the NIST. Prepared in response to EO 13859, this report guides the formulation of a strategy that fosters U.S. government's involvement in AI standardization around the globe. It outlines important committees integral to AI standardization within international organizations such as the International Organization for Standardization (ISO), International Electrotechnical Commission (IEC), and Institute of Electrical and Electronics Engineers (IEEE). Acknowledged worldwide as authoritative arbiters, these committees wield decisive power in directing both the current state and the future course of AI standards.[18]

After identifying AI-centric standardization organizations and committees, we proceed with manual data collection directly from the respective websites of these committees. Although our primary interest centers on the more recent standards developed by these committees, we've curated a comprehensive timeline of their standards extending back to the 1970s. Moreover, we delve into the processes behind the creation of these standards, particularly identifying the countries leading these initiatives and those

[18] We identified 33 new AI-related standards not covered by NIST, on autonomous vehicles and health informatics, as listed by the UK government's AI Standards Hub. Updated results, incorporating these standards, are available upon request.

involved as committee members. Committee websites, however, offer membership information only as of the times of our data collection, April 2023. To circumvent this constraint and access historical data, we utilize the Wayback Machine (accessible at https://archive.org/web/). This resource enables us to retrieve archived versions of committee websites, thus permitting the collection of membership information from previous years, going back to 2017. This timeframe aligns well with our research focus, which leans more towards understanding the recent standards rather than the earlier ones. Notably, the post-2017 period encompasses 1,200 of the 5,456 standards published since the 1970s.

[Figure 1 about here]

Figure 1 illustrates the number of standards published each year by each ISO secretariat, shown on the left vertical axis. Secretariats are the countries that lead their assigned committees in the ISO standardization process. Typically, a national standardization body from a specific country holds this role. Hosting an ISO committee secretariat offers significant benefits to local businesses and industries. By taking on this responsibility, a country gains a central role in coordinating the standardization process, giving it more influence over the committee's work and the development of standards. This increased involvement allows governments to actively shape the standards that will later govern their local industries, ensuring their local needs and interests are considered.

As shown in Figure 1, the standardization process concerning AI, as indicated by the standards published by committees recognized by the US government as influential in the field, commenced in the 1970s. However, the advancement of AI standardization during the 1980s and 1990s exhibited a relatively slow pace. In the 2000s, the pace of AI standardization significantly accelerated. Notably, US and Japanese secretariats played a pivotal role in driving this progress. The timeline of AI standards development shown in Figure 1 aligns with the historical progression of AI as described by Russell and Norvig (2021), which is one of the most-used AI textbooks, adopted by over 1500 schools around the globe as of 2024. While the concept of AI originated as early as in the 1940s, significant advancements began in

2001, fueled by the availability of big data, which was enabled by remarkable increases in computing power and the creation of the World Wide Web (WWW).

Although NIST has considerable expertise in identifying committees that specialize in AI standards, we independently verify the AI relevance of the standards published by the committees selected by NIST. To do so, we compare the contents of these standards with contents of Russell and Norvig (2021).[19] To begin our analysis, we compile a list of unique words each year by merging the titles of all published standards in our sample. These annual word lists are then compared to the word list derived from the contents section of Russell and Norvig (2021), resulting in a unique AI relatedness measure for each year. The comparison process involves the following steps. First, we lemmatize both textual inputs and exclude words from the Cambridge Core Functional Words list (`https://bit.ly/4ff0ahV`), as well as numbers and terms such as 'Part,' 'Vocabulary,' and 'Addendum.' We then calculate similarity using two methods: strict and fuzzy string matching. In strict matching, we identify words that exist in both dictionaries, which suggests a 100% similarity based on Levenshtein distance. In fuzzy matching, we select words with at least 80% similarity based on Levenshtein distance.

The right vertical axis of Figure 1 shows the annual frequency of the book's contents reflected in the published AI standards. During our main sampling period, between 35% and 45% of the vocabulary from Russell and Norvig (2021) was exactly used in AI standards. When we apply fuzzy string matching rather than strict matching, these ratios increase to between 60% and 90%. These indicate that standards from NIST-selected committees are closely related to AI, at least collectively. Notably, these percentages are not cumulative; they reflect the inclusion of the book's vocabulary in AI standards for each year. However, caution is warranted, as an increase in the number of standards could mechanically incorporate more of the book's vocabulary over time. Furthermore, it is possible that only specific AI standards are driving the trends shown in Figure 1. To address these caveats, we shift our focus from the overall vocabulary

[19] The textbook's contents can be viewed here. Supportive evidence from using other AI textbooks is available upon request.

coverage to evaluating the degree to which each standard is related to the contents of Russell and Norvig (2021).

[Table 1 about here]

Panel A of Table 1 showcases the top 10 AI-related standards from our main sampling period (post-2017), identified through strict word matching between ISO standards' titles and the content section of Russell and Norvig (2021). The titles of ISO 4213, ISO 24030, and ISO 24029 explicitly mention "artificial intelligence," "machine learning," and "neural networks," directly aligning with AI themes. Similarly, titles of ISO 20547 and ISO 23092 highlight "big data" and "genomic information representation," areas heavily reliant on AI for data processing and analysis. ISO 24760, ranked second highest, specifies a framework for the secure management of identity-related data. Key AI applications, such as biometric recognition, rely on effective privacy protections for identity data, making this standard vital for maintaining trust and security within interconnected AI networks.[20] Furthermore, standards such as ISO 27034 and ISO 10373 address technologies and security measures essential for AI applications, including authentication and security, and provide guidelines for protecting AI systems.[21] Panel B of Table 1 features standards that cite AI-related concepts such as modern software, programming languages, and robotics between 2000 and 2017. Untabulated analyses show that adding the bibliography of Russell and Norvig (2021), which includes scientific research papers on AI, to our similarity measurement does not change our main observations, and AI standards with the lowest AI relatedness scores cover topics such as media formats. Overall, Table 1 suggests that based on similarity of content, standards published by NIST-chosen committees do publish several AI-related standards during the main sampling period of this paper.

[20] https://www.iso.org/standard/77582.html, https://bit.ly/3YhziYA, https://bit.ly/3SnbdvB, https://bit.ly/4bZSyx1.

[21] ISO 27034 prescribes a systematic approach to ensure the critical data used by an organization is adequately protected throughout the engineering lifecycle. See https://www.iso.org/standard/76070.html. ISO 10373 defines test methods for the effectiveness of personal identification cards, which store identity-related data potentially used by AI-assisted biometrics recognition. See https://www.iso.org/standard/73600.html.

[Table 2 about here]

Table 2 provides useful summary statistics on the AI-relatedness of AI standards. It also presents textual similarities between AI standards and other well-known textbooks with false triggers (i.e., vocabulary similar to AI vocabulary but in contexts not directly related to AI). These books are: (1) *A Primer in Game Theory* (1992), which contains sections on information (e.g., complete and perfect information), models (e.g., Stackelberg model of duopoly), and strategy (e.g., mixed strategy). (2) *Introducing Psychology: Brain, Person, Group* (2020), which contains sections on intelligence (e.g., intelligence: what is it?), ethics (e.g., ethics and social psychology), and memory (e.g., encoding information into memory stores). (3) *Shigley's Mechanical Engineering Design* (2015), which contains sections on safety (e.g., safety and production liability) and theorems (e.g., Castigliano's Theorem). (4) *Elements of Information Theory* (2006), which contains sections on entropy (e.g., relative entropy), coding (e.g., Channel coding theorem), and data (e.g., data compression). (5) *Introduction to Algorithms* (2009), which contains sections on algorithms (e.g., Strassen's algorithm), programming (e.g., dynamic programming), and computation (e.g., computational geometry).

If our relatedness measure indicates high similarities between AI standards and these textbooks, it could suggest that our AI-relatedness measure may be driven by factors unrelated to AI. Conversely, if our methodology demonstrates low similarities, this could provide evidence for the reliability of our approach. As shown in Table 2, the AI-relatedness score is significantly higher than all other scores in both strict and fuzzy matching. For strict matching, the AI-relatedness score has a mean of 24.98%, compared to lower means for Game Theory (6.24%), Psychology (8.15%), Mechanical Engineering (13.53%), Information Theory (11.85%), and Algorithms (12.41%). This suggests that, on average, around a quarter of the words in a given AI standard are exactly related to concepts in Russell and Norvig (2021). This rate increases to 40.12% when considering fuzzy matching.[22]

[22]The popular AI-related terms include *data*, which is essential for training and testing models; *model*, which represents

Collectively, our findings from Tables 1 and 2, along with Figure 1, suggest that the committees identified by NIST as critical to AI standardization have published a significant volume of AI-related standards during our main sampling period. We find supportive evidence that AI-relatedness is strong across a wide range of AI standards rather than being driven by only a few standards. These findings are robust to a stress test where we evaluate our AI-relatedness measures using vocabulary that resembles AI language but is not directly related to AI. Based on these observations, we next examine the participation of the United States and other countries in the global AI standardization process.

[Figure 2 about here]

Figure 2 presents a circle pack figure that visually represents the number of AI standards published under different committees and secretariats from 1972 to 2022. To enhance readability, the committee codes have been replaced with short descriptions–i.e., scopes–that reflect the operations of each committee, as outlined in Appendix Table C2. The figure highlights the diverse areas covered by AI standardization efforts under US secretariats, including industrial data, programming languages, human biometrics, guidance on AI, and interoperability. The United States has emerged as a significant contributor to AI standards, publishing a total of 2,572 standards. Similarly, Japan has played a prominent role, publishing 1,259 standards primarily focusing on digital information and electronic devices, including graphics and personal identification. Germany has made substantial contributions with 560 standards related to industrial device control, safety, information security, and governance. The United Kingdom has produced 480 standards covering graphics, personal identification, automation, and software. AI standardization efforts have extended beyond these specific countries, encompassing a wide range of domains globally. These efforts have included the development of standards in areas such as governance, industrial automation, robotics, IoT, and software development.

the algorithms used for predictions; *application*, referring to the practical use of AI in software; *representation*, which involves encoding or structuring information; *processing*, which is crucial for handling and analyzing data; and *training*, the process of teaching models with data.

[Figure 3 about here]

Members of ISO committees also play an important role in publishing global standards. This is because consensus within the ISO voting process is achieved when a substantial majority (i.e., two-thirds) of committee members vote in favor. Figure 3 provides a visualization of the involvement of countries around the globe in ISO committees and secretariat roles from 2017 to 2023. As shown in the figure, the United States takes the lead in terms of both secretariat years and committee membership years. Following the United States, countries such as the United Kingdom, Japan, Germany, and South Korea (along with France, Australia, and India, which also lead secretariats) demonstrate significant involvement, measured by their committee years.

While many countries actively participate in standardization efforts, as evident from their committee years, they do not hold secretariats. This group includes China, Russia, Canada, South Africa, Poland, as well as Western European countries like Spain and Portugal, and Southern European countries like Italy. South American countries (such as Brazil, Argentina, and Chile), Central American countries like Mexico, Central and Eastern European countries (including Czech Republic, Turkey, Romania, and Bulgaria), as well as Middle Eastern and African countries like Saudi Arabia and Iran exhibit weaker involvement. Additionally, several African and Asian countries show no involvement in AI standards development.

It's important to note that different committees may publish standards on similar subjects, leading to overlapping areas of standardization. For example, standards concerning data or machine learning may be published by committees such as the industrial data committee, data interchange committee, information security committee, or even the robotics committee, among others. Similarly, standards related to programming languages can be published by a dedicated committee on programming languages or by another committee focused on data privacy. Notably, this approach provides an additional measure of AI relatedness, based on contextual relatedness to the main subfields of AI, rather than solely on the contents of Russell and Norvig (2021).

Figure 4 provides an overview of the different yet non-exclusive categories of standards and their subject areas. We list some of these below and provide detailed descriptions for them in Figure 4 's caption. In the footnote following each category, we explain why this category is related to AI, and we provide examples of standards under that category. See Figure C5 for the correlation of these categories and Appendix Section D.2 for additional examples of AI standards.

- **Machine Learning**: Standards related to machine learning algorithms, natural language processing, fuzzy logic, neural networks, decision-making processes, semantic analysis, training methodologies, and speech and image recognition.[23]

- **Programming Languages**: Standards covering programming languages, software development practices, program design, software quality assurance, and specific languages like SQL, Pascal, BASIC, Linux, C#, Java, C++, and Python.[24]

- **Ethics and Accountability**: Standards addressing governance, ethics, security, explainability, trustworthiness, and societal impact of AI systems.[25]

- **Data**: Standards for data management, privacy, security, exchange, and interoperability, excluding those standards that are already labeled as machine learning standards.[26]

[23]The development in machine learning and neural networks fuel the recent advances in AI technology, and these techniques are applied to fields such as computer vision and robotics (Russell and Norvig, 2021). Examples of machine learning standards include: ISO/IEC TR 24029-1:2021 (Artificial Intelligence (AI) – Assessment of the robustness of neural networks – Part 1: Overview); ISO/IEC TR 24372:2021 (Information technology – Artificial intelligence (AI) – Overview of computational approaches for AI systems); ISO/IEC 15938-17:2022(Information technology –Multimedia content description interface – Part 17: Compression of neural networks for multimedia content description and analysis).

[24]Programming languages are the tools through which AI algorithms are implemented. Examples of programming language standards include: ISO/IEC TR 29119-11:2020 (Software and systems engineering — Software testing — Part 11: Guidelines on the testing of AI-based systems); ISO/IEC 24709-1:2017 (Information technology — Conformance testing for the biometric application programming interface (BioAPI) — Part 1: Methods and procedures); ISO/IEC 30106-2:2020 (Information technology — Object oriented BioAPI — Part 2: Java implementation).

[25]Ensuring ethical and responsible AI is an important objective of AI standardization. See https://www.iso.org/artificial-intelligence. Examples of ethical and accountability standards include: ISO/IEC TR 24368:2022 (Information technology — Artificial intelligence — Overview of ethical and societal concerns); ISO/IEC TR 24028:2020 (Information technology — Artificial intelligence — Overview of trustworthiness in artificial intelligence); ISO/IEC 24779-4:2017 (Information technology — Cross-jurisdictional and societal aspects of implementation of biometric technologies — Pictograms, icons and symbols for use with biometric systems — Part 4: Fingerprint applications); ISO/IEC 38507:2022 (Information technology — Governance of IT — Governance implications of the use of artificial intelligence by organizations).

[26]Data is the fuel for the AI technology, commonly regarded as the new "oil". Deep learning, for example, depends on the

- **Interchange**: Standards focusing on the interchange or exchange of data, including data formats, protocols, and representation standards.[27]

- **Privacy**: Standards for privacy protection, cybersecurity, biometric data, and human rights considerations.[28]

- **Automation**: Standards for automated decision-making, process automation, and workflows, excluding those that are already labeled as machine learning standards.[29]

- **Interoperability**: Standards addressing compatibility and connectivity between AI systems, as well as integration with other technologies such as IoT, digital twins, internet protocols, and IoT connectivity standards.[30]

[Figure 4 about here]

As illustrated in Figure 4, the standardization efforts within the field of AI have seen a significant surge in the domains of Machine Learning, Programming Languages, and Safety and Accountability during

availability of large amount of data (Russell and Norvig, 2021). Ensuring data quality, privacy, and effective interchange format is also a major objective for AI standardization. See https://www.iso.org/artificial-intelligence. Examples of data standards include: ISO/IEC TR 20547-1:2020 (Information technology — Big data reference architecture — Part 1: Framework and application process); ISO/IEC 38505-1:2017 (Information technology – Governance of IT – Governance of data – Part 1: Application of ISO/IEC 38500 to the governance of data); ISO/IEC 19794-13:2018 (Information technology – Biometric data interchange formats – Part 13: Voice data); ISO/TS 10303-1831:2019 (Industrial automation systems and integration – Product data representation and exchange – Part 1831: Application module: Scan data 3D shape).

[27] Effective exchange of data enhances the interoperability of AI systems, and it is a major objective for AI standardization. See https://www.iso.org/artificial-intelligence. Examples of interchange standards include: ISO/IEC 39794-16:2021 (Information technology — Extensible biometric data interchange formats — Part 16: Full body image data); ISO/IEC 21778:2017 (Information technology — The JSON data interchange syntax); ISO/IEC 30161-1:2020 (Internet of Things (IoT) — Requirements of IoT data exchange platform for various IoT services — Part 1: General requirements and architecture).

[28] Privacy protection and cybersecurity are essential for secure AI systems. Examples of privacy standards include: ISO/IEC 20547-4:2020 (Information technology — Big data reference architecture — Part 4: Security and privacy); ISO/IEC 27400:2022 (Cybersecurity — IoT security and privacy — Guidelines); ISO/IEC 27559:2022 (Information security, cybersecurity and privacy protection – Privacy enhancing data de-identification framework).

[29] Automation is closely related to AI because AI enables the automation of complex tasks such as manufacturing, healthcare, etc. Examples of automation standards include: ISO 23247-1:2021 (Automation systems and integration — Digital twin framework for manufacturing — Part 1: Overview and general principles); ISO 21919-1:2019 (Automation systems and integration — Interfaces for automated machine tending — Part 1: Overview and fundamental principles); ISO 14306:2017 (Industrial automation systems and integration — JT file format specification for 3D visualization).

[30] Improving the interoperability between AI systems is a major objective for AI standardization. See https://www.iso.org/artificial-intelligence. Examples of interoperability standards include: ISO/IEC 19763-3:2020 (Information technology — Metamodel framework for interoperability (MFI) — Part 3: Metamodel for ontology registration); ISO/IEC 30162:2022 (Internet of Things (IoT) — Compatibility requirements and model for devices within industrial IoT systems); ISO/IEC 21823-3:2021 (Internet of things (IoT) — Interoperability for IoT systems — Part 3: Semantic interoperability).

our sampling period from 2017 to 2022, aligning with the vision of EO 13859. It is worth noting that the relatively lower frequency of standards in the Data category does not diminish the importance of data standards. Instead, it indicates that extensive guidelines for data management have already been established through previous standardization efforts.

In the Data category, the new standards predominantly revolve around Machine Learning (and we count them as such) and incorporate accountability aspects. This signifies the evolving landscape of AI applications and reflects the need to address the challenges and considerations specific to ML models. Similarly, the standards related to Data Interchange follow a similar pattern, focusing on integrating data with ML models and ensuring effective and secure data exchange. Conversely, automation standards, including those associated with physical equipment, have experienced a decline in frequency. This shift in focus can be attributed to the increasing emphasis on advancing AI technologies and their integration into various processes.

In summary, this section offers an overview of our AI standards data. We demonstrate that the committees identified by NIST as crucial for AI standardization have produced a substantial number of AI-related standards. We delineate the data sources and emphasize the pivotal role of committees and secretariats in AI standardization. Furthermore, we present evidence showcasing the evolution of standards issued by AI-centric committees over time. In the subsequent section, we expand our analysis by providing descriptive statistics on AI-specific research activities.

4.2 Data on AI Research and Development

This section provides an overview of our data on firm-specific AI research and development activities. This data comes from the Private-sector AI-Related Activity Tracker (PARAT) database, maintained by the Emerging Technology Observatory (ETO). It contains detailed information on firms' research publications at major AI conferences, which serve as a proxy for their commitment to AI research and devel-

opment.[31] ETO compiles this data from over 260 million scholarly articles, linking publications to companies based on authors' institutional affiliations. Additionally, ETO employs machine learning models to identify research in AI, natural language processing, robotics, and computer vision, all of which are included in our analyses.

Our AI research sample consists of all public and private firms classified as 'mature' by ETO, excluding those with 'undefined' industry values, resulting in a final sample of 577 unique firms between 2018 and 2022. 504 of these firms are based in the United States, with the rest located in countries such as China, France, Germany, Ireland, Japan, Netherlands, South Korea, Sweden, Switzerland, and the United Kingdom. These firms operate across 26 sectors, with the largest being Software & IT Services (67 firms), Technology Equipment (47 firms), Industrial Goods (43 firms), Retailers (24 firms), and Transportation (14 firms).

We focus on AI research as our primary variable of interest because it reflects both firms' investments in AI development and their ability to push the boundaries of AI knowledge in the public domain. From a policy perspective, enhancing AI research thus serves dual objectives. That said, we also examine AI investments in the private domain. These additional analyses include monetary AI investments and AI patenting behavior, based on ETO's country-year panel. Detailed information about this dataset is provided in Appendix Section B.4.2.

4.3 Summary Statistics

In this section, we present descriptive statistics on the variables used in our empirical analyses. Panel A of Table 3 presents summary statistics on (AI innovator) firms that exist in ETO's AI research dataset.

[31] These conferences include the AAAI Conference on Artificial Intelligence (AAAI), International Joint Conference on Artificial Intelligence (IJCAI), IEEE Conference on Computer Vision and Pattern Recognition (CVPR), European Conference on Computer Vision (ECCV), IEEE International Conference on Computer Vision (ICCV), International Conference on Machine Learning (ICML), International Conference on Knowledge Discovery and Data Mining (SIGKDD), Conference on Neural Information Processing Systems (NeurIPS), Annual Meeting of the Association for Computational Linguistics (ACL), North American Chapter of the Association for Computational Linguistics (NAACL), Conference on Empirical Methods in Natural Language Processing (EMNLP), International Conference on Research and Development in Information Retrieval (SIGIR), and the Web Conference (WWW).

As shown, the mean value for logged AI research publications is 0.96. For computer vision research, the mean is 0.51, while both natural language processing and robotics research have means of 0.31. Panel B of Table 3 highlights important details regarding corporate outcomes on all firms in the Worldscope universe from 2017 to 2022. Two notable financial metrics in our analysis are the CAPEX/AT and R&D/AT ratios.[32] Their means (medians) stand at 4.82% and 5.31% (2.14% and 2.11%), respectively.

[Table 3 about here]

We report summary statistics on two additional variables in Panel B. The first one, Log(Committees), refers to the natural logarithm of the number of ISO committees that a country is a member of in a given year for each firm. It represents the level of participation and involvement of a firm's headquarters country in ISO committees. It displays a mean of 1.90 with a median of 2.48. The variable %UNSC Members indicates the percentage of rotating United Nations Security Council Members under a country's secretariat in a given year and remains at zero for countries without secretariats in all years.

In our main specification, the countries with non-zero %UNSC Members values are France, the United Kingdom, and the United States.[33] In later stages of the paper, we use countries with secretariats but without permanent UN Security Council positions as placebos because it is unlikely for such countries to exert influence over the AI standardization process using the UN Security Council. These countries are Sweden, Germany, India, Japan, Australia, and South Korea.[34] With an average of 2%, it suggests a low proportion of UNSC rotating member firms across all committees. However, the standard deviation of 4% illustrates substantial variability in this measure. Since Panel A focuses more on U.S.-centric data from ETO's AI innovators, the mean value for %UNSC Members in Panel A is 10%, with a median of 11%.

[32] Similar to Gutierrez and Philippon (2017); Rajan and Zingales (1998), we also deflate CAPEX with PPE, i.e., we use Worldscope ITEM 8411, which has significantly fewer observations. These results are available upon request.

[33] For example, the United States in 2021 had 5 UNSC members among the 44 countries under its secretariat. This suggests that the instrumental value for 2022 for the United States is equal to $\frac{5}{44} = 11.36\%$.

[34] Similarly, Germany had 49 countries in its secretariats in 2020, and 4 of these were UNSC members. This suggests that the placebo instrumental variable for Germany for 2021 is $\frac{4}{49} = 8.16\%$.

Figure C7 in the Appendix shows the distribution of permanent and rotating UNSC members in a secretariat-committee-year panel led by permanent members of the UNSC and other countries that are not permanent members of the UNSC. As shown, the average is 28.54%. Approximately 35.35% of this figure is driven by rotating UNSC members, highlighting the importance of the instrument. Importantly for us, there is considerable variability across committees, particularly for U.S.-led committees, which are critical for our analyses. For ISO/TC 184/SC 4, the total UNSC membership rate is 41.67%, with 33.33% driven by UNSC rotations. This suggests that UNSC members already satisfy near thirds of the votes necessary to publish new standards.[35] In ISO/TC 184/SC 5, the total UNSC membership rate is 36.67%, with 24.24% driven by UNSC rotations. In ISO/IEC JTC 1/SC 32, the total UNSC membership rate is 32.74%, with 35.14% driven by UNSC rotations.[36] We utilize the cross-committee variation in later stages of the paper and show evidence that the results are stronger in these committees where UNSC rotations have a greater influence.

Both panels of Table 3 provide descriptive statistics on AI standards. The variable Log(AI Standards) represents the logarithm of AI standards published under the secretariat of a given country in a given year, for all of its local firms. In Panel A (B), it has a mean of 4.05 (1.51) and a standard deviation of 1.37 (1.73). The average log value for machine learning standards is 2.25 (0.73) in Panel A (B), indicating the widespread adoption of these standards in the AI industry. Similarly, the mean of the logged data standards is 3.35 (0.55) in Panel A (B), reflecting considerable utilization of data-related standards. Log(Accountability Standards), a measure of accountability norms in AI utilization, shows a mean of 0.50 (0.23) in Panel A (B) and a standard deviation of0.80 (0.56). Log(Automation Standards) captures the extent of automation norms across firms with a mean of 3.31 (0.42) in Panel A (B) and a standard

[35] Consensus within the ISO voting process is achieved when a substantial majority (usually two-thirds) of participating members vote in favor of a draft, even if there is some opposition. This demonstrates that the issues have been thoroughly discussed, and efforts have been made to address any conflicting arguments. By setting a two-thirds majority requirement for acceptance, ISO ensures that a significant majority of its member bodies support the standard, establishing widespread acceptance and credibility within the international community.

[36] These figures are higher, and our main findings are robust when China is excluded from the committees, which may help with the interpretation of the shock.

deviation of 1.20. This is followed by Log(Programming Standards), and Log(Interoperability Standards) which hold similar implications in their respective areas.

Standards related to privacy and human biometrics are represented by Log(Privacy Standards) and Log(Human Biometric Standards), with means of 1.77 (0.34) and 1.73 (0.37) respectively in Panel A (B). Figure C5 in the Appendix illustrates the covariance matrix for Panel B variables. The figure reveals a notable 70% correlation between the adoption of machine learning and data standards, despite their distinct definitions. Conversely, the correlation between machine learning and ethical standards stands at 21%.

5 Empirical Framework

In this section, we present the empirical methods we use to validate the theoretical predictions discussed in Section 3. Our primary dependent variable, $y_{i,c,t}$, represents AI-specific or broader investments of firm i from country c in year t. AI-specific investments are quantified through firms' AI research activities, as evidenced by published research papers at leading AI conferences around the globe. Broader investment measures include the ratio of capital expenditures to lagged assets and R&D expenditures to lagged assets. All dependent variables are measured at the end of year t. We estimate

$$y_{i,c,t} = \beta_0 + \beta_1 Log(AI\ Standards_{i,c,t}) + \gamma X_{i,c,t-1} + \tau W_{c,t-1} + \text{ Fixed Effects} + \epsilon_{i,c,t}, \tag{2}$$

where $Log(AI\ Standards_{i,c,t})$ represents the logarithm of the number of AI standards published in year t by all committees under the secretariat of country c, where firm i is located. It's therefore equal to zero for firm-years belonging to countries without secretariats. $X_{i,c,t-1}$ is a vector of observable firm characteristics. It contains logged book value of assets, cash flows to assets, leverage, and logged age of firm i from country c in year *t-1*. $W_{c,t-1}$ is a vector of observable country characteristics. It contains the

logged number of AI committees country *c* is a member of in year *t-1*. It serves as a control variable to account for the potential impact of participating in global AI standardization efforts, even if a country is not *leading* those efforts as a committee leader.

Specification (2) also includes firm and year, or firm and industry × year fixed effects. With industry × year fixed effects we separate out the effects of AI standards from the potential effects of contemporaneous shocks at the industry-year level. This is necessary because AI standards can be more prevalent in certain industries compared with others in a given year. For example, AI standardization may matter more for tech firms in years of patenting spikes or in years with important tech regulations, e.g. CCPA (Canayaz et al. (2022)).

By incorporating firm fixed effects, we investigate firms over time. We include these fixed effects to account for the fact that AI standardization activity may have varying importance for different firms on average. Firm fixed effects help control for unobserved factors that could otherwise contribute to variations in investments, providing a more accurate analysis. We two-way cluster standard errors at country and industry (Fama-French 48) levels to account for the presence of serial correlation in each country and industry. Our findings are robust to employing alternative clustering methods. Specifically, we conducted additional analyses using clustering at the country level, industry level, and a two-way clustering approach at the country and year levels. Across all these clustering methods, the results consistently support our main findings, providing further confidence in the robustness of our results. Furthermore, to ensure maximum retention of the ETO sample in our main analyses, we utilize only fixed effect controls in our AI research regressions. However, results incorporating control variables from the merged PARAT-Worldscope universe are available upon request.

How do we estimate the causal effect of AI standards on investment? An ordinary least squares (OLS) estimate of β_1, our coefficient of interest, may not reveal any causal effect of AI standards on financial outcomes due to endogeneity. For instance, companies of higher unobserved "quality" can leverage

their influence to advocate for the development of more standards that benefit them, thereby reducing uncertainty about the nature of forthcoming standards for these firms. Consequently, these firms don't need to postpone their investments waiting for the standards to be announced, as they foresee that future standards will be aligned with their existing investment. This unobserved higher firm "quality" (i.e., an omited variable) is thus negatively correlated with firm investment post-publication, and positively correlated with the number of standards published, causing a downward bias on β_1.

We estimate specification (2) using a two-stage least squares (2SLS) procedure, employing the well-established shock of two-year rotations in ten of the fifteen UN Security Council (UNSC) seats (Kuziemko and Werker, 2006). To utilize this shock effectively, we need to establish two key points: the collaboration between the UN and ISO, and the UNSC's influence on UN policies. We begin by addressing the first link. The UN's active relationship with ISO is detailed in the report titled "ISO and the UN: Working Together for International Standardization."[37] This report outlines ISO's active engagement with the UN since 1947, highlighting the significant contributions of UN experts to ISO committees and listing 26 UN agencies involved in ISO standards development. Many ISO committees in our sample are officially in liaison with UN-affiliated organizations, which suggests that they make contribution to the committee's standard setting or indicated a wish to be informed.[38] For example, ISO/IEC JTC 1/SC 42 (Artificial intelligence) is in liaison with the International Telecommunication Union (ITU) and the United Nations Educational, Scientific and Cultural Organization (UNESCO), both are UN-agencies.[39] In addition,

[37] Available for download from the ISO website: https://www.iso.org/files/live/sites/isoorg/files/store/en/PUB100432.pdf.

[38] ISO defines an organization is in liaison with a committee if the organization (A) makes an effective contribution to the work of the technical committee or subcommittee for questions dealt with by this technical committee or subcommittee, or (B) indicated a wish to be kept informed of the work of the technical committee or subcommittee, or (C) makes a technical contribution to and participate actively in the work of a working group. See https://www.iso.org/organization/9777.html for the three types of liaison relationships.

[39] For additional examples, ISO/TC 184 (Automation systems and integration) is in liaison with the United Nations Economic Commission for Europe; ISO/TC 299 (Robotics) is connected to World Federation of Engineering Organizations (which is officially associated with UNESCO); ISO/IEC JTC 1/SC 7 (Software and systems engineering) is related to ITU; ISO/IEC JTC 1/SC 27 (Information Security) is related to ITU and United Nations High Commissioner for Refugees; ISO/IEC JTC 1/SC 29 (Coding of audio, picture, multimedia and hypermedia information) is connected to ITU and World Intellectual Property Organization. See information provided under "organizations in liaison" in the corresponding committee websites on ISO, e.g., https://www.iso.org/committee/6794475.html.

a notable example of UN-ISO collaboration in artificial intelligence is the work of the Standardization Programme Coordination Group (SPCG) in the World Standards Cooperation. The SPCG website clearly outlines joint efforts between ITU and ISO on topics such as AI, big data, and machine learning.[40]

Given the evidence for the influence of the UN over ISO, we next explore whether the UNSC can influence UN policies. Economics literature provides insight into this question. Kuziemko and Werker (2006) show that a rotating member country's US aid increases by 59 percent and its UN aid by 8 percent when it joins the council.[41] This suggests that the UNSC does use the UN as a vehicle to influence policy in a quid pro quo manner and allows us to make a formally testable relevance assumption. We hypothesize that the number of AI standards published under the secretariats of the United States and other permanent UNSC members will increase (decrease) as the percentage of rotating UNSC members under these secretariats increases (decreases). This is based on the expectation that more (fewer) countries will align with and support the initiatives of these leading secretariats in their respective committees. We empirically support this assumption by employing F-tests with well-known rules of thumb (Lee et al., 2022) and confirm that our test statistics comfortably surpass the necessary threshold values.

The remaining identifiability assumptions of the 2SLS procedure are instrumental unconfoundedness and exclusion. The unconfoundedness assumption (also known as independence) states that there are no backdoor paths between the instrument and the dependent variables of specification (2). This relies on the conditional orthogonality between elections of rotating UNSC members and our financial outcome variables ($y_{i,c,t}$) beyond the control structures introduced in specification (2). Although unconfoundedness is not a formally verifiable assumption, we provide ample empirical evidence for the

[40] Please see the SPCG website here: https://www.worldstandardscooperation.org/what-we-do/spcg/. Additionally, the US government directs its agencies, such as the Department of Commerce, to advance the AI agenda established by NIST. A prime example of this is the U.S.-India initiative on Critical and Emerging Technology, which seeks to enhance U.S.-Indian collaboration on standard-setting on trustworthy AI, among other objectives (https://bit.ly/49fZFkW). This initiative was established in 2022, which was one year after India rotated into UNSC in 2021 and received a spike of US foreign aid (i.e., obligations increased from $161 million in 2020 to $316 million in 2021, data source: https://foreignassistance.gov/data).

[41] Kuziemko and Werker (2006) find that these effects increase during years in which key diplomatic events take place. In untabulated results, we confirm that our main findings do not change if we study "import years", but based on our observation most years after 2017 are "important years" based on the war in Ukraine.

rotating countries' inability to time their two-year UNSC memberships based on observable proxies for investment such as economic complexity indices (Hidalgo et al. (2009)).[42] We also find no evidence for rotating UNSC members timing their AI committee and UNSC memberships in coordination. These provide supplementary evidence for the arguments in Kuziemko and Werker (2006) on the orthogonality of two-year UNSC rotations against other world events.

The exclusion restriction assumption is also formally untestable, and it states that our instrument's effect on financial outcome variables are fully through AI committee membership. Thanks to our controls variables and the fixed effects (i.e., firm and industry × year), backdoor paths through which rotating UNSC membership can influence financial outcomes are limited.[43]

Based on the identification assumptions above, we run first-stage regressions on the below model:

$$Log(AI\ Standards_{i,c,t}) = \alpha_0 + \alpha_1\ \%\ UNSC\ Members_{i,c,t-1} + \gamma X_{i,c,t-1}$$
$$+\tau W_{c,t-1} + \text{ Fixed Effects} + \epsilon_{i,c,t}, \tag{3}$$

where % UNSC Members$_{i,c,t-1}$ serves as an instrumental variable, representing the percentage of rotating UNSC members in the year *t-1* within the secretariats of permanent UNSC member country *c*. To calculate the ratio, we divide the total number of rotating UNSC members across the committees under the secretariat of country *c* in a given year by the total number of committee members under the same secretariat in that year. We assign this percentage value to all firms *i* headquartered in country *c*. It therefore measures the percentage of ISO members in the secretariats of the United States, the United Kingdom, and France for a specific year. However, it is equal to zero for all other countries in the

[42] See, for example, Appendix Figure C4, which presents empirical evidence indicating that rotating UNSC members do not specifically target AI Committees.

[43] We also conduct an informal test of the exclusion restriction with a zero-first-stage test that evaluates the usefulness of our instrument in a subsample, e.g., industries that are weakly dependent on AI, in which the instrument affects financial outcomes minimally (Angrist et al. (2010); Altonji et al. (2005)). The underlying idea is that if the first stage, which captures the effect of the instrumental variable (IV) on the treatment variable, is zero within a specific subsample, then the reduced form, which represents the effect of the IV on the outcome, should also be zero if the exclusion restriction is met. Our results on these tests are also available upon request

Worldscope universe. This instrumental variable enables us to compare the standards issued under the secretariats of countries that experience random variations in the composition of committee members, against countries that do not undergo such changes.

In the second stage of our 2SLS procedure, we run regressions on the below model:

$$y_{i,c,t} = \beta_0 + \beta_1 Log(\widehat{AI\ Standards}_{i,c,t}) + \gamma X_{i,c,t-1} + \tau W_{c,t-1} + \text{ Fixed Effects} + \epsilon_{i,c,t}, \tag{4}$$

where $Log(\widehat{AI\ Standards}_{i,c,t})$ denotes the instrumented $Log(AI\ Standards_{i,c,t})$ from the first stage. This identification strategy allows us to estimate the effect of an increase in the number of AI standards under a country's secretariat on financial outcomes *locally* on firms headquartered there. In doing so, we exploit time-series variation in AI standard publications driven by changes in the prevalence of politically-aligned AI committee members under a secretariat.

5.1 A Discussion of Placebo Tests and Committee-Level Shocks

Although we have compelling evidence for the relevance condition and well-founded arguments for the unconfoundedness and relevance assumptions, we refine our empirical approach with two key improvements that support our identification strategy and provide important tests for effect heterogeneity. First, we conduct a placebo test by analyzing the percentage of UNSC rotating members under the secretariats of Sweden, Germany, India, Japan, Australia, and South Korea—countries that are not permanent UNSC members but hold secretariat positions. In this placebo analysis, we retain the empirical specifications outlined in (3) and (4) and apply our two-stage procedure. Our only modification is the definition of %UNSC Members$_{i,c,t-1}$, which now represents the percentage of UNSC rotating members within the secretariats of these countries, while being zero for all other countries in the sample. If UNSC rotations significantly affect firm investments in these placebo countries, it would indicate the presence of potential confounding factors or alternative channels (e.g., competition), which may complicate our analyses.

Second, we significantly refine our identification strategy by shifting from using two-year rotations as a shock to each secretariat to using them as a shock to each committee. The proportion of favorable members in U.S.-led committees, for example, varies depending on the composition of each committee prior to UNSC rotation announcements. Consequently, we use the percentage of UNSC members in each committee as an instrument for the number of standards published by each committee. This adjustment also allows us to examine effect heterogeneity, which should be crucial for policymakers. In particular, activities of certain committees could help or hurt US businesses and policy recommendations should take this into account. Importantly, these analyses also help us highlight that our results are stronger in U.S.-lead committees where our instrument has a greater influence. While these analyses are important, we present them in Appendix Section C.1 due to space constraints.

6 Main Findings

This section presents our main empirical findings on the relation between AI standards and corporate outcomes. Section 6.1 details our core findings on firm-level AI research. Section 6.2 covers capital and R&D expenditure. Section 6.3 presents our findings on effect heterogeneity based on the AI relatedness of standards. Section 6.4 presents findings on effect heterogeneity based on topics of AI standards. Lastly, Section 6.5 highlights our findings on firm value. For brevity, additional important findings are presented in Appendix Section C, including effect heterogeneity based on our committee-level instrument, country-level AI investments and AI patents, and a robustness check where we randomly exclude 250 AI standards and rerun the 2SLS regressions.

6.1 The Influence of AI Standards on Firm-Level AI Research

In this section, we present the results of our analysis on the impact of AI standards on firm-specific AI research. We employ the 2SLS procedure outlined in Section 5 to estimate the effects locally. Table 4

displays our findings.

[Table 4 about here]

The results from the second-stage regressions (Panel A) demonstrate that the logarithm of AI standards exerts a significant and positive influence on research outputs in AI, computer vision, natural language processing, and robotics, with respective coefficients of 0.23, 0.22, 0.14, and 0.18. These coefficients translate to standard deviation increases of 0.21 for AI research activity, 0.27 for CV research, 0.22 for NLP research, and 0.32 for robotics research, per standard deviation increase in AI standards. The tF critical values confirm that the estimated effects are statistically significant at the 1% level. Additionally, untabulated results indicate that clustering standard errors only at the sector level yields comparable or in some cases even stronger statistical significance.

Panels B and C provide insights into the drivers of the second-stage regression coefficients through reduced form and first-stage regressions. As anticipated, the instrument substantially increases the logged value of AI standards. The first-stage regressions reveal that a one standard deviation increase in UNSC membership rotation in secretariats of the permanent UNSC member nations results in a 0.59 standard deviation increase in AI standards, underscoring the instrument's effectiveness in the adoption of AI standards. Panel D's OLS regression results suggest a downward bias, as expected and discussed in Section 5. The placebo test in Panel E, using nations not affiliated with the UNSC, provides supportive evidence for the mechanism in play.

Overall, the results from Table 4 demonstrate that AI standards have an economically meaningful and statistically significant influence on firm-specific AI research. As our sample of standards is predominantly represented by technological standards rather than privacy/safety standards, as demonstrated by Table C1 and C2, these findings are consistent with part (i) of our Hypothesis 1, which predicts a positive relationship between AI investments and technological standards. It's important to note also that AI standards not only influence corporate investments but also enhance AI technology for the broader com-

munity through firms' published research. This underscores the value of AI standards beyond merely shaping corporate investment.

In Appendix Section C, we also estimate the influence of AI standards on AI investments and AI patents at the country level. Our findings in Table C3 highlight that a unit increase in Log(AI Standards) is associated with increases in logged AI investments, patent applications, and total AI patents granted by 0.23, 0.46, and 0.35, respectively. In Appendix Figure C8, we show how AI standards influence different areas of AI investments and patent applications. As shown in this figure, AI standards boost investments in areas such as robotics, manufacturing, cybersecurity, privacy, data analytics, software, face recognition, and education. Furthermore, the number of AI patent applications increases in sectors such as banking and finance, security, industrial manufacturing, machine learning, transportation, telecommunications, and computer vision, following the adoption of AI standards.[44]

6.2 The Influence of AI Standards on Capex and R&D Investments

In this section, we present the results of our analysis on the impact of AI standards on capital and R&D investments based on the 2SLS procedure outlined in Section 5. Table 5 displays our findings from the second stage regressions, reporting the coefficient estimates in percentage terms.

[Table 5 about here]

Table 5 reveals that AI standards lead to increases in both capital and R&D expenditures by the year's end. This is demonstrated by the coefficients of 0.48% and 0.50% in the first two columns (representing capital expenditures), and 1.86% and 1.65% in the third and fourth columns (representing R&D expenditures), respectively. Based on the corresponding critical values, these estimates are statistically significant at the 5% level and suggest that a standard deviation increase in AI standards drives a 0.11 standard

[44] We also find an increase in firm-level patenting activity using the PARAT dataset. Our results are available upon request. It's important to note also that several of our statistical estimates in Appendix Figure C8 are statistically significant at 5% and 1% levels based on their tF critical values of 2.31 and 3.85, respectively.

deviation increase in capital expenditures and a 0.28 standard deviation increase in R&D expenditures.

[Table 6 about here]

Table 6 is divided into four panels, presenting findings from reduced-form regressions (Panel A), first-stage regressions (Panel B), OLS regressions (Panel C), and our placebo test (Panel D). These analyses provide a deeper understanding of the effect of AI standards on corporate investments estimated in Table 5. Panel A highlights a clear, positive link between the percentage of UNSC rotating members and the ratios of both capital expenditures and R&D expenditures to total assets. Our findings suggest that a one standard deviation increase in the percentage of UNSC rotating members results in a 0.29% increase in capital expenditures and a 1.10% increase in R&D. Appendix Figure C9 shows our second-stage coefficient estimates after randomly removing 250 AI standards 1,000 times. All estimates remain economically and statistically significant, confirming that the effects of AI standards on CAPEX and R&D hold up under this robustness test.

Panel B highlights a strong positive first stage. Interpreting our estimates suggests that a one standard deviation increase in the percentage of UNSC rotating members results in a growth in AI standards by up to 0.34 standard deviations. Panel C presents the OLS estimates. The coefficients show a positive and significant association across all specifications, amounting to 0.35% for CAPEX/AT and varying from 0.74% to 0.84% for R&D/AT. However, compared to the results in Table 5, our OLS estimates yield smaller coefficients—up to 70% and 45% of the 2SLS coefficients. This comparison illustrates the potential underestimation of the effect of AI standards on corporate investments in the OLS regressions. Lastly, the placebo test results shown in Panel D indicate that the instrument used for the placebo test does not have any meaningful impact on our variables of interest.

Overall, these findings align with part (i) of Hypothesis 1, which posits a positive relationship between physical investment and technological standards. Appendix Table C5 shows that among firms in the United States, United Kingdom, and France—leaders in AI standardization committees—U.S. firms

realize the greatest benefits from AI standards. Even excluding the United States, UNSC member countries continue to exhibit significant advantages over other permanent members like China and Russia, which do not lead any secretariats. Additionally, firms from countries not involved in AI standardization process as committee members suffer, underscoring a clear hierarchy in the impact of AI standards based on country participation in the standardization process.

6.3 Effect Heterogeneity Based on AI Relatedness of AI Standards

In Section 4, we present two key findings concerning the relationship between AI standards and AI as a field of science. First, our analysis reveals that during our main sampling period (i.e., after 2017), the vocabulary from a prominent AI textbook (Russell and Norvig, 2021) was extensively cited in AI standards. Specifically, fuzzy word matching indicates that approximately 90% of Russell and Norvig (2021)'s contents section was referenced by AI standards published in 2018 and 2019. Even under a strict matching approach, around 45% of the book's vocabulary was found in these standards. Second, we develop a novel metric for assessing AI relatedness, which evaluates how well the vocabulary of each AI standard aligns with the contents section of Russell and Norvig (2021). We demonstrate that this metric effectively identifies standards closely related to AI and remains robust when tested with textbooks that contain popular AI terms but are not directly related to the field.

Building on these insights, we next explore how the estimated effects discussed in Sections 6.1 and 6.2 vary based on AI relatedness. In doing so, we analyze the top 50%, 25%, and 10% of AI standards according to their AI relatedness scores, obtained through strict word matching. For each subset, we apply the 2SLS procedure described in Section 5. The findings for these groups are detailed in Panels A through C of Table 7.

[Table 7 about here]

Table 7 shows that the economic significance of AI standards increases with their AI relatedness. Pan-

els A, B, and C reveal a clear upward trend in effect estimates as we move from the top 50% to the top 10% of AI standards by AI relatedness. Moreover, the coefficient for Log(AI Research) in Panel C rises to 0.28, compared to 0.23 in the full sample (Column (1) of Table 4). Similarly, Log(CV Research) increases from 0.21 to 0.28, and Log(NLP Research) grows from 0.14 to 0.17. The coefficient for Log(Robotics Research) goes up to 0.22 from 0.18, while CAPEX/AT rises to 0.58 from 0.50. Notably, RD/AT jumps to 1.99 from 1.65. These findings underscore that effects are more pronounced for standards with higher AI relatedness. All estimates are statistically significant based on the provided tF critical values. This result shows that higher AI-relatedness of standards induces not only higher AI investment, but also higher broader investment. The former result further supports the validity of our AI-relatedness measure. The latter implies that the publications of standards more related to AI increase firms' *overall* productivity, leading to higher general investment. This could be due to the increasing relevance of AI technology in our sample period.

6.4 Effect Heterogeneity Based on Contents of AI Standards

The previous section shows that the influence of AI standards varies with their relatedness to AI, with greater relatedness resulting in more significant effects on both AI and broader investments. In this section, we examine how relatedness to a diverse array of AI topics impacts our results. To that end, we categorize AI standards into the following distinct topics: Machine Learning, Data, Automation, Programming Languages, Interchange, Machinery & Equipment, Ethics & Accountability, and Privacy, which are first introduced in Section 4.1. Notably, we do not find significant results for interoperability and exclude this variable for conciseness. This approach enables us to assess the impact of each AI standards category on AI and broader investments, offering a clear understanding of how different aspects of AI relatedness shape the overall effects.

[Table 8 about here]

Table 8 presents the results of this detailed breakdown, revealing how different AI standard categories impact firm-specific AI research outcomes. The results from Panel A reveal that Data standards, Automation standards, Interchange standards, and Machinery & Equipment standards have significantly positive effects on broad AI research. In contrast, Ethics & Accountability standards exhibit a significant negative impact. Looking at Panels B, C, and D, we see that Data standards have the strongest positive effect on Language Processing research, while Automation, Machinery & Equipment, and Interchange standards have the strongest effect on Computer Vision research. Ethics & Accountability standards have the strongest (negative) effect on Natural Language Processing research. As can be seen from the table, we have omitted tF critical values to ensure the table's fit. Our untabulated findings confirm that all second-stage estimates are statistically significant at the 5% level or better, with the exception of the estimate for Ethics & Accountability standards, which is significant when we cluster the standard errors only at the industry level.

[Table 9 about here]

Table 9 shows how different AI standard categories influence capital and R&D expenditures. The results show significant positive relationships between capital expenditures and standards associated with Machine Learning, Data, Automation, Programming Language, Interchange, and Machinery & Equipment. The magnitude of these effects varies, with Machine Learning and Interchange Standards showing the strongest impacts, with 1.58% and 0.30% increases in CAPEX/AT, respectively. However, standards related to Ethics & Accountability and Privacy show a negative, albeit insignificant, relationship with CAPEX. Panel B examines the impact on R&D expenditures. Machine Learning, Data, Automation, Interchange, and Machinery & Equipment standards all have significant positive relationships with R&D, with Machine Learning and Interchange Standards again having the most substantial impact (5.17% and 1.00% increase in R&D/AT, respectively). Ethics & Accountability standards show a negative, but insignificant impact on R&D. Privacy standards, on the other hand, show a significant negative relationship with

R&D, resulting in a 9.36% decrease in R&D/AT.[45]

Consistent with Hypothesis 1, the findings in Table 8 and 9 highlight the nuanced ways in which different categories of AI standards can drive or hinder AI investment and broader investment in CAPEX and R&D. Firm investments are positively influenced by the number of published technological standards such as (a) Data and Interchange Standards, which serve the AI eco-system, and (b) Machine Learning and Automation standards, which aim to provide technological instructions on implementations of AI technologies. However, investment is discouraged after the publication of Privacy and Ethical standards, which impose constraints on AI technologies. This underscores the importance of individual categorization and consideration when interpreting the effects of AI standards on corporate investment decisions.

Table C4 of the Appendix reveals several related and important findings. First, after restricting our sample to the top 10% of AI standards by AI relatedness, all AI standard categories demonstrate economically larger effects on both CAPEX and R&D expenditures. Second, the previously insignificant Programming Languages category now exhibits both economic and statistical significance for CAPEX and R&D in this restricted sample.[46]

Tables C6 and C7 of the Appendix show the impact of different standardization committees on AI and broader investments by using a more sophisticated 2SLS procedure explained in Section 5.1. As shown, our findings are robust to the exclusion of committee TC 184/SC 4, which publishes many of the AI standards. We also show that not all committees positively influence investments. For example, the Programming Languages committee significantly increases investment, while committees on Data Interchange and Guidance on AI have negative effects. Overall, this section highlights the significant role of the issuing committees in shaping corporate investment decisions. They suggest that a blanket assessment of AI standards as universally good or bad is flawed; their effectiveness depends on both their

[45] Once again, we have omitted tF critical values to ensure the table's fit. Our untabulated findings confirm that all second-stage estimates are statistically significant at the 5% level or better.

[46] The smaller sample size for AI research data limits our ability to conduct a comparable analysis. Nevertheless, detailed results for this smaller sample are available upon request.

content and the issuing committee, as demonstrated in this and previous sections.

6.5 AI Standards and Firm Value

The effects of AI standards on firm valuation are important to analyze, as they provide a forward-looking perspective regarding the influence of AI standards on firms. In this section, we employ two approaches to analyze firm valuation. Firstly, we examine the one-year ahead impact of AI standards on valuation ratios and provide insights into how AI standards influence investors' expectations and market perception of firms' long-term prospects. Secondly, we assess the dynamic treatment effects on valuation ratios by examining valuations from a year ago up to three years later. By observing the shifts in Tobin's Q or M/B over time, we explain the anticipation, persistence, and trajectory of the impact of AI standards on firm valuation.

[Table 10 about here]

Table 10 provides insights into our initial approach. It outlines the local treatment effects of AI standards on future Tobin's Q and M/B ratios, indicating a significant increase in firm value. Based on our estimates, an increase of one standard deviation in AI standards increases next year's firm value by up to 0.12 and 0.14 standard deviations (respectively based on M/B and Tobin's Q regressions) for the average firm. Crucially, our first-stage estimates surpass the necessary threshold for the relevance condition. It's important to note that AI standards can offer effects beyond a single year as their imprint on firm activities deepens. For this reason, we further scrutinize firm value dynamics over an extended period.

[Figure 5 about here]

Figure 5 illustrates the dynamics of the effects. As shown, the pre-standardization period reveals no distinguishable trends. However, a pronounced positive impact on firm value becomes evident from the first year onward, demonstrating economic and statistical significance, along with a sense of persistence.

Our Tobin's Q regression estimates indicate that a surge of one standard deviation in AI standards can boost firm value by up to 0.31 and 0.46 standard deviations in the second and third years respectively. Collectively, this section signifies that the ripple effects of AI standards extend beyond the initial near-term impacts, showcasing a compelling compound effect.

7 Conclusion

Standardization is an influential force in shaping innovation and business performance across various sectors. However, its impact on emerging technologies such as AI is understudied. This paper aims to bridge this gap by examining how AI standards shape corporate outcomes. In line with the adage, 'Frameworks are akin to toothbrushes. Everyone needs one but prefers not to use another's,' the standardization of AI is a painful yet vital task. It has multifaceted effects for businesses. On the one side, standards offer a concrete roadmap for AI applications, lower the entry threshold for firms, diminish uncertainty, boost compatibility among AI systems, and encourage beneficial network externalities. On the other hand, AI standards enforcing restrictions or compliance to certain norms can curtail AI efficiency, deplete investment, amplify market concentration, create entry barriers, impede radical innovation, and disproportionately favor certain firms at the expense of others.

In this paper, we provide extensive evidence on the relationship between AI standards and AI as a field, as well as empirical insights into how AI standards influence AI research and broader firm investments. Our findings suggest that the universal adoption of AI standards significantly impacts AI research and development, as well as capital investment and R&D expenditure. AI standards leadership, particularly in the United States, spurs higher investment levels than countries with secretariats, like China and Russia, or non-participating countries. The committee issuing AI standards also plays a vital role in investment decisions, with certain committees prompting substantial investment growth while others deter it. We further delve into the nature of AI standards by conducting a content analysis. Our results

underscore the growing importance of machine learning, AI safety and accountability, programming language, and big data standards. Standards related to machine learning, data interchange, and privacy show significant effects on investment, while automation and machinery and equipment standards also have positive impacts. These insights deepen our understanding of the repercussions of AI standardization, underlining the necessity for careful development of AI standards to cultivate transparent, reliable, and profitable outcomes.

Table 1. **Evolution of AI Standards and Their AI Relatedness Since 2000**

This table highlights the standards published by the committees identified by NIST as pivotal for AI standardization across different time frames. Panel A showcases the top 10 AI-related standards from our main sampling period (post-2017). Panel B includes the top 10 standards from the period between 2000 and 2017. Each panel ranks the standards by their AI-relatedness scores, providing details on the standard identifier, committee, title, publication year, and secretariat. To assess the AI relatedness of each standard, we compile a list of unique words from each standard's title. These word lists are then compared to the word list derived from the contents section of Russell and Norvig (2021), resulting in an individual similarity measure for each standard. The comparison process includes several steps. First, we lemmatize both inputs and exclude words from the Cambridge Core Functional Words list (https://bit.ly/4ff0ahV), as well as numbers and terms such as 'Part,' 'Vocabulary,' and 'Addendum.' We then calculate similarity using strict string matching. In strict matching, we identify words that exist in both lists, e.g., with 100% similarity based on Levenshtein distance. We report the ten AI standards with the highest AI-relatedness scores (i.e., % of strictly matched words) within the sampling periods of each panel.

Panel A: Standards with High AI-Relatedness Scores (After 2017)

Rank	Standard	Committee	Title of Standard	Year	Secretariat
1	ISO 4213	SC 42	Artificial intelligence - Assessment of machine learning classification performance	2022	United States
2	ISO 24760	SC 27	A framework for identity management - Part 1: Terminology and concepts	2019	Germany
3	ISO 23092	SC 29	Genomic information representation - Part 1: Transport and storage of genomic information	2020	Japan
4	ISO 20547	SC 42	Big data reference architecture - Part 1: Framework and application process	2020	United States
5	ISO 24030	SC 42	Artificial intelligence (AI) - Use cases	2021	United States
6	ISO 10373	SC 17	Test methods - Part 6: Contactless proximity objects	2020	United Kingdom
7	ISO 24029	SC 42	Assessment of the robustness of neural networks - Part 1: Overview	2021	United States
8	ISO 20000	SC 40	Service management - Part 2: Guidance on the application of service management systems	2019	Australia
9	ISO 27034	SC 27	Application security - Part 3: Application security management process	2018	Germany
10	ISO 23842	SC 36	Human factor guidelines for virtual reality content - Part 2: Considerations when making VR content	2020	South Korea

Panel B: Standards with High AI-Relatedness Scores (Between 2000 and 2017)

Rank	Standard	Committee	Title of Standard	Year	Secretariat
1	ISO 11694	SC 17	Optical memory cards - Linear recording method - Part 4: Logical data structures	2001	United Kingdom
2	ISO 15939	SC 7	Software measurement process	2002	India
3	ISO 10373	SC 17	Test methods - Part 6: Proximity cards	2001	United Kingdom
4	ISO 9899	SC 22	Programming languages - C - Technical Corrigendum 1	2011	United States
5	ISO 1989	SC 22	Programming languages - COBOL	2002	United States
6	ISO 13568	SC 22	Z formal specification notation - Syntax, type system and semantics	2002	United States
7	ISO 13335	SC 27	Guidelines for the management of IT Security - Part 5: Management guidance on network security	2001	Germany
8	ISO 10303	SC 4	Product data representation and exchange - Part 21: Implementation methods	2002	United States
9	ISO 18646	TC 299	Performance criteria and related test methods for service robots - Part 1: Locomotion for wheeled robots	2016	Sweden
10	ISO 15909	SC 7	High-level Petri nets - Part 2: Transfer format - Technical Corrigendum 1	2011	India

Table 2. **AI-Relatedness of AI Standards: Correctly Identifying AI Contexts**

This table presents summary statistics measuring the textual similarity of AI standards with six popular textbooks. It presents two similarity measures: (1) based on strict word matching (Panel A) and (2) on fuzzy word matching (Panel B). To calculate these measures, we first compile a list of unique words from each standard's title. These word lists are then compared to the word list derived from the contents section of a textbook, resulting in an individual similarity measure for each standard with the book. This process includes several steps. First, we lemmatize both inputs and exclude words from the Cambridge Core Functional Words list (https://bit.ly/4ff0ahV), as well as numbers and terms such as 'Part,' 'Vocabulary,' and 'Addendum.' In strict matching, we identify the number of unique words that exist in both lists (i.e., with 100% Levenshtein similarity) as a percentage of the number of unique words in the standard's title. In fuzzy matching, we report the number of unique words with at least 80% similarity based on Levenshtein distance as a percentage of the number of unique words in the standard's title. All statistics are reported in percentage terms. The AI-Relatedness Score is based on Russell and Norvig (2021), a widely-used textbook on AI. The remaining relatedness scores are based on five well-known books, chosen because they contain vocabulary similar to AI-related vocabulary but used in contexts less related to AI, as described in Section 4.1. These five books are Gibbons (1992), Kosslyn and Rosenberg (2018), Budynas and Nisbett (2015), Cover and Thomas (2006), and Cormen et al. (2009), respectively related to game theory, psychology, mechanical engineering, information theory, and non-ML (non-machine-learning) algorithms.

Panel A: Statistics on Strict Word Matching for AI Standards

	N	Mean	Median	SD	P5	P95
AI-Relatedness Score	1,200	24.98	24.00	7.33	15.09	37.50
Game Theory-Relatedness Score	1,200	6.24	5.71	4.34	0.00	15.00
Psychology-Relatedness Score	1,200	8.15	7.39	4.46	2.70	16.67
Mechanical Engineering-Relatedness Score	1,200	13.53	13.17	6.61	2.57	25.00
Information Theory-Relatedness Score	1,200	11.85	10.27	6.50	4.55	25.00
Algorithms-Relatedness Score	1,200	12.41	11.76	5.43	5.13	22.22

Panel B:Statistics on Fuzzy Word Matching for AI Standards

	N	Mean	Median	SD	P5	P95
AI-Relatedness Score	1,200	40.12	39.43	8.58	26.67	54.42
Game Theory-Relatedness Score	1,200	8.83	8.30	5.03	2.07	17.90
Psychology-Relatedness Score	1,200	12.02	11.48	4.93	5.56	21.43
Mechanical Engineering-Relatedness Score	1,200	21.23	20.55	7.57	9.52	34.29
Information Theory-Relatedness Score	1,200	16.86	15.90	7.00	8.33	28.57
Algorithms-Relatedness Score	1,200	20.12	19.40	7.70	9.03	33.33

Table 3. **Summary Statistics**

This table presents summary statistics on our main variables of interest. Panel A examines AI innovator firms, based on AI research data from the Emerging Technology Observatory (ETO). Log(AI Research$_{i,c,t}$), Log(CV Research$_{i,c,t}$), Log(NLP Research$_{i,c,t}$), and Log(Robotics Research$_{i,c,t}$) represent the log of one plus the number of research papers in AI, computer vision, natural language processing, and robotics written by employees of firm *i* from country *c* and published at global AI conferences in year *t*. Panel B presents statistics on financial outcome variables from Worldscope. Both panels present statistics on the number of AI standards (in specific categories or overall) published in year *t* under the secretariat of country *c*, where firm *i* is headquartered. These data are hand-collected based on AI-critical committees identified by NIST in their report "U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools," in response to Executive Order (EO) 13859. %UNSC Members$_{i,c,t-1}$ is nonzero only for firms headquartered in permanent UN Security Council member countries (the USA, France, and the UK), showing the percentage of rotating Security Council members under the secretariats of these countries in year *t-1*. It is zero for all other firms and countries. Detailed variable descriptions are provided in Appendix Section B.

Panel A: Summary Statistics on AI Innovator Firms

	N	Mean	Median	SD	P5	P95
Log(AI Research$_{i,c,t}$)	2,865	0.96	0.00	1.48	0.00	4.03
Log(CV Research$_{i,c,t}$)	2,865	0.51	0.00	1.10	0.00	3.04
Log(NLP Research$_{i,c,t}$)	2,865	0.31	0.00	0.88	0.00	2.08
Log(Robotics Research$_{i,c,t}$)	2,865	0.31	0.00	0.77	0.00	2.08
%UNSC Members$_{i,c,t-1}$	2,865	0.10	0.11	0.05	0.00	0.17
Log(AI Standards$_{i,c,t}$)	2,865	4.05	4.16	1.37	0.00	5.46
Log(Machine Learning Standards$_{i,c,t}$)	2,865	2.25	2.40	0.80	0.00	3.04
Log(Data Standards$_{i,c,t}$)	2,865	3.35	3.95	1.65	0.00	5.35
Log(Ethics & Accountability Standards$_{i,c,t}$)	2,865	0.50	0.69	0.53	0.00	1.10
Log(Automation Standards$_{i,c,t}$)	2,865	3.31	3.76	1.65	0.00	5.34
Log(Programming Standards$_{i,c,t}$)	2,865	2.14	2.30	0.97	0.00	3.43
Log(Interchange Standards$_{i,c,t}$)	2,865	3.29	3.83	1.68	0.00	5.33
Log(Interoperability Standards$_{i,c,t}$)	2,865	1.53	1.95	0.72	0.00	2.08
Log(Privacy Standards$_{i,c,t}$)	2,865	1.77	1.79	0.64	0.00	2.40
Log(Human Biometric Standards$_{i,c,t}$)	2,865	1.73	1.79	0.64	0.00	2.40
Log(Multimedia Standards$_{i,c,t}$)	2,865	1.02	1.10	0.47	0.00	1.39
Log(IoT Standards$_{i,c,t}$)	2,865	0.41	0.00	0.62	0.00	1.61
Log(Machinery & Equipment Standards$_{i,c,t}$)	2,865	1.09	1.10	0.92	0.00	2.71
Log(Unlabeled Standards$_{i,c,t}$)	2,865	0.58	0.69	0.39	0.00	1.10

Panel B: Summary Statistics on All Firms

	N	Mean	Median	SD	P5	P95
CAPEX/AT$_{i,c,t}$	201,833	4.82	2.14	7.87	0.01	18.67
RD/AT$_{i,c,t}$	77,563	5.31	2.11	10.38	0.04	22.17
Sales/AT$_{i,c,t}$	201,732	84.68	67.19	82.09	1.07	238.21
Log(BVA)$_{i,c,t-1}$	201,701	2.95	2.95	0.13	2.75	3.16
CF/AT$_{i,c,t-1}$	201,762	-0.03	0.03	0.42	-0.29	0.17
Leverage$_{i,c,t-1}$	199,149	0.25	0.18	0.33	0.00	0.64
ST Leverage$_{i,c,t-1}$	173,048	0.51	0.48	0.35	0.00	1.00
Log(Q)$_{i,c,t}$	185,455	0.95	0.80	0.47	0.48	1.86
Log(M/B)$_{i,c,t}$	185,557	0.69	0.55	0.55	0.09	1.77
Log(Age)$_{i,c,t-1}$	199,357	2.48	2.71	0.82	0.69	3.56
Log(Committees)$_{i,c,t-1}$	176,108	1.90	2.48	1.19	0.00	2.94
%UNSC Members$_{i,c,t-1}$	187,632	0.02	0.00	0.04	0.00	0.11
Log(AI Standards)$_{i,c,t}$	201,833	1.51	0.00	1.73	0.00	4.16
Log(Machine Learning Standards)$_{i,c,t}$	201,833	0.73	0.00	1.10	0.00	3.00
Log(Data Standards)$_{i,c,t}$	201,833	0.55	0.00	1.23	0.00	3.95
Log(Ethics & Accountability Standards)$_{i,c,t}$	201,833	0.23	0.00	0.56	0.00	1.10
Log(Automation Standards)$_{i,c,t}$	201,833	0.42	0.00	1.20	0.00	3.76
Log(Programming Standards)$_{i,c,t}$	201,833	0.73	0.00	1.10	0.00	2.77
Log(Interchange Standards)$_{i,c,t}$	201,833	0.43	0.00	1.19	0.00	3.83
Log(Interoperability Standards)$_{i,c,t}$	201,833	0.35	0.00	0.68	0.00	2.08
Log(Privacy Standards)$_{i,c,t}$	201,833	0.34	0.00	0.70	0.00	2.08
Log(Human Biometric Standards)$_{i,c,t}$	201,833	0.37	0.00	0.71	0.00	2.08
Log(Multimedia Standards)$_{i,c,t}$	201,833	0.60	0.00	1.07	0.00	3.37
Log(IoT Standards)$_{i,c,t}$	201,833	0.14	0.00	0.44	0.00	1.61
Log(Machinery & Equipment Standards)$_{i,c,t}$	201,833	0.35	0.00	0.71	0.00	1.95
Log(Unlabeled Standards)$_{i,c,t}$	201,833	0.34	0.00	0.53	0.00	1.61

Table 4. **Effects of AI Standards on Firms' AI Research Activities**

This table presents our findings on the influence of AI standards on firms' AI research activities, utilizing data from the Emerging Technology Observatory (ETO). Log(AI Research$_{i,c,t}$), Log(CV Research$_{i,c,t}$), Log(NLP Research$_{i,c,t}$), and Log(Robotics Research$_{i,c,t}$) denote the natural logarithm of one plus the number of research papers in AI, computer vision, natural language processing, and robotics, respectively, authored by employees of firm i from country c and published at global AI conferences in year t. Panels A to D display results from second stage, reduced form, first stage, and OLS regressions as specified in Section 5. Panel E presents the findings from our placebo test, where we instrument the logged number of AI standards published by non-permanent UNSC members that were ISO secretariats—namely, Sweden, Germany, India, Japan, Australia, and South Korea—using the percentage of UNSC rotating members under their secretariats. Panel F displays the fixed effects structures applicable to all panels. Robust standard errors, two-way clustered at the year and industry (FF48) levels, are reported in parentheses beneath the coefficients, with significance levels denoted as ⋆⋆⋆ (1%), ⋆⋆ (5%), and ⋆ (10%). In Panel A, we report tF critical values for 5% and 10% level tests ($\sqrt{c_{0.05}(F)}$ and $\sqrt{c_{0.10}(F)}$) as in Lee et al. (2022) to further assess the significance of the second stage coefficient estimates.

Panel A: Second-Stage Regressions on AI Research Outcomes

	Log(AI Research$_{i,c,t}$)	Log(CV Research$_{i,c,t}$)	Log(NLP Research$_{i,c,t}$)	Log(Robotics Research$_{i,c,t}$)
	(1)	(2)	(3)	(4)
Log(AI $\widehat{Standards}_{i,c,t}$)	0.23**	0.22***	0.14**	0.18**
	(4.34)	(5.17)	(2.95)	(3.19)
$\sqrt{c_{0.10}(F)}$	1.89	1.89	1.89	1.89
$\sqrt{c_{0.05}(F)}$	2.79	2.79	2.79	2.79
Observations	2,865	2,865	2,865	2,865

Panel B: Reduced-Form Regressions on AI Research Outcomes

	Log(AI Research$_{i,c,t}$)	Log(CV Research$_{i,c,t}$)	Log(NLP Research$_{i,c,t}$)	Log(Robotics Research$_{i,c,t}$)
	(1)	(2)	(3)	(4)
% UNSC Members$_{i,c,t-1}$	3.67**	3.61**	2.25**	2.90**
	(3.58)	(3.63)	(3.16)	(4.42)
Observations	2,865	2,865	2,865	2,865
R-squared	0.012	0.017	0.009	0.016

Panel C: First-Stage Regressions on *Log(AI Standards$_{i,c,t}$)*

	(1)	(2)	(3)	(4)
% UNSC Members$_{i,c,t-1}$	16.27**	16.27**	16.27**	16.27**
	(4.00)	(4.00)	(4.00)	(4.00)
Observations	2,865	2,865	2,865	2,865
R-squared	0.501	0.501	0.501	0.501

Panel D: Ordinary Least Squares (OLS) Regressions on AI Research Outcomes

	Log(AI Research$_{i,c,t}$)	Log(CV Research$_{i,c,t}$)	Log(NLP Research$_{i,c,t}$)	Log(Robotics Research$_{i,c,t}$)
	(1)	(2)	(3)	(4)
Log(AI Standards$_{i,c,t}$)	0.15*	0.15**	0.07	0.10
	(2.35)	(3.80)	(1.55)	(1.33)
Observations	2,865	2,865	2,865	2,865
R-squared	0.012	0.016	0.005	0.010

Panel E: A Placebo Test Using UNSC Rotations as an Instrument for Non-UNSC Affiliated Nations

	Log(AI Research$_{i,c,t}$)	Log(CV Research$_{i,c,t}$)	Log(NLP Research$_{i,c,t}$)	Log(Robotics Research$_{i,c,t}$)
	(1)	(2)	(3)	(4)
Log(AI $\widehat{Standards}^{Placebo}_{i,c,t}$)	-0.01	0.01	-0.14	0.45
	(-0.16)	(0.10)	(-0.84)	(1.80)
Observations	2,865	2,865	2,865	2,865
R-squared	0.002	0.003	0.035	0.114

Panel F: Additional Information on Panels A, B, C, D, and E

	(1)	(2)	(3)	(4)
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes

Table 5. **Effects of AI Standards on Capital and R&D Expenditures**

This table presents our estimates of the local treatment effects of AI standards on capital and R&D expenditures using the 2SLS procedure explained in Section 5. Our sampling period is from 2017 to 2022. The number of AI standards is instrumented with the % of UNSC members in a given year under a given secretariat. The control variables included in the analysis are described as follows: $Log(BVA_{i,c,t-1})$: The logarithm of firm-level book value of assets at time $t-1$, representing the financial health of the firm.$CF/AT_{i,c,t-1}$: Cash flow scaled by total assets at time $t-1$, indicating the firm's liquidity position. $Leverage_{i,c,t-1}$: The leverage ratio of the firm at time $t-1$, measuring the extent of debt financing. $Log(Age_{i,c,t-1})$: The logarithm of the firm's age at time $t-1$, capturing the maturity of the firm. $Log(Committees_{i,c,t-1})$: The logarithm of the number of committees the firm is involved in at time $t-1$, reflecting the firm's level of engagement in standardization activities. Detailed variable descriptions can be found in Appendix Section B. Our findings from reduced-form, first-stage and ordinary least squares (OLS) regressions, and placebo tests are presented separately in Table 6. Coefficient estimates are reported in percentage terms and marked with ⋆⋆⋆, ⋆⋆, and ⋆ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The standard errors are two-way clustered at the country and industry (FF48) levels. We also report F-statistics for the excluded instrument from the first stage regressions and tF critical values for 5% and 10% level tests ($\sqrt{c_{0.05}(F)}$ and $\sqrt{c_{0.10}(F)}$) as in Lee et al. (2022) to further assess the significance of the second stage coefficient estimates.

	$CAPEX/AT_{i,c,t}$	$CAPEX/AT_{i,c,t}$	$RD/AT_{i,c,t}$	$RD/AT_{i,c,t}$
	(1)	(2)	(3)	(4)
$Log(\widehat{AI\ Standards}_{i,c,t})$	0.48***	0.50***	1.86***	1.65***
	(4.65)	(3.80)	(9.46)	(4.88)
$Log(BVA_{i,c,t-1})$	45.84***	44.99***	-6.34***	-5.72***
	(6.86)	(6.90)	(-3.04)	(-3.65)
$CF/AT_{i,c,t-1}$	-2.17***	-2.18***	-5.91***	-5.88***
	(-11.82)	(-11.06)	(-8.61)	(-8.43)
$Leverage_{i,c,t-1}$	-1.04	-0.94	2.45***	2.46***
	(-0.92)	(-0.85)	(3.06)	(3.03)
$Log(Age_{i,c,t-1})$	-2.84***	-2.74***	-3.89**	-3.54**
	(-5.26)	(-5.26)	(-2.10)	(-2.11)
$Log(Committees)_{i,c,t-1}$	-0.04	0.04	0.40	0.53
	(-0.10)	(0.11)	(0.46)	(0.63)
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	No	Yes	No
Industry × Year	No	Yes	No	Yes
Observations	171,238	171,238	67,654	67,647
F-stat (Excl. Inst.)	66.10	63.68	97.02	93.12
$\sqrt{c_{0.10}(F)}$	2.06	2.07	1.97	1.98
$\sqrt{c_{0.05}(F)}$	3.26	3.28	3.05	3.06

Table 6. **Capital and R&D Expenditures: Reduced-form, First-stage, and Placebo Results**

This table presents the outcomes of reduced-form, first-stage, and ordinary least squares regressions and our placebo tests to provide additional evidence on the influence of AI standards on corporate investments. Panel A displays the reduced-form regression results where the $CAPEX/AT_{i,c,t}$ and $RD/AT_{i,c,t}$ ratios are regressed on the lagged percentage of UNSC rotating members for each country. Panel B presents the first-stage regression results on the natural logarithm of AI Standards ($Log(AI\ Standards_{i,c,t})$), again using the lagged percentage of UNSC members as the instrumental variable. Panel C reports the ordinary least squares (OLS) regression estimates, with $Log(AI\ Standards_{i,c,t})$ as the key explanatory variable. Panel D displays our findings from our placebo test. We utilize the percentage of UNSC rotating members under the secretariats of countries without permanent UNSC membership (e.g., Sweden, Germany, India, Japan, Australia, and South Korea) as an instrument for their AI standardization efforts. We present second-stage coefficient estimates for the instrumented variable, $Log(AI\ Standards^{Placebo}_{i,c,t})$. Finally, Panel E delineates the control variables employed in the analyses across Panels A, B, C, and D, each applied in corresponding specifications in their columns. Detailed variable descriptions can be found in Appendix Section B. Our sampling period is from 2017 to 2022. Coefficient estimates are reported in percentage terms. The robust standard errors, two-way clustered at the country and industry (FF48) levels, are reported in parentheses under the coefficients, and significance levels are marked as ⋆⋆⋆ (1%), ⋆⋆ (5%), and ⋆ (10%).

Panel A: Reduced-Form Regressions on Corporate Outcomes

	$CAPEX/AT_{i,c,t}$	$CAPEX/AT_{i,c,t}$	$RD/AT_{i,c,t}$	$RD/AT_{i,c,t}$
	(1)	(2)	(3)	(4)
$\%\ UNSC\ Members_{i,c,t-1}$	7.08***	7.33***	27.54***	24.57***
	(4.33)	(3.57)	(13.50)	(5.18)
Observations	171,238	171,238	67,654	67,647
R-squared	0.029	0.028	0.134	0.126

Panel B: First-Stage Regressions on $Log(AI\ Standards_{i,c,t})$

	(1)	(2)	(3)	(4)
$\%\ UNSC\ Members_{i,c,t-1}$	14.64***	14.63***	14.80***	14.85***
	(8.13)	(7.98)	(9.85)	(9.65)
Observations	171,238	171,238	67,654	67,647
R-squared	0.343	0.339	0.334	0.331

Panel C: Ordinary Least Squares (OLS) Regressions on Corporate Outcomes

	$CAPEX/AT_{i,c,t}$	$CAPEX/AT_{i,c,t}$	$RD/AT_{i,c,t}$	$RD/AT_{i,c,t}$
	(1)	(2)	(3)	(4)
$Log(AI\ Standards_{i,c,t})$	0.35***	0.35***	0.84***	0.74**
	(4.08)	(3.67)	(2.86)	(2.52)
Observations	171,238	171,238	67,654	67,647
R-squared	0.029	0.028	0.132	0.125

Panel D: A Placebo Test Using UNSC Rotations as an Instrument for Non-UNSC Affiliated Nations

	$CAPEX/AT_{i,c,t}$	$CAPEX/AT_{i,c,t}$	$RD/AT_{i,c,t}$	$RD/AT_{i,c,t}$
	(1)	(2)	(3)	(4)
$Log(AI\ \widehat{Standards}^{Placebo}_{i,c,t})$	0.27	0.06	0.23	-0.54
	(0.41)	(0.06)	(0.13)	(-0.56)
Observations	171,238	171,238	67,654	67,647
R-squared	0.029	0.027	0.131	0.117

Panel E: Explanatory Variables for Panels A, B, C, and D

	(1)	(2)	(3)	(4)
Table 5 Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry × Year FE	No	Yes	No	Yes

Table 7. **Effect Heterogeneity: AI Relatedness**

This table provides estimates of the local treatment effects of AI standards with high AI relatedness scores on our main dependent variables. Panels A, B, and C apply the 2SLS procedure detailed in Section 5 to the top 50%, 25%, and 10% of AI standards, selected through strict word matching. Panel D describes the control structures employed in each case. To assess AI relatedness, we compile unique words from each standard's title and compare them to a vocabulary list derived from the contents section of Russell and Norvig (2021). This comparison yields an individual similarity measure for each standard. The process includes lemmatizing the text and excluding functional words from the Cambridge Core list (`https://bit.ly/4ff0ahV`), as well as numbers and terms such as 'Part,' 'Vocabulary,' and 'Addendum.' We then calculate the proportion of unique words in each standard's title that match the textbook's vocabulary. Only standards in the top 50%, 25%, or 10% by AI relatedness are included in our analyses. Variable descriptions are detailed in Section 4. Coefficient estimates in columns (5) and (6) are reported as percentages. ⋆⋆⋆, ⋆⋆, and ⋆ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. We also provide tF critical values for 5% and 10% level tests ($\sqrt{c_{0.05}(F)}$ and $\sqrt{c_{0.10}(F)}$), as described in Lee et al. (2022), to evaluate the significance of the second-stage coefficient estimates.

Panel A: Second-Stage Regressions Using the Top 50% of AI Standards by AI Relatedness

	Log(AI Research$_{i,c,t}$)	Log(CV Research$_{i,c,t}$)	Log(NLP Research$_{i,c,t}$)	Log(Robotics Research$_{i,c,t}$)	$CAPEX/AT_{i,c,t}$	$RD/AT_{i,c,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Log(AI\widehat{Standards}_{i,c,t})$	0.22**	0.21***	0.13**	0.17**	0.43***	1.46***
	(4.57)	(5.24)	(3.23)	(3.76)	(3.76)	(4.23)

Panel B: Second-Stage Regressions Using the Top 25% of AI Standards by AI Relatedness

	Log(AI Research$_{i,c,t}$)	Log(CV Research$_{i,c,t}$)	Log(NLP Research$_{i,c,t}$)	Log(Robotics Research$_{i,c,t}$)	$CAPEX/AT_{i,c,t}$	$RD/AT_{i,c,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Log(AI\widehat{Standards}_{i,c,t})$	0.24***	0.23***	0.15**	0.19**	0.51***	1.75***
	(5.80)	(6.59)	(3.55)	(3.91)	(3.90)	(4.37)

Panel C: Second-Stage Regressions Using the Top 10% of AI Standards by AI Relatedness

	Log(AI Research$_{i,c,t}$)	Log(CV Research$_{i,c,t}$)	Log(NLP Research$_{i,c,t}$)	Log(Robotics Research$_{i,c,t}$)	$CAPEX/AT_{i,c,t}$	$RD/AT_{i,c,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Log(AI\widehat{Standards}_{i,c,t})$	0.28**	0.28**	0.17*	0.22*	0.58***	1.99***
	(3.69)	(4.06)	(2.50)	(2.38)	(3.65)	(3.41)

Panel D: Additional Information on Panels A, B, and C

	(1)	(2)	(3)	(4)	(5)	(6)
Controls	No	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,865	2,865	2,865	2,865	171,238	67,647
$\sqrt{c_{0.10}(F)}$	1.89	1.89	1.89	1.89	1.98	1.98
$\sqrt{c_{0.05}(F)}$	2.79	2.79	2.79	2.79	2.07	2.07

Table 8. **Effect Heterogeneity: AI Research and AI Standard Categories**

This table offers a detailed breakdown of how AI standard categories impact firm-specific research in broader AI (Panel A), computer vision (Panel B), language processing (Panel C), and robotics (Panel D). Our AI categories - Machine Learning, Data, Automation, Programming Language, Interoperability, Machinery & Equipment, Ethics & Accountability, and Privacy - are based on our content analysis outlined in Section 4.1. The estimated coefficients displayed here are second-stage regression coefficients. These coefficients were obtained through a two-stage least squares procedure, utilizing instrumented variables such as the log of the number of yearly standards in each category and the percentage of UNSC rotating members as instruments. To save space, instrumented variables are labelled without logarithmic transformations. For example, "Machine Learning Standards" represents Log(Machine Learning Standards)$_{i,c,t}$. Detailed descriptions of all variables can be found in Appendix Section B. Control structures are as in Table 4. Asterisks denote significance levels: ⋆ ⋆ ⋆ (1%), ⋆⋆ (5%), and ⋆ (10%). Details on tF critical values are discussed in Section 6.4 of the article.

Panel A: AI-Standard Categories and All AI Research (N=2,865)

	Machine Learning Standards	Data Standards	Automation Standards	Programming Language Standards	Interchange Standards	Machinery & Equipment Standards	Ethics & Accountability Standards	Privacy Standards
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	0.83	0.12**	0.12**	-1.18	0.12**	0.12**	-0.68*	-0.85
Log(AI Research$_{i,c,t}$)	(0.77)	(3.02)	(3.25)	(-0.29)	(3.20)	(2.97)	(-2.27)	(-1.20)

Panel B: AI-Standard Categories and Computer Vision Research (N=2,865)

	Machine Learning Standards	Data Standards	Automation Standards	Programming Language Standards	Interchange Standards	Machinery & Equipment Standards	Ethics & Accountability Standards	Privacy Standards
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	0.82	0.12**	0.12**	-1.16	0.12**	0.12**	-0.67*	-0.84
Log(CV Research$_{i,c,t}$)	(0.78)	(3.16)	(3.39)	(-0.29)	(3.45)	(3.00)	(-2.21)	(-1.19)

Panel C: AI-Standard Categories and Language Processing Research (N=2,865)

	Machine Learning Standards	Data Standards	Automation Standards	Programming Language Standards	Interchange Standards	Machinery & Equipment Standards	Ethics & Accountability Standards	Privacy Standards
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	0.51	0.07**	0.08**	-0.72	0.08*	0.08*	-0.42*	-0.52
Log(NLP Research$_{i,c,t}$)	(0.72)	(2.78)	(2.90)	(-0.29)	(2.69)	(2.65)	(-2.46)	(-1.25)

Panel D: AI-Standard Categories and Robotics Research (N=2,865)

	Machine Learning Standards	Data Standards	Automation Standards	Programming Language Standards	Interchange Standards	Machinery & Equipment Standards	Ethics & Accountability Standards	Privacy Standards
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	0.66	0.09**	0.10**	-0.93	0.10**	0.10**	-0.54	-0.68
Log(Robotics Research$_{i,c,t}$)	(0.69)	(3.60)	(3.72)	(-0.30)	(3.34)	(3.68)	(-2.05)	(-1.42)

Table 9. **Effect Heterogeneity: Capital/R&D Expenditures and AI Standard Categories**

This table offers a detailed breakdown of how specific AI standard categories impact capital (Panel A) and R&D (Panel B) expenditures. Our AI categories - Machine Learning, Data, Automation, Programming Language, Interoperability, Machinery & Equipment, Ethics & Accountability, and Privacy - are based on our content analysis outlined in Section 4.1. The estimated coefficients displayed here are second-stage regression coefficients. These coefficients were obtained through a two-stage least squares procedure, utilizing instrumented variables such as the log of the number of yearly standards in each category and the percentage of UNSC rotating members as instruments. To save space, instrumented variables are labelled without logarithmic transformations. For example, "Machine Learning Standards" represents Log(Machine Learning Standards)$_{i,c,t}$. Detailed descriptions of all variables can be found in Appendix Section B. Control structures are as in Table 5. Asterisks denote significance levels: ⋆⋆⋆ (1%), ⋆⋆ (5%), and ⋆ (10%). Details on tF critical values are discussed in Section 6.4 of the article.

Panel A: AI-Standard Categories and Capital Expenditures (N=171,238)

	Machine Learning Standards	Data Standards	Automation Standards	Programming Language Standards	Interchange Standards	Machinery & Equipment Standards	Ethics & Accountability Standards	Privacy Standards
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	1.58**	0.27***	0.30***	-6.22	0.31***	0.28***	-3.72	-2.76
$CAPEX/AT_{i,c,t}$	(2.11)	(3.50)	(2.96)	(-0.51)	(3.04)	(3.82)	(-0.43)	(-1.62)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: AI-Standard Categories and R&D Expenditures (N=67,647)

	Machine Learning Standards	Data Standards	Automation Standards	Programming Language Standards	Interchange Standards	Machinery & Equipment Standards	Ethics & Accountability Standards	Privacy Standards
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	5.17	0.86***	0.96***	-13.72	1.00***	0.93***	-7.63	-9.36**
$RD/AT_{i,c,t}$	(1.62)	(5.15)	(5.03)	(-0.96)	(5.03)	(5.08)	(-1.01)	(-2.35)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10. **Effects of AI Standards on Firm Valuation**

This table presents our estimates for the local treatment effects of AI standards on logged future Tobin's Q and M/B ratios using our 2SLS procedure explained in Section 5. Our sampling period is from 2017 to 2022. The control variables incorporated in this analysis align with those in Table 5, with the exclusion of the book value of assets and cash flow variables, as they can function as mediators of AI standards in the event dynamics. Detailed variable descriptions can be found in Appendix Section B. Our findings from reduced-form, first-stage and ordinary least squares (OLS) regressions, and placebo tests are available upon request. Coefficient estimates are reported in percentage terms and marked with $\star\star\star$, $\star\star$, and $\star$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The standard errors are two-way clustered at the country and industry (FF48) levels. We also report F-statistics for the excluded instrument from the first-stage regressions and tF critical values for 5% and 10% level tests ($\sqrt{c_{0.05}(F)}$ and $\sqrt{c_{0.10}(F)}$) as in Lee et al. (2022) to further assess the significance of the second-stage coefficient estimates.

	$\text{Log(M/B}_{i,c,t+1})$	$\text{Log(M/B}_{i,c,t+1})$	$\text{Log(Q}_{i,c,t+1})$	$\text{Log(Q}_{i,c,t+1})$
	(1)	(2)	(3)	(4)
$Log(\widehat{AI\ Standards}_{i,c,t})$	3.67**	2.84**	3.60***	3.08**
	(2.25)	(2.08)	(2.93)	(2.74)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	No	Yes	No
Industry × Year	No	Yes	No	Yes
Observations	134,353	134,352	134,252	134,251
F-stat (Excl. Inst.)	66.10	63.68	97.02	93.12
$\sqrt{c_{0.10}(F)}$	2.14	2.15	2.13	2.15
$\sqrt{c_{0.05}(F)}$	3.47	3.48	3.44	3.48

Figure 1. **Yearly Publication of Standards by ISO Secretariats**

This figure presents the annual publication count of AI standards by each secretariat, alongside their AI relatedness determined through textual similarity to AI concepts. The data are hand-collected from the report "U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools" by the National Institute of Standards and Technology (NIST), in response to Executive Order (EO) 13859. The horizontal axis represents the years in chronological order, while the left vertical axis indicates the number of published AI standards, with each secretariat distinguished by color. The right vertical axis displays AI similarity scores, derived from both strict and fuzzy string matching methods. To obtain these scores, we compare the titles of all published AI standards against the contents section of Russell and Norvig (2021). Annual word lists from these titles are compared to a word list from Russell and Norvig (2021) after lemmatization and the exclusion of functional words, numbers, and specific terms. Strict matching identifies words present in both lists, indicating 100% similarity, whereas fuzzy matching selects words with at least 80% similarity based on Levenshtein distance. We report the percentage of words in the contents section of Russell and Norvig (2021) that match the language of the standards using the strict and fuzzy matching strategies described above.

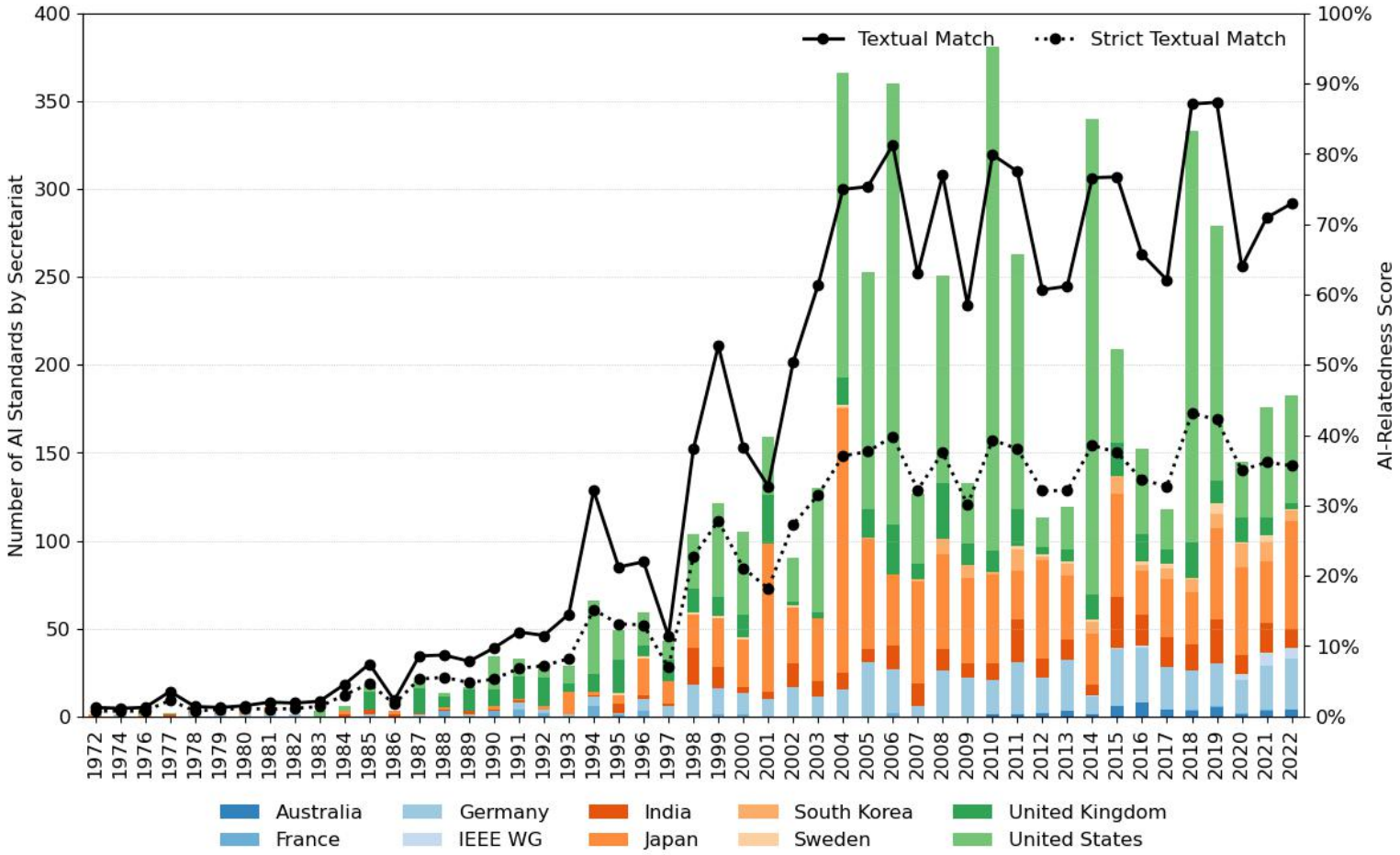


Figure 2. **Power Spheres: Standards by Each Secretariat**

This circle pack figure visually represents the number of standards published under each scope for each secretariat, covering the sampling period from 1972 to 2022. The sizes of the circles correspond to the numbers of standards published, providing a visual representation of the relative volume of standards within each scope. To save space, the names of secretariats are presented in ISO-2 format, and the number of circles is limited for better readability. Each secretariat is labeled in distinct colors.

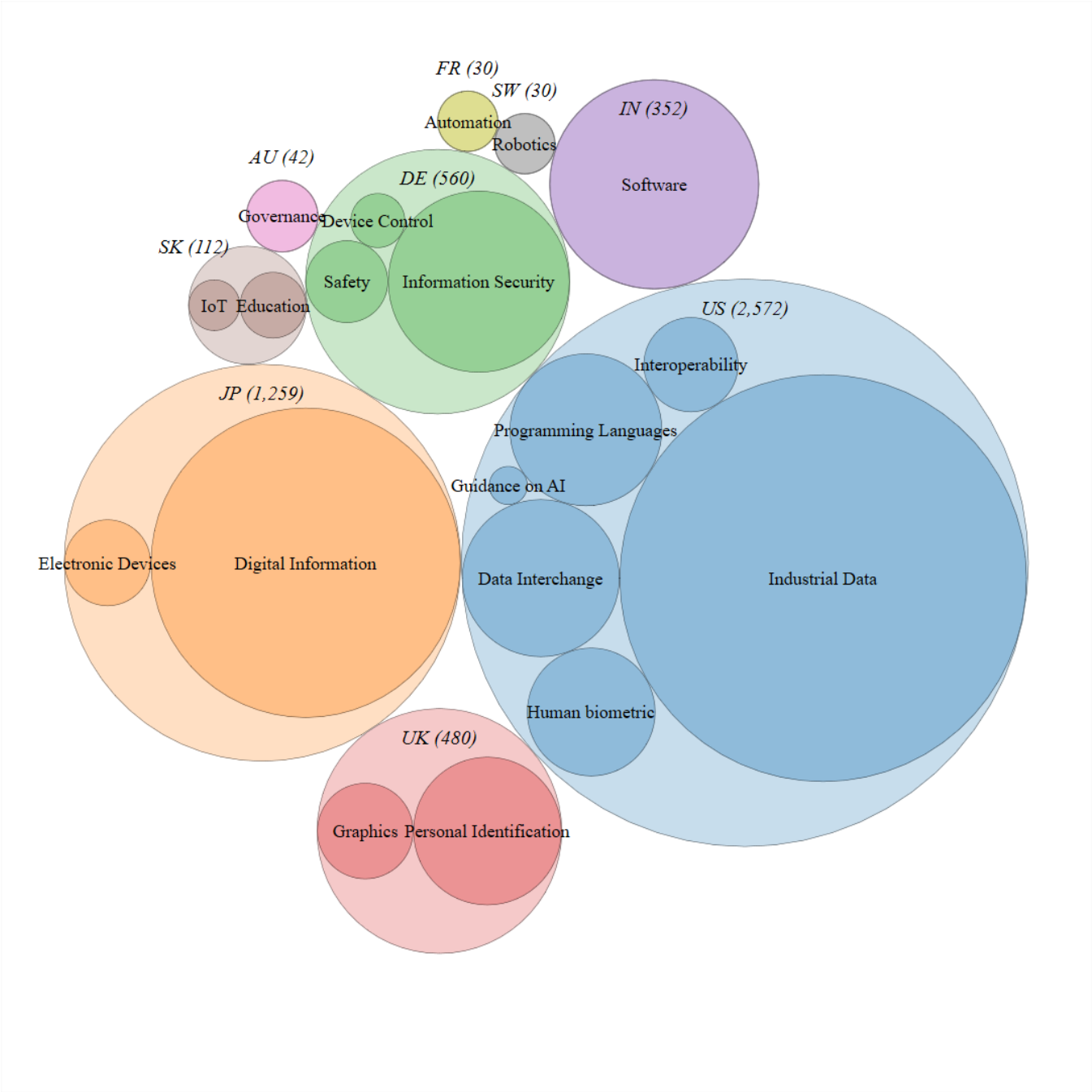


Figure 3. **ISO Committee and Secretariat Involvement by Country**

The world map provides a visualization of countries' involvement in ISO committees and secretariat roles from 2017 to 2023. Using distinct color gradients, each country is painted to indicate the number of secretariat and committee years. The two-dimensional figure on the right side presents the distribution of secretariat and committee years. It uses a color-coded system to categorize countries based on the combination of their involvement. Countries without ISO involvement are shown in white.

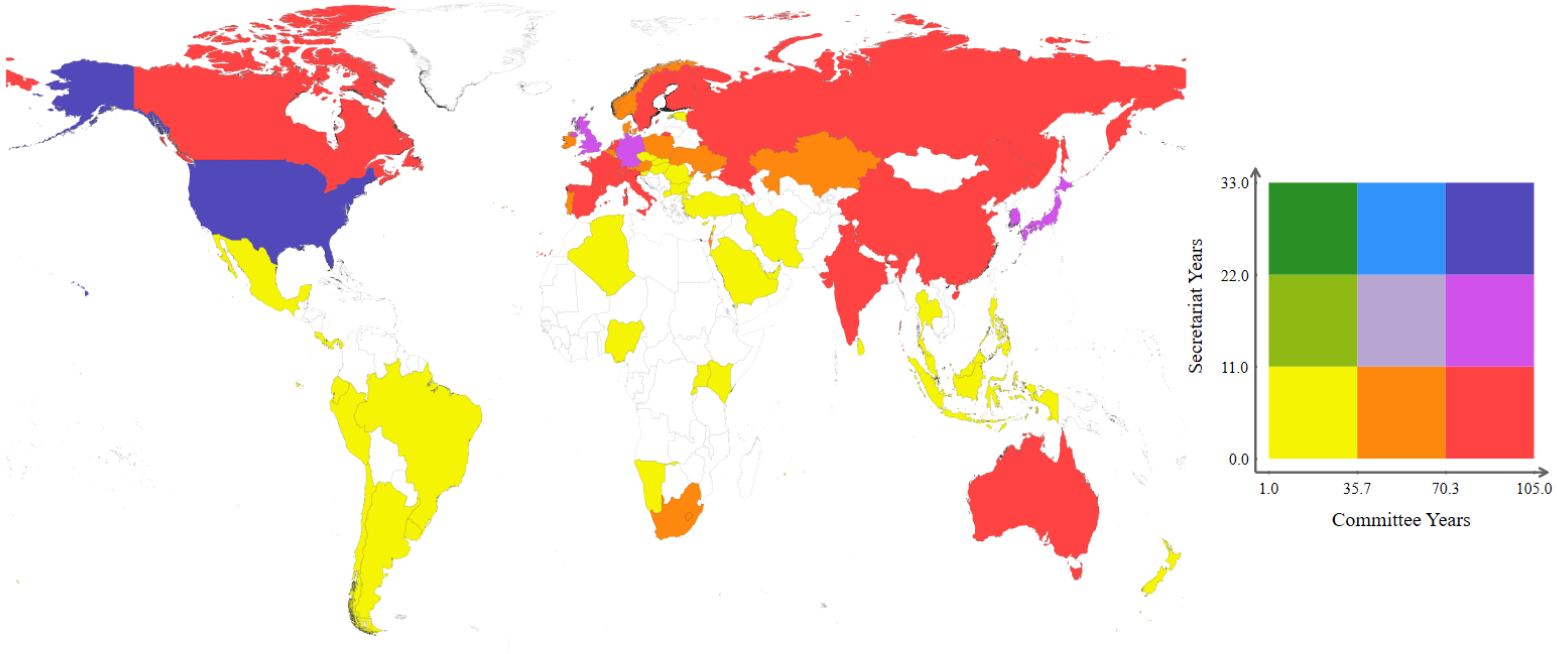


Figure 4. **The Rise of AI Standards**

The figure illustrates the types of AI standards published by secretariats within the ISO. We use categories introduced in Section 4.1 with minor modifications for better fit. *Machine Learning* includes standards that pertain to different aspects of machine learning, such as artificial intelligence, learning algorithms, natural language processing, fuzzy logic, neural networks, decision-making processes, semantic analysis, training methodologies, and speech and image recognition. *Safety and Accountability* focus on issues of accountability, governance, safety, ethics, robustness, security, and societal impact concerning AI systems and technologies. *Data* comprises standards related to data management, processing, and analytics, covering areas such as data governance, data privacy, data security, data exchange, data interoperability, and data quality assurance. We exclude machine learning standards from data standards. *Programming Languages* encompasses standards related to programming languages, software development practices, program design, software quality assurance, and specific programming languages like SQL, Pascal, BASIC, Linux, C#, Java, C++, and Python. *Interoperability* covers standards addressing interoperability, compatibility, and connectivity between AI systems, as well as integration with other technologies, including the Internet of Things (IoT), digital twins, internet protocols, and IoT connectivity standards. *Interchange* denotes standards related to the interchange or exchange of data, including data formats, data protocols, and data representation standards. *Automation* includes standards associated with automation technologies, addressing aspects like automated decision-making, process automation, and the integration of AI systems into automated workflows. We exclude machine learning standards from automation standards. Standards under *Privacy* are on privacy protection, cybersecurity, secure data handling, biometric data privacy, human rights considerations, and ensuring the privacy of personal information within AI systems. The *Unlabelled* category represents standards that do not fall into any of the specific types mentioned above along with *Human-related* and *Graphics*, which are not plotted to save space. *Human-related* includes standards addressing human-related aspects of AI, such as biometrics, human-machine interaction, genomics, and ethical considerations related to the impact of AI on individuals and society. *Graphics* concern graphics, visualization, multimedia technologies, audio and video encoding, and media formats. Detailed descriptions are presented in Appendix Section B.

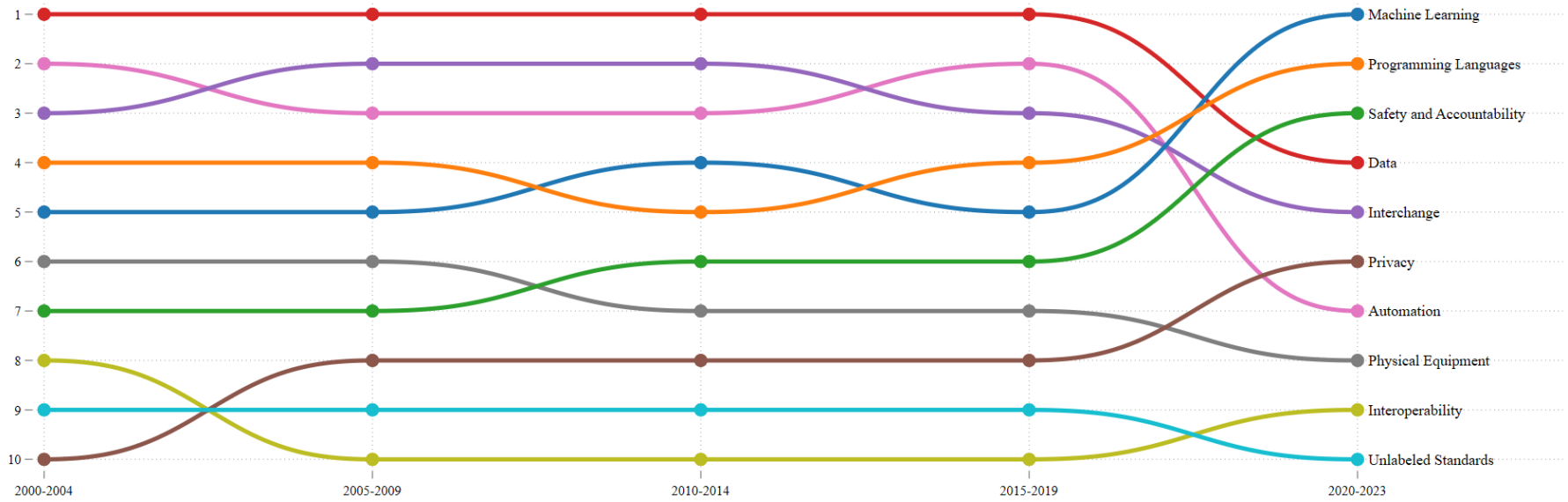
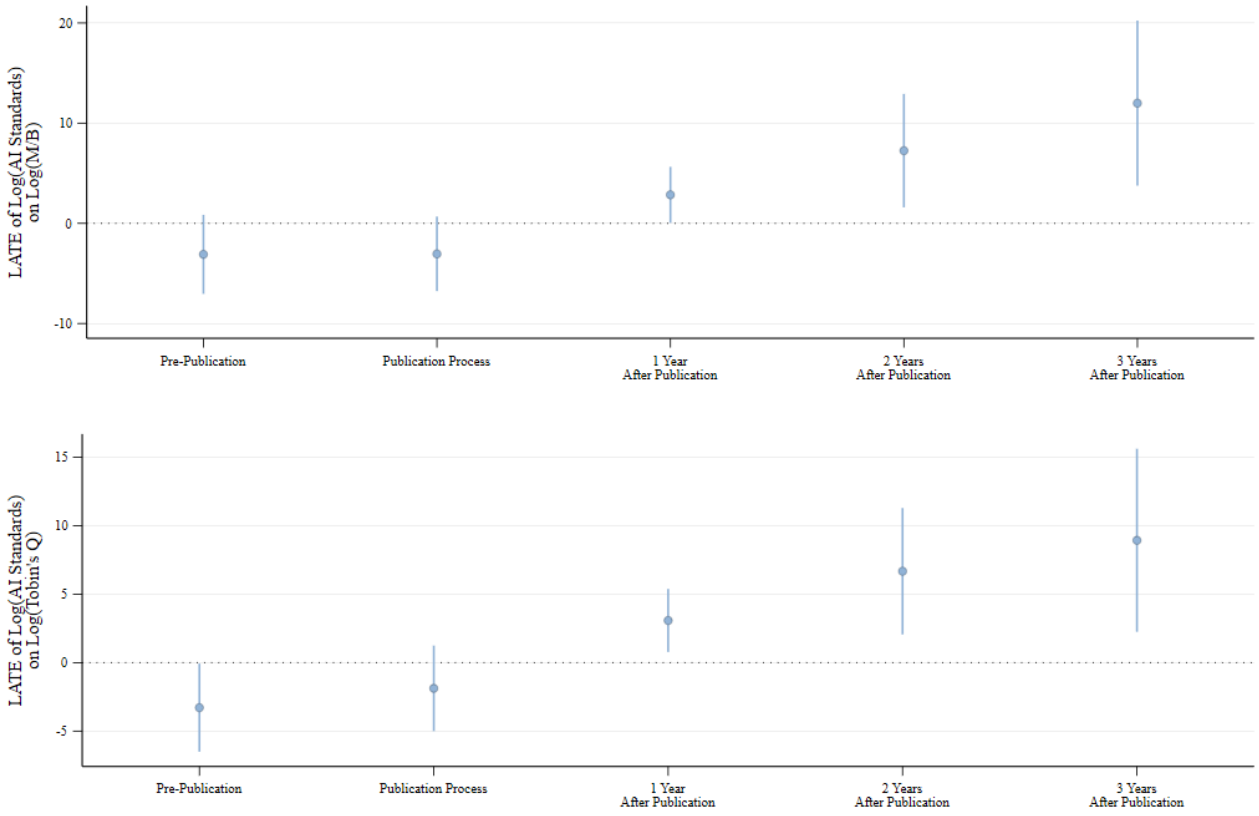


Figure 5. **Effect Dynamics Based on Valuation Regressions**

This figure displays estimates for the local average treatment effects (LATE) on Logged Tobin's Q and M/B during the event time of AI standards implementation. The LATE estimates are derived following our base regression models, where the dependent variables are Logged Tobin's Q and M/B from one year before ("Pre-Publication") to three years after AI standardization ("3 Years After Publication"). Each x-axis label corresponds to the LATE derived from a different 2SLS regression. The coefficient estimates are in percentage terms. The figure also outlines the 95% confidence intervals for these estimates. For details on our instrumental variable approach, please refer to Section 6.4.



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Internet Appendix

for

Crafting an AI Compass:
The Influence of Global AI Standards on Firms

March 10, 2025

A Theory

To illustrate how AI standards affect firm investment, we introduce a stylized model featuring investment under uncertainty.

A.1 Model Setup

Firm Investment Consider one firm with an infinite horizon. Time is discrete. In each period t, the firm decides on its AI-related investment, which may include the R&D investment to install and/or improve the AI application/system. There are N domains of AI investment that are accessible to the firm. Examples of AI domains are voice recognition, computer vision, robotics, etc. Within each domain, there are two competing types of AI technologies the firm can invest in, type A and type B. The capital stock of domain-n, type-i AI technology at the end of period t is denoted as $AI_t^{n,i}$, $n \in \{1,2,...,N\}$, for $i = A, B$. Denote the total AI factor as

$$AI_t \equiv \sum_{n=1}^{N} \left(\tilde{s}_t^{n,A} F(AI_t^{n,A}) + \tilde{s}_t^{n,B} F(AI_t^{n,B}) \right) \tag{5}$$

is the summation of AI factors across N domains. Within each domain n, the AI factor is the summation across the two competing technologies, where $\tilde{s}_t^{n,i} \geq 0$ is the (potentially random) productivity of technology i within domain n; $F(\cdot) > 0$ is strictly increasing, concave, and satisfies Inada condition that $F(0) = 0$, $F'(0) = \infty$ and $F'(\infty) = 0$.

To produce the output of the firm, the AI factor needs to be combined with two other input factors, namely, physical capital K_t and data. The firm adjusts the physical capital K_t through choosing the capital expenditure at the start of each period. Let D be the hypothetical data pool accessible to the firm, absence of any privacy restrictions (e.g., constraints on data collection and data sharing). To focus on the investment in AI and physical capital, we abstract away from the investment in data and instead, assume the firm takes D as given.

The firm's production function in each period t is

$$Y_t = AI_t^{\alpha} K_t^{1-\alpha} D(1 - \tilde{\tau}_t), \tag{6}$$

where $\alpha \in (0,1)$ and $\tilde{\tau}_t \in [0,1)$. The (potentially random) variable $\tilde{\tau}_t$ embodies the prevailing limitations on data privacy. As the restrictions on data privacy increase, the actual data pool accessible to a firm shrinks, either due to reduced data collection or diminished data sharing. In addition, $\tilde{\tau}_t$ captures the constraining effect of ethical AI requirements on the productivity of AI technologies, as the focus on ethical considerations may limit the scope of automation and the speed of decision-making processes.

Observe that the three input factors enter the production function through a multiplicative structure. This is motivated by the fact that the three factors are complements of each other, as an increase in one factor boosts the marginal product of another. To start with, AI investment complements physical investment in property, plant, and equipment (PP&E), as AI is commonly regarded as the technology that may lead to the fourth industrial revolution, i.e., Industry 4.0 (Peres et al., 2020). A more advanced AI technology has the potential to make machines and equipment significantly more productive, thereby increasing the return of investment in PP&E. Moreover, AI complements data, as more investment in AI advances the AI technology, enabling the firm to utilize its data more efficiently; meanwhile, a bigger data pool helps to train and improve the AI algorithms, empowering the algorithms (O'Leary, 2013).

At the start of each period, the firm decides and makes the investment on all types of AI investments and physical investment. Both types of investment are partially irreversible in the sense that disinvestment is costly. Given

investment I in AI-domain n and type i, the cost of investment is $CI_n(I) = I$ if $I \geq 0$ (positive investment), and $CI_n(I) = C^n I$ if $I < 0$ (disinvestment), with $C^n \in (0,1)$. That is, only a fraction C^n of disinvestment amount can be salvaged. Similarly, the investment cost for physical investment K is that $CI_K(I) = I$ if $I \geq 0$, and $CI_K(I) = C^K I$ if $I < 0$, with $C^K \in (0,1)$. The partially irreversible feature of investment aligns with the vast body of literature on real options following Dixit and Pindyck (1994) and is motivated by the significant cost of disinvestment (e.g., due to fire-sales).

The firm's investment problem in each period $j \geq 1$ is

$$\begin{aligned}
\max_{\{I^{n,A}_{AI,t}, I^{n,B}_{AI,t}, I_{K,t}\}_{t=j}^{\infty}} \mathbb{E} \sum_{t=j}^{\infty} \beta^{t-1} \Big\{ AI_t^{\alpha} K_t^{1-\alpha} D(1-\tilde{\tau}_t) - \sum_{n=1}^{N} \Big(CI_n(I^{n,A}_{AI,t}) + CI_n(I^{n,B}_{AI,t}) \Big) - CI_K(I_{K,t}) \Big\} \\
s.t. \text{(AI factor) } AI_t = \sum_{n=1}^{N} \Big(\tilde{s}_t^{n,A} F(AI_t^{n,A}) + \tilde{s}_t^{n,B} F(AI_t^{n,B}) \Big) \\
\text{(capital dynamics) } AI_t^{n,i} = AI_{t-1}^{n,i} + I^{n,i}_{AI,t}, \text{ for } i = A, B, n \in \{1, 2, ..., N\}. \\
K_t = K_{t-1} + I_{K,t}. \\
\text{(costly disinvestment) } CI_n(I) = \begin{cases} I & \text{if } I \geq 0 \\ C^n I & \text{if } I < 0 \end{cases} \quad CI_K(I) = \begin{cases} I & \text{if } I \geq 0 \\ C^K I & \text{if } I < 0 \end{cases}
\end{aligned} \tag{7}$$

where $\beta \in (0,1)$ is the discount factor, and the initial capital stock is $AI_0^{n,i} = K_0 = 0$, for $i = A, B$, $n \in \{1, 2, ..., N\}$.[47]

AI-Related Standards The firm's investment decisions are crucially influenced by the future publications of AI-related standards. We assume that the firm expects an event with potential AI-standards publication to arrive on a random future period, period T. For simplicity, the arrival can happen at most once. The publication event follows Poisson arrival. That is, for any period t prior to which the arrival has occurred, the likelihood of the publication event happening within that period is $\lambda \in [0,1]$. Without loss of generality, we assume the publication event takes place at the end of period T, after period T investment has been made and period T profit has been realized. That is, the publication of standards affects the production in period $T+1$ and onwards.

Conditional on the arrival of the event, the type of standards potentially published is random. With probability $\pi \in (0,1)$, only technological standards are potentially published, while with probability $1-\pi$, only privacy and ethical standards can be published.[48] The publication of AI standards alters the economic environment the firm faces, depending on the nature of the standards.

Technological AI Standards Suppose the standards that are published are technological AI standards, which may specify the recommended "foundation and architecture" as well as the "best practices" of AI technologies. The publication of such standards narrows the future paths of AI development by endorsing a subset of AI technology paths over other competing ones. We model this effect by assuming that if a technological standard pertaining AI domain n is published, then one of the two AI technologies in domain n is endorsed by the standard. Consequently, after the publication, the productivity of the endorsed technology increases relative to the pre-publication level, while the productivity of the unendorsed type decreases relative to the pre-publication level. This *bifurcation* of productivity is due to the network effect. That is, a positive feedback loop occurs to the standard-endorsed technology, as the wider

[47] For simplicity, we assume zero depreciation rate. The qualitative results hold as long as the depreciation rate is not too high.

[48] For simplicity, we do not consider the simultaneous publications of both technological and ethical standards within the event. The reason is to highlight the fundamental differences in how these two types of standards affect productivity. This separate analysis is also aligned with our empirical analysis in Table 8 and 9, where we separately consider the impact of technological and ethical/privacy standards publication on firm investment.

adoption of the technology after the standard publication induces more systems and applications being developed to be compatible with it. This enhanced interoperability feeds back positively into the attractiveness of using this technology. On the contrary, a negative loop occurs with the technology not endorsed, as standards publication results in a smaller user base.

To capture the effect of the publication of technological AI standards, we assume that conditional on (1) the arrival of a publication event in period T and (2) only technological standards can be published, domain n of AI technology sees a standard publication with probability $q \in (0,1)$. The publication of AI standards across domains are independent and identically distributed. Denote $m \in \{0,1,2,...,N\}$ as the realized number of total technological standards published. Higher m implies that more domains of AI technologies have standards published.

To characterize the bifurcation of productivity within domain n, we assume the productivity before the publication of standards is constant over time, that is, $\tilde{s}_t^{n,A} = \tilde{s}_t^{n,B} = s^n > 0$, for $t \leq T$, where T denotes the random publication period. There is a divergence in productivity between the two technologies after the publication. With probability $p^{n,A} \in (0,1)$, type-A is endorsed by the standard, so $(\tilde{s}_t^{n,A}, \tilde{s}_t^{n,B}) = (\bar{s}^n, \underline{s}^n)$, for all $t > T$; while with probability $p^{n,B} = 1 - p^{n,A}$, type-B is endorsed, so $(\tilde{s}_t^{n,A}, \tilde{s}_t^{n,B}) = (\underline{s}^n, \bar{s}^n)$, for all $t > T$. Here we assume $0 < \underline{s}^n < s^n < \bar{s}^n$.

Privacy and Ethical AI Standard In the scenario where only privacy and ethical standards are potentially published, the publication of such standards can constrain the firm's *overall* productivity with AI, physical capital, and data by specifying requirements of data privacy and ethical AI algorithms. These restrictions shrink the firm's data pool and limit the scope of AI applications, as certain practices previously employed to maximize efficiency might no longer be permissible under new privacy and ethics rules. The publication of such standards enhances the enforceability of the ethical restrictions by making these concepts more tangible and providing a framework for shaping future government policies.

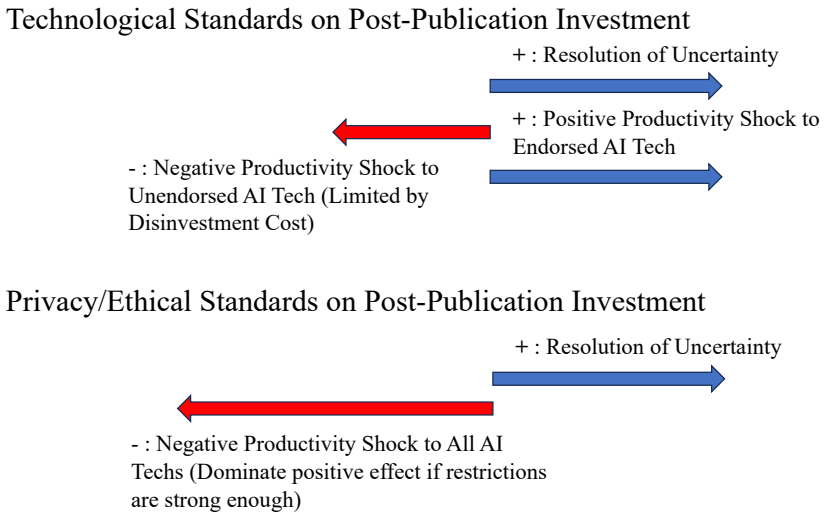
To capture the constraining effects of privacy and ethical AI standards, we normalize the pre-publication level of $\tilde{\tau}_t = 0$ for all $t \leq T$ and the post-publication level to be $\tau(m_e) \in (0,1)$, where $m_e \in \{0,1,2,...,N_e\}$ is the realized number of total privacy/ethical standards published. Higher m_e implies that more and stronger constraints have been imposed on AI technologies and data in general. The variable $\tau(m_e)$ is assumed to be strictly increasing in m_e, implying that more ethical/privacy standards published lead to a larger overall drop in firm productivity. Conditional on (1) the arrival of the publication event in period T and (2) only privacy/ethical standards can be published, m_e follows Binomial distribution with N_e possible candidate standards for publication, each being published with probability $q_e \in (0,1)$.

Standards and Firm Investment In this setting, there are several forces affecting how investment responses to standard publications. First, the firm cannot predict which technology will be endorsed by technological standards or how restrictive privacy/ethical standards will be. Therefore, the option value of delaying its partially irreversible investment drives the firm to wait until the publication of standards resolves this uncertainty. This consideration tends to increase the post-publication investment above its pre-publication levels.

Second, beyond the uncertainty resolution effect, the publication of standards can lead to productivity shocks relative to the pre-publication levels, affecting the optimal capital stock. This impact varies depending on whether the standards are privacy/ethical or technological, and for technological standards, whether the investment is in endorsed or unendorsed technology.

Privacy/ethical standards typically reduce productivity below the pre-publication levels, leading to disinvestment that lowers the capital stock. This counters the investment-boosting effect of uncertainty resolution. When even the most benign restrictions imposed by such standards are sufficiently strict, this investment-deterrence ef-

Appendix Figure A1. Intuition: Standards Publication and Investment



fect dominates the investment-boosting effect of uncertainty resolution, leading to strictly negative investments post-publication. Furthermore, the publication of more such standards lead to stronger restrictions, resulting in even larger post-publication disinvestment.

Technological standards, on the other hand, increase productivity for the endorsed AI technology. This in turn results in positive post-publication investment, which is aligned with the uncertainty resolution effect. Conversely, productivity decreases for the unendorsed technology, which tends to induce disinvestment and opposes the uncertainty resolution effect. However, the overall effect on investment remains positive due to the partial irreversibility of investment, that is, there is no adjustment cost for positive investment in the endorsed technology but a cost for disinvestment for the unendorsed technology. Thus, the investment-boosting effect on the endorsed technology dominates, and the total investment increases post-publication of technological standards. Furthermore, more technological standards publications resolve more uncertainties and generate positive productivity shocks in more AI domains, potentially boosting post-publication investment even further.

Figure A1 illustrates the varies forces discussed above. The next proposition formalizes these insights. Denote the net total AI investment in period $T+1$, across all domains and types of AI technologies, as

$$I_{AI,T+1} = \sum_{n=1}^{N} \left(I^{n,A}_{AI,T+1} + I^{n,B}_{AI,T+1} \right), \tag{8}$$

where T is the period with standard publications. That is, this term is the total AI investment one-period immediately after the publication.

Proposition 1 (Investment and Standards Publication)**.** *(i) Consider the scenario where only technological standards can be published. There exists $\hat{l} \in (0,1)$, such that when $\underline{s}^n / s^n \geq \hat{l}$ for all $n = 1,2,...,N$, the firm's net total AI investment post-publication, $I_{AI,T+1}$, as defined in (8), is strictly positive. In addition, $I_{AI,T+1}$ increases in the total number of technological standards published, m. The same argument holds for the firm's post-publication capital expenditure investment, $I_{K,T+1}$.*

(ii) Consider the scenario where only privacy/ethical standards can be published. There exists $\hat{\tau} \in (0,1)$, such that when $\tau(m_e) \geq \hat{\tau}$ for all $m_e = 1,2,...,N_e$, the firm's net total AI investment $I_{AI,T+1}$ post-publication is strictly negative. In addition, $I_{AI,T+1}$ decreases in the total number of privacy/ethical standards published, m_e. The same argument holds

for the firm's post-publication capital expenditure investment, $I_{K,T+1}$.

We use the following example to illustrate the equilibrium. Suppose there are two domains of AI, each hosting two types of AI technologies. Therefore, there are only two potential technological standards that can be published ($N = 2$). Also, suppose there are two potential privacy/ethical standards that can be published ($N_e = 2$). Let the probability of each standard being published be $q = q_e = 1/2$. Let $\tau(0) = 0$, $\tau(1) = 0.35$, and $\tau(2) = 0.7$. Assume full symmetry between and within domains, that is, $s^n = 1$, $\bar{s}^n = h = 1.2$, $\underline{s}^n = l = 0.8$, $C^n = C^K = C = 0.75$, and $p^{n,A} = 1/2$, for all n. Lastly, let $\pi = 0.9$, $\alpha = 1/2$, $\beta = 0.8$, and $D = 1$. For simplicity, assume $\lambda \to 1$ (but still $\lambda < 1$), that is, the probability of publication event will arrive is very high.

Suppose the publication event occurs at period 9. Figure A2 plots the equilibrium investment in period 10, which is the period immediately after the publication event. Consistent with Proposition 1, if the standards published are technological standards, then both the AI investment $I_{AI,10}$ and physical investment $I_{K,10}$ after publication are strictly higher than zero, which is the pre-publication level in period 9. In addition, both $I_{AI,10}$ and $I_{K,10}$ increase in the number of standards published. As the number of technological standards published increases from one to two, $I_{AI,10}$ increases from 14.2 to 15.2, while $I_{K,10}$ increases from 27.3 to 29.1. On the contrary, if the standards published are privacy and ethical standards, both the AI investment $I_{AI,10}$ and physical investment $I_{K,10}$ after publication are strictly lower than zero, the pre-publication investment level. In addition, both $I_{AI,10}$ and $I_{K,10}$ decrease in the number of standards published. As the number of privacy and ethical standards published increases from one to two, $I_{AI,10}$ decreases from -3.9 to -24.9, while $I_{K,10}$ decreases from -8.5 to -50.6.

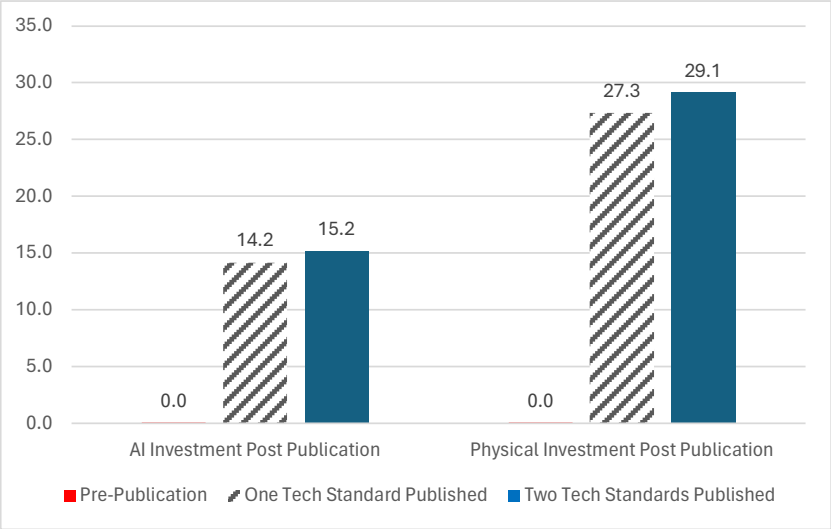
Next, we decompose the total AI investment plotted in Figure A2 into investment regarding individual AI technologies. Consider first the scenario where only one technological standard is published. In period 10, the endorsed AI technology receives an investment of 7.6, the unendorsed AI technology within the same domain receives an investment of zero, while the two AI technologies within the domain that has no standard publication receive an investment of 3.3. Next, consider the case where both domains see publications of technological standards. In period 10, the endorsed AI technology receives an investment of 7.6, while the unendorsed AI technology within the same domain receives an investment of zero. Lastly, if privacy/ethical standards are published, each AI technology receives a negative investment of -1.0 (-6.2) if one standard is (two standards are) published.

Lastly, Figure A3 plots the time series of investment to further highlight the change in investment pre- and post-publication. Panel (a) shows that if there is publication of one technological standard in, for example, Domain 1, then the AI-investments are zero from period 2 to period 9 (i.e., before publication) and from period 11 onwards. In the period 10, which is the period right after publication, the endorsed technology A (represented by the solid line) receives a positive investment of 7.6, while the unendorsed investment (represented by the dashed line) receives zero investment. Panel (b) shows that the pattern of the physical investment is similar to that of the endorsed technology. Panel (c) shows that if there is publication of one privacy/ethical standard, then the AI-investments are zero from period 2 to period 9 and from period 11 onwards. In the period 10, each AI technology receives a negative investment of -1.0. Panel (d) shows that a similar pattern happens to the physical investment.[49]

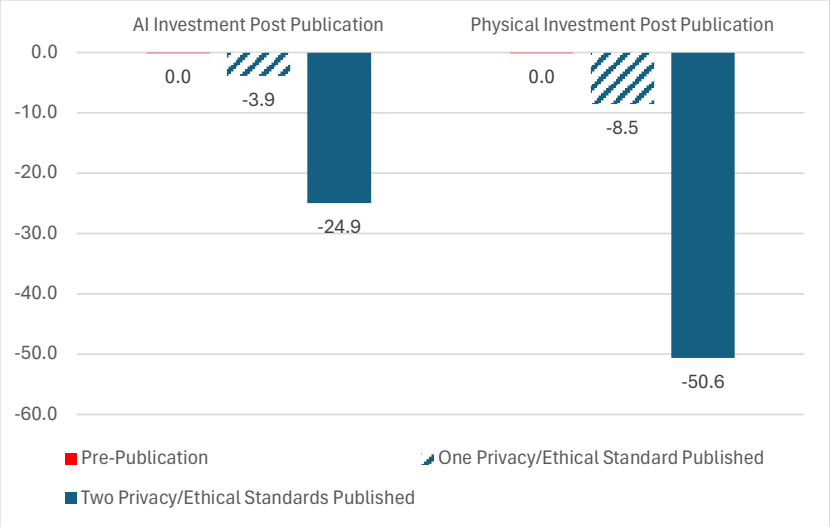
[49] At the pre-publication investment level, we exclude the first period when the firm establishes its capital stock. This is because the initial period is empirically less relevant compared to other pre-publication periods, as it occurs less frequently.

Appendix Figure A2. Pre- and Post-Publication Investment and the Number of Standards Published

(a) Pre- and Post-Publication Investment: Technological Standards

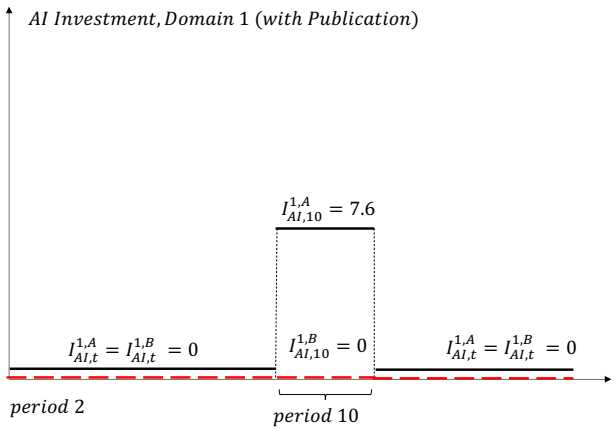


(b) Pre- and Post-Publication Investment: Privacy and Ethical Standards

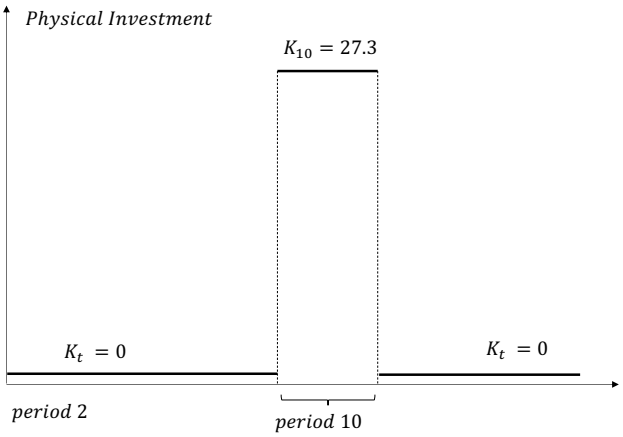


Appendix Figure A3. Investment over Time

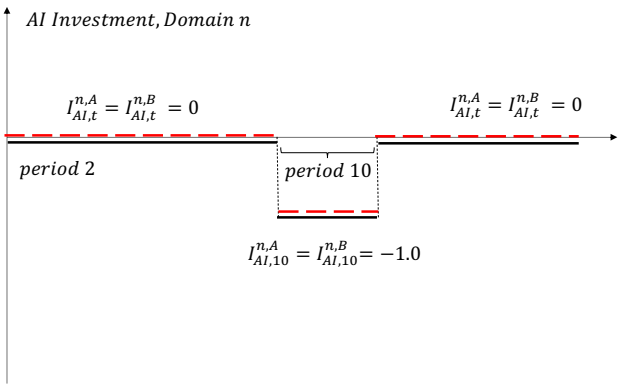
(a) AI Investment: One Tech Standard Published



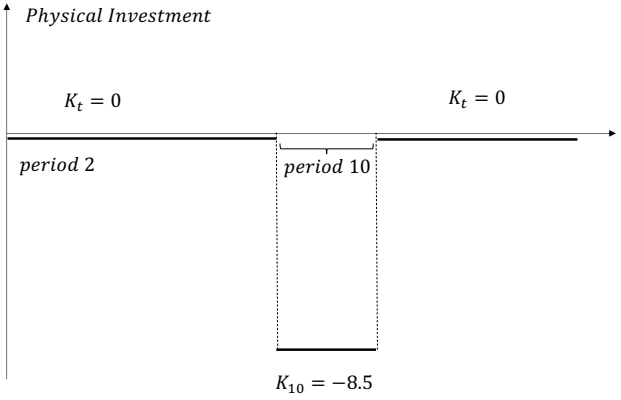
(b) Physical Investment: One Tech Standard Published



(c) AI Investment: One Privacy/Ethical Published



(d) Physical Investment: One Privacy/Ethical Published



A.2 Mathematical Proofs

Proof of Proposition 1

Proof. First, consider the continuation decision problem in period $T+1$, when either a subset $\mathscr{M} \subset \{1,\dots,N\}$ of tech standards are endorsed at the end of period T, or $\tilde{\tau}_t$ increases to τ. Due to symmetry, we analyze only the case where A technology is endorsed for every $n \in \mathscr{M}$. The problem writes:

$$\max_{\{AI_t^{n,j},K_t\}_{t,n,j}} \sum_{t=T+1}^{\infty} \beta^{t-T-1} \left(\left(\sum_{n,j} \tilde{s}^{n,j} F(AI_t^{n,j}) \right)^{\alpha} K_t^{1-\alpha} D(1-\tau) - \sum_{n,j} c_t^{n,j} (AI_t^{n,j} - AI_{t-1}^{n,j}) - c_t^K (K_t - K_{t-1}) \right),$$

where $\tilde{s}^{n,j} = \overline{s}^n$ if $j = A$ and $n \in \mathscr{M}$, $\tilde{s}^{n,j} = \underline{s}^n$ if $j = B$ and $n \in \mathscr{M}$, $\tilde{s}^{n,j} = s^n$ if $n \notin \mathscr{M}$. Moreover, $c_t^{n,j}$ is the subgradient w.r.t. $AI_t^{n,j}$ at $AI_{t-1}^{n,j}$, with $c_t^{n,j} = 1$ if $AI_t^{n,j} > AI_{t-1}^{n,j}$, $c_t^{n,j} = C^n \in (0,1)$ if $AI_t^{n,j} < AI_{t-1}^{n,j}$, and $c_t^{n,j} \in [C^n, 1]$ if $AI_t^{n,j} = AI_{t-1}^{n,j}$. Similarly, $c_t^K \in [C^K, 1]$ is the subgradient w.r.t. K_t. Denoting $AI_t \equiv \sum_{n,j} \tilde{s}^{n,j} F(AI_t^{n,j})$, the first-order conditions w.r.t. $AI_t^{n,j}$ and K_t read:

$$c_t^{n,j} - \beta c_{t+1}^{n,j} = D(1-\tau)\alpha \tilde{s}^{n,j} F'(AI_t^{n,j}) AI_t^{\alpha-1} K_t^{1-\alpha}, \tag{9}$$

$$c_t^K - \beta c_{t+1}^K = D(1-\tau)(1-\alpha) AI_t^{\alpha} K_t^{-\alpha}. \tag{10}$$

Let:

$$\underline{AI}_t^{n,j} \equiv (F')^{-1}\left(\frac{1-\beta}{D(1-\tau)\alpha \tilde{s}^{n,j} AI_t^{\alpha-1} K_t^{1-\alpha}} \right), \qquad \overline{AI}_t^{n,j} \equiv (F')^{-1}\left(\frac{C^n(1-\beta)}{D(1-\tau)\alpha \tilde{s}^{n,j} AI_t^{\alpha-1} K_t^{1-\alpha}} \right), \tag{11}$$

$$\underline{K}_t \equiv \left(\frac{1-\beta}{D(1-\tau)(1-\alpha) AI_t^{\alpha}} \right)^{-1/\alpha}, \qquad \overline{K}_t \equiv \left(\frac{C^K(1-\beta)}{D(1-\tau)(1-\alpha) AI_t^{\alpha}} \right)^{-1/\alpha}. \tag{12}$$

If $AI_{t+1}^{n,j} > AI_t^{n,j}$ but $AI_{t+1}^{n',j'} < AI_t^{n',j'}$ for some $(n,j) \neq (n',j')$, then $c_{t+1}^{n,j} = 1$ and $c_{t+1}^{n',j'} = C^{n'}$, and (9) implies:

$$\frac{\tilde{s}^{n,j} F'(AI_t^{n,j})}{\tilde{s}^{n',j'} F'(AI_t^{n',j'})} = \frac{c_t^{n,j} - \beta c_{t+1}^{n,j}}{c_t^{n',j'} - \beta c_{t+1}^{n',j'}} \leqslant \frac{c_{t+1}^{n,j} - \beta c_{t+2}^{n,j}}{c_{t+1}^{n',j'} - \beta c_{t+2}^{n',j'}} = \frac{\tilde{s}^{n,j} F'(AI_{t+1}^{n,j})}{\tilde{s}^{n',j'} F'(AI_{t+1}^{n',j'})} < \frac{\tilde{s}^{n,j} F'(AI_t^{n,j})}{\tilde{s}^{n',j'} F'(AI_t^{n',j'})},$$

a contradiction. Therefore, $AI_{t+1}^{n,j} > AI_t^{n,j}$ implies $AI_{t+1}^{n',j'} \geqslant AI_t^{n',j'}$, and similarly, $AI_{t+1}^{n,j} < AI_t^{n,j}$ implies $AI_{t+1}^{n',j'} \leqslant AI_t^{n',j'}$.

Next, if $AI_{t+1}^{n,j} > AI_t^{n,j}$ for some (n,j), then $K_{t+1} < K_t$ will lead to a contradiction with a similar argument to the previous paragraph. Moreover, if $K_{t+1} > K_t$, then $c_{t+1}^{n,j} = 1$ and $c_{t+1}^K = 1$, and (9) and (10) imply:

$$(D(1-\tau))^{\frac{1}{\alpha}} \alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}} F'(AI_t^{n,j}) = \frac{c_t^{n,j} - \beta c_{t+1}^{n,j}}{(c_t^K - \beta c_{t+1}^K)^{\frac{\alpha-1}{\alpha}}} \leqslant \frac{c_{t+1}^{n,j} - \beta c_{t+2}^{n,j}}{(c_{t+1}^K - \beta c_{t+2}^K)^{\frac{\alpha-1}{\alpha}}}$$

$$= (D(1-\tau))^{\frac{1}{\alpha}} \alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}} F'(AI_{t+1}^{n,j}) < (D(1-\tau))^{\frac{1}{\alpha}} \alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}} F'(AI_t^{n,j}),$$

a contradiction. Therefore, we must have $K_{t+1} = K_t$. Symmetrically, one can show that $AI_{t+1}^{n,j} < AI_t^{n,j}$ also implies $K_{t+1} = K_t$.

Suppose $AI_{t+1}^{n,j} > AI_t^{n,j}$ for some (n,j), then $c_{t+1}^{n,j} = 1$, $AI_{t+1}^{n,j} \geqslant AI_t^{n,j}$ for all (n,j), and $K_{t+1} = K_t$. From (9), we have $c_{t+1}^{n,j} - \beta c_{t+2}^{n,j} < c_t^{n,j} - \beta c_{t+1}^{n,j}$, which leads to $c_{t+2}^{n,j} < C^n$, a contradiction. Similarly, $AI_{t+1}^{n,j} < AI_t^{n,j}$ leads to a contradiction. Therefore, $AI_{t+1}^{n,j} = AI_t^{n,j}$ for all (n,j). Applying the same logic to (10), we also conclude $K_{t+1} = K_t$.

In summary, after period T, $AI_t^{n,j}$ and K_t remain constant for all (n,j). With the definition of $c_t^{n,j}$ and c_t^K, (9) and (10) imply $AI_{T+1}^{n,j}$, AI_{T+1} and K_{T+1} as solution to the following system:

$$\begin{aligned} AI_{T+1}^{n,j} &= \max\left\{\min\left\{AI_T^{n,j}, \overline{AI}_{T+1}^{n,j}\right\}, \underline{AI}_{T+1}^{n,j}\right\}, \ \forall\ n,j, && (13)\\ K_{T+1} &= \max\left\{\min\left\{K_T, \overline{K}_{T+1}\right\}, \underline{K}_{T+1}\right\}, && (14)\\ AI_{T+1} &= \sum_{n,j} \tilde{s}^{n,j} F(AI_{T+1}^{n,j}). && (15) \end{aligned}$$

Due to path dependence, we also need to study the properties of $AI_T^{n,j}$ and K_T, right before the announcement. Consider the problem in period 1, where the firm started with no capital:

$$\max_{\{AI_t^{n,j},K_t\}_{t,n,j}} \sum_{t=1}^{\infty} (\beta(1-\lambda))^{t-1}\Bigg(\left(\sum_{n,j} s^n F(AI_t^{n,j})\right)^{\alpha} K_t^{1-\alpha} D - \sum_{n,j} c_t^{n,j}(AI_t^{n,j} - AI_{t-1}^{n,j}) - c_t^K(K_t - K_{t-1}) + \beta\lambda W\left(\{AI_t^{n,j}\}_{n,j}, K_t\right)\Bigg),$$

where $W\left(\{AI_t^{n,j}\}_{n,j}, K_t\right)$ is the expected continuation value if the announcement arrives at the end of period t. The first-order conditions w.r.t. $AI_t^{n,j}$ and K_t read:

$$\begin{aligned} c_t^{n,j} - \beta(1-\lambda)c_{t+1}^{n,j} - \beta\lambda\mathbb{E}c_{T+1}^{n,j} &= D\alpha s^n F'(AI_t^{n,j}) AI_t^{\alpha-1} K_t^{1-\alpha}, && (16)\\ c_t^K - \beta(1-\lambda)c_{t+1}^K - \beta\lambda\mathbb{E}c_{T+1}^K &= D(1-\alpha) AI_t^{\alpha} K_t^{-\alpha}. && (17) \end{aligned}$$

With the same logic as before, one can show that $AI_t^{n,j}$ and K_t must be constants until after the announcement period T. Because the firm starts with no capital, it has to be the case that $c_t^{n,j} = c_t^K = 1$ for all $t \leqslant T$. The constants satisfy:

$$\begin{aligned} AI_T^{n,j} &= (F')^{-1}\left(\frac{1-\beta+\beta\lambda(1-\mathbb{E}c_{T+1}^{n,j})}{D\alpha s^n AI_T^{\alpha-1} K_T^{1-\alpha}}\right), && (18)\\ K_T &= \left(\frac{1-\beta+\beta\lambda(1-\mathbb{E}c_{T+1}^K)}{D(1-\alpha) AI_T^{\alpha}}\right)^{-1/\alpha}, && (19)\\ AI_T &= \sum_{n,j} s^n F(AI_T^{n,j}). && (20) \end{aligned}$$

Now consider the change of capital stocks from period T to $T+1$, after a set $\mathscr{M}$ of technology standards are published but no ethical standard published ($\tau = 0$). Suppose $AI_{T+1} = AI_T$, then $K_{T+1} \geqslant \underline{K}_{T+1} \geqslant K_T$, $AI_{T+1}^{n,A} = \underline{AI}_{T+1}^{n,A} > AI_T^{n,A}$ and $\overline{AI}_{T+1}^{n,B} > AI_T^{n,B}$ for $n \in \mathscr{M}$ provided $\frac{s^n}{\bar{s}^n} > C^n$, $AI_{T+1}^{n,j} = \underline{AI}_{T+1}^{n,j} \geqslant AI_T^{n,j}$ for $n \notin \mathscr{M}$, $j = A,B$. Therefore, $AI_{T+1} > AI_T$, a contradiction. Suppose instead $AI_{T+1} < AI_T$, then there exists (n,j) such that $\overline{AI}_{T+1}^{n,j} < AI_T^{n,j}$, which implies $\frac{K_{T+1}}{AI_{T+1}} < \frac{K_T}{AI_T}$ by (11). However, (12) requires that $\frac{K_{T+1}}{AI_{T+1}} \geqslant \frac{\underline{K}_{T+1}}{AI_{T+1}} \geqslant \frac{K_T}{AI_T}$, a contradiction. Therefore, we must have $AI_{T+1} > AI_T$ and $K_{T+1} = \underline{K}_{T+1} > K_T$. This means $\frac{K_{T+1}}{AI_{T+1}} = \frac{\underline{K}_{T+1}}{AI_{T+1}} \geqslant \frac{K_T}{AI_T}$. As a result, $\underline{AI}_{T+1}^{n,A} > AI_T^{n,A}$ and $\overline{AI}_{T+1}^{n,B} > AI_T^{n,B}$ for $n \in \mathscr{M}$, $\underline{AI}_{T+1}^{n,j} \geqslant AI_T^{n,j}$ for $n \notin \mathscr{M}$, $j = A,B$. Therefore, $\sum_{n,j} AI_{T+1}^{n,j} > \sum_{n,j} AI_T^{n,j}$ and $K_{T+1} > K_T$.

Alternatively, consider the change of capital stocks from period T to $T+1$, after a number of ethical standards are published but no technological standard published ($\tilde{s}^{n,j} = s^n$ for all n,j). Suppose $AI_{T+1} = AI_T$, then $K_{T+1} \leqslant \overline{K}_{T+1} < K_T$ for $\tau > (1-C^K)\frac{1-\beta+\beta\lambda}{1-\beta+\beta\lambda(1-C^K)}$, and $AI_{T+1}^{n,B} \leqslant \overline{AI}_{T+1}^{n,B} < AI_T^{n,B}$ for all n,j, when $\tau > (1-C^n)\frac{1-\beta+\beta\lambda}{1-\beta+\beta\lambda(1-C^n)}$. Therefore, $AI_{T+1} < AI_T$, a contradiction. Suppose instead $AI_{T+1} > AI_T$, then there exists (n,j) such that $\underline{AI}_{T+1}^{n,j} > AI_T^{n,j}$, which

implies $\frac{K_{T+1}}{AI_{T+1}} > \frac{K_T}{AI_T}$ by (11). However, (12) requires that $\frac{K_{T+1}}{AI_{T+1}} \leqslant \frac{\overline{K}_{T+1}}{AI_{T+1}} < \frac{K_T}{AI_T}$, a contradiction. Therefore, we must have $AI_{T+1} < AI_T$ and $K_{T+1} = \overline{K}_{T+1} < K_T$. This means $\frac{K_{T+1}}{AI_{T+1}} = \frac{\overline{K}_{T+1}}{AI_{T+1}} < \frac{K_T}{AI_T}$. As a result, $AI^{n,j}_{T+1} = \overline{AI}^{n,j}_{T+1} < AI^{n,j}_T$ for all n, j. Therefore, $\sum_{n,j} AI^{n,j}_{T+1} < \sum_{n,j} AI^{n,j}_T$ and $K_{T+1} < K_T$.

Next, consider the comparative statics on the set $\mathscr{M}$, i.e., the effect of adding n^* to $\mathscr{M}$ on capital stocks in period $T+1$. Holding all $\tilde{s}^{n,j}$ fixed except that $\tilde{s}^{n^*,A} = \overline{s}^{n^*} > s^{n^*}$ and $\tilde{s}^{n^*,B} = \underline{s}^{n^*} \in (C^{n^*} s^{n^*}, s^{n^*})$. From the previous paragraph we know that with any realized $\mathscr{M}$, $K_{T+1} = \underline{K}_{T+1}$, $AI^{n,A}_{T+1} = \underline{AI}^{n,A}_{T+1}$ and $AI^{n,B}_{T+1} = \max\{\underline{AI}^{n,B}_{T+1}, AI^{n,B}_T\}$ for $n \in \mathscr{M}$, $AI^{n,A}_{T+1} = \underline{AI}^{n,j}_{T+1}$ for $n \notin \mathscr{M}$, $j = A, B$. In particular, $\frac{K_{T+1}}{AI_{T+1}}$ does not change with the addition of n^*. Then, $AI^{n^*,A}_{T+1}$ strictly increases, $AI^{n^*,B}_{T+1}$ remains unchanged because $\overline{AI}^{n^*,B}_{T+1}$ after the inclusion of n^* is higher than $\underline{AI}^{n^*,B}_{T+1}$ before the inclusion. $AI^{n,j}_{T+1}$ remains unchanged for $n \notin \mathscr{M}$. As a result, $\sum_{n,j} AI^{n,j}_{T+1}$ and K_{T+1} both strictly increase with the inclusion of n^*.

Finally, consider the comparative statics on τ. With an increase in τ, suppose $AI^{n,j}_{T+1}$ strictly increases for some (n, j). Then $\underline{AI}^{n,j}_{T+1}$ and $\overline{AI}^{n,j}_{T+1}$ must strictly increase for all (n, j), and as a result, AI_{T+1} strictly increases according to (15). Also, $\frac{K_{T+1}}{AI_{T+1}}$ must strictly increase according to (11) and (13). Since (12) implies that $\frac{K_{T+1}}{AI_{T+1}}$ and $\frac{\overline{K}_{T+1}}{AI_{T+1}}$ both decrease, and $\frac{K_T}{AI_{T+1}}$ strictly decreases, we have $\frac{K_{T+1}}{AI_{T+1}}$ decreases, a contradiction. Therefore, $AI^{n,j}_{T+1}$ decreases, and K_{T+1} decreases from (12) and (14). □

B Data Description

B.1 Financial Variables

In this section, we define financial variables in Panel B of Table 3, where are derived using data from Worldscope. CAPEX/AT refers to the capital expenditures to total assets ratio, calculated as the ratio of capital expenditures to lagged total assets (ITEM4601/L.ITEM2999), and it's presented in percentage terms. RD/AT is the R&D expenditures to total assets ratio, calculated as the ratio of R&D expenditures to lagged total assets (ITEM1201/L.ITEM2999), and it's presented in percentage terms. Sales/AT denotes the proportion of sales to lagged book value of assets (ITEM1001/L.ITEM2999), and it's presented in percentage terms. Log(BVA) represents the logarithm of the book value of assets (ITEM2999). CF2AT (NI/BVA) indicates the cash flow to total assets ratio, calculated as the ratio of net income to business value added (NI/L.ITEM2999). Leverage refers to the leverage ratio, calculated as the ratio of debt to lagged total assets (ITEM3255/L.ITEM2999). ST Leverage denotes the short-term leverage ratio, representing the proportion of short-term debt in relation to the sum of short-term debt and long-term debt (ITEM3051/(ITEM3051+ITEM3251)). To ensure data quality, we excluded rows with return on equality values below -100%, firms with less than five observations, countries with less than 250 observations, and Fama French 48 industries categorized as "Other (48)". We winsorize all variables at 2% levels and report summary statistics on rows with non-missing CAPEX/AT values.

B.2 ISO Committee and UNSC Related Variables

Log(Committees) refers to the natural logarithm of the number of ISO committees that a country is a member of in a given year for each firm. It represents the level of participation and involvement of a firm in ISO committees, which are international standardization bodies. % UNSC Members$_{i,c,t-1}$ is the percentage of UNSC members in the year *t-1* within the secretariats of permanent UNSC member country *c*. To calculate the ratio, we divide the total number of rotating UNSC members across the committees under the secretariat of country *c* in a given year by the total number of committee members under the same secretariat in that year. We assign this percentage value to all firms *i* headquartered in country *c*. It therefore measures the percentage of ISO members in the secretariats of the

United States, the United Kingdom, and France for a specific year. However, it is equal to zero for all other countries in the Worldscope universe. We manually collect this data from the UNSC website.

B.3 Variables on Standard Types

Log(AI Standards) denotes the logged number of AI standards published under the secretariat of a given country and year, and it's equal to zero for countries without secretariats. The remaining variables denote the number of standards published by a given country's secretariat in a given year, categorized based on their standard titles in lowercase. Machine Learning Standards refer to the standards which contain any of the following terms related to machine learning in their titles: "algo", "code", "decision", "fuzzy", "image", "intelligence", "language", "learning", "logic", "neural", "processing", "probabi", "recognition", "robot", "semantic", "speech", "training", "vision". Data Standards refer to the standards which contain the term "data" in their titles but do not contain terms associated with machine learning. Ethics & Accountability Standards refer to the standards which contain any of the following terms related to accountability in their titles: "accountability", "ethic", "governance", "robustness", "safety", "security", "societal". Automation Standards refer to the standards which contain the term "automation" in their titles but do not contain terms associated with machine learning. Programming Standards refer to the standards which contain any of the following terms related to programming in their titles: "basic", "c#", "c++", "java", "language", "linux", "pascal", "program", "programming", "python", "software", "sql". Interchange Standards refer to the standards which contain any of the following terms related to interchange in their titles: "exchange", "interchange". Interoperability Standards refer to the standards which contain any of the following terms related to interoperability in their titles: "compatib", "connectiv", "Internet", "IoT", "of things", "opera", "twin". Privacy Standards refer to the standards which contain any of the following terms related to privacy in their titles: "biomet", "children", "cybersecurity", "human", "private", "privacy". Human Biometric Standards refer to the standards which contain any of the following terms related to humans in their titles: "biomet", "genom", "human". Multimedia Standards refer to the standards which contain any of the following terms related to graphics in their titles: "acoust", "audio", "graphic", "media", "mpeg", "picture", "visual". Internet of Things (IoT) Standards refer to the standards which contain any of the following terms related to the Internet of Things (IoT) in their titles: "Internet", "IoT", "of things", "twin". Machinery & Equipment Standards refer to the standards which contain any of the following terms related to equipment in their titles: "card", "circuit", "equipment", "machine", "office", "physical", but do not contain terms related to privacy. Unlabeled Standards refer to the standards which do not contain any terms related to the previously defined categories (Machine Learning, Data, Ethics & Accountability, Automation, Programming, Interchange, Interoperability, Privacy, Human Biometric, Multimedia, IoT, Machinery & Equipment) in their titles. If none of the terms are found, the standards are classified as "Unlabeled Standards".

B.4 Variables on AI-Specific Research and Investment

B.4.1 Firm-Level AI Research

Log(AI Research), Log(CV Research), Log(NLP Research), and Log(Robotics Research) represent the logarithm of one plus the number of research publications in AI, computer vision, natural language processing, and robotics, respectively.[50] This data comes from the Private-sector AI-Related Activity Tracker (PARAT) database, maintained by the Emerging Technology Observatory (ETO).[51]

[50] AI includes research in computer vision, natural language processing, and robotics, as well as unlabelled research.

[51] See https://eto.tech/dataset-docs/private-sector-ai-indicators/ for detailed description of the data and variables.

B.4.2 Country-Level AI-Specific Investments and Patents

Our research delves into AI-specific investments and patents, utilizing data from the Country Activity Tracker (CAT), a comprehensive dataset developed by CSET. This dataset offers a broad view of national AI activities, providing a foundation for our investigation of AI-specific investments and patenting.

AI Investment Data CAT's AI-investment data, sourced from Crunchbase, concentrates on equity investments into private AI-focused companies. This dataset excludes publicly traded companies and non-equity funding types like debt finance, grants, and crowdfunding. It encompasses venture capital, private equity transactions, and mergers and acquisitions. AI companies are identified through keywords, industry tags, and inclusion in the CSET's private-sector AI-Related Activity Tracker (PARAT), with investments categorized by application fields based on Crunchbase data.[52] Company and investor nationalities are determined by headquarters location.

CAT aggregates investment data first at the AI-company level, adding up disclosed values. It then calculates country-level AI investment figures, considering the target's location, investor nationalities, and the investment's primary application field. These country-level figures, representing the AI investment landscape, require careful interpretation due to the intricate nature of investment transactions involving multiple parties.[53]

Using the CAT AI-investment data, we construct a measure of country-level AI investment, Log(AI Investment$_{c,t}$), which is the logarithm of one plus the AI investments made in country c in year t. That is, Log(AI Investment$_{c,t}$)=Log(1+ Incoming Disclosed Investment$_{c,t}$), where Incoming Disclosed Investment$_{c,t}$ is the total AI-related investment made into the target country c by all countries in year t.

Patent Data On the patent side, CAT includes data from 1790 Analytics, PATSTAT, and The Lens. Through a collaborative effort between CSET and 1790, this data is carefully structured to offer insights into AI-related patent families, which includes both applications and granted patents. The organization into patent families aids in understanding the landscape of AI innovations and how they are protected across different legal jurisdictions. This dataset is pivotal for analyzing the spread and focus of AI-related patenting activities worldwide.

In particular, CAT's patent dataset aggregates data from 52 patent offices globally, encompassing both national (e.g., U.S. Patent and Trademark Office) and international bodies (e.g., European Patent Office). It provides metrics on the number of patent filings per country, focusing on where patents are filed rather than the inventors' nationality. CAT exclusively features AI-related patents, identified from the extensive databases of 1790 and The Lens. This identification leverages a method developed by CSET and 1790 Analytics, using keywords and patent classification codes to pinpoint AI patents and link them to specific AI techniques.[54].

Using the CAT AI-patent data, we develop two measures on AI patents: Log(AI Patent Applications$_{c,t}$), which is the logarithm of one plus the number of AI patent applications filed in country c in year t, and Log(AI Patents Granted$_{c,t}$), which is the logarithm of one plus the number of AI patents granted in country c in year t.

Our investigation into AI-specific investments leverages data sourced from the Country Activity Tracker (CAT), developed by the Center for Security and Emerging Technology (CSET). The CAT offers a detailed and novel dataset that highlights national-level AI activities. It covers a broad spectrum of metrics, such as patents, research, and investments in the private sector, thereby illuminating the global landscape of AI competition. Importantly, the CAT also provides the capability to delve into specific AI subfields and applications, offering novel insights into AI

[52] See https://bit.ly/3BfrOMo.
[53] For a detailed explanation of the methodology and its application, refer to the CSET report's methodology section and appendices.
[54] Details on patent data methodology are available in CSET's paper on AI patents and the associated Github repository.

investments and patent activities.[55]

The CAT dataset encompasses a broad spectrum of AI investments, covering 36 diverse categories including, but not limited to, agriculture, biotechnology, cybersecurity, finance, manufacturing, natural language processing (NLP), and robotics. Furthermore, it extends to AI patent activities, encapsulating both applications and granted patents across 22 categories. These categories range from banking and finance to computer vision, machine learning, industrial manufacturing, logic and programming, security, telecommunications, and transportation.

C Additional Findings

C.1 Estimation of Effect Heterogeneity Based on Committee-Level Instruments

In this section, we provide evidence on effect heterogeneity based on UNSC membership rates across different AI committees. This is important for three main reasons. The first reason is that it supports the causal claims of the paper by utilizing an arguably more exogenous instrument. The proportion of UNSC members across different committees varies depending on the composition of each committee prior to UNSC rotation announcements. It is unlikely that this percentage for each given committee is driven by future expectations of UNSC rotations. This is also supported by Figure C4, which shows that countries do not time their AI committee memberships based on observable economic development characteristics.

[Figure C4 about here]

The second reason why using committee-level UNSC rates is important is because it gives us shocks with different importance. The motivation behind this argument is that a percentage change in the UNSC membership in a committee may be more marginal and effective if it makes the secretariat much more likely to pass resolutions and publish standards. For example, in ISO/TC 184/SC 4, the total UNSC membership rate is 41.67%, with 33.33% driven by UNSC rotations. This suggests that UNSC members already satisfy nearly a third of the votes necessary to publish new standards. Therefore, we should expect the influence of UNSC membership rotations to be more evident in this committee. Other examples include ISO/IEC JTC 1/SC 32 and ISO/TC 184/SC 5 committees. In summary, looking at committee-level instruments helps us provide a stronger economic mechanism.

The third reason why looking at committees separately is important is because of policy implications. The general theme in NIST's report, "US Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools," and EO 13859 is that AI standards matter for business, and these are the committees that publish them. However, there is no evidence on which committees help or hurt. Committee-level analysis tackles this problem and aims to identify effect heterogeneity based on committees. We are able to conduct this analysis because our instrument can be reproduced at the committee-year level for each secretariat country.

[Figure C3 about here]

Furthermore, regarding AI relatedness through the contents of published standards, as shown in Figure C3, subcommittees 4, 5, and 32 actively contribute to automation, industrial data, and interchange standards, which drive many of our main findings. Consequently, we expect these subcommittees to exert a strong influence in those areas.

[55] We express our gratitude to Zachary Arnold for providing the CAT data. For more information, see https://www.brookings.edu/articles/can-democracies-cooperate-with-china-on-ai-research/.

As mentioned in Section 5.1, we employ the following 2SLS procedure, beginning with first-stage regressions on

$$Log(AI\ Standards^{k}_{i,c,t}) = \alpha^{k}_{0} + \alpha^{k}_{1}\%\ UNSC\ Members^{k}_{i,c,t-1} + \gamma^{k} X_{i,c,t-1} + \tau^{k} W_{c,t-1} + \text{ Fixed Effects} + \epsilon^{k}_{i,c,t}, \tag{21}$$

separately for each AI committee k. $Log(AI\ Standards^{k}_{i,c,t})$ above denotes the logged number of AI standards published in year t by committee k under the secretariat of country c where firm i is located at. $\%\ UNSC\ Members^{k}_{i,c,t-1}$ is equal to the percentage of UNSC members in committee k in year *t-1* for firms from the permanent UNSC member secretariats, and zero otherwise.

[Figure C1 about here]

Figure C1 illustrates the variation of committee-level instruments across different AI committees and over time. The instrumental variable, $\%UNSC\ Members^{k}_{i,c,t-1}$, displays different patterns among each committee k. Comparing the years 2018 and 2019, for example, we observe an increase in $\%UNSC\ Members^{k}_{i,c,t-1}$ for committees SC 17, SC 4, and SC 42, indicating a higher percentage of rotating UNSC members within these committees during that period. In contrast, a decrease in our instruments is observed for committees SC 32, SC 22, SC 5, SC 24, and SC 37. These variations reflect the dynamic nature of rotating UNSC member composition across different AI committees over time.

[Figure C7 about here]

Related to this, Figure C7 presents a histogram illustrating the distribution of combined committee-level instruments, represented by $\%UNSC\ Members^{k}_{i,c,t-1}$, across AI committees. The figure also shows the distribution of rotating and total UNSC members across all AI committees, revealing an average UNSC membership of 28.54%. Of this, approximately 35.35% is driven by rotating UNSC members, underscoring the significance of the instrument. Notably, there is considerable variability across committees, particularly in U.S.-led committees, which are pivotal for our analyses. As mentioned above, in ISO/TC 184/SC 4, the total UNSC membership rate is 41.67%, with 33.33% attributed to UNSC rotations. In ISO/TC 184/SC 5, the total UNSC membership rate is 36.67%, with 24.24% driven by UNSC rotations. In ISO/IEC JTC 1/SC 32, the total UNSC membership rate is 32.74%, with 35.14% driven by UNSC rotations.

In the second stage of our 2SLS procedure, we run regressions on:

$$y_{i,c,t} = \beta^{k}_{0} + \beta^{k}_{1} \widehat{Log(AI\ Standards^{k}_{i,c,t})} + \gamma^{k} X_{i,c,t-1} + \tau^{k} W_{c,t-1} + \text{ Fixed Effects} + \epsilon^{k}_{i,c,t}, \tag{22}$$

where $y_{i,c,t}$ represents our main dependent variables, i.e., firm-specific AI research and broader investment characteristics as described in Tables 4 and 5. $\widehat{Log(AI\ Standards^{k}_{i,c,t})}$ denotes the instrumented $Log(AI\ Standards^{k}_{i,c,t})$ from the first stage, and β^{k}_{1} provides an estimate of the average effect of AI standards published by committee k on firms headquartered in the secretariat country, separately for each committee k. The coefficients β^{k}_{1} represent different local effects compared to β_1 in equation (4). While β_1 captures the overall effect of AI standards on firms headquartered in all countries with secretariats, β^{k}_{1} quantifies the specific effects of AI standards published by committee k on firms located in particular countries with secretariats (e.g., depending on the country of the secretariat).

[Tables C6 and C7 about here]

We present our results in Tables C6 and C7. These tables reveal the influence of various types of AI standards, which include but aren't limited to Machine Learning, Data, Automation, Programming Language, Interoperability, Machinery & Equipment, Ethics & Accountability, and Privacy.

In Table C6, we show that SC 4 has a strong influence on AI research publications, particularly in computer vision. This makes sense given SC 4's focus on industrial data and its extensive publication of standards related to automation, interoperability, and industrial data (see Figure C3). Conversely, SC 32 appears to negatively impact AI research overall, including in computer vision, natural language processing, and robotics. The influence of SC 5 on AI research is not statistically significant, likely because it publishes a mix of standards that have both positive (data-related) and negative (programming language-related) effects. Additionally, it is important to note that the last two committees publish fewer standards, resulting in a smaller dataset, which makes it more challenging to identify significant effects.

In Table C7, Group 3, the committee focusing on Programming Languages, shows a significant positive relationship (1.27%) with CAPEX, whereas Group 4 (Data Interchange) and Group 6 (Guidance on AI) demonstrate significant negative relationships (-0.86% and -0.78% respectively). Moreover, Groups 7 and 10, centered on Automation and IT Governance, show substantial positive impacts (5.69% and 8.59%) on CAPEX. In Panel C, the analysis of R&D Expenditures reveals significant positive relationships for Group 1 (Industrial Data), Group 2 (Interoperability), and Group 3 (Programming Languages), with increases of 0.34%, 1.85%, and 3.27%, respectively. Conversely, negative relationships are observed for Group 4 (Data Interchange), Group 5 (Biometrics), and Group 6 (Guidance on AI), with decreases of -1.52%, -1.54%, and -1.91%, respectively.

Overall, our findings in this section indicate that the type of committee issuing AI standards has a notable influence on AI and broader investment decisions. This further underscores the importance of nuanced interpretation when considering the impacts of AI standards on corporate investment choices.

C.2 AI Standards and Country-Level AI Investments

In this section we present our findings on the influence of AI standards on AI-specific investments at the country level. To that end, we run regressions on the below model:

$$y_{c,t} = \beta_0 + \beta_1 Log(\widehat{AI\ Standards}_{c,t}) + \alpha_c + \gamma_t + \epsilon_{c,t}, \tag{23}$$

Our main dependent variable of interest, $y_{c,t}$, refers to one of Log(AI Investment$_{c,t}$), which is defined as the logarithm of one plus the AI investments made in country c in year t; Log(AI Patent Applications$_{c,t}$), which represents the logarithm of one plus the number of AI patent applications filed in country c in year t, and Log(AI Patents Granted$_{c,t}$), which is the logarithm of one plus the number of AI patents granted in country c in year t. $Log(\widehat{AI\ Standards}_{c,t})$ denotes the instrumented $Log(AI\ Standards_{c,t})$ from the first stage. % UNSC Members$_{c,t-1}$ serves as an instrumental variable, representing the percentage of rotating UNSC members in the year *t-1* within the secretariats of permanent UNSC member country *c*.

[Table C3 about here]

We present our findings in Table C3. Our findings indicate a positive and statistically significant relationship between Log(AI Standards) and other AI-related investments within countries over time. Specifically, a unit increase in Log(AI Standards) is associated with increases in logged AI investments, patent applications, and total AI patents granted by coefficients of 0.23, 0.46, and 0.35, respectively. These results underline the strong influence of AI stan-

dards on investment and patenting activities in the AI domain. These findings are also consistent with part (i) of our Hypothesis 1, which predicts a positive relationship between AI investments and technological standards.

[Figure C8 about here]

We further examine how AI standards influence different areas of AI investments and patent applications. Figure C8 shows that AI standards notably boost investments in areas such as robotics, manufacturing, cybersecurity, privacy and finance security, data analytics, software, face recognition, and education. This demonstrates the wide-ranging impact of standardizing AI across various fields. Furthermore, the number of AI patent applications increases in sectors like banking and finance, security, industrial manufacturing, machine learning, transportation, telecommunications, and computer vision, following the adoption of AI standards.[56] Overall, our findings highlight that as AI standards are adopted, both the funding for AI technologies and the number of AI patent applications, including those patents that are granted, increase.

C.3 Additional Figures and Tables

Additional Figures. Figure C2 illustrates the life cycle events of AI standards published from 1972 to 2023. Figure C5 provides a correlation matrix for our committee-level instrumental variables.

Figure C6 illustrates each country's contributions to machine learning and safety & accountability standards from 2017 to 2023 using color gradients. Countries including the United States, Canada, China, Russia, India, Australia, and several Western European nations are significantly engaged in the global standardization efforts for both machine learning and ethical AI, as evident from the considerable number of standards published by the committees they are part of. This considerable involvement suggests that unprecedented shocks assisting the US or other countries in promoting their strategic objectives, especially when supported by politically-aligned countries within the committee or under its secretariats, can have substantial implications for the direction and pace of machine learning and ethical AI standardization. On examining the global landscape, we also observe that countries such as Mexico, Argentina, Saudi Arabia, Iran, and South Africa appear to wield more influence over the formulation of ethical standards as compared to machine learning standards. This disparity may potentially stem from the technical capacities inherent to the complexity of their economies. The emphasis on ethical standards in these countries might reflect their societal and regulatory focus on AI's broader implications, highlighting the importance they place on ethical considerations in AI's deployment and use.[57]

Figure C9 shows the results from re-running the main regressions in columns 2 and 4 of Table 5 after randomly excluding AI standards from the sample. We conducted 1,000 regressions, each with 250 randomly dropped AI standards. The Y-axis displays the 1,000 coefficient estimates, while the X-axis shows their corresponding t-statistics. All estimates remain economically and statistically significant, confirming that the effects of AI standards on CAPEX and R&D hold up under this robustness test.

Table C1: Decomposition of Standards by Committee and Secretariats. Table C1 provides a detailed breakdown of the published standards, categorized by responsible committees and secretariats. In this context, secretariats refer to the countries that lead the standardization efforts for their respective committees. They play a vital role in the ISO standardization process. A secretariat is typically held by a national standardization body from a specific

[56] Although we have additional results indicating that AI standards related to specific domains further stimulate patenting and investments in those domains, these details are not included here but are available upon request.

[57] Section C of the Appendix discusses the role of bias in AI systems and AI-based decision making.

country. Hosting a secretariat for an ISO committee can bring significant benefits to local firms and industries. By assuming the responsibility of a secretariat, a country gains a central coordinating role in the standardization process, allowing it to have a more direct influence on the committee's work and the development of standards. This heightened involvement presents a unique opportunity for local firms to actively shape the standards governing their industries. It ensures that their specific needs and interests are taken into account, reducing uncertainty related to their innovation paths.

Moreover, managing an ISO secretariat requires a high level of expertise in the specific field of standardization. This expertise, developed by the national standardization body hosting the secretariat, can directly benefit local firms by enhancing their knowledge and understanding of international standards and best practices. It allows them to stay at the forefront of technological advancements, adapt to global market requirements, and maintain a competitive edge in their respective industries. Hosting a secretariat also creates networking opportunities for the country's industries, enabling them to establish valuable relationships with stakeholders from other countries. This international collaboration can foster knowledge sharing, innovation, and the exchange of ideas, ultimately driving growth and competitiveness for local firms. In summary, hosting an ISO secretariat not only grants a country a more influential role in the standardization process but also provides local firms with the advantages of less uncertain innovation paths, enhanced expertise, and international networking, all of which can contribute to business growth.

[Table C1 about here]

As displayed in Table C1, the total number of AI standards published by AI-centric committees from 1972 to 2023 is 5,456.[58] The table reveals that ISO committees have published 2,055 AI standards, while joint ISO/IEC committees have contributed 3,382 standards. In comparison, IEEE, operating independently, has published 19 standards. These numbers underscore the significant contributions of ISO and ISO/IEC in the standardization of AI, with ISO/IEC committees leading in terms of the total number of standards published. Within the ISO Committees section, notable contributions include TC 184/SC 4 with the highest number of standards at 1,771 publications, followed by TC 184/SC 5 with 96 standards. Turning to the ISO/IEC Committees section, notable examples include SC 29 with 1,168 standards, SC 27 with 432 standards, SC 7 with 352 standards, and SC 17 with 338 standards.

Table C2: Scopes and Activities of AI Standardization Committees. Table C2 offers a comprehensive overview of the activities and scopes of AI standardization committees listed previously in Table C1, encompassing a wide range of domains such as data interchange, ethical AI, robotics, and industrial automation. For instance, ISO/IEC JTC 1/SC 42 focuses on providing guidance and developing standards for AI while assisting other ISO and IEC committees. For this reason, it's named as the Artificial Intelligence committee. ISO/IEC JTC 1/SC 41 specializes in standardization within the field of the Internet of Things (IoT) and digital twin technologies. Governance aspects related to IT, data, and IT-enabled services are the focus of ISO/IEC JTC 1/SC 40. Noteworthy committees such as TC 184, TC 184/SC 1, and TC 199 are engaged in industrial automation, industrial cyber and physical device control, and safety standards for machinery, respectively. ISO/TC 299 focuses exclusively on robotics standards, while TC 184/SC 4 and TC 184/SC 5 specialize in industrial data exchange and industrial interoperability, respectively.[59]

[58] it is worth noting that additional AI-related standards from the AI Standards Hub are not included in this table due to formatting constraints. Nevertheless, our analysis remains robust even when considering these additional standards.

[59] Section D.3 of the Appendix discusses the role of AI in enhancing operational efficiency, safety, and decision-making in oil and gas production facilities. AI implementation not only contributes to superior performance but also aids in maintaining regulatory compliance and fostering transparent communication with various stakeholders. The application of AI in this sector spans predictive maintenance, advanced analytics for decision support, automation of routine tasks, and real-time monitoring of safety and performance indicators. As explained in this section, several AI committees are dedicated to the task of establishing standards that facilitate such applications in the oil and gas

[Table C2 about here]

Table C4: Effect Heterogeneity: Top 10% of AI Standards by AI Relatedness & AI Standard Categories. Table C4 offers a detailed breakdown of how specific AI standard categories impact capital (Panel A) and R&D (Panel B) expenditures by utilizing the top 10% of AI standards by AI relatedness. Compared to the results in Table 9, after restricting our sample to the top 10% of AI standards by AI relatedness, all AI standard categories demonstrate economically larger effects on both CAPEX and R&D expenditures. In addition, the previously insignificant Programming Languages category now exhibits both economic and statistical significance for CAPEX and R&D in this restricted sample.

[Table C4 about here]

Table C5: Cross-Country Difference in the Impact of AI Standards. Table C5 examines the cross-country difference in the Impact of AI standards on Capital and R&D Expenditures. It shows that among firms in the United States, United Kingdom, and France—leaders in AI standardization—U.S. firms realize the greatest benefits from AI standards. Even excluding the United States, UNSC member countries continue to exhibit significant advantages over other permanent members like China and Russia, which do not lead any secretariats. Additionally, firms from countries not involved in AI standardization process as committee members suffer, underscoring a clear hierarchy in the impact of AI standards based on country participation in the standardization process.

[Table C5 about here]

Table C8: Higher Uncertainty. Table C8 examines the effect of AI standards associated with higher uncertainty, specifically focusing on new standards rather than existing standards undergoing reevaluation. Our results suggest that all coefficient estimates increase once the higher uncertainty is resolved, providing evidence for our proposed mechanism. Although the first four columns are not statistically significant based on tF critical values, the last two columns are comfortably significant, likely due to the larger sample size.

[Table C8 about here]

industry. These committees help create a structured and safe environment for the adoption of AI technologies, ensuring these tools are used in an efficient, ethical, and regulation-compliant manner.

Appendix Table C1. **Breakdown of Standards by AI-Centric Organizations and Secretariats**

This table presents the number of standards published by international standardization organizations, categorized by responsible committees and secretariats (i.e., countries tasked with leading the standardization endeavors of their respective committees, provided in ISO alpha-3 format). Standards published by the Institute of Electrical and Electronics Engineers (IEEE) are presented separately, and IEEE is shown as an independent secretariat. The committees are derived from "U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools" report produced by the National Institute of Standards and Technology (NIST) in response to Executive Order (EO) 13859. The data covers the period from 1972 to 2022.

	Secretariat										
	AUS	**FRA**	**DEU**	**IEEE**	**IND**	**JPN**	**KOR**	**SWE**	**GBR**	**USA**	**Total**
ISO Committees											
TC 184	0	30	0	0	0	0	0	0	0	0	30
TC 184/SC 1	0	0	39	0	0	0	0	0	0	0	39
TC 184/SC 4	0	0	0	0	0	0	0	0	0	1,771	1,771
TC 184/SC 5	0	0	0	0	0	0	0	0	0	96	96
TC 199	0	0	89	0	0	0	0	0	0	0	89
TC 299	0	0	0	0	0	0	0	30	0	0	30
Subtotal	**0**	**30**	**128**	**0**	**0**	**0**	**0**	**30**	**0**	**1,867**	**2,055**
ISO/IEC Committees											
JTC 1/SC 7	0	0	0	0	352	0	0	0	0	0	352
JTC 1/SC 17	0	0	0	0	0	0	0	0	338	0	338
JTC 1/SC 22	0	0	0	0	0	0	0	0	0	248	248
JTC 1/SC 24	0	0	0	0	0	0	0	0	142	0	142
JTC 1/SC 27	0	0	432	0	0	0	0	0	0	0	432
JTC 1/SC 28	0	0	0	0	91	0	0	0	0	0	91
JTC 1/SC 29	0	0	0	0	1,168	0	0	0	0	0	1,168
JTC 1/SC 32	0	0	0	0	0	0	0	0	0	265	265
JTC 1/SC 36	0	0	0	0	0	0	70	0	0	0	70
JTC 1/SC 37	0	0	0	0	0	0	0	0	0	176	176
JTC 1/SC 40	42	0	0	0	0	0	0	0	0	0	42
JTC 1/SC 41	0	0	0	0	0	0	42	0	0	0	42
JTC 1/SC 42	0	0	0	0	0	0	0	0	0	16	16
Subtotal	**42**	**0**	**432**	**0**	**352**	**1,259**	**112**	**0**	**480**	**705**	**3,382**
IEEE Committee	**0**	**0**	**0**	**19**	**0**	**0**	**0**	**0**	**0**	**0**	**19**
Total	**42**	**30**	**560**	**19**	**352**	**1,259**	**112**	**30**	**480**	**2,572**	**5,456**

Appendix Table C2. **Scopes and Activities of AI Standardization Committees**

This table provides an overview of the activities and scopes of AI standardization committees, with the names of the secretariats associated with each committee listed in parentheses and in italic format. The committees (represented in bold) are derived from "U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools" report produced by the National Institute of Standards and Technology (NIST) in response to Executive Order (EO) 13859. The data represented in the table are manually collected from the official ISO webpage. The sources for any additional information provided in the table are cited for reference.

Committee	Scope	Description of Standardization Activities
ISO/IEC JTC 1/SC 42 *(Sec: United States)*	Guidance on AI	Development of AI standards and guidance to other ISO and IEC committees developing AI applications. Standardization in the areas of foundational AI standards, Big Data, AI trustworthiness, use cases, governance implications of AI, computational approaches of AI, testing, ethical and societal concerns. Sources: https://bit.ly/42XocXH and https://bit.ly/42YSklq.
ISO/IEC JTC 1/SC 41 *(Sec: South Korea)*	IoT	Standardization in the area of Internet of Things (IoT) and digital twin, i.e., virtual modelling of physical world. Sources: https://bit.ly/41WntFp and https://bit.ly/44ZPizj.
ISO/IEC JTC 1/SC 40 *(Sec: Australia)*	Governance	Standardization in (i) governance of IT, (ii) governance of data, (iii) IT service management, and (iv) IT-enabled services. Sources: https://bit.ly/44Z5Veq.
ISO/IEC JTC 1/SC 37 *(Sec: United States)*	Human Biometric	Standardization of generic biometric technologies pertaining to human beings to support interoperability and data interchange among applications and systems. Sources: https://bit.ly/41Dkxgz.
ISO/IEC JTC 1/SC 36 *(Sec: South Korea)*	Education	Standardization in the field of information technologies for learning, education, and training to support individuals, groups, or organizations, and to enable interoperability and reusability of resources and tool. Examples: learning analytics interoperability, individualized adaptability and accessibility in e-learning, education and training, and human factor guidelines for VR content. Source: https://bit.ly/3WqBpWT.
ISO/IEC JTC 1/SC 32 *(Sec: United States)*	Data Interchange	Standards for data management within and among local and distributed information systems environments. Help set up the structure of data, i.e., data domains, data types and structures, and programming languages. Create rules for storing data safely and for allowing simultaneous access and updates without conflicts; develop languages, services, and protocols for sharing data among different systems; organize and register metadata (data about data), which is essential for sharing data and making systems interoperable. Source: https://bit.ly/43f9D1W.
ISO/IEC JTC 1/SC 29 *(Sec: Japan)*	Digital Information	Standardization in the field of (a) efficient coding of digital representations of images, audio and moving pictures, including conventional (natural, computer-generated and immersive) images, moving pictures and audio, invisible light and other sensory (e.g. medical and satellite) images, and static and dynamic graphic objects; (b) efficient coding of other digital information, including multimedia, environment and user-related metadata, sensor and actuator information related to audiovisual information, and other digital data in agreement with the relevant committee, such as genomics; (c) digital information support, including synchronization, presentation, storage and transport of single or combinations of media, media security and privacy management, and quality of experience evaluation and system performance metrics. Source: https://bit.ly/3ohCX92.

Committee	Scope	Description of Standardization Activities
ISO/IEC JTC 1/SC 28 *(Sec: Japan)*	Electronic Devices	Standardization of basic characteristics, test methods and other related items of products such as 2D and 3D Printers/Scanners, Copiers, Projectors, Fax and Systems composed of their combinations. Source: https://bit.ly/3MqoVtK.
ISO/IEC JTC 1/SC 27 *(Sec: Germany)*	Information Security	The development of standards for the protection of information and ICT. This includes generic methods, techniques and guidelines to address both security and privacy aspects. Source: https://bit.ly/3pTTvV3.
ISO/IEC JTC 1/SC 24 *(Sec: United Kingdom)*	Graphics	Computer graphics, image processing, virtual reality, augmented reality, and mixed reality, environmental data representation, visualization of, and interaction with, information. Source: https://bit.ly/3IvmXHz.
ISO/IEC JTC 1/SC 22 *(Sec: United States)*	Programming Languages	Programming languages, their environments and system software interfaces. Source: https://bit.ly/3MK7ohr
ISO/IEC JTC 1/SC 17 *(Sec: United Kingdom)*	Personal Identification	Identification and related documents, cards, security devices and tokens and interface associated with their use in inter-industry applications and international interchange. Source: https://bit.ly/3Ot83VT.
ISO/IEC JTC 1/SC 7 *(Sec: India)*	Software	Standardization of processes, supporting tools and supporting technologies for the engineering of software products and systems. Source: https://bit.ly/3ClcTNK.
ISO/TC 184 *(Sec: France)*	Industrial Automation	Standardization in automation systems and their integration for design, sourcing, manufacturing, production and delivery, support, maintenance and disposal of products and their associated services. Source: https://bit.ly/42V0agu.
ISO/TC 184/SC 1 *(Sec: Germany)*	Industrial Device Control	Develop standards on industrial cyber and physical device control. Examples: data modeling and numerical control systems for industrial automation systems, functional safety for automated machines, and integration of manufacturing operations. Source: https://bit.ly/3ojzW8m.
ISO/TC 184/SC 4 *(Sec: United States)*	Industrial Data	Establishes common rules and guidelines for exchanging data with stakeholders in industrial environments. Examples: data models, data exchange formats, and data access interfaces. Source: https://bit.ly/41TpJgv.
ISO/TC 184/SC 5 *(Sec: United States)*	Industrial Interoperability	Standards on interoperability between devices, integration, and architectures for enterprise systems and automation applications. Source: https://bit.ly/3omW8hW.
ISO/TC 199 *(Sec: Germany)*	Safety	Standardization of basic concepts and general principles for safety of machinery incorporating terminology, methodology, guards and safety devices. Source: https://bit.ly/439ghGO.
ISO/TC 299 *(Sec: Sweden)*	Robotics	Standardization in the field of robotics, excluding toys and military applications. Examples: safety, performance, and robotic applications (e.g., in healthcare). Source: https://bit.ly/43hZly7.

Appendix Table C3. **Effects of AI Standards on AI Investments and AI Patents**

This table provides our estimates for the local treatment effects of AI standards on AI investments, AI patent applications, and AI patents granted. We utilize a two-stage least squares (2SLS) procedure for the coefficient estimates presented in the first three columns. The fourth column presents the results of the first stage. Our sampling period is from 2017 to 2022. The number of AI standards is instrumented with the % of UNSC members in a given year under a given secretariat. Detailed variable descriptions can be found in Appendix B. Coefficient estimates marked with ⋆⋆⋆, ⋆⋆, and ⋆ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The standard errors are clustered at the country level.

	Log(AI Investment$_{c,t}$)	Log(AI Patent Apps.$_{c,t}$)	Log(AI Patents Granted$_{c,t}$)	Log(AI Standards$_{c,t}$)
	(1)	(2)	(3)	(4)
Log($\widehat{AI\ Standards}_{c,t}$)	0.23**	0.46**	0.35***	
	(2.19)	(2.23)	(6.40)	
% UNSC Members$_{c,t-1}$				7.10***
				(2.86)
Fixed Effects				
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	684	684	684	684

Appendix Table C4. **Additional Evidence on Effect Heterogeneity: Top 10% of AI Standards by AI Relatedness & AI Standard Categories**

This table offers a detailed breakdown of how specific AI standard categories impact capital (Panel A) and R&D (Panel B) expenditures by utilizing the top 10% of AI standards by AI relatedness. Our AI categories - Machine Learning, Data, Automation, Programming Language, Interoperability, Machinery & Equipment, Ethics & Accountability, and Privacy - are based on our content analysis outlined in Section 4.1. The estimated coefficients displayed here are second-stage regression coefficients. These coefficients were obtained through a two-stage least squares procedure, utilizing instrumented variables such as the log of the number of yearly standards in each category and the percentage of UNSC Members as instruments. To save space, instrumented variables are labelled without logarithmic transformations. For example, "Machine Learning Standards" represents Log(Machine Learning Standards)$_{i,c,t}$. Detailed descriptions of all variables can be found in Appendix Section B. Control structures are as in Table 5. Asterisks denote significance levels: ⋆ ⋆ ⋆ (1%), ⋆⋆ (5%), and ⋆ (10%).

Panel A: AI-Standard Categories and Capital Expenditures (N=171,238)

	All Standards	Machine Learning Standards	Data Standards	Automation Standards	Programming Language Standards	Interchange Standards	Machinery & Equipment Standards	Ethics & Accountability Standards	Privacy Standards
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable									
$CAPEX/AT_{i,c,t}$	0.58***	3.33**	0.35***	0.47***	1.90***	0.39**	0.90***	-3.82	-2.10**
	(3.65)	(2.75)	(2.86)	(2.82)	(3.01)	(2.52)	(3.59)	(-0.43)	(-2.14)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: AI-Standard Categories and R&D Expenditures (N=67,647)

	All Standards	Machine Learning Standards	Data Standards	Automation Standards	Programming Language Standards	Interchange Standards	Machinery & Equipment Standards	Ethics & Accountability Standards	Privacy Standards
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable									
$RD/AT_{i,c,t}$	1.99***	14.61**	1.11***	1.47***	6.83***	1.20***	3.08***	-7.69	-6.20***
	(3.41)	(2.47)	(4.78)	(4.76)	(4.30)	(4.31)	(4.40)	(-1.02)	(-4.16)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix Table C5. **Comparative Analysis of the Impact of AI Standards on Capital and R&D Expenditures**

The table presents our estimates for the local treatment effects of AI standards on capital and R&D expenditures, employing a pairwise estimation methodology across nine distinct groups of units. "Included*" units consist of combinations of permanent United Nations Security Council (UNSC) member nations that have ISO Secretariats, while "Included" units include (i) nations with ISO Secretariats that are not permanent UNSC members, (ii) permanent UNSC member nations without ISO Secretariats, and (iii) nations not associated with either UNSC or ISO. Panel A exhibits the Included* and Included group framework, and the total count of non-missing capital expenditure (CAPEX) observations per group. Panel B presents our estimates for the local treatment effects (LATE) of AI standards for each group. The dependent variables are capital and R&D expenditures, both scaled by total assets. The reported coefficients correspond to estimated treatment effects, with standard errors in parentheses. The estimation incorporates covariates, firm-specific fixed effects, industry-year interactive fixed effects same as Table 5. Detailed variable descriptions can be found in Appendix Section B. Our sampling period is from 2017 to 2022. The robust standard errors, clustered at the industry (FF48) level, are reported in parentheses under the coefficients, and significance levels are marked as ⋆⋆⋆ (1%), ⋆⋆ (5%), and ⋆ (10%).

Panel A: Groups of Included* and Included Units

	"Included" Units: Countries with ISO Secretariats			"Included" Units: Perm. UNSC Members w/o Secretariats			"Included" Units: Countries w/o ISO or UNSC Membership		
	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)
United States	Included*	Included*	X	Included*	Included*	X	Included*	Included*	Included*
Australia	Included	Included	Included	X	X	X	X	Included	Included
Germany	Included	Included	Included	X	X	X	X	Included	Included
India	Included	Included	Included	X	X	X	X	Included	Included
Japan	Included	Included	Included	X	X	X	X	Included	Included
South Korea	Included	Included	Included	X	X	X	X	Included	Included
Sweden	Included	Included	Included	X	X	X	X	Included	Included
China	X	X	X	Included	Included	Included	X	X	Included
France	X	Included*	Included*	X	Included*	Included*	Included*	Included*	Included*
Russia	X	X	X	Included	Included	Included	X	X	Included
United Kingdom	X	Included*	Included*	X	Included*	Included*	Included*	Included*	Included*
Other Countries	X	X	X	X	X	X	Included	Included	Included
Observations	68,537	76,875	57,626	45,413	53,751	34,502	54,277	95,908	122,078

Panel B: Local Average Treatment Effect of *Log(AI Standards*$_{i,c,t}$*)* Estimated for Each Group

	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)
Dependent Variables									
$CAPEX/AT_{i,c,t}$	0.35**	0.33**	0.25	0.77***	0.73***	0.86***	0.69**	0.52***	0.64***
	(2.33)	(2.40)	(1.35)	(3.40)	(3.78)	(2.82)	(2.62)	(3.49)	(4.18)
$RD/AT_{i,c,t}$	1.42***	1.29***	0.81	1.03***	1.17***	1.49**	2.00***	1.30***	1.71***
	(2.96)	(2.89)	(1.30)	(3.40)	(4.95)	(2.69)	(3.45)	(3.20)	(3.76)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix Table C6. **Effect Heterogeneity in AI Research Driven by Standardization Committees**

This table provides a detailed examination of how standards published by different ISO committees impact research in broader AI (Panel B), computer vision (Panel C), language processing (Panel D), and robotics (Panel E). Control structures are as in Table 4. Detailed variable descriptions can be found in Appendix Section B. Asterisks denote significance levels: ⋆ ⋆ ⋆ (1%), ⋆⋆ (5%), and ⋆ (10%).

Panel A: Groups of Treatment and Control Units Based on ISO Committees									
	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)
Committee	SC 4	SC 5	SC 22	SC 32	SC 37	SC 42	TC 184	SC 17	SC 24
Scope	Industrial data	Interoperability	Prog. Lang.	Data Interchange	Biometrics	Guidance on AI	Automation	Personal Id.	Graphics
Organization	ISO/TC 184	ISO/TC 184	ISO/IEC JTC 1	ISO/IEC JTC 1	ISO/IEC JTC 1	ISO/IEC JTC 1	ISO/TC	ISO/IEC JTC 1	ISO/IEC JTC 1
Secretariat	United States	United States	United States	United States	United States	United States	France	United Kingdom	United Kingdom
Panel B: ISO Committees and AI Research (N= 2,865)									
	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)
Dependent Variable"	0.12*	0.48	0.48	-0.37*	-1.18	-0.44	8.56	-0.04	0.32
Log(AI Research$_{i,c,t}$)	(2.23)	(0.80)	(0.62)	(-2.66)	(-0.76)	(-1.95)	(0.58)	(-0.22)	(1.07)
Panel C: ISO Committees and Computer Vision Research (N= 2,865)									
	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)
Dependent Variable:	0.11**	0.39	0.41	-0.35*	-1.07	-0.38	-3.97	-0.16	0.42
Log(CV Research$_{i,c,t}$)	(3.04)	(0.77)	(0.61)	(-2.65)	(-0.76)	(-1.86)	(-0.45)	(-0.62)	(1.02)
Panel D: ISO Committees and Language Processing Research (N= 2,865)									
	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)
Dependent Variable:	0.05	0.34	0.35	-0.22*	-0.55	-0.32*	1.58	0.07	0.29
Log(NLP Research$_{i,c,t}$)	(1.45)	(0.84)	(0.63)	(-2.53)	(-0.62)	(-2.29)	(0.49)	(0.57)	(0.78)
Panel E: ISO Committees and Robotics Research (N= 2,865)									
	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)
Dependent Variable:	0.08	0.37	0.35	-0.23*	-0.70	-0.30	-1.44	-0.24	0.19
Log(Robotics Research$_{i,c,t}$)	(1.64)	(0.78)	(0.61)	(-2.37)	(-0.78)	(-1.99)	(-1.53)	(-0.90)	(0.71)
Panel F: Controls									
	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix Table C7. **Effect Heterogeneity in Broader Investments Driven by Standardization Committees**

This table provides a detailed examination of how standards published by different ISO committees impact capital expenditures (Panel B) and R&D expenditures (Panel C). The estimated coefficients represent local average treatment effects, where the dependent variables are CAPEX and R&D expenditures scaled by total assets ($CAPEX/AT_{i,c,t}$ and $RD/AT_{i,c,t}$ respectively). Coefficients are presented with standard errors in parentheses. Estimation procedures account for two-way clustering at the country and industry (FF48) levels. All models contain control variables, firm fixed effects, and industry × year fixed effects. Detailed variable descriptions can be found in Appendix Section B. Asterisks denote significance levels: ⋆⋆⋆ (1%), ⋆⋆ (5%), and ⋆ (10%).

Panel A: Groups of Treatment and Control Units Based on ISO Committees

	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)	(Group 10)
Committee	SC 4	SC 5	SC 22	SC 32	SC 37	SC 42	TC 184	SC 17	SC 24	SC 40
Scope	Industrial data	Interoperability	Prog. Lang.	Data Interchange	Biometrics	Guidance on AI	Automation	Personal Id.	Graphics	IT Governance
Organization	ISO/TC 184	ISO/TC 184	ISO/IEC JTC 1	ISO/IEC JTC 1	ISO/IEC JTC 1	ISO/IEC JTC 1	ISO/TC	ISO/IEC JTC 1	ISO/IEC JTC 1	ISO/IEC JTC 1
Secretariat	United States	United States	United States	United States	United States	United States	France	United Kingdom	United Kingdom	Australia

Panel B: ISO Committees and Capital Expenditures (N= 171,238)

	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)	(Group 10)
Dependent Variable										
$CAPEX/AT_{i,c,t}$	0.16**	0.11	1.27***	-0.86***	-0.36	-0.78***	5.69***	0.02	-0.72***	8.59**
	(2.56)	(0.52)	(5.60)	(-5.02)	(-0.60)	(-5.26)	(3.78)	(0.08)	(-2.90)	(2.67)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: ISO Committees and R&D Expenditures (N= 67,647)

	(Group 1)	(Group 2)	(Group 3)	(Group 4)	(Group 5)	(Group 6)	(Group 7)	(Group 8)	(Group 9)	(Group 10)
Dependent Variable										
$RD/AT_{i,c,t}$	0.34***	1.85***	3.27***	-1.52***	-1.54*	-1.91***	0.59	0.41	-0.37	-0.27
	(4.57)	(7.14)	(5.98)	(-7.05)	(-1.89)	(-7.25)	(0.22)	(1.04)	(-0.70)	(-0.02)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix Table C8. **Effect Heterogeneity: AI Standards With Higher Uncertainty**

This table presents estimates of the local treatment effects of AI standards with high uncertainty on our main dependent variables in Panel A. Panel B describes the control structures employed in each case. To identify AI standards with high uncertainty, we manually collect data on each standard's lifecycle and exclude from our sample the standards labeled previously as "International Standard under systematic review," indicating that they are existing standards which are being reevaluated. Coefficient estimates in columns (5) and (6) are reported as percentages. ⋆⋆⋆, ⋆⋆, and ⋆ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. We also provide t_F critical values for 5% and 10% level tests ($\sqrt{c_{0.05}(F)}$ and $\sqrt{c_{0.10}(F)}$), as described in Lee et al. (2022), to evaluate the significance of the second-stage coefficient estimates.

Panel A: Second-Stage Regressions Using Standards With Higher Uncertainty

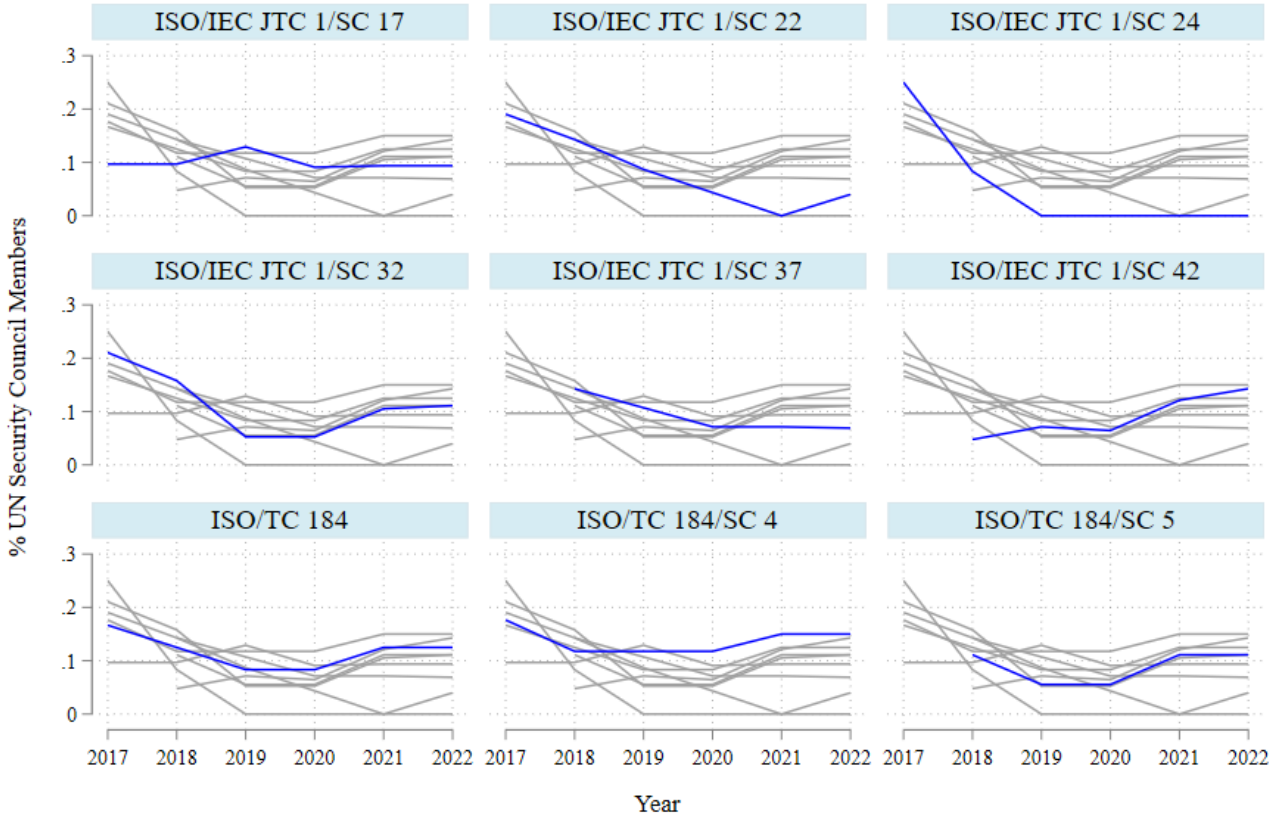
	Log(AI Research$_{i,c,t}$)	Log(CV Research$_{i,c,t}$)	Log(NLP Research$_{i,c,t}$)	Log(Robotics Research$_{i,c,t}$)	$CAPEX/AT_{i,c,t}$	$RD/AT_{i,c,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Log(\widehat{AI\ Standards}_{i,c,t})$	0.45*	0.45**	0.28	0.36	1.04***	3.49***
	(2.66)	(2.91)	(2.01)	(1.98)	(3.48)	(3.48)

Panel B: Additional Information on Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
Controls	No	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,865	2,865	2,865	2,865	171,238	67,647
$\sqrt{c_{0.10}(F)}$	3.42	3.42	3.42	3.42	1.66	1.66
$\sqrt{c_{0.05}(F)}$	9.97	9.97	9.97	9.97	2.31	2.31

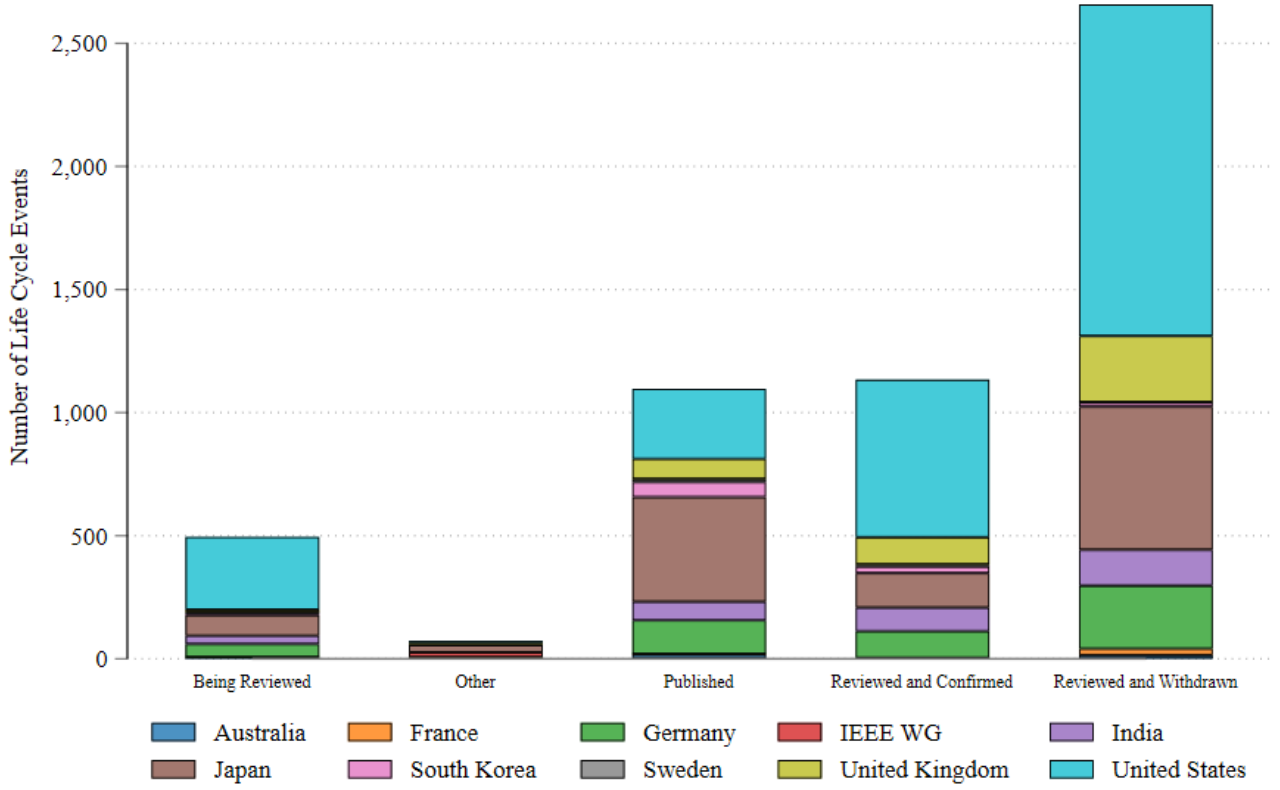
Appendix Figure C1. **Committee-Level Instruments: UNSC Rotations and ISO Committees**

This figure displays the percentage of rotating United Nations Security Council (UNSC) members in AI committees with permanent UNSC member countries being the secretariats between 2017 and 2022. Committee membership data is collected manually using the Wayback Machine (https://archive.org/web/), which provides ISO committee membership data from 2017. The figure illustrates the dynamic changes in $\%UNSC\ Members^{k}_{i,c,t-1}$ for different AI committees, highlighting the varying composition of rotating UNSC members within these committees over time.



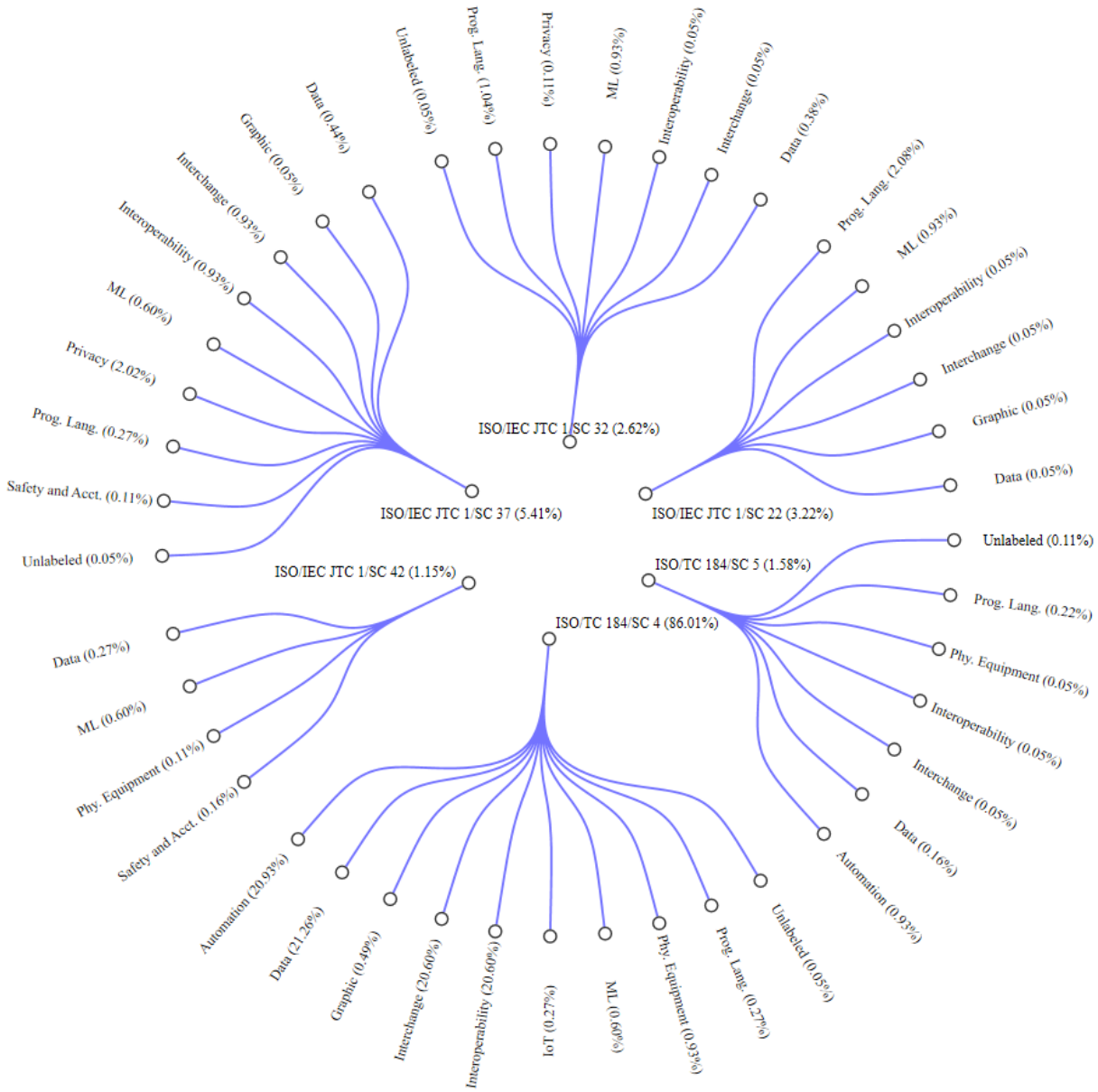
Appendix Figure C2. **The Life Cycle of Standards Published by AI-Critical Committees**

The figure illustrates the life cycle events of AI standards published by each secretariat within the International Organization for Standardization (ISO) from 1972 to 2023. These life cycle events are color-coded and labeled based on ISO's international harmonized stage codes. The "Published" stage (60) represents the successful completion of the review process and the official release of the standard. The "Being reviewed" stage (90) signifies the ongoing development of standards, where thorough reassessment takes place. The "Reviewed and confirmed" stage (90.93) indicates the validation and endorsement of a standard after periodic reviews, ensuring its relevance and applicability. Lastly, the "Reviewed and withdrawn" stage (90.95) signifies the removal or retirement of previously published standards for various reasons. Each secretariat is color-coded, facilitating easy differentiation.



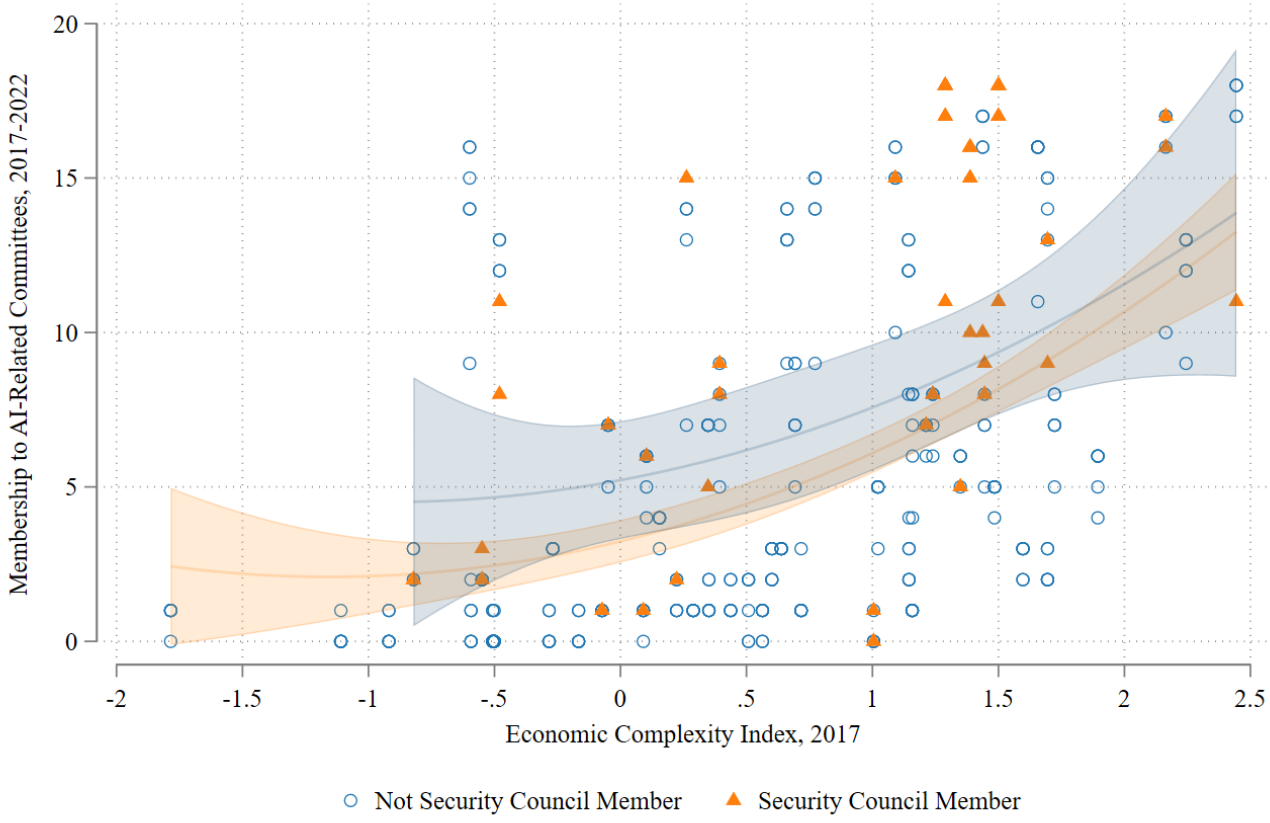
Appendix Figure C3. **Categories of Standards Published by U.S.-lead AI Committees**

The tree cluster figure represents the distribution of published standards by US secretariats between 2017 and 2022, showcasing the various types of standards as a percentage of the total. The committee names of standards included in the figure can be found in Table C1. The types of standards (e.g., ML, Data) are defined in Appendix Section B.



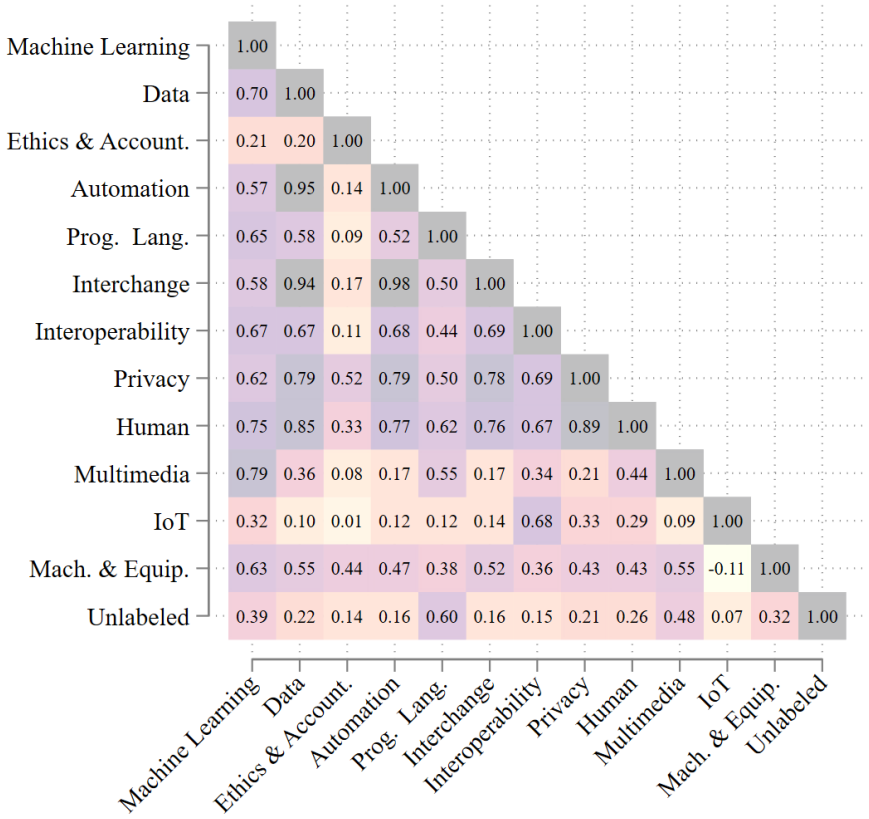
Appendix Figure C4. **Do Rotating UN Security Council Members Target AI Committees?**

This figure provides an empirical analysis on the potential influence of Economic Complexity Index (ECI) as in Hidalgo et al. (2009) on the number of AI committee memberships for each country from 2017 to 2022. UNSC and non-UNSC member countries are denoted by orange triangles and blue hollow circles, respectively. Blue and orange fitted lines represent quadratic predictive models for non-UNSC and UNSC nations based on ECI and its square. Each line is accompanied by a 95% confidence interval. .



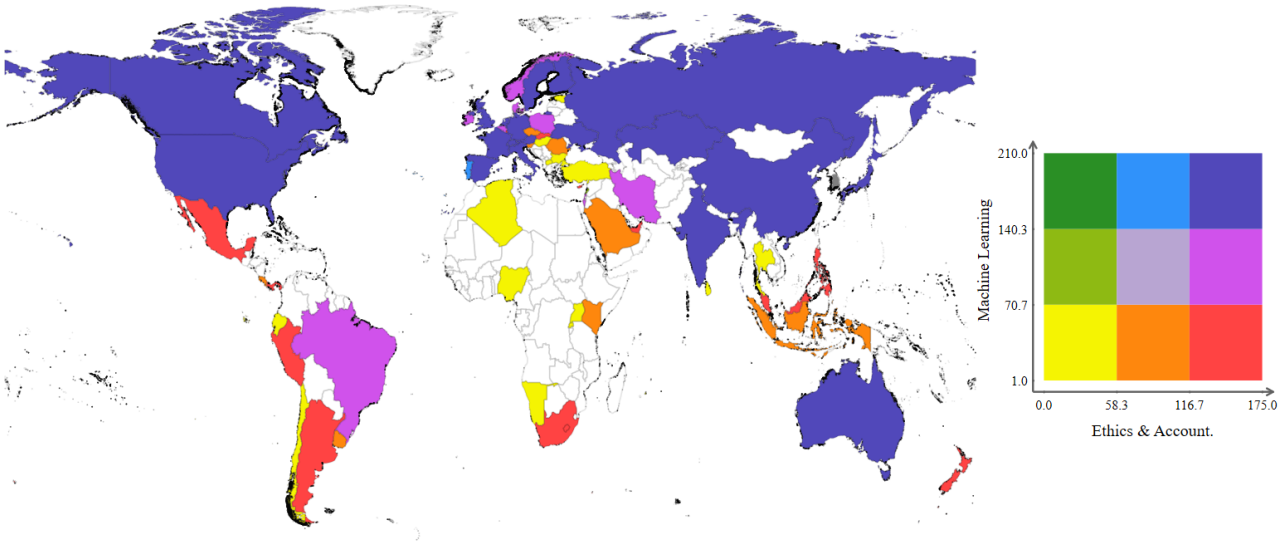
Appendix Figure C5. **Covariance Matrix: Interplay of Variables in AI Standard Categories**

This figure provides a correlation matrix for the following variables: Log(AI Standards)$_{i,c,t}$, Log(Machine Learning Standards)$_{i,c,t}$, Log(Data Standards)$_{i,c,t}$, Log(Accountability Standards)$_{i,c,t}$, Log(Automation Standards)$_{i,c,t}$, Log(Programming Standards)$_{i,c,t}$, Log(Interchange Standards)$_{i,c,t}$, Log(Interoperability Standards)$_{i,c,t}$, Log(Privacy Standards)$_{i,c,t}$, Log(Human Biometric Standards)$_{i,c,t}$, Log(Multimedia Standards)$_{i,c,t}$, Log(IoT Standards)$_{i,c,t}$, Log(Equipment Standards)$_{i,c,t}$, and Log(Unlabeled Standards)$_{i,c,t}$. Detailed variable descriptions can be found in Appendix Section B.



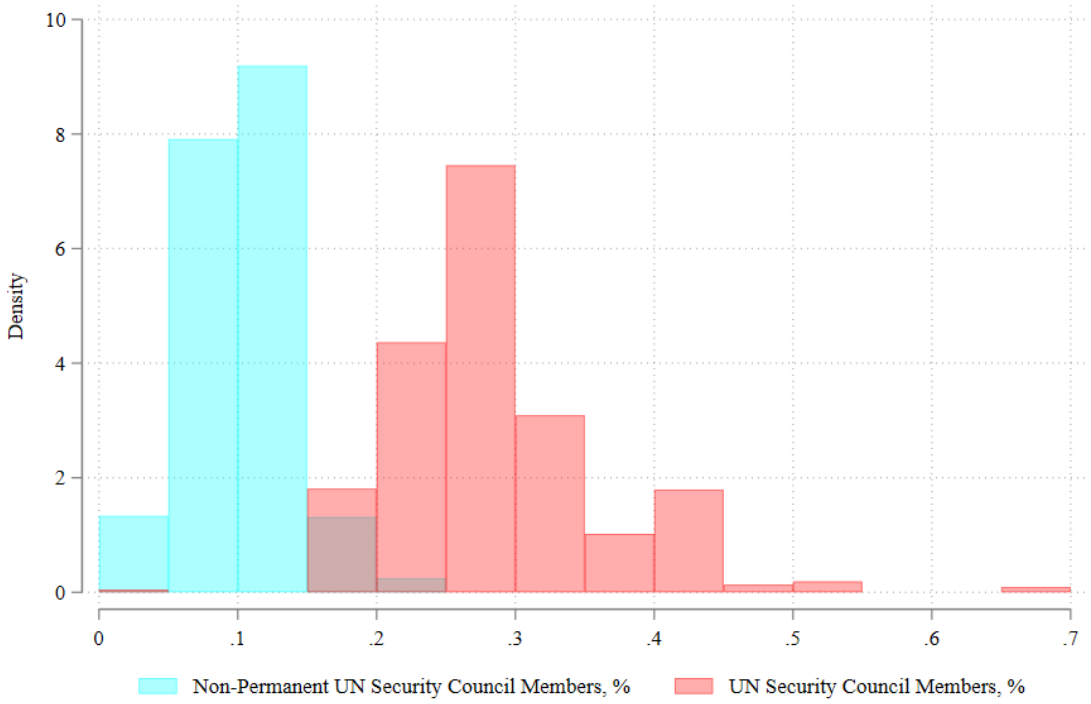
Appendix Figure C6. **Involvement in Machine Learning and Ethical AI Standards by Country**

This world map illustrates each country's contributions to machine learning and ethics & accountability standards from 2017 to 2023 using color gradients. Countries are shaded based on their roles as either committee members or secretariats in publishing committees. The two-dimensional figure on the right side categorizes countries based on their respective involvement. Countries without any contributions remain white. The definition of machine learning and ethical AI standards can be found in Appendix Section B.



Appendix Figure C7. **The Distribution of Committee-Level Instruments**

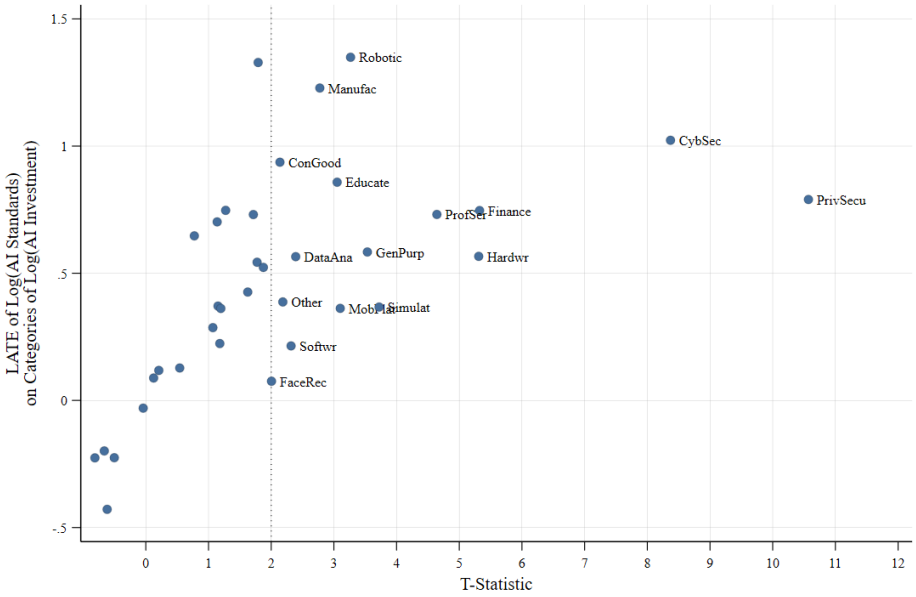
The figure illustrates permanent and rotating UNSC membership in a secretariat-committee-year panel led by permanent members of the UNSC and other countries that are not permanent members of the UNSC. It shows the distribution of our committee-level instruments, denoted as $\%UNSC\ Members^{k}_{i,c,t-1}$, across all AI committees. In doing so, it highlights the distribution of rotating UNSC members and total UNSC members. For a more detailed explanation of our instrument, please refer to Section 5.1. Detailed variable descriptions can be found in Appendix Section B.



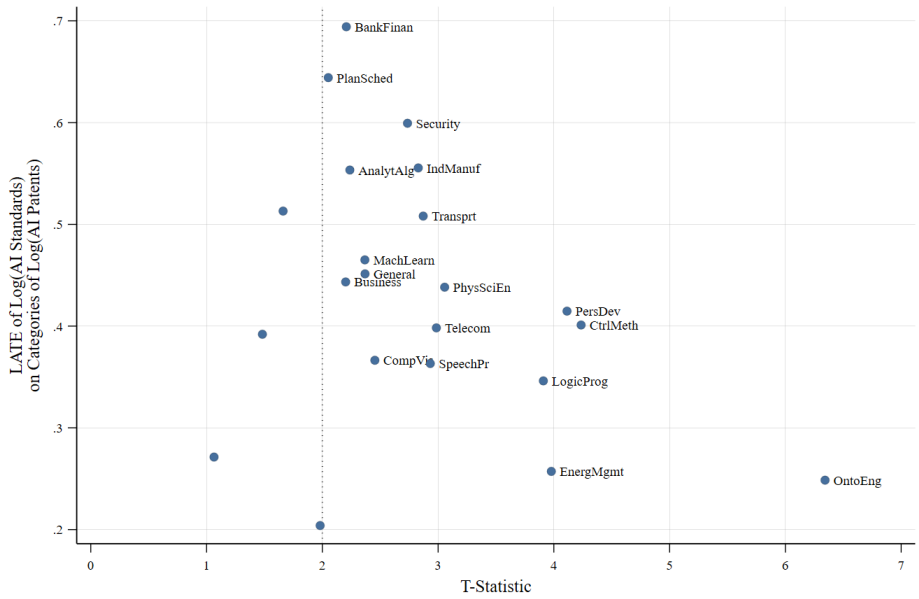
Appendix Figure C8. **The Influence of AI Standards on Categories of AI Investment and AI Patents**

This table provides our estimates for the local treatment effects of AI standards on different types of AI investments. The y-axis presents the coefficient estimates based on Equation (23), and the x-axis presents t-statistics. AI investment or patent types with t-statistics less than two are not labeled for readability. In Panel A, *Robotic* stands for robotics, *Manufac* for manufacturing, *CybSec* for cyber security, *PrivSecu* for privacy and security, *ConGood* for consumer goods, *Educate* for education, *Finance* for finance, *ProfSer* for professional service, *DataAna* for data and analytics, *GenPurp* for general purpose, *Hardwr* for hardware, *Simulat* for simulation, *MobPlat* for mobile, platforms, and internet services, *Softwr* for software, and *FaceRec* for facial recognition. In Panel B, *BankFinance* stands for Banking and Finance, *PlanSched* for Planning and Scheduling, *Security* for Security, *IndManuf* for Industry and Manufacturing, *AnalytAlg* for Analytics and Algorithms, *Transprt* for Transportation, *MachLearning* for Machine Learning, *General* for General, *Business* for Business, *PhysSciEn* for Physical Sciences and Engineering, *PersDev* for Personal Devices and Computing, *Telecom* for Telecommunications, *CtrlMeth* for Control Methods, *CompV* for Computer Vision, *SpeechPr* for Speech Processing, *LogicProg* for Logic Programming, *EnergMgmt* for Energy Management, *OntoEng* for Ontology Engineering. Detailed variable descriptions can be found in Appendix Section B.

Panel A: Effect Heterogeneity Across AI Investment Categories



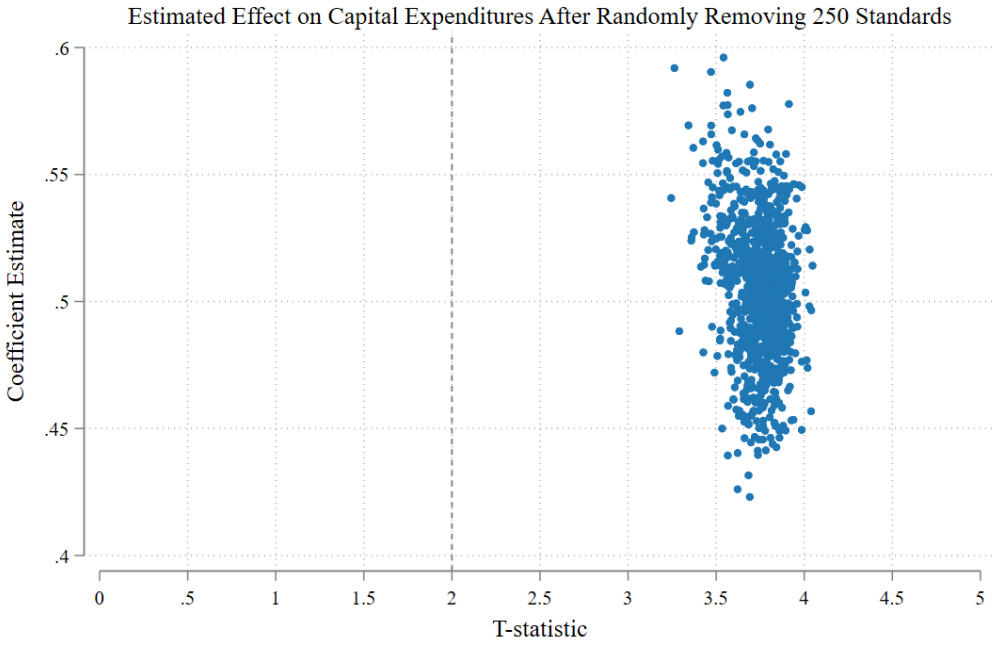
Panel B: Effect Heterogeneity Across AI Patent Categories



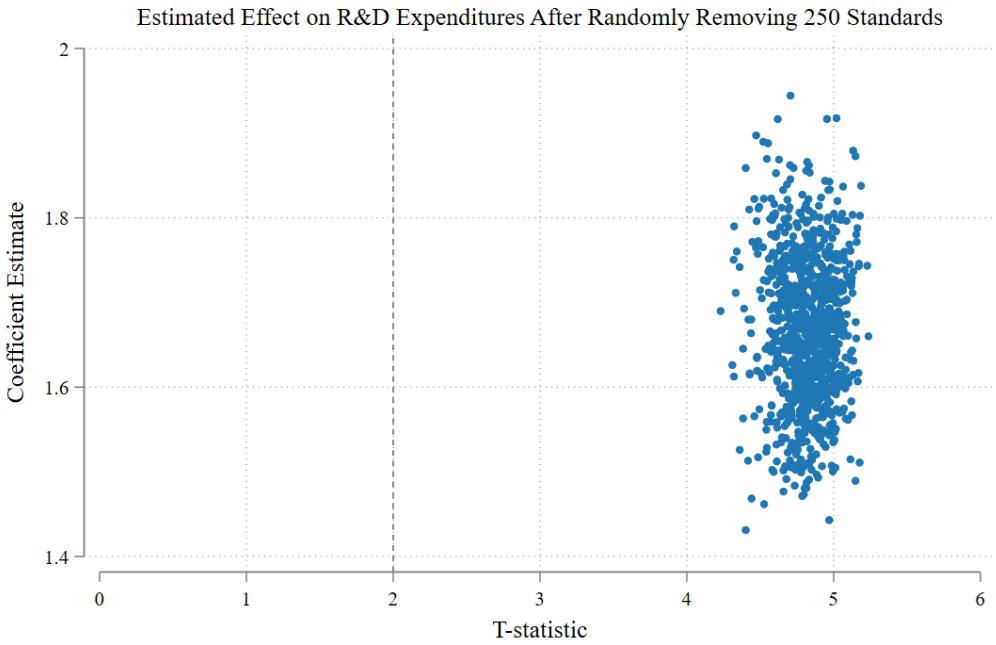
Appendix Figure C9. **Stability of Main Findings After Random Exclusion of 250 AI Standards**

This figure shows the results from re-running the main regressions in columns 2 and 4 of Table 5 after randomly excluding AI standards from the sample. We conducted 1,000 regressions, each with 250 randomly dropped AI standards. The Y-axis displays the 1,000 coefficient estimates, while the X-axis shows their corresponding t-statistics.

Panel A: Estimated Effect of AI Standards on Capital Expenditures



Panel B: Estimated Effect of AI Standards on R&D Expenditures



D Additional Details in AI and AI Standards

D.1 What is AI?

In a widely-used AI textbook, Russell and Norvig (2021) define AI as "the study of agents that receive percepts from the environment and perform actions." The textbook prescribes six disciplines in AI: natural language processing (to communicate successfully in a human language); knowledge representation (to store what it knows or hears); automated reasoning (to answer questions and to draw new conclusions); machine learning (to adapt to new circumstances and to detect and extrapolate patterns); computer vision and speech recognition (for a robot to perceive the world); robotics (for a robot to manipulate objects and move about). The development of AI dated back to 1940s, with the most recent breakthrough marked by Krizhevsky et al. (2012), who developed a deep learning system with dramatic improvement over previous systems. Since then, AI systems have exceeded human performance on many aspects, such as computer vision and game playing.[60]

D.2 Additional Examples of AI Standards

Unlike conventional standards, which primarily ensure compatibility across devices, AI-related standards are dedicated to guiding the ethical, secure, and interoperable development and operation of AI systems.[61] Many standards in our sample establish globally accepted criteria for data quality, format, and interchange.[62] As data is the essential fuel for AI-systems, these data standards play a crucial role in ensuring the accuracy, interoperability, and security of AI systems. In addition, AI standards prescribe best practices for evaluating AI models and integrating them into older technologies, such as manufacturing. Furthermore, they aim to enable AI-based systems to operate in an transparent, explainable, and fair manner, facilitating seamless integration across AI platforms and technologies.

In this section, we provide additional examples of AI standards published from 2017-2022, which complement the standards listed in Table 1.

Standard ID	Title
ISO/IEC TS 4213:2022	Information technology – Artificial intelligence – Assessment of machine learning classification performance
ISO/IEC 23053:2022	Framework for Artificial Intelligence (AI) Systems Using Machine Learning (ML)
ISO/TR 22100-5:2021	Safety of machinery – Relationship with ISO 12100 – Part 5: Implications of artificial intelligence machine learning
ISO/IEC TR 24029-1:2021	Artificial Intelligence (AI) – Assessment of the robustness of neural networks – Part 1: Overview

[60] According to Russell and Norvig (2021), "one quick way to summarize the milestones in AI history is to list the Turing Award winners: Marvin Minsky (1969) and John McCarthy (1971) for defining the foundations of the field based on representation and reasoning; Ed Feigenbaum and Raj Reddy (1994) for developing expert systems that encode human knowledge to solve real-world problems; Judea Pearl (2011) for developing probabilistic reasoning techniques that deal with uncertainty in a principled manner; and finally Yoshua Bengio, Geoffrey Hinton, and Yann LeCun (2019) for making 'deep learning' (multilayer neural networks) a critical part of modern computing. "

[61] See the International Organization for Standardization (ISO)'s article on AI standardization: https://www.iso.org/artificial-intelligence.

[62] Such standards not only cover general data topics, but also cover image format, coding, and compression. Recent literature show that image format (e.g., JPEG) is important for facial recognition. Bousnina et al. (2022) find that the format of image coding has a significant impact on the performance of AI-based facial recognition technologies that use decoded image.

Standard ID	Title
ISO/IEC TR 29119-11:2020	Software and systems engineering – Software testing – Part 11: Guidelines on the testing of AI-based systems
ISO/IEC TR 24028:2020	Information technology – Artificial intelligence – Overview of trustworthiness in artificial intelligence
ISO/IEC TR 24372:2021	Information technology – Artificial intelligence (AI) – Overview of computational approaches for AI systems
ISO/IEC TR 24368:2022	Information technology – Artificial intelligence – Overview of ethical and societal concerns
ISO/IEC TR 24027:2021	Information technology – Artificial intelligence (AI) – Bias in AI systems and AI aided decision making
ISO/IEC TR 24030:2021	Information technology – Artificial intelligence (AI) – Use cases
ISO/IEC 38507:2022	Information technology – Governance of IT – Governance implications of the use of artificial intelligence by organizations
ISO/IEC 22989:2022	Information technology – Artificial intelligence – Artificial intelligence concepts and terminology
ISO/IEC 15938-17:2022	Information technology – Multimedia content description interface – Part 17: Compression of neural networks for multimedia content description and analysis
ISO/IEC 14496-15:2022/CD Amd 3	Information technology – Coding of audio-visual objects – Part 15: Carriage of network abstraction layer (NAL) unit structured video in the ISO base media file format – Amendment 3: Support for neural-network post-filter supplemental
ISO/IEC 2382-37:2022	Information technology – Vocabulary – Part 37: Biometrics
ISO/IEC 21838-2:2021	Information technology – Top-level ontologies (TLO) – Part 2: Basic Formal Ontology (BFO)
ISO/IEC 24707:2018	Information technology – Common Logic (CL) – A framework for a family of logic-based languages
ISO/IEC 23008-12:2017/Amd 1:2020	Information technology – High efficiency coding and media delivery in heterogeneous environments – Part 12: Image File Format – Amendment 1: Support for predictive image coding, bursts, bracketing and other improvements
ISO/IEC TR 23842-1:2020	Information technology for learning, education and training – Human factor guidelines for virtual reality content – Part 1: Considerations when using VR content
ISO/IEC 18038:2020	Information technology – Computer graphics, image processing and environmental representation – Sensor representation in mixed and augmented reality
IEC 80601-2-77:2019	Medical electrical equipment – Part 2-77: Particular requirements for the basic safety and essential performance of robotically assisted surgical equipment
IEC/TR 60601-4-1:2017	Medical electrical equipment – Part 4-1: Guidance and interpretation – Medical electrical equipment and medical electrical systems employing a degree of autonomy
ISO/TR 23482-2:2019	Robotics – Application of ISO 13482 – Part 2: Application guidelines
ISO/TR 20218-1:2018	Robotics – Safety design for industrial robot systems – Part 1: End-effectors
ISO 18646-2:2019	Robotics – Performance criteria and related test methods for service robots – Part 2: Navigation
ISO 22166-1:2021	Robotics – Modularity for service robots – Part 1: General requirements
ISO/TR 20218-2:2017	Robotics – Safety design for industrial robot systems – Part 2: Manual load/unload stations
ISO/TR 23482-1:2020	Robotics – Application of ISO 13482 – Part 1: Safety-related test methods
ISO 18646-3:2021	Robotics – Performance criteria and related test methods for service robots – Part 3: Manipulation
ISO 18646-4:2021	Robotics – Performance criteria and related test methods for service robots – Part 4: Lower-back support robots
ISO/IEC 30107-3:2017	Information technology – Biometric presentation attack detection – Part 3: Testing and reporting
ISO/IEC 19989-1:2020	Information security – Criteria and methodology for security evaluation of biometric systems – Part 1: Framework
ISO/IEC 30107-4:2020	Information technology – Biometric presentation attack detection – Part 4: Profile for testing of mobile devices
ISO/IEC 19989-3:2020	Information security – Criteria and methodology for security evaluation of biometric systems – Part 3: Presentation attack detection
ISO/IEC 19989-2:2020	Information security – Criteria and methodology for security evaluation of biometric systems – Part 2: Biometric recognition performance
ISO/IEC 30137-1:2019	Information technology – Use of biometrics in video surveillance systems – Part 1: System design and specification
ISO/IEC 24745:2022	Information security, cybersecurity and privacy protection – Biometric information protection
ISO/IEC 19795-1:2021	Information technology – Biometric performance testing and reporting – Part 1: Principles and framework
ISO/IEC TR 22116:2021	Information technology – A study of the differential impact of demographic factors in biometric recognition system performance

Standard ID	Title
ISO/IEC 24779-5:2020	Information technology – Cross-jurisdictional and societal aspects of implementation of biometric technologies – Pictograms, icons and symbols for use with biometric systems – Part 5: Face applications
ISO/IEC 27400:2022	Cybersecurity – IoT security and privacy – Guidelines
ISO/IEC 27005:2022	Information security, cybersecurity and privacy protection – Guidance on managing information security risks
ISO/IEC 15408-1:2022	Information security, cybersecurity and privacy protection – Evaluation criteria for IT security – Part 1: Introduction and general model
ISO/IEC TS 27110:2021	Information technology, cybersecurity and privacy protection – Cybersecurity framework development guidelines
ISO/IEC 30147:2021	Information technology – Internet of things – Methodology for trustworthiness of IoT system/service
ISO 23247-3:2021	Automation systems and integration – Digital twin framework for manufacturing – Part 3: Digital representation of manufacturing elements
ISO 23704-1:2022	General requirements for cyber-physically controlled smart machine tool systems (CPSMT) – Part 1: Overview and fundamental principles
ISO/IEC TR 63306-2:2021	Smart manufacturing standards map (SM2) – Part 2: Catalogue
ISO 23247-4:2021	Automation systems and integration – Digital twin framework for manufacturing – Part 4: Information exchange
ISO/IEC TR 30174:2021	Internet of Things (IoT) – Socialized IoT system resembling human social interaction dynamics
ISO/IEC TS 27570:2021	Privacy protection – Privacy guidelines for smart cities
ISO/IEC 30106-2:2020	Information technology – Object oriented BioAPI – Part 2: Java implementation
ISO/IEC TS 21544:2018	Programming languages – Extensions to C++ for modules
ISO/IEC 19794-15:2017	Information technology – Biometric data interchange format – Part 15: Palm crease image data
ISO/IEC 19794-13:2018	Information technology – Biometric data interchange formats – Part 13: Voice data
ISO/IEC TR 19583-23:2020	Information technology – Concepts and usage of metadata – Part 23: Data element exchange (DEX) for a subset of ISO/IEC 11179-3
ISO/IEC 23093-3:2019	Information technology – Internet of media things – Part 3: Media data formats and APIs
ISO 8000-2:2022	Data quality – Part 2: Vocabulary
ISO/IEC 24668:2022	Information technology – Artificial intelligence – Process management framework for big data analytics
ISO/IEC 20547-4:2020	Information technology – Big data reference architecture – Part 4: Security and privacy
ISO/IEC 19774-1:2019	Information technology – Computer graphics, image processing and environmental data representation – Part 1: Humanoid animation (HAnim) architecture
ISO/IEC 38505-1:2017	Information technology – Governance of IT – Governance of data – Part 1: Application of ISO/IEC 38500 to the governance of data
ISO/TS 10303-1003:2019	Industrial automation systems and integration – Product data representation and exchange – Part 1003: Application module: Curve appearance
ISO/TS 10303-1111:2019	Industrial automation systems and integration – Product data representation and exchange – Part 1111: Application module: Classification with attributes
ISO/TS 10303-1521:2018	Industrial automation systems and integration – Product data representation and exchange – Part 1521: Application module: Product data quality criteria
ISO/TS 10303-1831:2019	Industrial automation systems and integration – Product data representation and exchange – Part 1831: Application module: Scan data 3D shape
ISO/IEC TR 29170-1:2017	Information technology – Advanced image coding and evaluation – Part 1: Guidelines for image coding system evaluation
ISO/IEC 14496-12:2022	Information technology – Coding of audio-visual objects – Part 12: ISO base media file format
ISO/IEC 15444-1:2019	Information technology – JPEG 2000 image coding system – Part 1: Core coding system
ISO/IEC 19566-7:2022	Information technologies – JPEG systems – Part 7: JPEG linked media format (JLINK)
ISO/IEC 23003-3:2020	Information technology – MPEG audio technologies – Part 3: Unified speech and audio coding

D.3 Standards on Industrial Data

In this section, we describe how AI can be utilized in oil and gas production facilities to improve efficiency, safety, and decision-making, while also allowing for the necessary compliance with regulators and the exchange of necessary information with different stakeholders. Figure D1 summarizes the life-cycle model of a typical plant in oil and gas industry.[63] As shown, several parts of the plant's operations rely on the measurement of data that is utilized by computer systems which perform tasks such as learning, reasoning, problem-solving, and forecasting. Such systems further provide results to various stakeholders such as customers, regulators, employees, and various decision makers within the company. Below, we provide a list of how AI can be used in oil and gas production facilities.

- **Predictive Maintenance:** AI can analyze sensor data from equipment and machinery to identify patterns and predict potential failures or maintenance needs. This allows for proactive maintenance scheduling, minimizing downtime and reducing costs. These could, for example, be done under "Field Maintenance" or "Shop Maintenance" models in Figure D1. The relevant ISO standards could be published, for example, by ISO/TC 184/SC 4 (Industrial Data).

- **Asset Optimization:** AI algorithms can optimize the performance of oil and gas assets by analyzing large amounts of data and providing opportunities to improve interoperability. This includes optimizing drilling parameters, production rates, and reservoir management to maximize production and minimize costs. These could, for example, be done under the "Performance Analysis" model in Figure D1. The relevant ISO standards could be published, for example, by ISO/TC 184/SC 1 (Device Control) or ISO/IEC JTC 1/SC 32 (Data Interchange).

- **Environmental and Reservoir Monitoring:** AI can analyze sensor data and satellite imagery to monitor and detect environmental changes, such as oil spills, leaks, or emissions. This enables early detection and timely response to minimize the environmental impact. AI can also analyze seismic data, well logs, and historical production data to create accurate reservoir models. These models help in understanding subsurface characteristics, predicting reservoir behavior, and optimizing production strategies. These could, for example, be done under the "Performance Analysis", 'Demolishment & Uninstalling" and "Demolishment & Disposal" models in Figure D1. The relevant ISO standards could be published, for example, by ISO/IEC JTC 1/SC 42 (Guidance on AI related to ethical and societal concerns).

- **Production Optimization:** AI can optimize production rates by analyzing real-time data from multiple sources, including production sensors, weather conditions, and market demand. This enables operators to make informed decisions on adjusting production levels and scheduling maintenance activities. These could, for example, be done under the "Feedstock Acquisition", "Operations" and "Product Sales" models in Figure D1. The relevant ISO standards could be published, for example, by ISO/TC 184/SC 1 (Device Control) or ISO/TC 184 (Automation).

[63] See https://bit.ly/3P9Bb4S for details on a plant life-cycle model.

- **Robotics and Automation:** AI-powered robots and autonomous systems are used for various tasks, such as pipeline inspection, maintenance, and hazardous operations. These technologies improve safety by reducing the need for human intervention in potentially dangerous environments. These could, for example, be done under the "Performance Analysis" and "Operations" models in Figure D1. The relevant ISO standards could be published, for example, by ISO/TC 299 (Robotics).

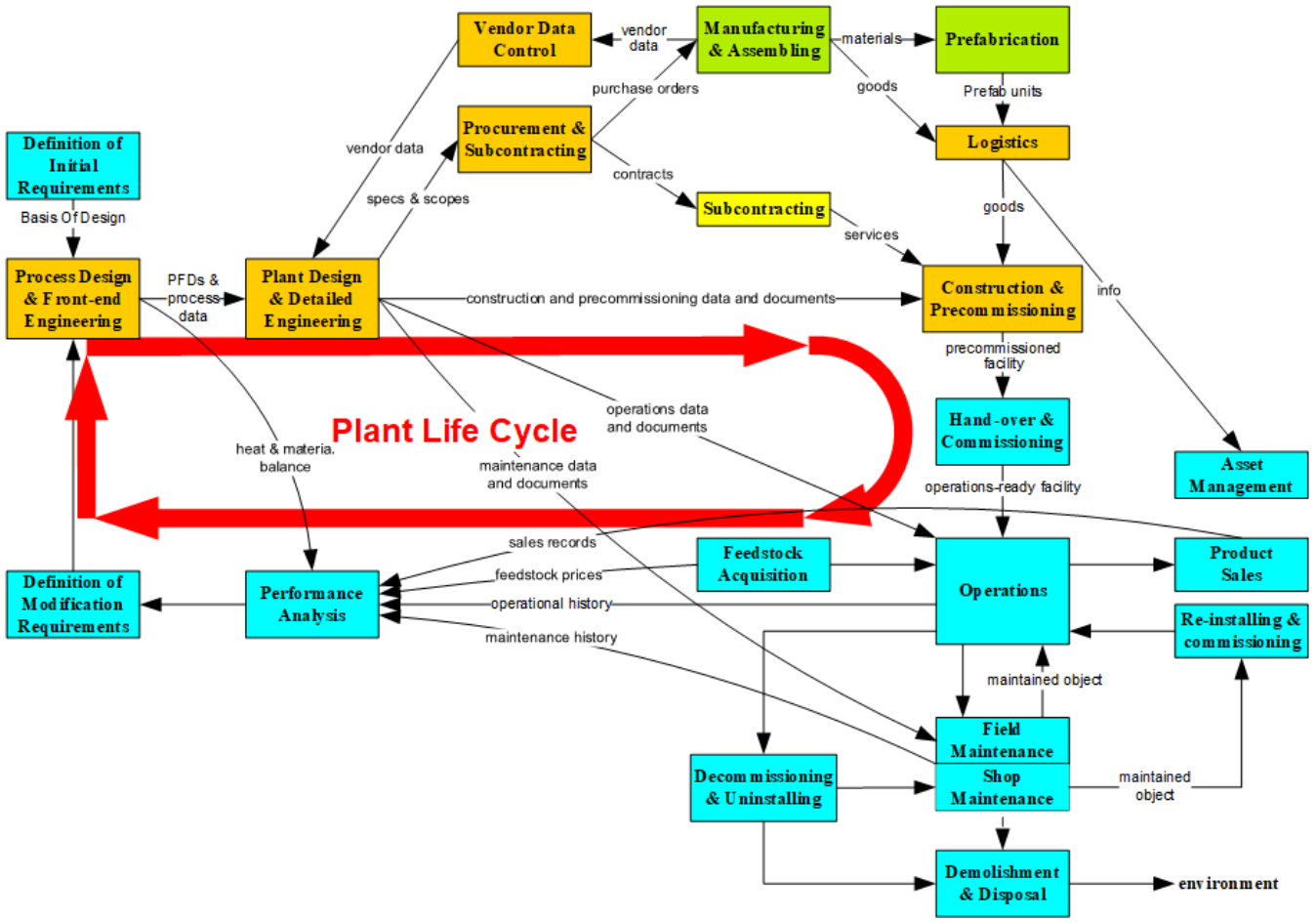
- **Biometrics and Natural Language Processing:** AI techniques enable the extraction and analysis of information from unstructured data sources, such as technical documents and reports from various vendors, or facial recognition and security services for restricted access. This helps in gathering insights, identifying trends, and making informed decisions based on a vast amount of information. These could, for example, be done under the "Procurement & Subcontracting" model in Figure D1. The relevant ISO standards could be published, for example, by ISO/TC 184/SC 4 (Industrial Data), ISO/IEC JTC 1/SC 37 (Human Biometric), or ISO/IEC JTC 1/SC 22 (Programming Languages).

- **Safety and Risk Management:** AI is used for risk analysis and safety management, helping to identify potential hazards and mitigate risks. It can also analyze historical data and real-time conditions to predict safety incidents and enable proactive measures. These could, for example, be done under the "Performance Analysis" and "Demolishment & Disposal" models in Figure D1. The relevant ISO standards could be published, for example, by ISO/TC 199 (Safety).

The above list outlines the applications of AI in a typical oil and gas production facility. It is crucial to note that throughout the entire lifespan of a facility, starting from conceptual design, through engineering and construction, to ongoing operations and maintenance, the exchange of information among the involved parties is imperative. Accomplishing this on a global scale and across all software systems utilized in the process industries is an immensely challenging task. The relevant ISO standards could be published by ISO/TC 184/SC 4 (Industrial Data). To provide an example of how standardization of data that AI models rely on, we use ISO standard 15926 on the integration of life-cycle data for oil and gas production facilities.

Appendix Figure D1. **A Plant Life-cycle Model For oil and gas production facilities**

The figure portrays a plant's Life-cycle (Activity) Model, crucial in industries such as oil and gas production. It offers a comprehensive overview of a plant's life stages, encompassing everything from inception and planning to design, construction, operation, maintenance, and ultimate decommissioning. This model fosters a complete understanding of the plant's lifecycle, enabling more informed decisions, enhancing sustainability, and bolstering efficiency at each stage. For a more detailed view of the figure and related information, please refer to the provided link: https://15926.org/topics/plant-lifecycle-model/index.htm.



ISO 15926 provides standards for data integration, sharing, exchange, and hand-over between computer systems.[64] Suppose, for example, that operations of a gas production plant heavily depend on the performance of a 101-pump (see, e.g., https://bit.ly/42Arf7u). The facility therefore actively collects data on the performance of the pump, reports to the regulators, and runs a machine learning algorithm to predict potential failures or maintenance needs. How is the data collected by the facility reported and standardized for safety? ISO 15926 allows different plants with different pumps to report their data and predictions to interested parties in a readable and explaninable way. Each data point is linked with a knowledge graph (e,g,, pump id 1 is linked with heat 100 F and timestamp January 1st, 2024 etc.) and shared with regulators in the correct way following, for example, https://bit.ly/3NlpHKn and https://bit.ly/3NpGNa7.[65]

D.4 Bias in AI Systems and AI-Aided Decision Making

AI systems are becoming more prevalent in various industries, including finance, IT, defense, healthcare, and others, where they play a greater role in corporate decision-making. However, it is important to recognize that these systems are susceptible to biases that can arise unintentionally within their algorithms or be introduced through biased training data (see Caliskan et al. (2017), for example). One relevant ISO standard that addresses bias in AI systems is ISO/IEC TR 24027:2021. This standard, published by the International Organization for Standardization (ISO), provides guidelines for identifying and managing bias in AI systems. It emphasizes the importance of understanding and assessing the potential biases that can arise at different stages of the AI system's lifecycle, including data collection, algorithm design, and system deployment. By following the guidelines outlined in this standard, organizations can proactively mitigate bias and promote fairness in their AI systems.

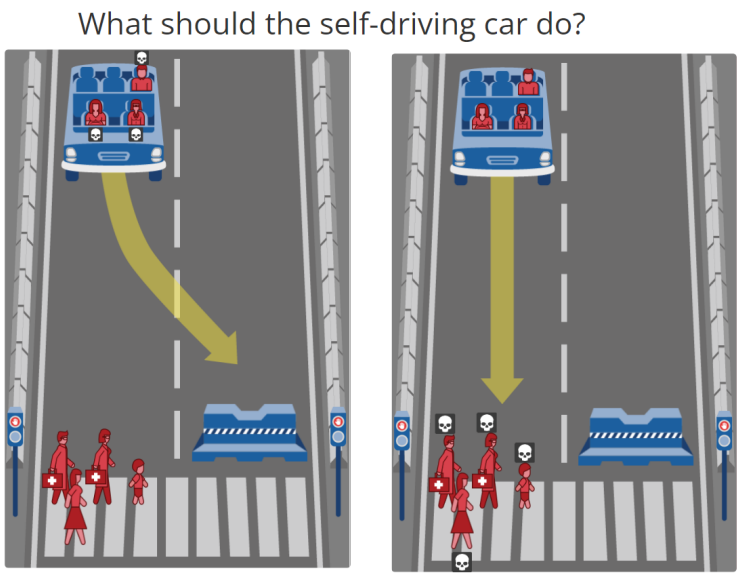
Autonomous vehicles (AVs) serve as a prime example of how AI-aided decision making and bias can significantly impact outcomes. AVs have the potential to revolutionize transportation by enhancing safety and efficiency. Nevertheless, they encounter challenging scenarios where they must make complex choices, such as prioritizing passenger safety or minimizing harm to pedestrians. Designing algorithms to govern these moral decisions is a complex endeavor that incorporates societal values and preferences. What ethical principles guide the decision-making process of machine learning algorithms?

Experiments conducted by Bonnefon et al. (2016) have demonstrated that people generally approve of AVs that prioritize the greater good, even if it means sacrificing the passengers based on experiments like the one shown in Figure D2. However, when it comes to their own safety, individuals prefer AVs that prioritize their well-being over others. This discrepancy in preferences poses a challenge in designing AI systems that align with societal values while also considering individual preferences. They also drive uncertainty regarding AI investments and along with potential litigation risk. It's not immediate what the ethical standards should be in this scenario, but a systemic way of measuring the influence of data biases on the machine learning algorithms can still be helpful.

[64] see https://bit.ly/3qJuAUs and https://bit.ly/3p60DNY for details.
[65] Also see the slides at https://bit.ly/3NoiWY7.

Appendix Figure D2. **Moral Machine Experiment**

Image taken from the Moral Machine Experiment–see for example Bonnefon et al. (2016)–, which presents an intriguing survey that explores the ethical dilemma faced by autonomous vehicles. The experiment raises the question of whether the vehicle should prioritize the lives of individuals inside the vehicle or those of pedestrians. To delve deeper into the details of this thought-provoking experiment, visit the official website at https://www.moralmachine.net/.



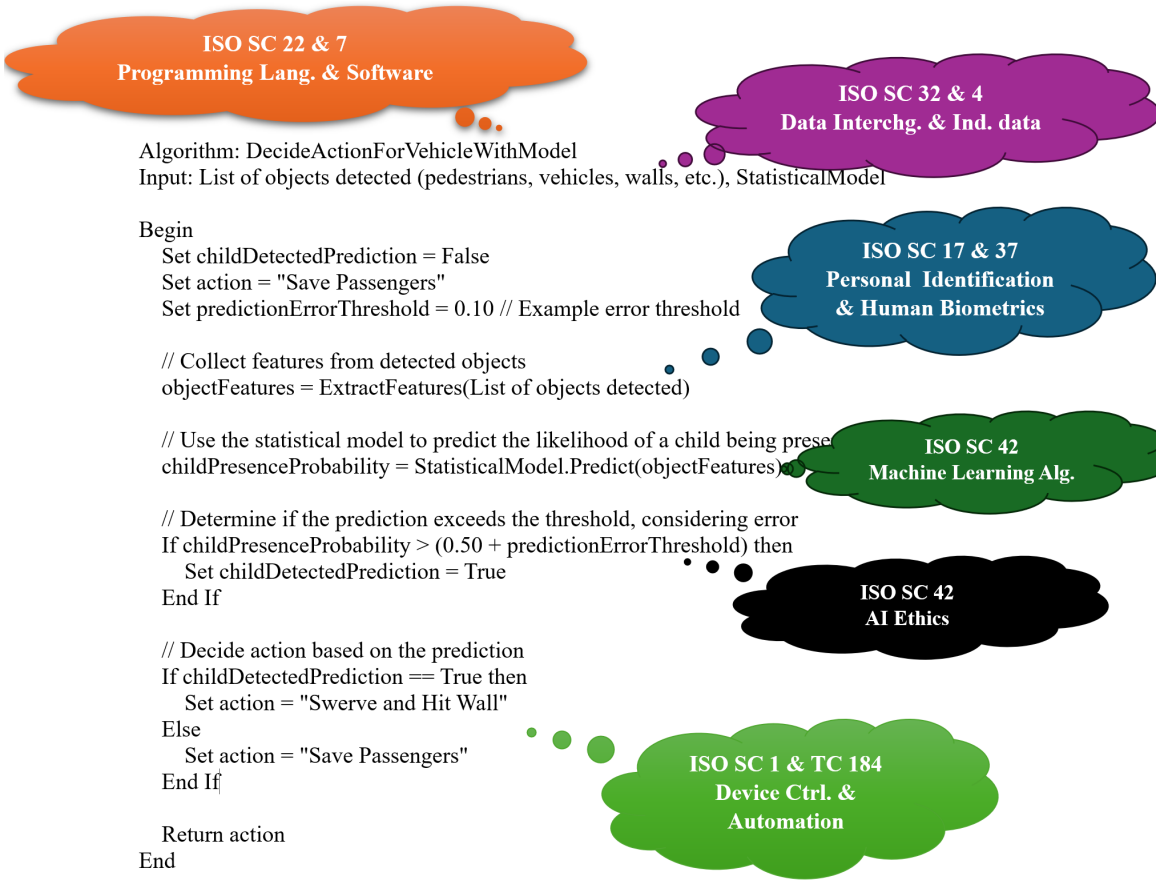
By following the guidelines outlined in ISO/IEC TR 24027:2021, firms in the AV industry can work towards developing AV systems that are fair, transparent, and accountable. The standard promotes the use of metrics to assess bias and fairness, allowing organizations to evaluate and improve their AV systems. For example, in section 3.2 of the document, it provides clear definitions for automation bias, bias, human cognitive bias, confirmation bias, data bias, and statistical bias, which are helpful for the manufacturers to fix bias in their machine learning models by following a universally accepted norms. Implementing the recommendations from ISO/IEC TR 24027:2021 can therefore help promote safety, equity, and public trust. By addressing bias, the standard can contribute to the wider adoption of AV technology by alleviating concerns about unfair decision-making and potential negative impacts on different stakeholders, such as passengers and pedestrians. Ultimately, the standard can help shape the development and deployment of AVs that prioritize ethical considerations, enhance public safety, and minimize societal harm.

Figure D3 further illustrates a pseudo code, which is a simplified version of a computer program, designed to save the lives of children in vehicle crashes. As shown, the code uses programming languages to process collected data. It identifies key features from this data through a process called feature extraction. These features are then used in modeling to predict and respond to crash scenarios, specifically focusing on protecting children. However, predicting such events isn't always perfect, and the pseudo code includes assumptions about possible errors in its predictions. The accuracy and safety of this program depend heavily on the standards set by the shown ISO committees, which ensure that the tech-

nology meets international safety and quality guidelines. These standards are crucial in making sure the program not only functions correctly but also reliably saves lives in real-world situations.

Appendix Figure D3. **Pseudo Code: AI-Driven Child Safety Protocol in Vehicle Crashes**

This figure shows a pseudo code aimed at child safety in vehicle crashes, utilizing programming languages to process data and feature extraction for critical safety factors. It models crash scenarios to protect children, acknowledging potential prediction errors. The program's effectiveness is rooted in adherence to ISO standards, ensuring global safety and quality compliance, crucial for saving young lives.




```
Algorithm: DecideActionForVehicleWithModel
Input: List of objects detected (pedestrians, vehicles, walls, etc.), StatisticalModel

Begin
   Set childDetectedPrediction = False
   Set action = "Save Passengers"
   Set predictionErrorThreshold = 0.10 // Example error threshold

   // Collect features from detected objects
   objectFeatures = ExtractFeatures(List of objects detected)

   // Use the statistical model to predict the likelihood of a child being prese
   childPresenceProbability = StatisticalModel.Predict(objectFeatures)

   // Determine if the prediction exceeds the threshold, considering error
   If childPresenceProbability > (0.50 + predictionErrorThreshold) then
      Set childDetectedPrediction = True
   End If

   // Decide action based on the prediction
   If childDetectedPrediction == True then
      Set action = "Swerve and Hit Wall"
   Else
      Set action = "Save Passengers"
   End If

   Return action
End

Function: ExtractFeatures(objects)
   // Process the list of objects and extract relevant features for the model
   // This can include size, shape, movement patterns, etc.
   // Return a structured format of features
End Function
```