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

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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 and AI patents but also boost 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
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1 Introduction

Technological standardization, the process of establishing universal rules and guidelines for firms, is the foundation upon which innovation is built (Tassey, 2017). Once a standard is set, companies operating within its domain are compelled to align their investments accordingly (Lerner and Tirole, 2015; Baron and Schmidt, 2019). This alignment contributes to a substantial increase in productivity and GDP growth rates, often approaching double-digit percentages.[1] While academic research has contributed to our understanding of the economics tied to standard setting (Lerner and Tirole, 2006; Chiao, Lerner and Tirole, 2007; Lerner and Tirole, 2014; Simcoe, 2012), 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, which primarily ensure compatibility, interoperability, and performance across devices, AI standards are dedicated to guiding the secure, ethical, and interoperable development and operation of AI systems. They establish globally accepted criteria for data quality, ensuring the accuracy, relevance, and security of the data used in AI systems. They prescribe best practices for efficiently and reliably training AI models and integrating them into older technologies, such as manufacturing. Furthermore, they aim to enable autonomous AI-based systems to operate in a transparent, explainable, and fair manner, facilitating seamless integration across various AI platforms and technologies.

Recognizing the significance of AI standardization for business, the US government has proactively mandated the National Institute of Standards and Technology (NIST), through Executive Order (EO) 13859, to develop a federal strategy aimed at bolstering US involvement in the creation of global AI standards. The European Commission, alongside other global play-

[1] The French Standardization Association (AFNOR) estimates that standardization is responsible for nearly a quarter of France's GDP growth. In a similar vein, the UK's Department for Trade and Industry (DTI) suggests that from 1948 to 2002, growth in standards played a pivotal role in fuelling approximately 13% of labor productivity growth. Meanwhile, data from Canada shows that standardization accounted for 17% of the labor productivity growth rate from 1981 to 2004, which translates to about 9% of the real GDP growth rate. Sources: https://bit.ly/3Cvj6a0, https://bit.ly/3Nbqw7n, https://bit.ly/3JegGQU, https://bit.ly/3XniFs5.

ers, is equally poised to assume a leading role in this endeavor.[2] Standardizing AI however presents unique challenges, not only because its decision-making can be opaque but also because it carries risks of unethical behavior or spiraling out of control.[3] The commercialization of AI therefore faces unique obstacles that necessitate the establishment of technical and ethical standards, fostering transparent, reliable, and ultimately profitable outcomes.

In this paper, we provide the first investigation of the influence of AI standards on corporate outcomes. While previous research indicates that standards boost capital expenditures and R&D in the telecommunications industry (Baron and Schmidt, 2019), the effect of AI standards on firm decisions remains unexplored. Considering AI's role as a general-purpose technology across multiple industries (Agrawal et al., 2018; Cockburn et al., 2018), addressing this gap is crucial for advancing our understanding of AI's corporate implications at large. This paper fills this gap by providing the first evidence of the influence of AI standards on AI-specific investments and patenting activity, as well as broader capital and R&D spending.

The establishment of AI standards carries a multitude of implications for firms. On the positive side, AI standards offer widely accepted frameworks for implementing AI technologies, thereby reducing the economic uncertainty faced by firms and encouraging higher corporate investment. They delineate "best practices", favoring certain technologies over competing alternatives, potentially leading to positive productivity shocks for endorsed technologies and negative ones for others. They can also enhance compatibility, thereby fostering positive network externalities and accelerating diffusion of AI technologies.

On the flip side, AI standards that impose constraints and mandate adherence to certain

[2] See the Government Accountability Office (GAO) report on US government's definition of and investments in AI at https://bit.ly/3Jee856. See European Commission's AI Strategy at https://bit.ly/42FRidI.

[3] Survey data indicates that the opaque nature of AI poses adoption challenges for business leaders. Practitioners argue that AI standards serve to "unlock the box", enhancing the transparency of AI. Sources: https://bit.ly/445kz2D,https://bit.ly/3N9IZBc. In May 2023, OpenAI's ChatGPT attracted 1.8 billion visits. OpenAI is acutely aware of AI risks, acknowledging on their website that the pros and cons of AI, including potential misuse, societal disruption, and unsafe competition, could reach a critical juncture. Moreover, a 2023 survey by the Centre for the Governance of AI found that 91% of a diverse 13,000-person sample from 11 countries concurred on the necessity of prudent AI management. Sources: https://bit.ly/43WIFfJ,https://bit.ly/3Copos1,https://bit.ly/3NauEnN.

norms can curb the effectiveness of AI, potentially leading to reduced investment. Furthermore, the improved compatibility and positive network externalities encouraged by standards may unintentionally stifle radical innovation by incentivizing conformity to existing technologies, potentially leading to technological lock-in. Finally, AI standards can open up a new avenue for large companies with strong lobbying power to turn more of their patents into standard-essential patents (SEPs). This can hurt other companies, forcing them to pay higher royalties to use AI technologies, and limit their ability to develop and use their own innovations.[4]

To provide empirical evidence on how standardization of AI impacts businesses, we manually collect 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 EO 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 AI standards from each committee's respective website and enrich it with additional textual analysis and detailed 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 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 specifics of AI standards through textual analysis, documenting a wide spectrum of AI components to provide a deeper understanding of the subject matter. These components include but are not limited to machine learning (including language models), big

[4]Qualcomm's licensing practices, notably the "no license, no chip" policy, often draw criticism for stifling innovation, driving over 75% of its pre-tax profits and highlighting their central role in the company's business model. See `https://bit.ly/4afsUDS`.

[5]This report is publicly accessible and can be downloaded from the following URL: `https://bit.ly/43yw0oz`.

[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`.

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.

To estimate the influence of AI standards on firms, we rely on the exogenous nature of United Nations Security Council (UNSC) membership rotations. 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 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 mentioned above, we show that increases in AI standards have a significant impact on investment in capital and R&D expenditures. Under US secretariat, an increase of one standard deviation in AI standards results in a 0.24 standard deviation increase in R&D investments for the average US firm, relative to firms from countries with secretariats. In terms of capital investments, the same increase in AI standards under US leadership corresponds to a 0.08 standard deviation increase compared to firms from countries with secretariats, and a 0.15 standard deviation increase compared to firms from other countries.

Countries other than the US that hold secretariats also experience positive effects on their investment activity. For instance, under the leadership of the United Kingdom and France, an increase of one standard deviation in AI standards leads to a 0.19 standard deviation increase in capital investments. Similarly, compared to non-participating countries, it results in a 0.14 standard deviation increase in capital investments and a 0.29 standard deviation increase in R&D investments. These estimates for the local average treatment effects of AI standards underscore the significance of leadership in AI standards in driving local corporate activity.

To provide insights into the content of global AI standards, we conduct a detailed textual analysis. We categorize AI standards into groups such as machine learning (including large language models), big data, AI safety, privacy, physical equipment, and automation, among others. Machine learning, data interchange, and privacy standards exhibit notable effects on investment. A one standard deviation increase in machine learning standards leads to a 0.22 standard deviation increase in capital expenditures, while a one standard deviation increase in data interchange standards corresponds to a 0.12 standard deviation increase in R&D investments. Conversely, a one standard deviation increase in privacy standards results in a significant 0.61 standard deviation decrease in R&D investments. Standards related to automation and machinery and equipment also demonstrate statistically significant effects on investment behavior. These findings highlight the nuanced ways in which different categories of AI standards can drive or hinder capital and R&D investments.

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. Overall, our findings underscore the crucial role AI standards play in influencing investment decisions and firm valuations.

Does the influence of AI standards extend to AI-specific investments? To explore this question, we utilize novel data from the Center for Security and Emerging Technology (CSET) on

AI-specific investments across 36 categories and AI-specific patent activity across 22 distinct fields at the country-year level. Our evidence suggests that AI standards indeed foster increased investments and patents in AI-related domains. Notably, AI standards spur growth in areas such as robotics, manufacturing, cybersecurity, privacy, data analytics, software, facial recognition technology, and education. We also observe a rise in AI patent applications in fields including banking, finance, security, industrial manufacturing, machine learning, transportation, telecommunications, and computer vision, following the adoption of AI standards.

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 revolution, i.e., Industry 4.0 (Peres, Jia, Lee, Sun, Colombo and Barata, 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. In Section 5, we introduce our identification strategy and empirical findings in support of the theoretical predictions above. Section 6 concludes the article. To keep the main text concise, we present additional material in the Appendix. Appendix Section A presents our theoretical framework and mathematical proofs. In Appendix Section B, we delve deeper into our supplementary summary statistics and findings. Appendix Section C describes the data on AI-specific investments and patents. Appendix Section D demonstrates a concrete example of how AI, guided by appropriate standards, can be implemented in oil and gas production facilities to enhance efficiency, safety, and decision-making, while ensuring regulatory compliance and efficient information exchange with different stakeholders. Appendix Section E discusses the issue of bias in AI-assisted decision-making and the standardization efforts made to address these challenges.

2 Literature Review

Our paper's main contribution is to the emerging literature in financial economics on AI. Cao et al. (2020) argue that AI influences corporate disclosure by reducing negative tones that algorithms perceive unfavorably, and Cao et al. (2021) show that an AI-based analyst beats most human analysts. D'Acunto et al. (2019) highlight that adopters of robo advisors experience diversification benefits, and Rossi and Utkus (2020) show robo advisors reduce investors' holdings in money market mutual funds and increases bond holdings. A strand of research argues that AI-related investment (e.g., through the labor channel) increases firm innovation and productivity (Aghion, Jones and Jones, 2018; Babina, Fedyk, He and Hodson, 2021); meanwhile, there also have been discussions on the concerns of labor replacement (Acemoglu and Restrepo, 2018), data privacy (Cong, Xie and Zhang, 2021b; Chen, Huang, Ouyang and Xiong, 2022; Canayaz, Kantorovitch and Mihet, 2022; Liu, Sockin and Xiong, 2023), as well as decision biases, reliability, and interpretability of AI algorithms (Wellman and Rajan, 2017; Agrawal, Gans and Goldfarb, 2019a; Clark and Hadfield, 2019; Acemoglu, 2021).[7] We contribute to the literature with a

[7]See also Agrawal, Gans and Goldfarb (2019b), which is a book with a comprehensive discussion of the economics of AI and Goldstein et al. (2021); Farboodi and Veldkamp (2022); Cong et al. (2021a) on big or unstructured data. See Cheng, Sokol and Zang (2023) on online platforms.

unique perspective to examine the economic impact of AI standards.

Some recent papers discuss AI-related policies and regulations. Cuéllar, Larsen, Lee and Webb (2022), for example, examine the impacts of potential AI regulations on managers' perceptions of AI ethical issues and their intentions to adopt AI technologies. Agrawal, Gans and Goldfarb (2019a) emphasize three aspects of AI economic policies: data privacy, international coordination, and AI liability. There are also papers comparing standards, which belong to self-regulations, to compulsory government regulations. Using survey data, Blind, Petersen and Riillo (2017) show that standards lead to higher innovation efficiency than public regulations in markets with higher uncertainty. As AI technologies involve high uncertainty due to their evolving nature, an implication of their result is that standards could be more important than government regulations in promoting AI innovations and adoptions. Similarly, Clark and Hadfield (2019) argued 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. Our work contributes to the literature as being among the first to study the effect of AI standards on firms' actual investment decisions.[8]

Our paper also contributes 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 by codifying knowledge (Marcus and Naveh, 2005; Großmann et al., 2016) and securing minimum quality (Mirtsch et al., 2020). In addition, technological standards reduce the variety and increase the compatibility of technologies. This incentivizes innovation by accelerating the wide adoption of new technologies because users won't be trapped with a standalone technology that barely interfaces with other systems and is scarcely used by others. Instead, they will gain from the positive network externalities, where the value of a technology increases in its user base size (Pelkmans, 2001; Lerner and Tirole, 2014). The importance of

[8]We also find that AI standards benefit younger firms more than older firms, which is in contrast with the conventional wisdom that smaller and younger firms are more likely to be the victims of regulations than larger firms (Canayaz, Kantorovitch and Mihet, 2022). These results are available upon request.

compatibility and interoperability is especially pronounced for Information and Communication Technologies, because such technologies are subject to strict compatibility requirements (Baron and Schmidt, 2019).[9] On the other hand, standardization may hinder R&D investment by reducing an industry's degree of radical innovation (Foucart and Li, 2021) or increasing market concentration (Windrum, 2004). However, the majority of the work is either conceptual or using survey data. We contribute to the literature as being among the first to look at the causal relationship between the publication of standards and firms' actual investment decisions.

Our work is also related to the literature on the economics of standard-setting organizations (SSOs). Lerner and Tirole (2006) and Chiao, Lerner and Tirole (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.[10] Simcoe (2012) showed 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.[11] We enrich the literature by being among the first to suggest the presence of conflicts of interest in SSO using firm-level investment data. That is, the SSO leading participant (i.e., the ISO committee secretariat country) actively promotes standards that prioritize companies from their respective countries, because an increase in the publication of standards leads to a greater investment boost for firms hailing from the secretariat countries compared to firms outside of those countries.

Finally, our observation that firms tend to postpone their investments until the establishment and publication of relevant standards, which consequently resolves the uncertainty sur-

[9] The importance of interoperability was also emphasized in the following public statement made by the Federal Trade Commission. See https://bit.ly/3JbRkmw.

[10] They made 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.

[11] In addition, Baron and Gupta (2018) describes a database on standardization procedures at the 3rd Generation Partnership Project (3GPP), which is the most relevant SSO in the field of mobile telecommunications. Baron and Spulber (2018) also supply information on technology standards, SSO membership, and SSO characteristics, without a specific focus on AI.

rounding productivity, finds parallels with established theories in the field of investment and economics. This relationship specifically echoes the principles embodied within the literature on real options theory and investment under uncertainty (Dixit and Pindyck, 1994; Grenadier, 2002; Grenadier and Wang, 2007).

3 Hypothesis Development

To motivate our empirical tests, we develop hypotheses on how a firm's investment is affected by the expected future publications of AI standards. We build a theoretical model in Internet Appendix A to formally establish these hypotheses. In this section, we summarize the structure of the model and the testable implications.

A firm lives for an infinite horizon. In each period, it faces decisions on the AI investment in multiple AI domains. Examples of AI domains include computer vision and voice recognition. Within each domain, the firm can invest in two types of competing AI technologies. In addition, the firm faces capital expenditure (CapEx) investment decisions on physical investment, that is, property, plant and equipment (PP&E). Both the investment in AI technologies and CapEx are partially irreversible, i.e., disinvestment is costly due to fire sales.

The firm uses both PP&E and AI capital as inputs for production. Importantly, AI-related capital and PP&E enter the production function with a multiplicative structure. That is, AI-related capital *complements* physical capital. AI is commonly regarded as a general purpose technology (GPT) that may lead to the fourth industrial revolution, i.e., Industry 4.0 (Peres, Jia, Lee, Sun, Colombo and Barata, 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.

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 swifter 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 productivity 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. The firm does not know ahead of time which technology will receive endorsement. Anticipating the random bifurcation of productivity, the option value of postponing its partically irreversible investment drives the firm to delay its investment until the publication of standards resolves the uncertainty. Therefore, firm investment should increase after the publication of standards.

In addition, suppose each technological standard that can be potentially published covers one particular domain of AI technology. Then more technological standards being published imply that more domains of AI technology see resolution of uncertainty, boosting investment even further. That is, we should see a positive correlation between the number of technological standards published and AI-related investment post-publication. Furthermore, as AI-related investment complements CapEx, the firm's CapEx should also increase with the number of technological standards published.

The situation is very different if the published standards are *privacy/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.[12] Unlike technological standards that boost productivity of the endorsed AI technology over an unendorsed one, the privacy/ethical standards reduces the productivity on all types of AI investment. Therefore, where more such standards are published, the restrictions on AI productivity becomes more concrete and stringent, leading to less investment or more disinvestment post-publication.

Based on our theoretical framework, we make the following empirical predictions.

Hypothesis 1. *(i) Firm's AI-related investment and CapEx are higher after the publication of standards, if a higher number of technological standards are published.*
(ii) Firm's AI-related investment and CapEx are lower after the publication of standards, if a higher number of privacy/ethical standards are published.

4 Data Collection and Summary Statistics

This section elucidates the methodology employed in our data gathering process (see to Section 4.1) and offers a comprehensive overview of the main variables through summary statistics (see Section 4.3).

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 National Institute of Standards and Technology (NIST). Prepared in response to Executive Order (EO) 13859, this report guides the formulation of a strategy that fosters Federal involvement in AI standard creation. It outlines important committees integral

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

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 evolution and future course of AI standards.[13]

After identifying AI-centric standardization organizations and their corresponding 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 involved as committee members. Committee websites, as of 2023, typically offer the latest membership information. 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 (AI-related) standards rather than the earlier ones.

Table 1 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 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

[13] 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.

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 1 about here]

As displayed in Table 1, the total number of AI standards published by AI-centric committees from 1972 to 2023 is 5,456.[14] 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

[14]it is worth noting that approximately 180 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.

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.

[Figure 1 about here]

Figure 1 illustrates the number of standards published in a given year by each ISO secretariat. As shown in the figure, 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. It is important to note that AI standards undergo cyclicality due to periodic reevaluation, typically occurring every three to five years. During these evaluations, standards may be withdrawn or accepted again, reflecting the evolving landscape and advancements in AI technologies.[15]

[15]We are in the process of manually collecting detailed data on the life cycle of each standard. See Figure B1 on the life-cycle of standards published since 1972. The creation and acceptance of ISO standards follow a rigorous, multi-stage process designed to ensure broad consensus, technical validity, and market relevance. The process begins with a proposal stage, where a new work item proposal (NWIP) is made and requires approval from a two-thirds majority of the national bodies that are members of the relevant technical committee or subcommittee, with a commitment from at least five countries to actively participate in the work. Subsequently, a working draft (WD) is developed in the preparatory stage, followed by the circulation of the draft to the technical committee or subcommittee members for review and comment, resulting in a committee draft (CD). The draft then proceeds to the enquiry stage as a Draft International Standard (DIS), where it must receive approval from at least two-thirds of the national bodies that are voting members of the relevant committee, with no more than one-quarter of the total votes cast being negative. If the DIS is approved, it moves to the approval stage as a Final Draft International Standard (FDIS), requiring at least two-thirds approval from the voting members and no more than one-quarter of the total votes cast being negative. Finally, upon successful completion of the approval stage, the ISO standard is published and recognized as an International Standard.

Appendix Table B1 offers a comprehensive overview of the activities and scopes of AI standardization committees listed previously in Table 1, 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.[16]

[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 clarity, the committee codes have been replaced with short descriptions–i.e., scopes–that reflect the operations of each committee, as outlined in Table B1. 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

[16]Section D 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 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.

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.

[Figure 3 about here]

Members of ISO committees play an important role in publishing global standards as well. 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.

To account for this diversity and offer a comprehensive analysis of AI standardization, content analysis based on the titles of standards becomes crucial. For this reason, by analyzing the titles of standards, we identify common themes, emerging topics, and trends across various committees and secretariats. This approach allows for a broader exploration of the standardization landscape, enabling insights into the focus areas and evolving priorities within the AI domain. 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.

- **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.
- **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.
- **Safety and Accountability**: Standards addressing governance, ethics, security, explainability, trustworthiness, and societal impact of AI systems.
- **Data**: Standards for data management, privacy, security, exchange, and interoperability, excluding those standards that are already labeled as machine learning standards.
- **Interchange**: Standards focusing on the interchange or exchange of data, including data formats, protocols, and representation standards.

- **Privacy**: Standards for privacy protection, cybersecurity, biometric data, and human rights considerations.
- **Automation**: Standards for automated decision-making, process automation, and workflows, excluding those that are already labeled as machine learning standards.
- **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.

[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 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.

[Figure 5 about here]

Figure 5 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.[17]

In summary, this section offers an overview of our AI standards data. 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 standards data and its impact on business outcomes.

4.2 Data on AI Investments and AI Patents

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

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

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 investments and patent activities.[18]

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. For a more comprehensive elaboration of the CAT data, refer to the detailed descriptions provided in Appendix Section C.

4.3 Summary Statistics

In this section, we present an overview of the data used in our empirical analyses. Table 2 provides descriptive statistics on the variables employed in our study. Panel A specifically highlights important details regarding corporate outcomes. Our corporate data, obtained from the Worldscope database, covers the period from 2017 to 2022 based on the committee membership data from the Wayback Machine, encompassing firm-year (i, t) observations. Notably, we also label the headquarters location of each firm as country c, a critical element of our empirical approach.

[Table 2 about here]

Two notable financial metrics in our analysis are the CAPEX/AT and R&D/AT ratios, which

[18]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/.

serve as our primary dependent variables.[19] These ratios represent the proportions of capital and R&D expenditures in relation to the lagged total assets. Their medians (means) stand at 2.14% and 2.11% (4.82% and 5.31%), respectively. Sales/AT$_{i,c,t}$, which signifies the Sales-to-Assets ratio, or Asset Utilization, has an average value of 84.68% in the sample. Its median stands at 67.19%, and its standard deviation, a significant 82.09%, points to considerable variability in firms' efficiency at generating sales using their assets.

The Log(BVA) denotes the natural logarithm of the Book Value of Assets in US dollars. Its mean and median both align at 2.95, with a relatively small standard deviation of 0.13. For the Cash Flow-to-Assets ratio (CF/AT), the data suggests a median of 0.03. Its standard deviation of 0.42 denotes a significant variation across firms. The Leverage ratio (Leverage) presents an average value of 0.25, and Short-Term Leverage (ST Leverage) stands at a mean of 0.51. Finally, Log(Age) has a median (mean) of 2.71 (2.48), which suggests that the median (mean) firm in our sample is approximately 15 (12) years old.

At the bottom of Panel A, we report summary statistics on two additional variables. 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.[20] 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

[19]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.

[20]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 $\frac{5}{44} = 11.36\%$.

UN Security Council. These countries are Sweden, Germany, India, Japan, Australia, and South Korea.[21] With an average of 2%, it suggests a low proportion of UNSC member firms. However, the standard deviation of 4% illustrates substantial variability in this measure.

Panel B of the table pivots towards an examination of AI standards spanning diverse domains. It provides a detailed account of the log number of AI standards deployed in diverse areas including machine learning, data, accountability, automation, programming languages, interchange, interoperability, privacy, equipment, media, Internet of Things (IoT), and human biometrics, which are previously explained in Section 4.1. These measures correspond to the different categories of AI standards, providing a holistic perspective on the implementation and prevalence of these standards across firms.

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. It has a mean of 1.51 and a standard deviation of 1.73. This suggests, for the average firm, the number of yearly AI standards published in that firm's country's secretariat is 4.31. The range between the 5^{th} and 95^{th} percentiles is 0.00 and 64.07, showcasing the wide distribution of AI standardization activity across countries.

The average log value for machine learning standards is 0.73, indicating the widespread adoption of these standards in the AI industry. Similarly, the mean of the logged data standards is 0.55, reflecting considerable utilization of data-related standards. Log(Accountability Standards), a measure of accountability norms in AI utilization, shows a mean of 0.23 and a standard deviation of 0.56. Log(Automation Standards) captures the extent of automation norms across firms with a mean of 0.42 and a standard 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 Stan-

[21] 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 $\frac{4}{49} = 8.16\%$.

dards) and Log(Human Biometric Standards), with means of 0.34 and 0.37 respectively. Next, we have measures of multimedia and Internet of Things (IoT) standards, with Log(Multimedia Standards) and Log(IoT Standards) showing means of 0.60 and 0.14 respectively. The machinery-related standards are captured by Log(Equipment Standards) with a mean value of 0.35. Finally, any standards not falling under the previous categories are represented by Log(Unlabeled Standards), with a mean of 0.34. Each category's median is at zero, suggesting a large number of firms have yet to adopt these specific standards. The standard deviations, being consistently larger than the mean values, indicate a high level of variation in these practices across firms. Figure B4 in the Appendix illustrates the covariance matrix for these 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%.

Panel C of Table 2 provides summary statistics on the country-year level CAT data. As shown, the mean Log(AI Investment) is reported at 2.08, with a median of 0.69. Both Log(AI Patent Applications) and Log(AI Patents Granted) show lower mean values of 0.85 and 0.63, respectively.

In summary, this section offers a comprehensive overview of corporate performance metrics and the expansion of AI standards during our sampling period. In the following section, we discuss our empirical strategy and present the main empirical findings of our paper.

5 Empirical Findings

In this section, we lay out our empirical approach and deliver our primary empirical conclusions. Section 5.1 elucidates our empirical models and assumptions related to identifiability, while Section 5.2 details the various types of effect heterogeneity we quantify and the associated modeling choices. Section 5.3 outlines our core findings on investment, and Section 5.4 introduces supplementary results concerning other corporate outcomes.

5.1 Identification Strategy

Our main dependent variable of interest, $y_{i,c,t}$, refers to capital expenditures to lagged assets, or R&D expenditures to lagged assets of firm *i* from country *c* in year *t*. The dependent variables are measured at the end of year *t*. We assume that

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

where $\mathit{Log(AI\ Standards}_{i,c,t})$ 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.

Specification (1) 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 (see Canayaz et al. (2022)), and tech firms may coordinate and lobby for AI standards differently and make investments differently than firms from other industries in such years.

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.

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 therefore estimate specification (1) by using a two-stage least squares (2SLS) procedure. To do so, we employ a well-established shock previously utilized in the literature, namely two-year rotations in UN Security Council (UNSC) membership. These rotations can either facilitate or hinder the process of passing AI standards in committees led by US and other ISO secretariats, which also hold permanent UNSC membership.

Ten of the 15 seats on the UNSC are held by elected rotating members serving two-year terms. 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 rotates onto the council.[22] These allow us

[22] 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.

to make a formally testable relevance assumption. We assume that the number of AI standards published under the secretariats of the United States and other permanent members of the UNSC increases (decreases) as the percentage of rotating UNSC members under their secretariats increases (decreases). This is based on the expectation that more (or 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 (1). 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 (1). Although unconfoundedness is not a formally verifiable assumption, we provide ample empirical evidence for the 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)).[23] 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. Additionally, we perform a placebo test by employing the percentage of rotating mem-

[23] See, for example, Appendix Figure B3, which presents empirical evidence indicating that rotating UNSC members do not specifically target AI Committees.

bers 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. Importantly, this estimation yields both economically and statistically insignificant outcomes, suggesting that our instrument does not exert any influence on AI standardization beyond its specific local context.[24]

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

$$
\begin{aligned}
\textit{Log(AI Standards}_{i,c,t}) &= \alpha_0 + \alpha_1 \textit{\% UNSC Members}_{i,c,t-1} + \gamma X_{i,c,t-1} \\
&\quad + \tau W_{c,t-1} + \text{ Fixed Effects} + \epsilon_{i,c,t},
\end{aligned}
\tag{2}
$$

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 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.

[24]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

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

$$y_{i,c,t} = \beta_0 + \beta_1 Log(AI\ \widehat{Standards}_{i,c,t}) + \gamma X_{i,c,t-1} + \tau W_{c,t-1} + \text{ Fixed Effects} + \epsilon_{i,c,t}, \tag{3}$$

where $Log(AI\ \widehat{Standards}_{i,c,t})$ 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.

5.2 Estimation of Effect Heterogeneity

We employ three additional tests to address crucial economic questions related to the significance of AI standards for corporate investments. The first question we tackle is related to effect heterogeneity across AI standardization committees. Understanding the differential impact of AI standards published by various committees is crucial. The effects of an AI standard developed by a committee specializing in ethics, for example, can be fundamentally different from those of a standard issued by a committee focused on software or equipment.

Each committee's specific domain of expertise brings unique considerations and implications for the development, implementation, and outcomes of AI technologies. Analyzing these distinctions allows for a more nuanced understanding of the varied effects and potential benefits of AI standards across different sectors and application areas. Importantly, tackling this question also allows us to reduce our dependence on country-year level instruments and rather use instruments at the committee-secretariat-year level. For these reasons, we employ the following 2SLS procedure, beginning with first-stage regressions on

$$\begin{aligned} Log(AI\ Standards^k_{i,c,t}) = \alpha^k_0 + \alpha^k_1 \%\ UNSC\ Members^k_{i,c,t-1} + \gamma^k X_{i,c,t-1} \\ + \tau^k W_{c,t-1} + \text{ Fixed Effects} + \epsilon^k_{i,c,t}, \end{aligned} \tag{4}$$

separately for each AI committee k. *Log(AI Standards*$_{i,c,t}^{k}$) 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*$_{i,c,t-1}^{k}$ is equal to the percentage of UNSC members in committee k in year *t-1* for firms from the secretariat, and zero otherwise.

[Figure 6 about here]

Figure 6 illustrates the variation of committee-level instruments across different AI committees and over time. The instrumental variable, *%UNSC Members*$_{i,c,t-1}^{k}$, displays different patterns among each committee k. Comparing the years 2018 and 2019, for example, we observe an increase in *%UNSC Members*$_{i,c,t-1}^{k}$ 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.

Related to this, Appendix Figure B5 shows a histogram showcasing the distribution of the combined committee-level instruments, represented by *%UNSC Members*$_{i,c,t-1}^{k}$, across AI committees. Additionally, the figure also displays the distribution of permanent UNSC members in the corresponding committees. Importantly, it illustrates how rotating members can marginally – nearly by 50% incrementally, on average – influence the distribution of votes, potentially favoring permanent UNSC members by augmenting their influence.

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

$$y_{i,c,t} = \beta_0^k + \beta_1^k \widehat{Log(AI\ Standards}_{i,c,t}^{k}) + \gamma^k X_{i,c,t-1} + \tau^k W_{c,t-1} + \text{ Fixed Effects} + \epsilon_{i,c,t}^{k}, \qquad (5)$$

where $\widehat{Log(AI\ Standards}_{i,c,t}^{k})$ denotes the instrumented *Log(AI Standards*$_{i,c,t}^{k}$) from the first stage, and β_1^k 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_1^k represent different local effects compared to β_1 in equation (3). While β_1 captures the overall effect of AI standards on firms headquartered in all countries with secretariats, β_1^k 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).

The second question we address pertains to the different types of AI standards and their impact on corporate investment. While analyzing individual committees within AI standardization space is economically important and advantageous in terms of causal inference, it is insufficient to provide evidence on effect heterogeneity across categories of standards. Various types of AI standards, including machine learning, data, interoperability, and privacy standards, can have distinct effects on corporate investment outcomes. For instance, machine learning standards in robotics can stimulate innovation and drive investment and efficiency, while machine learning standards related to ethics or child privacy may impose constraints that potentially hinder investment and efficiency. Moreover, machine learning standards can be published by different committees, introducing variations in their effects that cannot be estimated by equation (5).

To comprehensively analyze the relationship between AI standards and investment, we conduct content analysis and provide novel indicators categorizing standards into Machine Learning, Safety and Accountability, Data, Programming Languages, Interoperability, Interchange, Automation, Privacy, Unlabeled, Human-related, and Graphics (Multimedia). Subsequently, we analyze the influence of these standards on corporate investment separately, enabling a more nuanced examination of their specific implications for different aspects of corporate outcomes. We provide detailed descriptions of how we conduct the content analysis in Section 4.1.

The third question we tackle explores the heterogeneity of effects relative to countries from diverse geographic and economic contexts. The impact of AI standards on US firms may, for example, differ when compared to firms from Germany, which also have secretariats, as well as when compared to firms from China or Russia, which are permanent members of the United Nations Security Council (UNSC) without secretariats. The effects of AI standards on US firms may further vary when compared to firms from countries that are not actively involved in AI standardization processes or countries that are not members of the United Nations Security Council (UNSC). By examining these variations, we can capture the nuanced effects of AI standardization across countries, offering valuable insights into the interplay between AI standards, corporate behavior, and international contexts.

To that end, we utilize a pairwise estimation approach across nine distinct groups of firms. In these groups, the treatment units consist of firms from various combinations of permanent United Nations Security Council (UNSC) member nations with ISO Secretariats. These include the United States, a combined group of France and the United Kingdom, and a group comprising the United States, France, and the United Kingdom. On the other hand, the control units consist of firms from nations with ISO Secretariats that are not permanent UNSC members (Germany, India, Japan, Australia, South Korea, and Sweden), as well as permanent UNSC member nations without ISO Secretariats (Russia and China), and nations not associated with either UNSC or ISO.

5.3 Main Findings

In this section, we present the results of our analysis on the impact of AI standards on capital and R&D investments. We employ the 2SLS procedure outlined in section 5.1 to estimate the effects. Table 3 displays our findings from the second stage regressions, reporting the coefficient estimates in percentage terms.

[Table 3 about here]

Table 3 shows that an increase in the logarithm of AI standards in year t significantly increases both capital and R&D expenditures at the end of year t. This is demonstrated by the coefficients of 0.48% and 0.50% for the first two models (representing capital expenditures), and 1.86% and 1.65% for the third and fourth models (representing R&D expenditures), respectively.

These results are statistically significant at the 1% level. These results suggest that a 100% increase in AI standards would increase capital expenditures by 0.50% and R&D expenditures by 1.65%. Translating these results into standard-deviation terms, a standard deviation increase in logged AI standards would increase capital expenditures by 0.11 standard deviations and R&D expenditures by 0.28 standard deviations. The F-statistics derived from the excluded first-stage instrument and the reported critical tF values at the bottom of the table provide support for the formally testable relevance condition of the 2SLS procedure. These findings indicate that AI standards have a significant impact on capital and R&D expenditures. They are also consistent with part (i) of our Hypothesis 1, as it predicts a positive relationship between investment and technological standards, which dominates the total number of AI standards being analyzed as depicted in Table B1.

[Table 4 about here]

Table 4 is divided into four panels, providing findings from reduced-form regressions (Panel A), first-stage regressions (Panel B), ordinary least squares (OLS) regressions (Panel C), and a placebo test (Panel D). These analyses help to deepen our understanding of the effect of AI standards on corporate investments estimated in Table 3. Panel A highlights a clear, positive link between the lagged percentage of United Nations Security Council (UNSC) members for each country and the ratios of both capital expenditures (CAPEX) and R&D expenditures to total assets (AT). The coefficients range from 7.08% to 7.33% for CAPEX/AT and from 27.54% to 24.57% for R&D/AT, respectively. Essentially, a standard deviation increase in the percentage of UNSC members correlates with a 0.29% rise in capital expenditures and a 1.10% increase in R&D.

Panel B emphasizes the strong positive correlation between the percentage of UNSC members and the natural logarithm of AI Standards. The coefficients, significant across all specifications, are between 14.63 and 14.85. Interpreting these results suggests that a 100% increase in the percentage of UNSC members correlates with a growth in AI standards by up to 15.96%.

Panel C presents the OLS regression estimates using Log(AI Standards) as the primary explanatory variable. 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, when compared to the results from Table 3, our OLS estimates yield smaller coefficients - as low as 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, in our placebo test results shown in Panel D, we find no significant effects on the variables $CAPEX/AT_{i,c,t}$ and $RD/AT_{i,c,t}$. The estimated coefficients for $Log(AI\ \widehat{Standards}_{i,c,t}^{Placebo})$ are 0.27%, 0.06%, 0.23%, and -0.54%, respectively. However, none of these estimates reach statistical significance, with p-values greater than the conventional threshold. These findings indicate that the instrument we used for the placebo test does not have any meaningful impact on the variables of interest.

5.3.1 Findings on Effect Heterogeneity

This section presents our findings on effect heterogeneity. Table 5 delivers a comparative analysis of the impact of AI standards on capital and R&D expenditures, featuring a pairwise estimation strategy across different groups of treatment and control units. As shown in Panel A, the treatment units comprise combinations of permanent UNSC member nations possessing ISO Secretariats. Meanwhile, the control units consist of three different categories: (i) countries with ISO Secretariats but without permanent UNSC membership, (ii) permanent UNSC member nations lacking ISO Secretariats, and (iii) countries unaffiliated with either UNSC or ISO. Countries labelled with "X" are excluded.

[Table 5 about here]

Panel B of Table 5 reveals the local average treatment effects of AI standards on both types of expenditures, scaled by total assets, for each group. Given the change in the table format, it is important to note that the displayed coefficients correspond to the estimated treatment effects for each group after incorporating covariates, firm-specific fixed effects, and industry-year interactive fixed effects as in Table 3. The results suggest nuanced relationships that highlight the differential advantages of leading an AI secretariat, particularly among UNSC member nations.

In Groups 1, 2, and 3, which consist of firms from the United States, United Kingdom, and France, countries leading an ISO Secretariat, we observe significant responses to AI standards. The coefficients associated with these groups indicate that AI standards have a substantial positive impact on both capital expenditure and research and development investment. Notably, the effects are primarily driven by firms from the United States. The maximum estimated economic magnitudes of these effects are 0.35% for CAPEX/AT and 1.42% for RD/AT.

In Groups 4, 5, and 6, the data indicates that leading an AI Secretariat provides a particular advantage to UNSC members, such as the United States, United Kingdom, and France. The firms from these nations boost their investments more substantially than those from China and Russia (the remaining permanent UNSC members) after the publication of AI standards. The economic magnitude of these effects is considerable, with increases ranging from 0.73% to 0.86% for CAPEX/AT and from 1.03% to 1.49% for R&D/AT.

Lastly, the results from Groups 7, 8, and 9 point to larger treatment effects when firms from treated countries are compared with firms from nations without ISO or UNSC affiliations during our sampling period. Interestingly, when we remove from consideration the countries that play a role in the AI standardization process—even if they do not lead the committees as secretariats—we find that firms from these outsider countries appear to suffer. The observed economic effects in these groups are substantial, with increases ranging from 0.52% to 0.69% for CAPEX/AT and from 1.30% to 2.00%for R&D/AT. Taken together, these results highlight the important role that AI standards play in corporate investment decisions and underscore the strategic benefits of leading an AI Secretariat, particularly for firms in UNSC member countries.

[Table 6 about here]

To achieve a comprehensive understanding of the relationship between AI standards and corporate investment, we carry out a content analysis that helps us categorize AI standards into distinct groups: Machine Learning, Safety and Accountability, Data, Programming Languages, Interoperability, Interchange, Automation, Privacy, Unlabeled, Human-related, and Graphics, as described in Section 4.1. In the subsequent analysis, we individually assess the influence of these standards on corporate investment, enabling a more granular examination of their specific implications for different aspects of corporate outcomes.

Table 6 presents the results of this detailed breakdown, revealing how different AI standard categories impact capital and R&D expenditures. The coefficients show the average effects of each AI standard category on CAPEX and R&D, both scaled by lagged total assets. Panel A focuses on the impacts on Capital Expenditures (CAPEX). 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.

Consistent with Hypothesis 1, these findings highlight the nuanced ways in which different categories of AI standards can drive or hinder investment in CAPEX and R&D. Firm investments in CapEx and R&D are positively correlated with the number of published technological standards such as (a) Interchange Standards, which serve to increase interoperability of the AI ecosystem, and (b) Machine Learning and Programming Language standards, which aim to provide instructions on implementations of AI technologies. However, investment is discouraged after the publication of Privacy 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.

It's also of economic importance to discern how the impact of an AI standard promulgated by a committee focusing on industrial data varies from one published by a committee addressing other aspects such as biometrics or ethics. Another significant scenario to consider is the case of standards related to programming languages. It is crucial to investigate whether the programming language standards published by their dedicated committee have a discernible impact. Addressing this question allows us to limit our dependence on country-year level instruments and instead employ instruments at the committee-secretariat-year level. To that end, we employ a two-stage least squares (2SLS) procedure, following specification (5).

[Table 7 about here]

In Table 7, we examine the effect heterogeneity driven by different standardization committees, focusing on CAPEX (Panel B) and R&D expenditures (Panel C). These panels 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.

Panel B highlights the impact of these standards on Capital Expenditures. 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.[25]

[25]See Appendix Figure B2 on the categories of standards published by US committees during our sampling period.

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.

The data thus indicates that the type of committee issuing AI standards has a notable influence on corporate investment decisions. While some committees, like the one focusing on Programming Languages (Group 3), stimulate significant increases in both types of investment, others, notably the Data Interchange committee (Group 4), seem to discourage investment. This further underscores the importance of nuanced interpretation when considering the impacts of AI standards on corporate investment choices.

The above findings provide evidence for effect heterogeneity. A comparative analysis is shown across different groups of treatment and control units, examining the impact of AI standards on capital and R&D expenditures. The results reveal that firms from the United States, United Kingdom, and France, countries leading ISO Secretariats, show significant positive responses to AI standards, driving higher levels of CAPEX and R&D investment. Additional findings highlight the importance of the type of AI standard and the issuing committee, with varying effects observed across different categories and committees.

5.4 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 8 about here]

Table 8 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 7 about here]

Figure 7 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.

5.5 AI Standards and 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:

$$y_{c,t} = \beta_0 + \beta_1 Log(\widehat{AI\ Standards}_{c,t}) + \alpha_i + \gamma_t + \epsilon_{c,t}, \tag{6}$$

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. $\widehat{Log(AI\ Standards_{c,t})}$ 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 9 about here]

We present our findings in Table 9. 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 standards 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 8 about here]

We further examine how AI standards influence different areas of AI investments and patent applications. Figure 8 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.[26] 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.

6 Conclusion

Standardization is an influential force in shaping innovation and business performance across various sectors. However, its impact on emerging technologies such as artificial intelligence (AI) remains largely untouched. 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 empirical evidence highlighting the influence of AI standards on corporate investments. Our findings suggest that universal adoption of AI standards significantly affect 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

[26]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.

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.

In summary, this paper illuminates the impact of AI standards on corporate outcomes, providing critical insights for both businesses and policymakers. Our empirical evidence indicates that AI standards substantially sway investment behavior, and the type of standards and issuing committees are crucial determinants. These insights deepen our understanding of the repercussions of AI standardization, underlining the necessity for meticulous planning and execution of AI standards to cultivate transparent, reliable, and profitable outcomes.

Table 1. **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**

Table 2. **Summary Statistics**

This table presents summary statistics of corporate outcomes (Panel A) and AI standards (Panel B) for the sampling period from 2017 to 2022. Panel A's data is from Worldscope, and Panel B's data is hand-collected following a report titled "U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools." This report is produced by the National Institute of Standards and Technology (NIST) in response to Executive Order (EO) 13859. The unit of observation is firm i from country c in year t. The statistics include the number of observations (N), mean, median, standard deviation (SD), 5th percentile (P5), and 95th percentile (P95) for each variable. Variable descriptions for Panels A, B, and C are provided in Appendix Sections B.1.1, B.1.2, and B.1.3, respectively.

Panel A: Summary Statistics on Corporate Outcomes

	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

Panel B: Summary Statistics on AI Standards

	N	Mean	Median	SD	P5	P95
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(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(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

Panel C: Summary Statistics on Country-Year Level AI Investments and AI Patents

	N	Mean	Median	SD	P5	P95
Log(AI Investment$_{c,t}$)	684	2.08	0.69	2.60	0.00	7.27
Log(AI Patent Apps.$_{c,t}$)	684	0.85	0.00	1.94	0.00	5.60
Log(AI Patents Granted$_{c,t}$)	684	0.63	0.00	1.69	0.00	4.85

Table 3. **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 a two-stage least squares (2SLS) procedure. 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. Fixed effects are included for both firm and year, and interaction effects are considered for industry and year. Detailed variable descriptions can be found in Table 2's caption. Our findings from reduced-form, first-stage and ordinary least squares (OLS) regressions, and placebo tests are presented separately in Table 4. 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 1% level tests ($\sqrt{c_{0.05}(F)}$ and $\sqrt{c_{0.01}(F)}$) 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
$\sqrt{c_{0.05}(F)}$	2.06	2.07	1.97	1.98
$\sqrt{c_{0.01}(F)}$	3.26	3.28	3.05	3.06

Table 4. **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 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, which include firm fixed effects (Firm FE), year fixed effects (Year FE), and industry-year fixed effects (Industry × Year FE), each applied in corresponding specifications in their columns. Detailed variable descriptions can be found in Table 2's caption. 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: Placebo Test

	$CAPEX/AT_{i,c,t}$	$CAPEX/AT_{i,c,t}$	$RD/AT_{i,c,t}$	$RD/AT_{i,c,t}$
	(1)	(2)	(3)	(4)
$\widehat{Log(AI\ Standards^{Placebo}_{i,c,t})}$	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

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

	(1)	(2)	(3)	(4)
Table 3 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 5. **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 3. Detailed variable descriptions can be found in Table 2's caption. 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

Table 6. **Effect Heterogeneity Driven by AI Standard Categories**

This table offers a detailed breakdown of how specific AI standard categories impact capital and R&D expenditures. We've defined these categories - Machine Learning, Data, Automation, Programming Language, Interoperability, Machinery & Equipment, Ethics & Accountability, and Privacy - based on our content analysis outlined in Section 4.1. The estimated coefficients displayed here show the average effects of each AI standard category on CAPEX and R&D, both scaled by lagged total assets. They 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 denoted without their respective logs. For example, "Machine Learning Standards" represents Log(Machine Learning Standards)$_{i,c,t}$. Detailed descriptions of all variables can be found in Table 2's caption. 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. Asterisks denote significance levels: $\star\star\star$ (1%), $\star\star$ (5%), and $\star$ (10%).

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								
$CAPEX/AT_{i,c,t}$	1.58**	0.27***	0.30***	-6.22	0.31***	0.28***	-3.72	-2.76
	(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								
$RD/AT_{i,c,t}$	5.17	0.86***	0.96***	-13.72	1.00***	0.93***	-7.63	-9.36**
	(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 7. **Effect Heterogeneity Driven by Standardization Committees**

This table provides a detailed examination of how standards published by different ISO committees impact capital expenditures (Panel A) and R&D expenditures (Panel B). 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. 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

Table 8. **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 two-stage least squares (2SLS) procedure. 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 incorporated in this analysis align with those in Table 3, 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. Fixed effects are included for both firm and year, and interaction effects are considered for industry and year. Detailed variable descriptions can be found in Table 2's caption. 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 1% level tests ($\sqrt{c_{0.05}(F)}$ and $\sqrt{c_{0.01}(F)}$) as in Lee et al. (2022) to further assess the significance of the second-stage coefficient estimates.

	Log(M/B$_{i,c,t+1}$)	Log(M/B$_{i,c,t+1}$)	Log(Q$_{i,c,t+1}$)	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
$\sqrt{c_{0.05}(F)}$	2.14	2.15	2.13	2.15
$\sqrt{c_{0.01}(F)}$	3.47	3.48	3.44	3.48

Table 9. **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 Section C. Coefficient estimates marked with $\star\star\star$, $\star\star$, and $\star$ 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	No	Yes	No
Observations	684	684	684	684

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

This figure illustrates the number of AI standards published in a given year by each secretariat. The data are hand collected following "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. On the horizontal axis, the years are listed chronologically, providing a timeline of the standards' development. The vertical axis represents the number of AI standards published. Each secretariat is color-coded to facilitate easy differentiation.

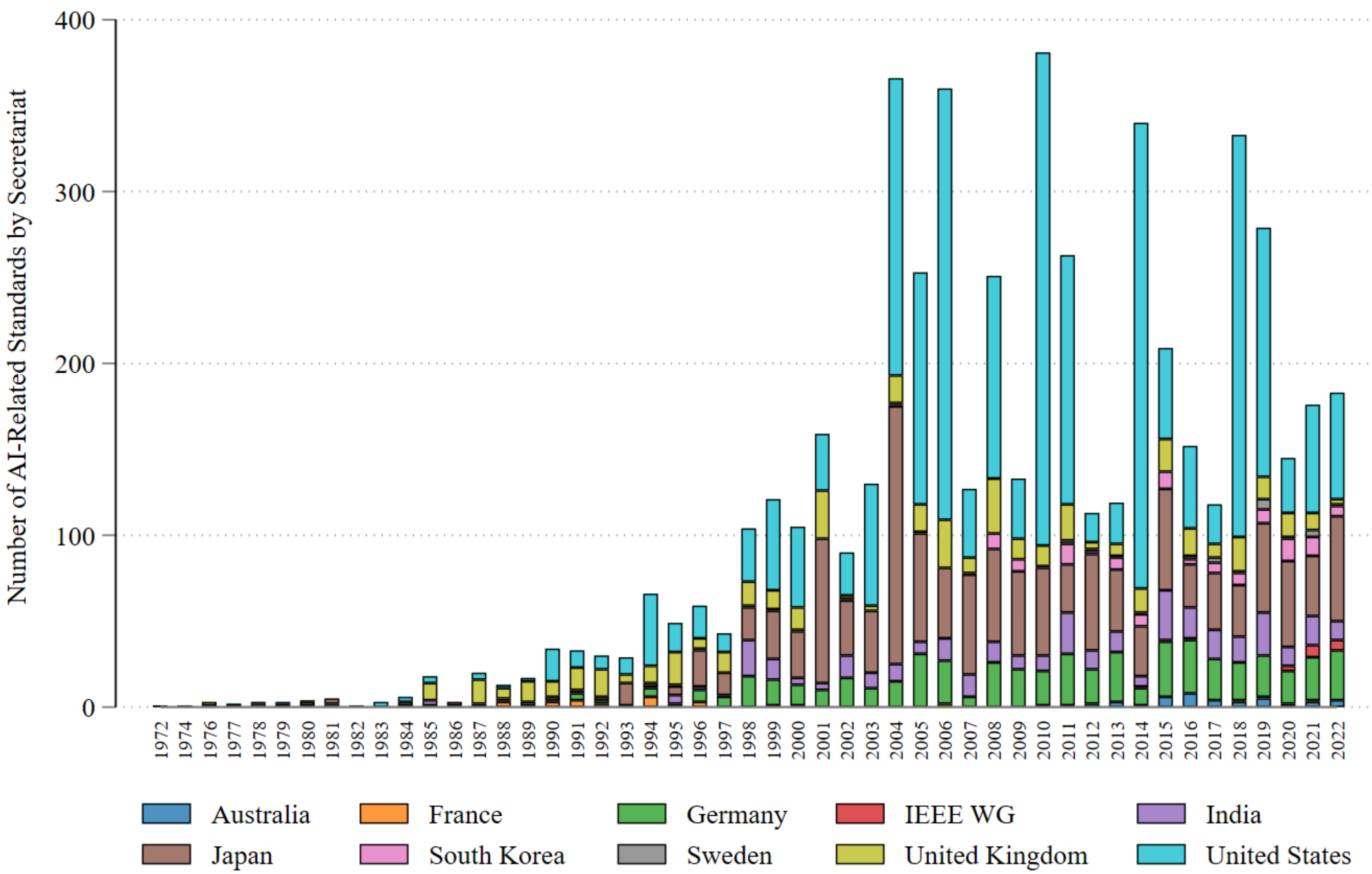


Figure 2. **Power Spheres: Standards by Each Secretariat**

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. Each secretariat is labeled in distinct colors.

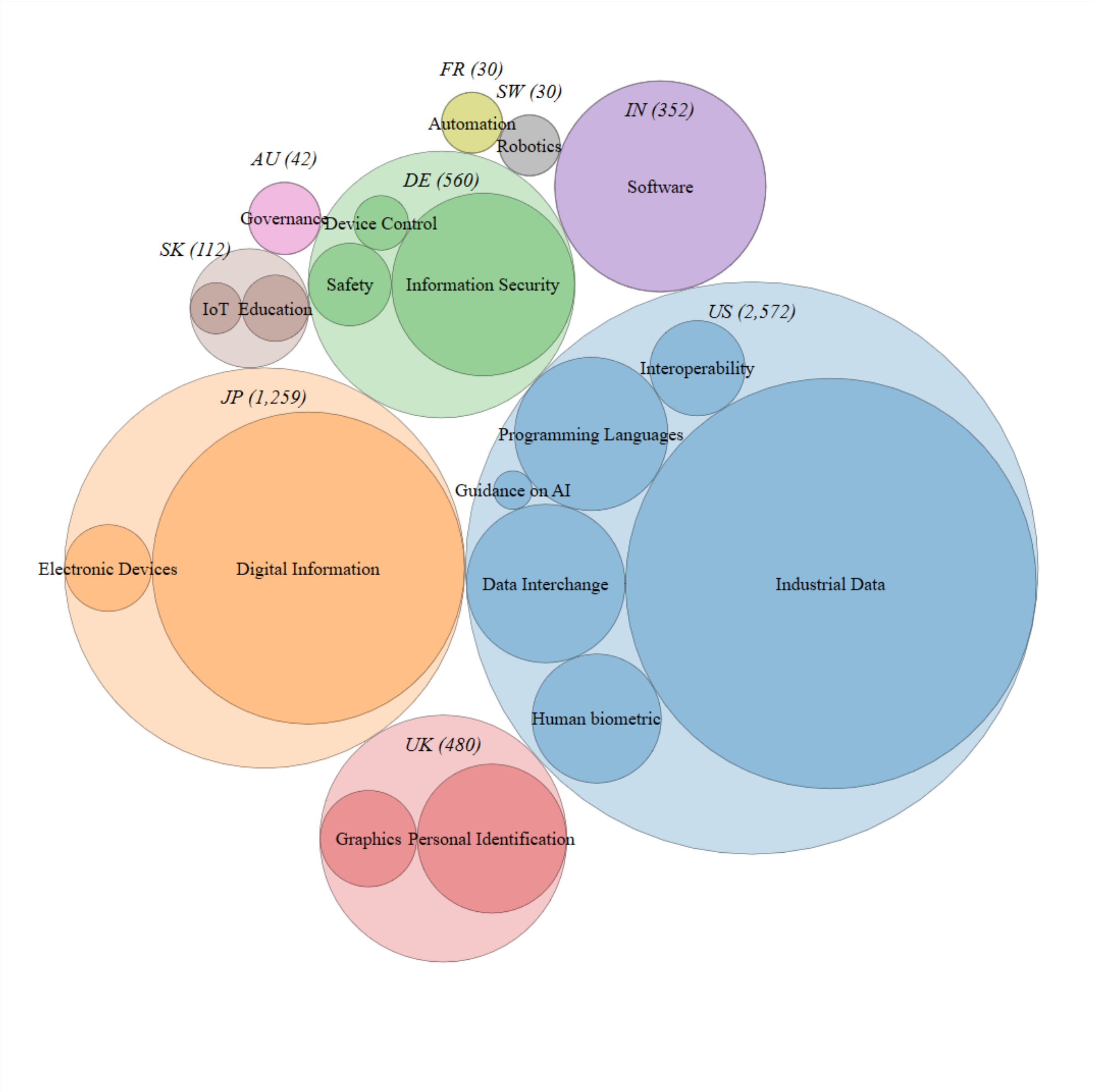


Figure 3. **ISO Committee and Secretariat Involvement by Country**

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.

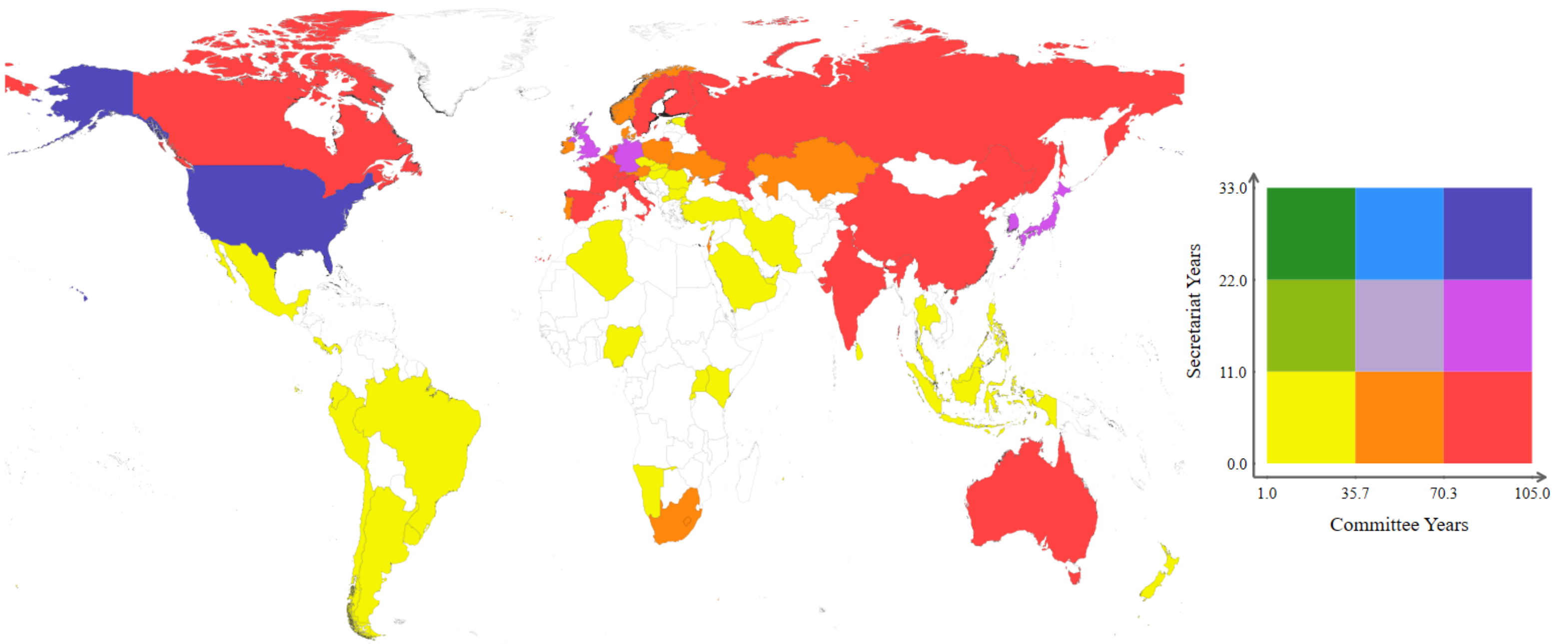


Figure 4. **The Rise of AI Standards**

The figure illustrates the types of AI standards published by secretariats within the International Organization for Standardization (ISO). *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 like MPEG and acoustics. Detailed descriptions are presented in Table 2's caption.

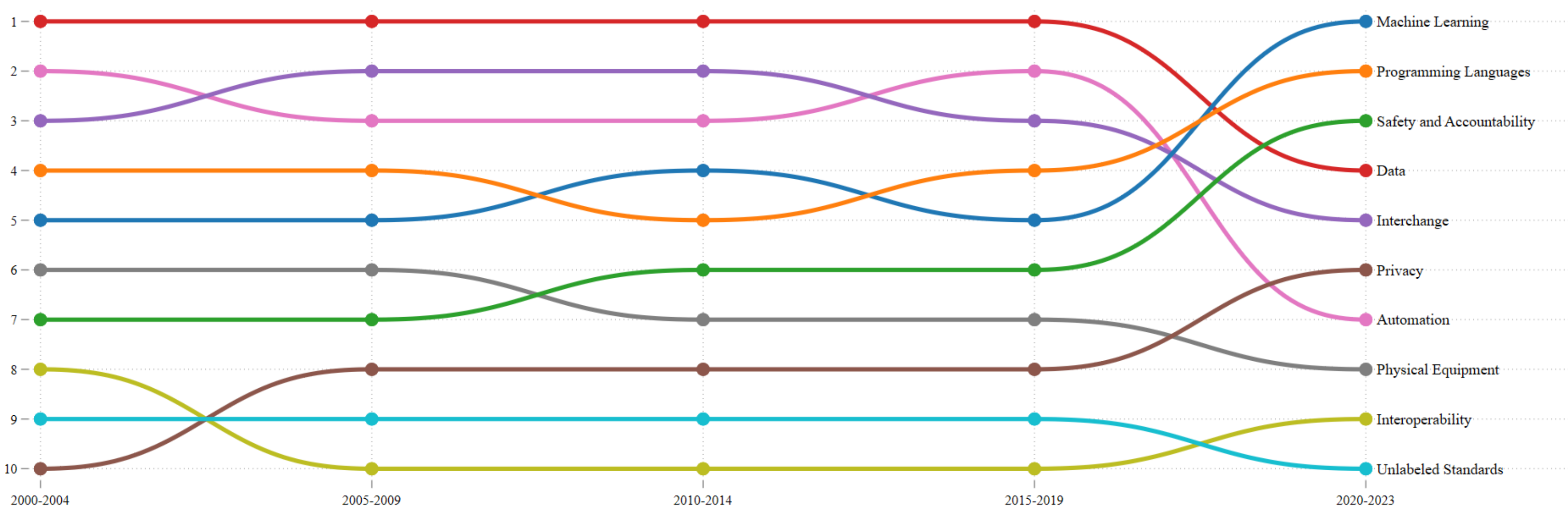


Figure 5. **Involvement in Machine Learning and Ethical AI Standards by Country**

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.

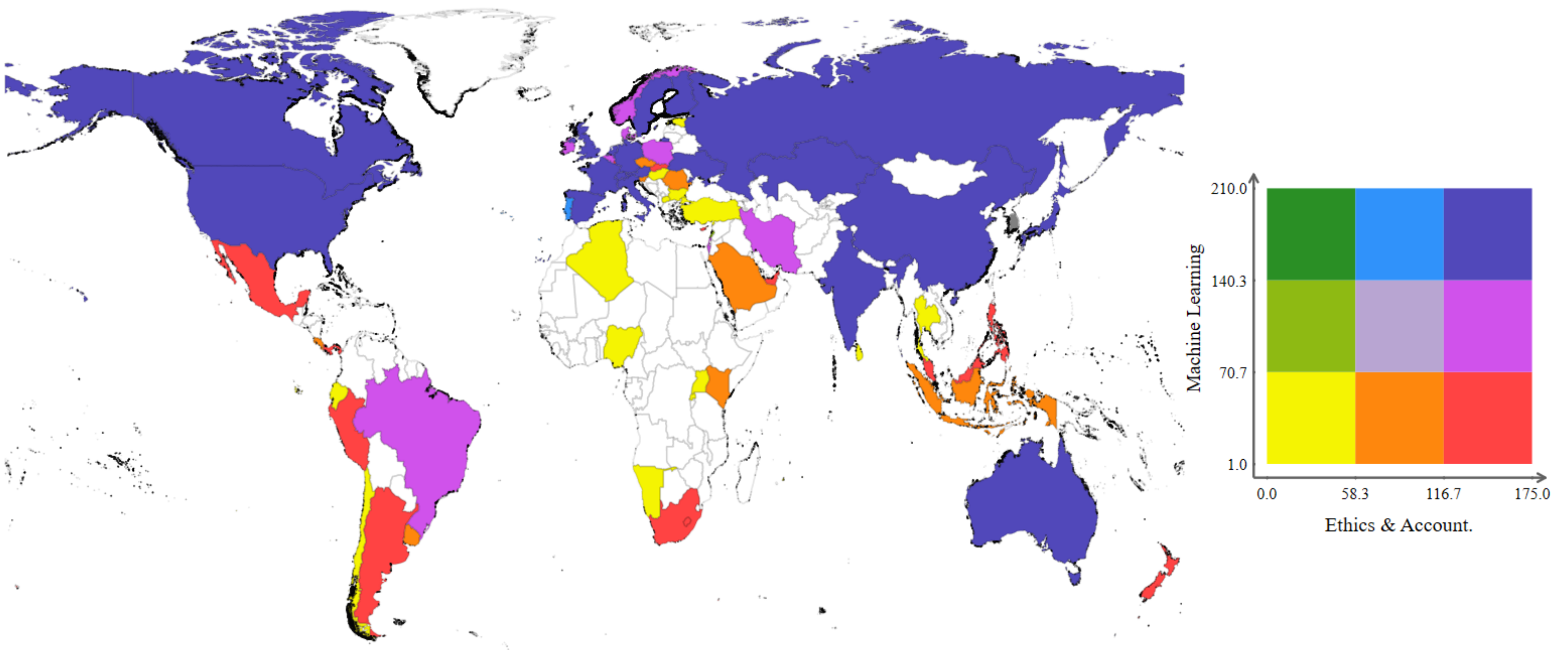


Figure 6. **Committee-Level Instruments: UNSC Rotations and ISO Committees**

This figure displays the percentage of rotating United Nations Security Council (UNSC) members in AI committees of permanent UNSC member countries 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.

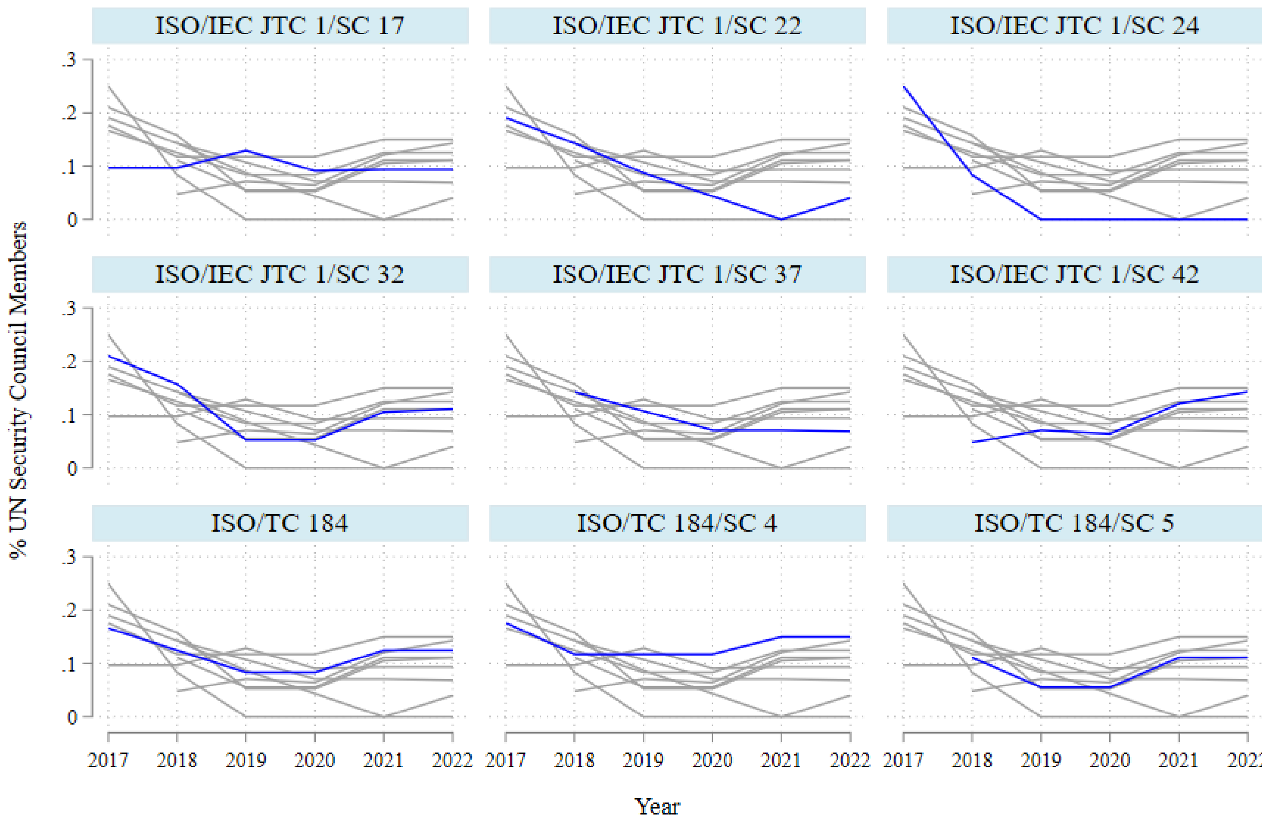


Figure 7. **Effect Dynamics Based on Valuation Regressions**

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 5.3.1.

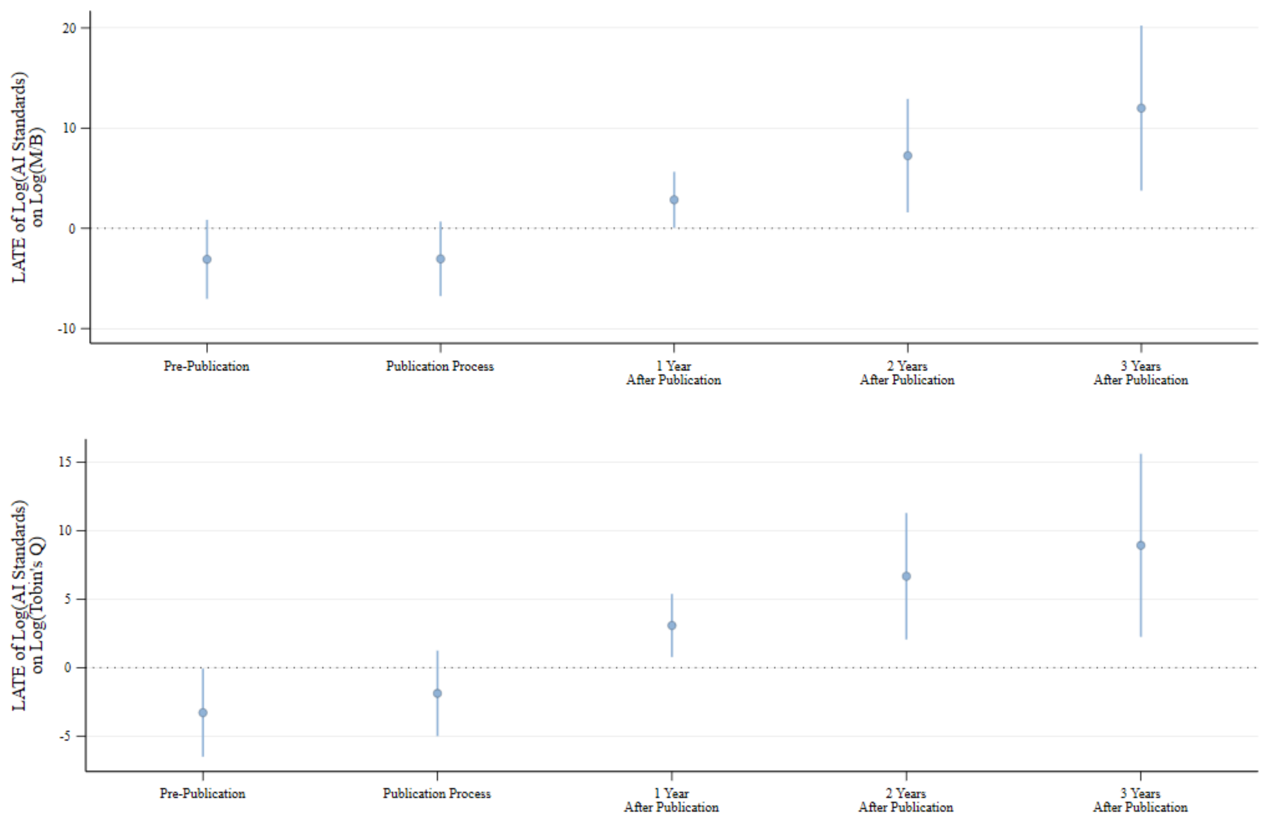
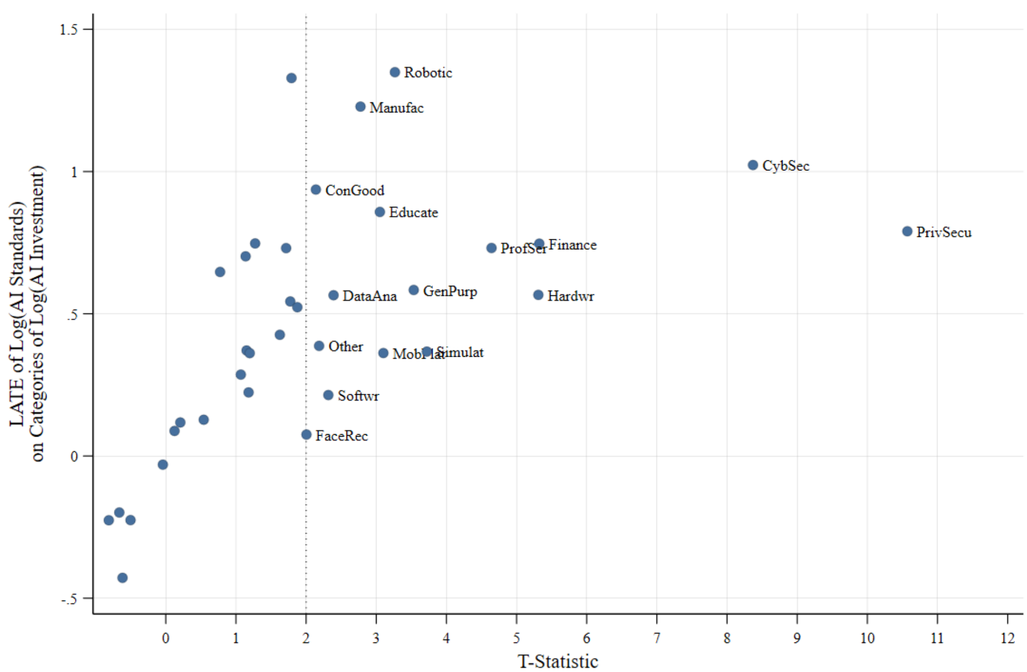


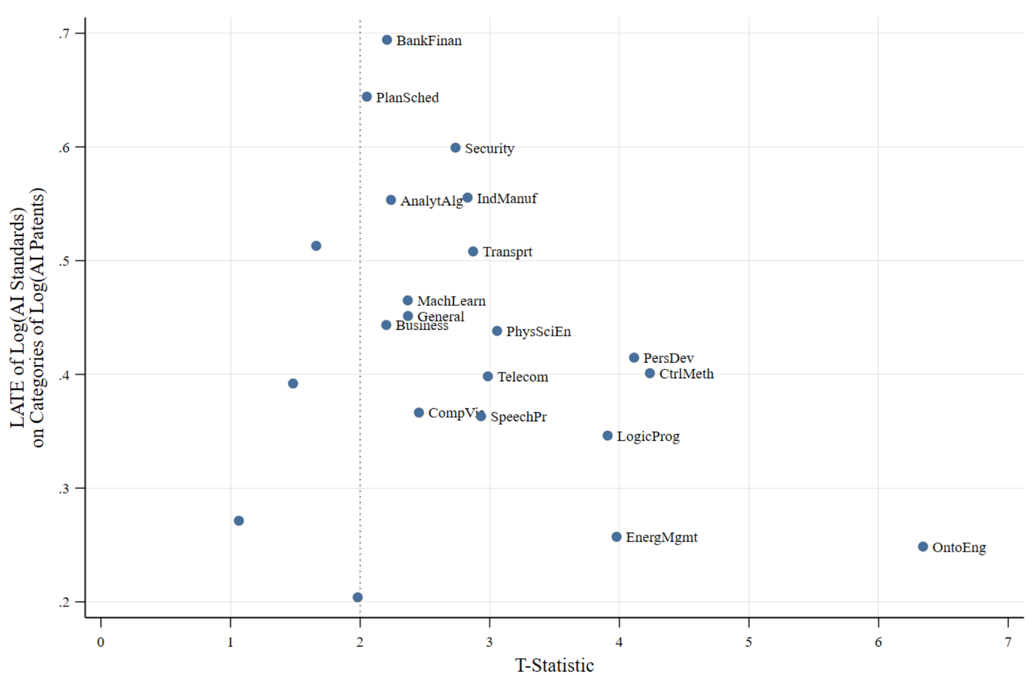
Figure 8. **The Influence of AI Standards on Categories of AI Investment and AI Patents**

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 (6), 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 Section C.

Panel A: Effect Heterogeneity Across AI Investment Categories



Panel B: Effect Heterogeneity Across AI Patent Categories



References

Acemoglu, Daron, "Harms of AI," Technical Report, National Bureau of Economic Research 2021.

__ **and Pascual Restrepo**, "Artificial intelligence, automation, and work," in "The economics of artificial intelligence: An agenda," University of Chicago Press, 2018, pp. 197–236.

Aghion, Philippe, Benjamin F Jones, and Charles I Jones, "Artificial intelligence and economic growth," in "The economics of artificial intelligence: An agenda," University of Chicago Press, 2018, pp. 237–282.

Agrawal, Ajay, John McHale, and Alexander Oettl, "Finding needles in haystacks: Artificial intelligence and recombinant growth," in "The economics of artificial intelligence: An agenda," University of Chicago Press, 2018, pp. 149–174.

__ **, Joshua Gans, and Avi Goldfarb**, "Economic policy for artificial intelligence," *Innovation policy and the economy*, 2019, *19* (1), 139–159.

__ **,** __ **, and** __ , *The economics of artificial intelligence: An agenda*, University of Chicago Press, 2019.

Altonji, Joseph, Todd Elder, and Christopher R. Taber, "An Evaluation of Instrumental Variable Strategies for Estimating the Effects of Catholic Schooling," *Journal of Human Resources*, 2005, *40* (4), 791–821.

Angrist, Joshua, Victor Lavy, and Analia Schlosser, "Multiple Experiments for the Causal Link between the Quantity and Quality of Children," *Journal of Labor Economics*, 2010, *28* (4), 773–824.

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson, "Artificial intelligence, firm growth, and product innovation," *Firm Growth, and Product Innovation (November 9, 2021)*, 2021.

Baron, J. and Julia Schmidt, "Technological Standardization, Endogenous Productivity and Transitory Dynamics," Working papers, Banque de France 2019.

Baron, Justus and Daniel F. Spulber, "Technology Standards and Standard Setting Organizations: Introduction to the Searle Center Database," *Journal of Economics & Management Strategy*, 2018, *27* (3), 462–503.

__ **and Kirti Gupta**, "Unpacking 3GPP standards," *Journal of Economics & Management Strategy*, 2018, *27* (3), 433–461.

Blind, Knut and Maximilian von Laer, "Paving the path: drivers of standardization participation at ISO," *The Journal of Technology Transfer*, 2022, pp. 1–20.

__ **, Sören S Petersen, and Cesare AF Riillo**, "The impact of standards and regulation on innovation in uncertain markets," *Research policy*, 2017, *46* (1), 249–264.

Bonnefon, Jean-François, Azim Shariff, and Iyad Rahwan, "The social dilemma of autonomous vehicles," *Science*, 2016, *352* (6293), 1573–1576.

Caliskan, Aylin, Joanna J. Bryson, and Arvind Narayanan, "Semantics derived automatically from language corpora contain human-like biases," *Science*, 2017, *356* (6334), 183–186.

Canayaz, Mehmet, Ilja Kantorovitch, and Roxana Mihet, "Consumer Privacy and Value of Consumer Data," *Working Paper*, 2022.

Cao, Sean, Wei Jiang, Baozhong Yang, and Alan L Zhang, "How to talk when a machine is listening?: Corporate disclosure in the age of AI," Technical Report, National Bureau of Economic Research 2020.

__ , __ , **Junbo L Wang, and Baozhong Yang**, "From man vs. machine to man+ machine: The art and AI of stock analyses," Technical Report, National Bureau of Economic Research 2021.

Chen, Long, Yadong Huang, Shumiao Ouyang, and Wei Xiong, "Data Privacy and Digital Demand," 2022.

Cheng, H. K., Daniel Sokol, and X. Zang, "The Rise of Empirical Online Platform Research in the New Millennium," *Journal of Economics Management Strategy*, 2023, pp. 1–36.

Chiao, Benjamin, Josh Lerner, and Jean Tirole, "The rules of standard-setting organizations: An empirical analysis," *The RAND Journal of Economics*, 2007, *38* (4), 905–930.

Clark, Jack and Gillian K Hadfield, "Regulatory markets for AI safety," *arXiv preprint arXiv:2001.00078*, 2019.

Cockburn, Iain M, Rebecca Henderson, and Scott Stern, *The impact of artificial intelligence on innovation*, Vol. 24449, National bureau of economic research Cambridge, MA, USA, 2018.

Cong, Lin William, Beibei Li, and Qingquan Tony Zhang, "Alternative data in fintech and business intelligence," *The Palgrave Handbook of FinTech and Blockchain*, 2021, pp. 217–242.

__ **, Danxia Xie, and Longtian Zhang**, "Knowledge accumulation, privacy, and growth in a data economy," *Management Science*, 2021, *67* (10), 6480–6492.

Cuéllar, Mariano-Florentino, Benjamin Larsen, Yong Suk Lee, and Michael Webb, "Does Information About AI Regulation Change Manager Evaluation of Ethical Concerns and Intent to Adopt AI?," *The Journal of Law, Economics, and Organization*, 2022.

Dixit, Avinash K and Robert S Pindyck, *Investment under uncertainty*, Princeton university press, 1994.

D'Acunto, Francesco, Nagpurnanand Prabhala, and Alberto G Rossi, "The promises and pitfalls of robo-advising," *The Review of Financial Studies*, 2019, *32* (5), 1983–2020.

Farboodi, Maryam and Laura Veldkamp, "Data and markets," *Annual Review of Economics*, 2022, *15.*

Farrell, Joseph and Timothy Simcoe, "Choosing the rules for consensus standardization," *The RAND Journal of Economics*, 2012, *43* (2), 235–252.

Foucart, Renaud and Qian Cher Li, "The role of technology standards in product innovation: Theory and evidence from UK manufacturing firms," *Research Policy*, 2021, *50* (2), 104157.

Goldstein, Itay, Chester S Spatt, and Mao Ye, "Big data in finance," *The Review of Financial Studies*, 2021, *34* (7), 3213–3225.

Grenadier, Steven R, "Option exercise games: An application to the equilibrium investment strategies of firms," *The Review of Financial Studies*, 2002, *15* (3), 691–721.

__ **and Neng Wang**, "Investment under uncertainty and time-inconsistent preferences," *Journal of Financial Economics*, 2007, *84* (1), 2–39.

Großmann, Anne-Marie, Ellen Filipović, and Luisa Lazina, "The strategic use of patents and standards for new product development knowledge transfer," *R&D Management*, 2016, *46* (2), 312–325.

Gutierrez, Germán and Thomas Philippon, "Investmentless Growth: An Empirical Investigation," *Brookings Papers on Economic Activity*, 2017, *48* (2), 89–190.

Hidalgo, Cesar A., Ricardo Hausmann, and Partha Sarathi Dasgupta, "The Building Blocks of Economic Complexity," *Proceedings of the National Academy of Sciences of the United States of America*, 2009, *106* (26), 10570–10575.

Kuziemko, Ilyana and Eric Werker, "How Much Is a Seat on the Security Council Worth? Foreign Aid and Bribery at the United Nations," *Journal of Political Economy*, 2006, *114* (5), 905–930.

Lee, David S., Justin McCrary, Marcelo J. Moreira, and Jack Porter, "Valid t-Ratio Inference for IV," *American Economic Review*, October 2022, *112* (10), 3260–90.

Lerner, Josh and Jean Tirole, "A model of forum shopping," *American economic review*, 2006, *96* (4), 1091–1113.

__ **and** __ , "A better route to tech standards," *Science*, 2014, *343* (6174), 972–973.

__ **and** __ , "Standard-essential patents," *Journal of Political Economy*, 2015, *123* (3), 547–586.

Liu, Zhuang, Michael Sockin, and Wei Xiong, "Data Privacy and Algorithmic Inequality," Technical Report, National Bureau of Economic Research 2023.

Marcus, Alfred and Eitan Naveh, "How a new rule is adjusted to context: Knowledge creation following the implementation of the ISO 9000 quality standard," *International Journal of Organizational Analysis*, 2005.

Mirtsch, Mona, Jan Kinne, and Knut Blind, "Exploring the adoption of the international information security management system standard ISO/IEC 27001: a web mining-based analysis," *IEEE Transactions on Engineering Management*, 2020, *68* (1), 87–100.

O'Leary, Daniel E, "Artificial intelligence and big data," *IEEE intelligent systems*, 2013, *28* (2), 96–99.

Pelkmans, Jacques, "The GSM standard: explaining a success story," *Journal of European Public Policy*, 2001, *8* (3), 432–453.

Peres, Ricardo Silva, Xiaodong Jia, Jay Lee, Keyi Sun, Armando Walter Colombo, and Jose Barata, "Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook," *IEEE access*, 2020, *8*, 220121–220139.

Rajan, Raghuram G. and Luigi Zingales, "Financial Dependence and Growth," *American Economic Review*, 1998, *88* (3), 559–586.

Rossi, Alberto G and Stephen P Utkus, "Who benefits from robo-advising? Evidence from machine learning," *Evidence from Machine Learning (March 10, 2020)*, 2020.

Simcoe, Timothy, "Standard setting committees: Consensus governance for shared technology platforms," *American Economic Review*, 2012, *102* (1), 305–336.

Tassey, Gregory, *The roles and impacts of technical standards on economic growth and implications for innovation policy*, NOW Publishers Incorporated, 2017.

Wellman, Michael P and Uday Rajan, "Ethical issues for autonomous trading agents," *Minds and Machines*, 2017, *27*, 609–624.

Windrum, Paul, "Leveraging technological externalities in complex technologies: Microsoft's exploitation of standards in the browser wars," *Research Policy*, 2004, *33* (3), 385–394.

Internet Appendix

for

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

April 29, 2024

A Theory

To illustrate how AI standards affect firm investment, we introduce a stylized model featuring delayed investment due to 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 stocks of domain-n, type-i AI technology at the start 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

$$AI_t \equiv \sum_{n}^{N} \left(\tilde{s}_t^{n,A} F(AI_t^{n,A}) + \tilde{s}_t^{n,B} F(AI_t^{n,B}) \right) \tag{7}$$

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 $F'(0) = \infty$ 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 is 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

$$Y_t = AI_t^{\alpha} K_t^{1-\alpha} D(1 - \tilde{\tau}_t), \tag{8}$$

where $\tilde{\tau}_t \in [0,1)$. 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, Jia, Lee, Sun, Colombo and Barata, 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 partically 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

$$\begin{aligned}
\max_{\{I^{n,A}_{AI,t}, I^{n,B}_{AI,t}, I_{K,t}\}_{t=j}^{\infty}} \mathbb{E}\sum_{t=j}^{\infty}\beta^{t-1}\{AI_t^{\alpha}K_t^{1-\alpha}D(1-\tilde{\tau}_t) - \sum_{n=1}^{N}\left(CI_n(I^{n,A}_{AI,t}) + CI_n(I^{n,B}_{AI,t})\right) - CI_K(I_{K,t})\} \\
s.t. (\text{AI factor})\ AI_t = \sum_{n}^{N}\left(\tilde{s}_t^{n,A}F(AI_t^{n,A}) + \tilde{s}_t^{n,B}F(AI_t^{n,B})\right) \\
(\text{capital dynamics})\ AI_t^i = AI_{t-1}^{n,i} + I^{n,i}_{AI,t},\ \text{for } i = A, B, n \in \{1,2,...,N\}. \\
K_t = K_{t-1} + I_{K,t}. \\
(\text{costly disinvestment})\ CI_n(I) = \begin{cases} I & \text{if } I \geq 0 \\ C^n I & \text{if } I < 0 \end{cases} \\
CI_K(I) = \begin{cases} I & \text{if } I \geq 0 \\ C^K I & \text{if } I < 0 \end{cases}
\end{aligned} \tag{9}$$

where $\beta \in (0,1)$ is the discount factor, and the initial capital stocks are $AI_0^{n,i} = K_0 = 0$, for $i = A, B$, $n \in \{1,2,...,N\}$.[27] For simplicity, we assume that $\max\{C^n, C^k\} < l$ for all $n = 1,2,...,N$. That is, the cost of disinvestment is sufficiently large.[28]

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 $\lambda \in [0,1]$. We assume the publication event takes place at the end of period T, after period T investment has been made and period T

[27]For simplicity, we assume zero depreciation rate. The qualitative results hold as long as the depreciation rate is not too high.
[28]Under this assumption, the firm does not reduce the investment in the unendorsed AI technology if a technological standard is published, as such disinvestment is too costly.

profit has been realized. That is, the publication of standards affects the production in period $T+1$ and onwards.[29]

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.[30] 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 standards. 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 standards-endorsed technology, as the wider adoption of the technology after standards 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.[31]

To capture effect of the publication of technological AI standard, we assume that conditional on (1) the arrival of the 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 being publishes.

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 $t > T$.

[29]This assumption does not affect the qualitative result.

[30]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 6, where we separately consider the impact of technological and ethical/privacy standards publication on firm investment.

[31]At the heart of the network effect argument is the importance of "interoperability" in AI ecosystem. This is motivated by the observation that interoperability is essential to the thriving of any information technologies. The bifurcation of productivity is exacerbated by the following two factors that further enhance the productivity of the endorsed technology: (i) technological standards often codify the details of the endorsed technology and provide a clear blueprint for the implementation, and (ii) technological standards enhance the interoperability of the endorsed technology by creating a compatible ecosystem that surrounds and supports this technology.

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 $t \le T$ 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 τ is assumed to be an 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 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 The firm understands the distribution of standards publication, but does not know ahead of time when and what standards will be published. That is, there is uncertainty about the future productivity of the two AI technologies before the publication date, while the publication of the standards resolves that uncertainty. Consequently, there is an option value of delaying investment, because the firm wants to hold off its partially irreversible investment decision until the publication of the standards reveals the general productivity of AI technology and which AI technology is relatively more productive.

Intuitively, more publication of technological standards resolves uncertainty of more AI domains, potentially boosting more investment post-publication. More publication of privacy and ethical standards, in contrast, imposes stronger restrictions on productivity, leading to larger disinvestment post-publication. The next proposition formalizes this insight. Denote the net total AI investment in period $T+1$, across all domains and types of AI technologies, as

$$I_{AI,T+1} = \sum_{n}^{N} \left(I^{n,A}_{AI,T+1} + I^{n,B}_{AI,T+1} \right), \tag{10}$$

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. Then the firm's net total AI investment post-publication, $I_{AI,T+1}$, as defined in (10), 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. Then the firm's net total AI investment $I_{AI,T+1}$ post-publication 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 also only 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 $D = 1$. Assume $\lambda = 1$, that is, the firm knows for sure that the publication event will arrive at the end of the first period, but the firm does not know which type of standards and how many standards will be published.

Figure A1 plots the equilibrium investment in period 2, which is the period immediately after the publication event. Consistent with Proposition 1, if the standards published are technological standards, then the investment after publication increases in the number of standards published for both AI investment $I_{AI,2}$ and for physical investment in $I_{K,2}$. In particular, as the number of technological standards published increases from one to two, $I_{AI,2}$ increases from 14.2 to 15.2, while $I_{K,2}$ increases from 27.3 to 29.1. On the contrary, if the standards published are privacy and ethical standards, then the investment after publication decreases in the number of standards published for both AI investment $I_{AI,2}$ and for physical investment in $I_{K,2}$. As the number of privacy and ethical standards published increases from one to two, $I_{AI,2}$ decreases from -3.9 to -24.9, while $I_{K,2}$ decreases from -8.5 to -50.6.

Next, we decompose the total AI investment plotted in Figure A1 into investment regarding individual AI technologies. Consider first the scenario where only one technological standard is published. In period 2, 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 receives an investment of 3.3. Next, consider the case where both domains see publications of technological standards. In period 2, 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.

A.2 Mathematical Proofs

Proof of Proposition 1

Proof. First, consider the continuation decision problem in period $T+1$, when either a subset $\mathcal{M} \subset \{1, \ldots, N\}$ of technological 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 $n \in \mathcal{M}$. The problem writes:

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

where $\tilde{s}^{n,j}=\overline{s}^n$ if $j=A$ and $n\in\mathcal{M}$, $\tilde{s}^{n,j}=\underline{s}^n$ if $j=B$ and $n\in\mathcal{M}$, $\tilde{s}^{n,j}=s^n$ if $n\notin\mathcal{M}$. 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:

$$\begin{aligned} c_t^{n,j}-\beta c_{t+1}^{n,j} &= D(1-\tilde{\tau}_t)\alpha\tilde{s}^{n,j}F'(AI_t^{n,j})AI_t^{\alpha-1}K_t^{1-\alpha}, && (11)\\ c_t^K-\beta c_{t+1}^K &= D(1-\tilde{\tau}_t)(1-\alpha)AI_t^{\alpha}K_t^{-\alpha}. && (12)\end{aligned}$$

Let:

$$\underline{AI}_t^{n,j}\equiv(F')^{-1}\left(\frac{1-\beta}{D(1-\tilde{\tau}_t)\alpha\tilde{s}^{n,j}AI_t^{\alpha-1}K_t^{1-\alpha}}\right),\qquad \overline{AI}_t^{n,j}\equiv(F')^{-1}\left(\frac{C^n(1-\beta)}{D(1-\tilde{\tau}_t)\alpha\tilde{s}^{n,j}AI_t^{\alpha-1}K_t^{1-\alpha}}\right),\tag{13}$$

$$\underline{K}_t\equiv\left(\frac{1-\beta}{D(1-\tilde{\tau}_t)(1-\alpha)AI_t^{\alpha}}\right)^{-1/\alpha},\qquad \overline{K}_t\equiv\left(\frac{C^K(1-\beta)}{D(1-\tilde{\tau}_t)(1-\alpha)AI_t^{\alpha}}\right)^{-1/\alpha}.\tag{14}$$

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 (11) 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 (11) and (12) imply:

$$\begin{aligned}(D(1-\tilde{\tau}_t))^{\frac{1}{\alpha}}\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}F'(AI_t^{n,j}) &= \frac{c_t^{n,j}-\beta c_{t+1}^{n,j}}{(c_t^K-\beta c_{t+1}^K)^{\frac{\alpha-1}{\alpha}}}\leqslant\frac{c_{t+1}^{n,j}-\beta c_{t+2}^{n,j}}{(c_{t+1}^K-\beta c_{t+2}^K)^{\frac{\alpha-1}{\alpha}}}\\ &= (D(1-\tilde{\tau}_t))^{\frac{1}{\alpha}}\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}F'(AI_{t+1}^{n,j})<(D(1-\tilde{\tau}_t))^{\frac{1}{\alpha}}\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}F'(AI_t^{n,j}),\end{aligned}$$

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 (11), 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 (12), 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, (11) and (12) imply $AI_{T+1}^{n,j}$, AI_{T+1} and K_{T+1} as solution to the following system:

$$AI_{T+1}^{n,j} = \max\left\{\min\left\{AI_T^{n,j}, \overline{AI}_{T+1}^{n,j}\right\}, \underline{AI}_{T+1}^{n,j}\right\}, \ \forall\ n, j, \tag{15}$$

$$K_{T+1} = \max\left\{\min\left\{K_T, \overline{K}_{T+1}\right\}, \underline{K}_{T+1}\right\}, \tag{16}$$

$$AI_{T+1} = \sum_{n,j} \tilde{s}^{n,j} F(AI_{T+1}^{n,j}). \tag{17}$$

Now consider the comparative statics on τ, conditional on $\tilde{\tau}_t = \tau$ after publication of privacy/ethical standards. With an increase in τ that is due to higher m_e, suppose $AI_{T+1}^{n,j}$ strictly increases for some (n, j). Then $\underline{AI}_{T+1}^{n,j}$ and $\overline{AI}_{T+1}^{n,j}$ must strictly increase for all (n, j), and as a result, AI_{T+1} strictly increases according to (17). Also, $\frac{K_{T+1}}{AI_{T+1}}$ must strictly increase according to (13) and (15). Since (14) implies that $\frac{\underline{K}_{T+1}}{AI_{T+1}}$ 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, $AI_{T+1}^{n,j}$ decreases, and K_{T+1} decreases from (14) and (16). Since capital stock prior to publication does not change with τ, we show that investment in both AI and K decreases.

To analyze the comparative statics on the set $\mathcal{M}$ conditional on the publication of technological standards, we need to study the properties of $AI_T^{n,j}$ and K_T, before the announcement. Consider the problem in period 1, where the firm just started with no capital:

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

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:

$$c_t^{n,j} - \beta(1-\lambda)c_{t+1}^{n,j} - \beta\lambda\mathbb{E}c_{T+1}^{n,j} = D\alpha s^n F'(AI_t^{n,j}) AI_t^{\alpha-1} K_t^{1-\alpha}, \tag{18}$$

$$c_t^K - \beta(1-\lambda)c_{t+1}^K - \beta\lambda\mathbb{E}c_{T+1}^K = D(1-\alpha) AI_t^{\alpha} K_t^{-\alpha}. \tag{19}$$

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:

$$AI_T^{n,j} = (F')^{-1}\left(\frac{1-\beta+\beta\lambda(1-\mathbb{E}c_{T+1}^{n,j})}{D\alpha s^n AI_T^{\alpha-1} K_T^{1-\alpha}}\right), \tag{20}$$

$$K_T = \left(\frac{1-\beta+\beta\lambda(1-\mathbb{E}c_{T+1}^K)}{D(1-\alpha) AI_T^{\alpha}}\right)^{-1/\alpha}, \tag{21}$$

$$AI_T = \sum_{n,j} s^n F(AI_T^{n,j}). \tag{22}$$

Now consider the change of capital stocks from period T to $T+1$, after a set $\mathcal{M}$ of technology standards are published but no ethical standard published. Suppose $AI_{T+1} = AI_T$, then $K_{T+1} \geqslant K_T$, $\underline{AI}^{n,A}_{T+1} > AI^{n,A}_T$ and $\overline{AI}^{n,B}_{T+1} > AI^{n,B}_T$ for $n \in \mathcal{M}$, $\underline{AI}^{n,j}_{T+1} \geqslant AI^{n,j}_T$ for $n \notin \mathcal{M}$, $j = A, B$. Therefore, $AI_{T+1} > AI_T$, a contradiction. Suppose instead $AI_{T+1} < AI_T$, then there exists (n, j) such that $\overline{AI}^{n,j}_{T+1} < \overline{AI}^{n,j}_T$, which means $\frac{K_{T+1}}{AI_{T+1}} < \frac{K_T}{AI_T}$ by (13). However, (14) requires that $\frac{\underline{K}_{T+1}}{AI_{T+1}} \geqslant \frac{K_T}{AI_T}$ and $\frac{\overline{K}_{T+1}}{AI_{T+1}} \geqslant \frac{\overline{K}_T}{AI_T}$, and therefore $\frac{K_{T+1}}{AI_{T+1}} \geqslant \frac{K_T}{AI_T}$, a contradiction. Therefore, we must have $AI_{T+1} > AI_T$ and $\underline{K}_{T+1} > K_T$. This means $K_{T+1} = \underline{K}_{T+1}$, and $\frac{K_{T+1}}{AI_{T+1}} > \frac{K_T}{AI_T}$. As a result, $\underline{AI}^{n,A}_{T+1} > AI^{n,A}_T$ and $\overline{AI}^{n,B}_{T+1} > AI^{n,B}_T$ for $n \in \mathcal{M}$, $\underline{AI}^{n,j}_{T+1} \geqslant AI^{n,j}_T$ for $n \notin \mathcal{M}$, $j = A, B$. Therefore, $\sum_{n,j} AI^{n,j}_{T+1} > \sum_{n,j} AI^{n,j}_T$ and $K_{T+1} > K_T$.

Finally, consider the effect of adding n^* to $\mathcal{M}$ 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 $\mathcal{M}$, $K_{T+1} = \underline{K}_{T+1}$, $AI^{n,A}_{T+1} = \underline{AI}^{n,A}_{T+1}$ and $AI^{n,B}_{T+1} = \max\{\underline{AI}^{n,B}_{T+1}, AI^{n,B}_T\}$ for $n \in \mathcal{M}$, $AI^{n,A}_{T+1} = \underline{AI}^{n,j}_{T+1}$ for $n \notin \mathcal{M}$, $j = A, B$. 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 $n \notin \mathcal{M}$. As a result, $\sum_{n,j} AI^{n,j}_{T+1}$ and K_{T+1} both strictly increase with the inclusion of n^*. $\square$

B Additional Analyses

B.1 Data Description

B.1.1 Financial Variables

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 represents 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. 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 denotes the percentage of rotating United National Security Council (UNSC) Members under a given country's secretariat and zero for countries without secretariats. We manually collect this data from the UNSC website.

B.1.2 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. Safety and 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 Languages 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". Physical 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. Graphics 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". Human Related Standards refer to the standards which contain any of the following terms related to humans in their titles: “biomet", "genom", "human". Unlabeled Standards refer to the standards which do not contain any terms related to the previously defined categories (Machine Learning, Data, Safety and Accountability, Automation, Programming Languages, Interchange, Interoperability, Privacy, Physical Equipment, Graphics, IoT, Human Related) in their titles. If none of the terms are found, the standards are classified as “Unlabeled Standards".

B.1.3 Variables on AI Investments and AI Patents

Log(AI Investment) is defined as the logarithm of one plus the AI investments made in a given country in the given year. Similarly, Log(AI Patent Apps.) represents the logarithm of one plus the number of

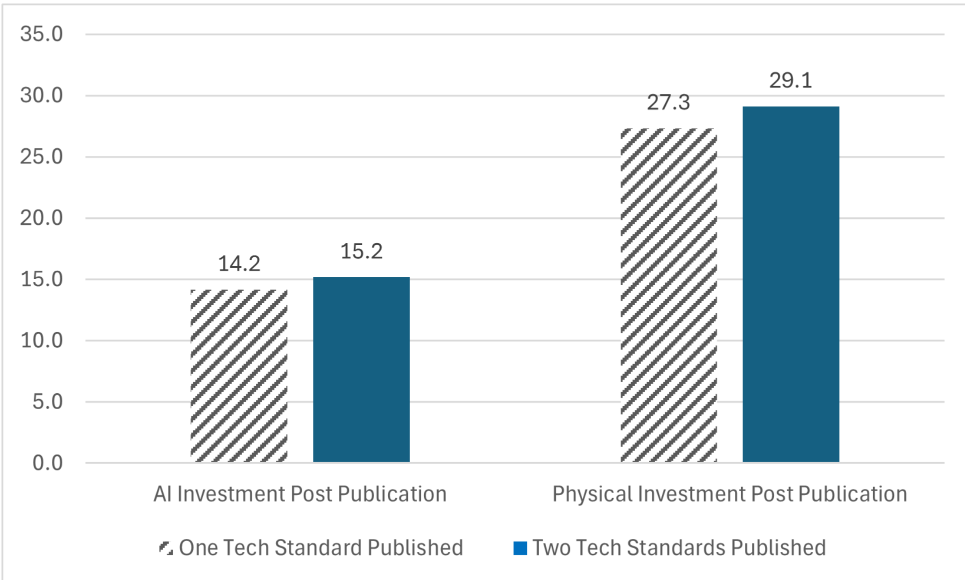
AI patent applications filed, and Log(AI Patents Granted) is the logarithm of one plus the number of AI patents granted. The dataset originates from the Center for Security and Emerging Technology (CSET). We begin with CSET's list of countries, excluding all countries with zero patent applications, grants, and investments. Data collection and description are detailed in Appendix Section C.

B.2 Additional Tables and Figures

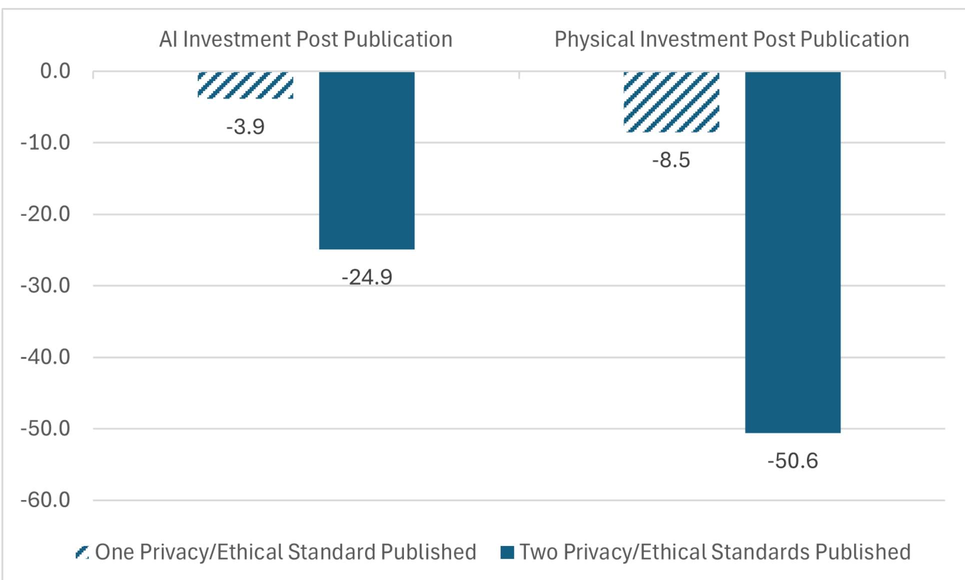
This section details our additional findings. Figure B1 illustrates the life cycle events of AI standards published from 1972 to 2023. Figure B2 represents the distribution of published standards by US secretariats between 2017 and 2022. Figure B3 examines the potential link between economic complexity Hidalgo et al. (2009) and AI committee membership. Figure B4 provides a correlation matrix for our committee-level instrumental variables.

Appendix Figure A1. Post-Publication Investment and the Number of Standards Published

(a) Post-Publication Investment: Technological Standards



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



Appendix Table B1. **Scopes and Activities of AI Standardization Committees**

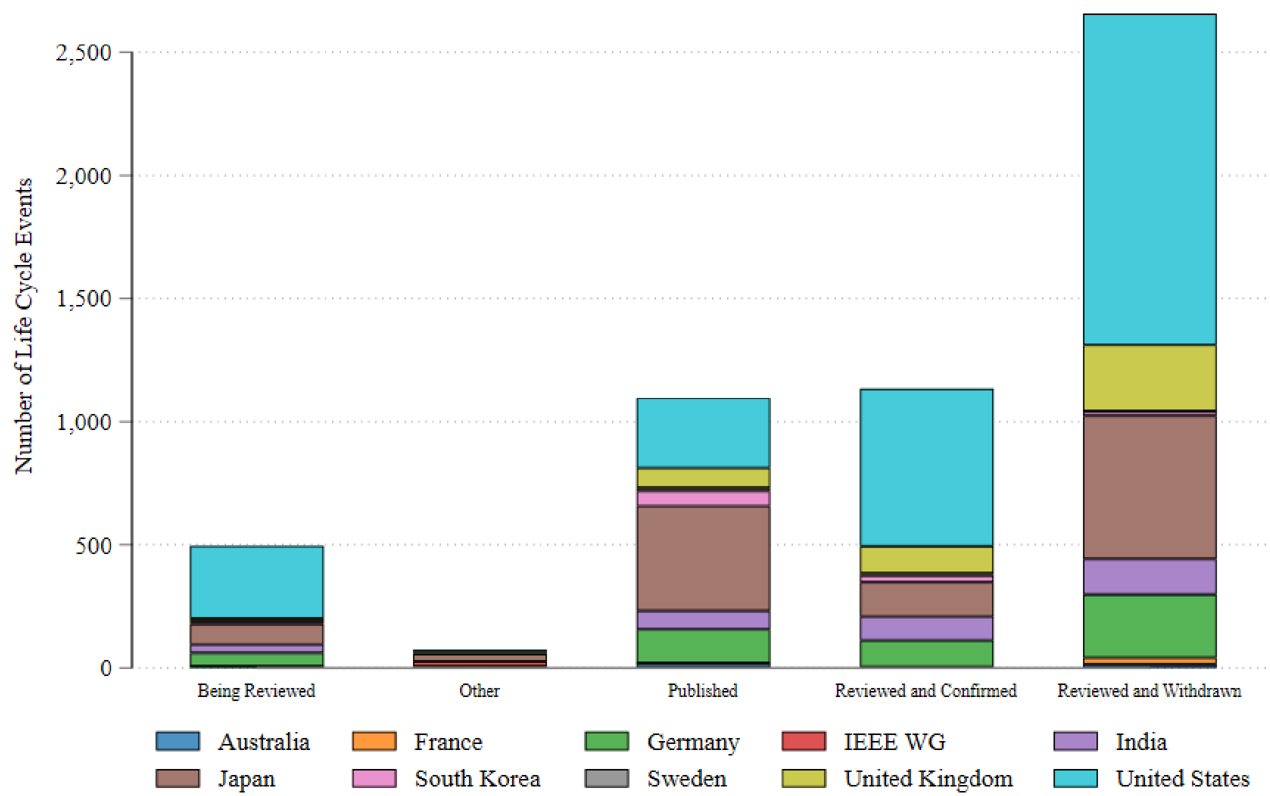
This table provides an overview of the activities and scopes of AI standardization committees, with the names of the secretariats associated with each committee listed in parentheses and in italic format. The committees (represented in bold) are derived from "U.S. Leadership in AI: A Plan for Federal 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 semantics. 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.

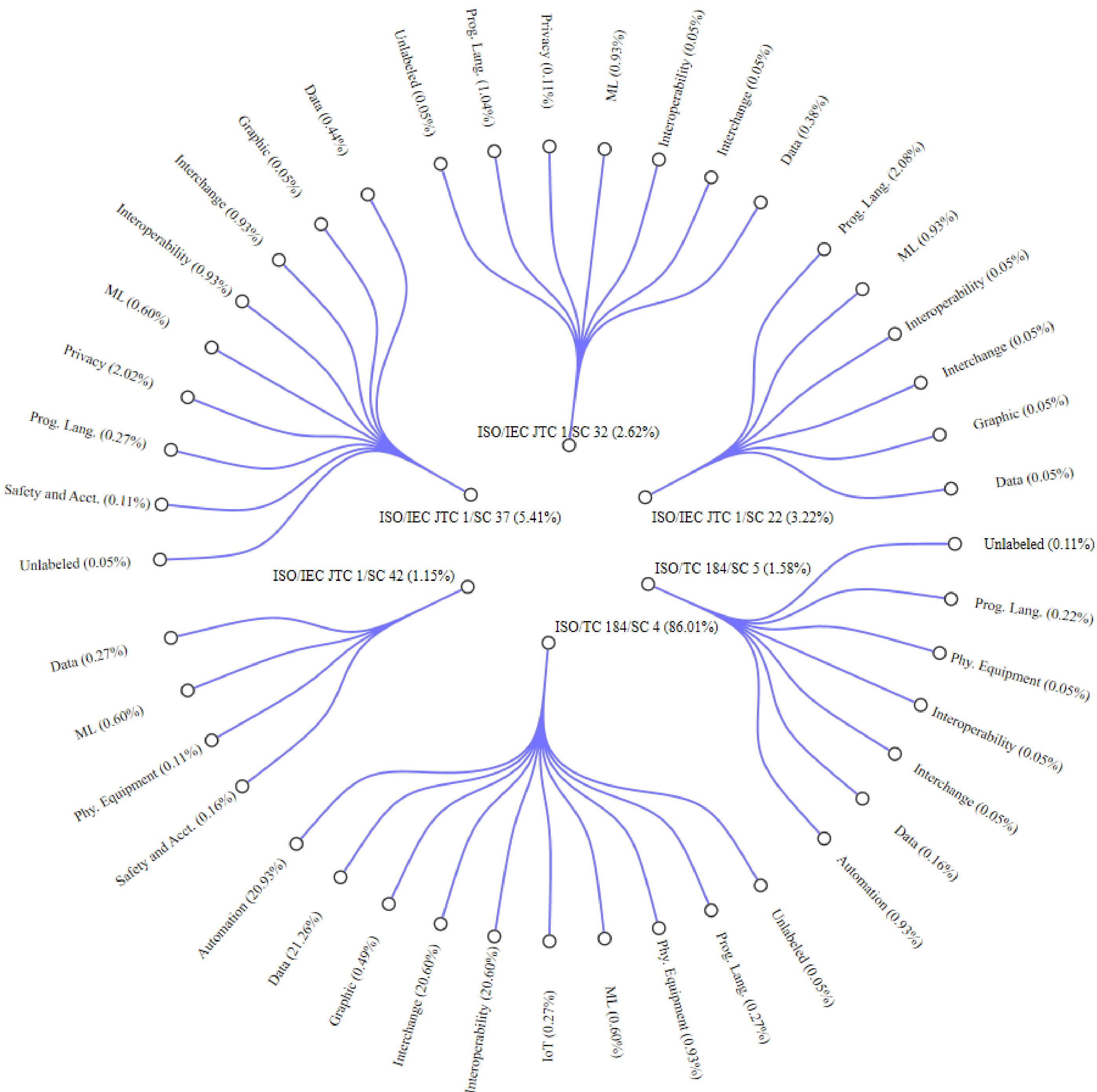
Appendix Figure B1. **The Life Cycle of Standards Published by AI-Critical Committees**

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.



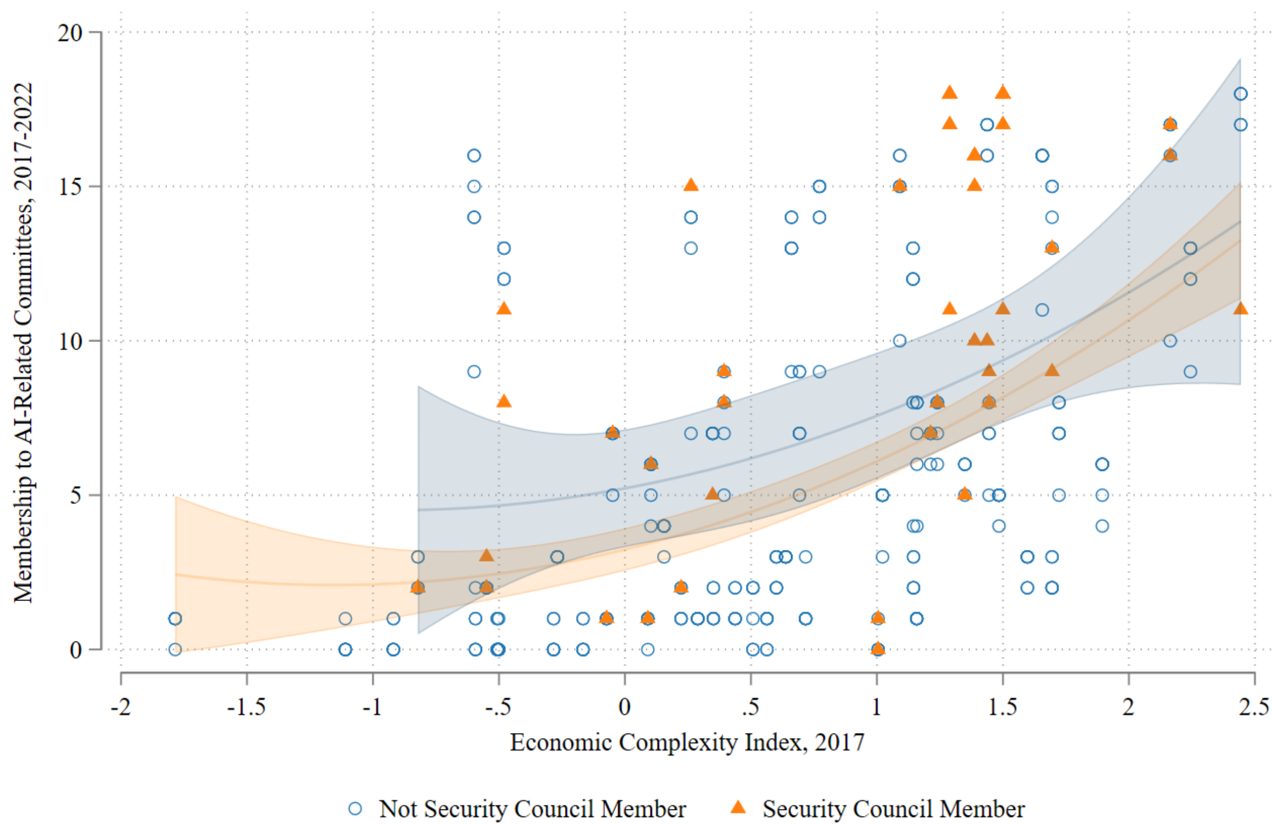
Appendix Figure B2. **Categories of Standards Published by U.S.-lead AI Committees**

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 types of standards included in the figure are as in Table B1.



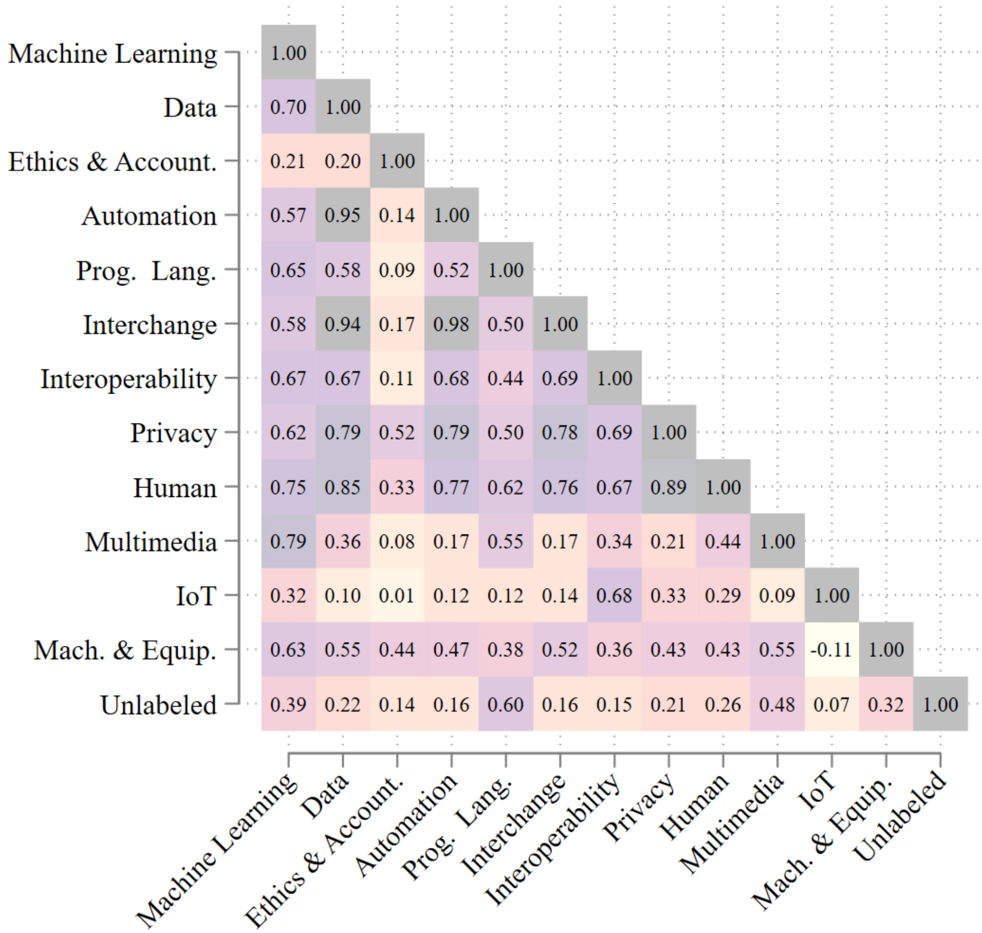
Appendix Figure B3. **Do Rotating UN Security Council Members Target AI Committees?**

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. .



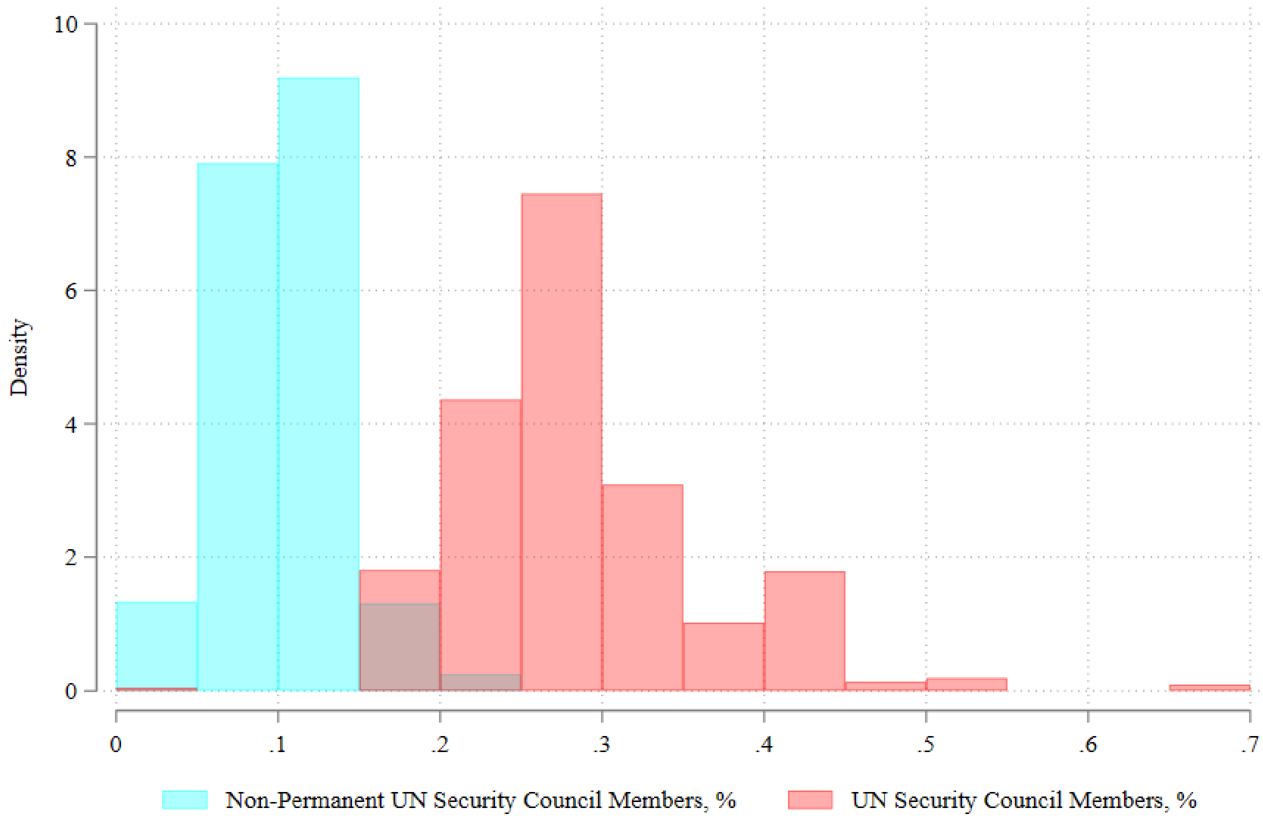
Appendix Figure B4. **Covariance Matrix: Interplay of Variables in AI Standard Categories**

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)$_{i,c,t}$.



Appendix Figure B5. **The Distribution of Committee-Level Instruments**

The figure illustrates a histogram depicting the distribution of combined committee-level instruments, denoted as $\%UNSC\ Members^{k}_{i,c,t-1}$, across AI committees. Furthermore, it also showcases the distribution of permanent UNSC members within the respective committees. For a more detailed explanation for our instrument, please refer to Section 5.3.1.



C Data on 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.[32] 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.[33]

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.[34].

[32] See https://shorturl.at/fipC0.

[33] For a detailed explanation of the methodology and its application, refer to the CSET report's methodology section and appendices.

[34] Details on patent data methodology are available in CSET's paper on AI patents and the associated Github repository.

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.

D 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.[35] 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).

[35] 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).

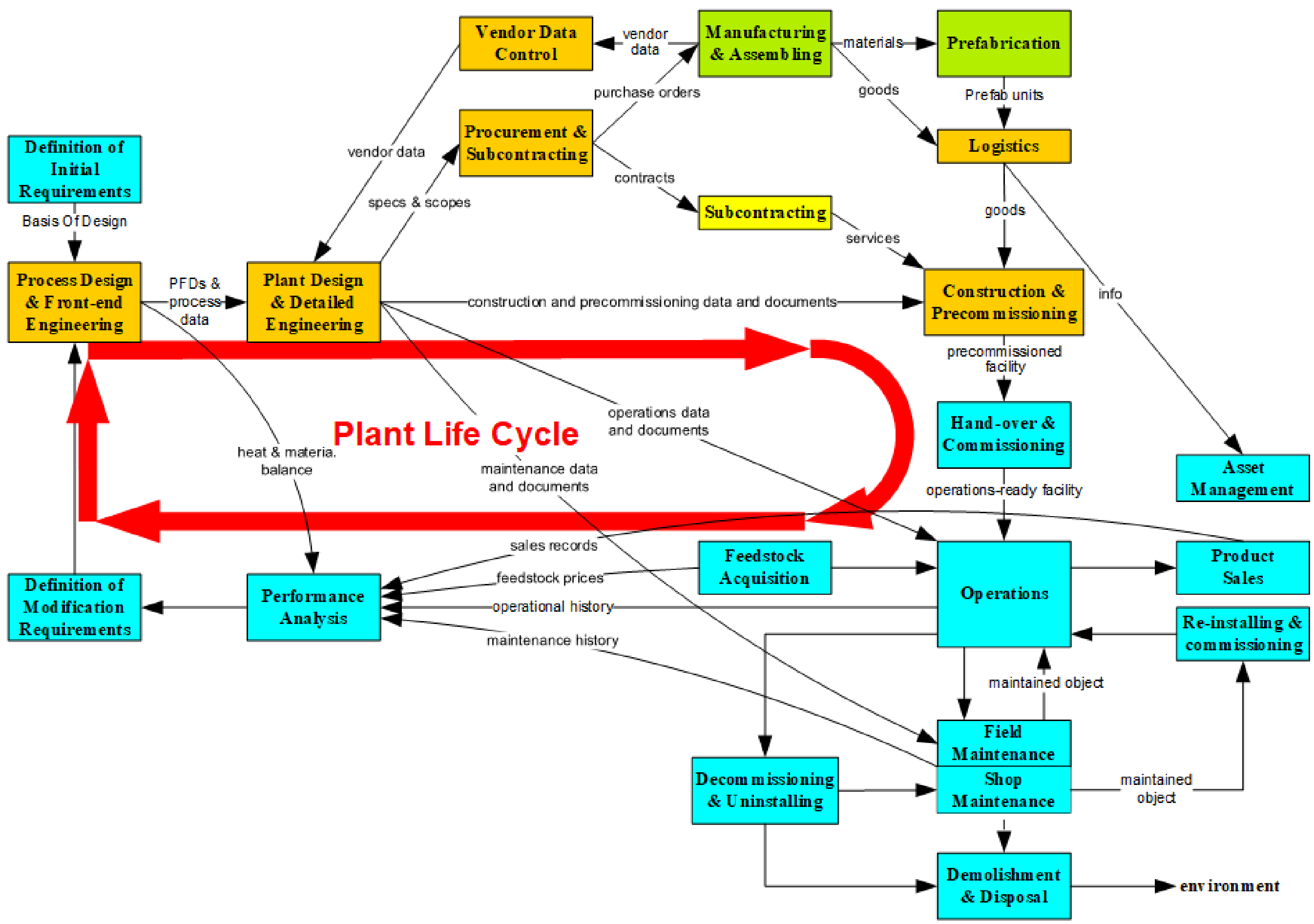
The above list outlines the applications of AI in a typical oil and gas production facility. It is crucial to note that throughout the entire lifespan of a facility, starting from conceptual design, through engineering and construction, to ongoing operations and maintenance, the exchange of information 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.

ISO 15926 provides standards for data integration, sharing, exchange, and hand-over between computer systems.[36] 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`.[37]

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

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`.



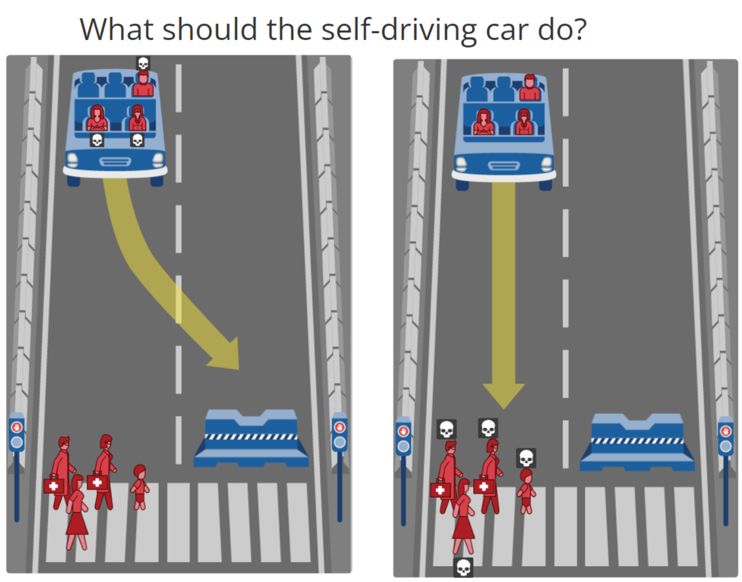
E Bias in AI Systems and AI-Aided Decision Making

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?

Appendix Figure E1. **Moral Machine Experiment**

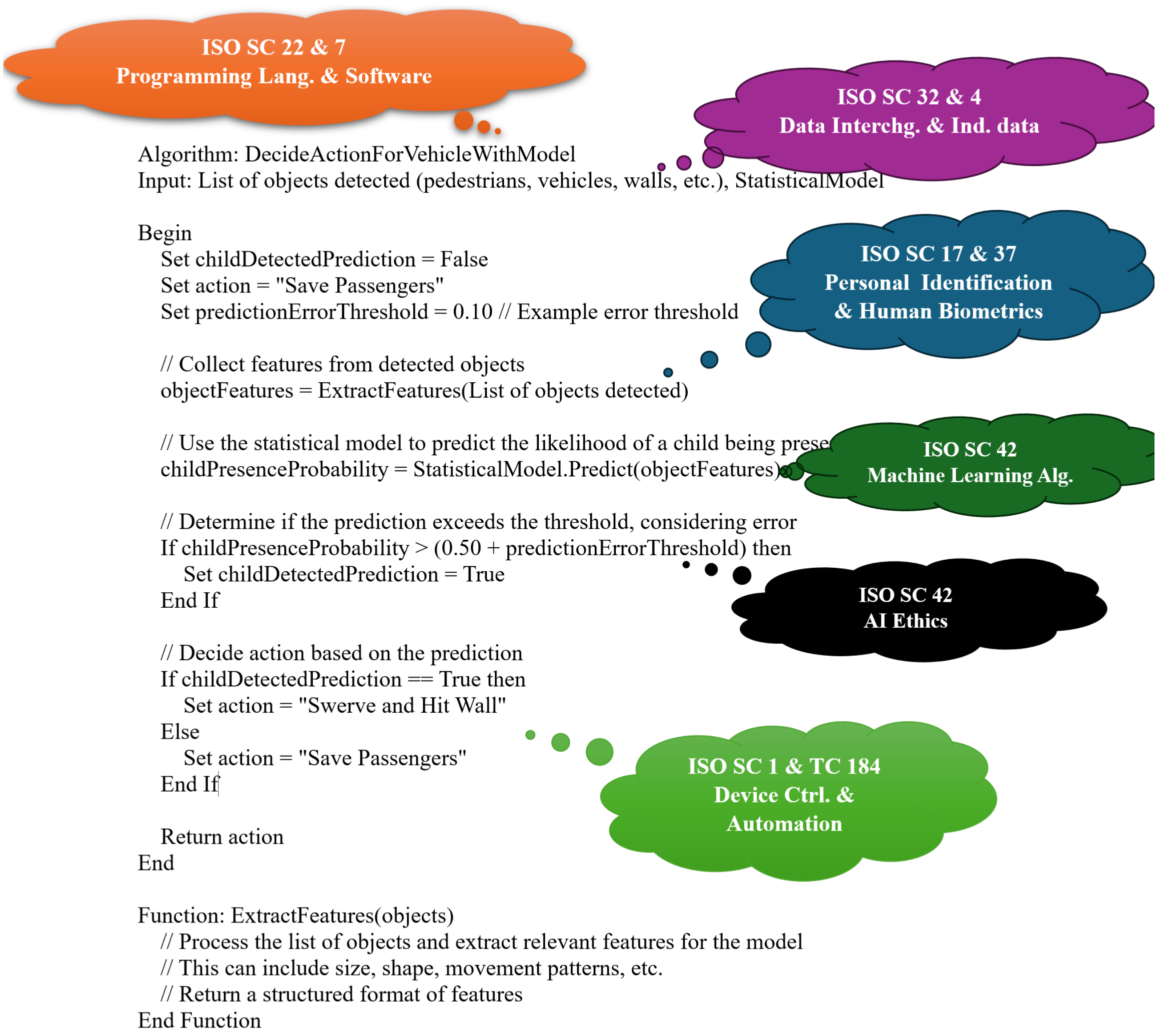
Image taken from the Moral Machine Experiment–see for example Bonnefon et al. (2016)–, which presents an intriguing survey that explores the ethical dilemma faced by autonomous vehicles. The experiment raises the question of whether the vehicle should prioritize the lives of individuals inside the vehicle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



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 E1. 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.

Appendix Figure E2. **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
```

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 E2 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 technology 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.