Artificial Intelligence Regulation and Investor Risk: Evidence from State and Local Artificial Intelligence Mandates*

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Abstract

Artificial intelligence (AI) is the new frontier in humankind's quest for creating intelligent systems to improve human capabilities. However, there are concerns that AI could harm consumers and employees exposing firms to AI risk. Some state- and local-level jurisdictions in the U.S. recently enacted laws intended to safeguard the rights of consumers and employees against AI-induced risk. We conjecture that these laws incentivize firms to address AI related concerns and thereby help lower investor risk. We find that investor risk, proxied by cost of equity, decreases following the passage of AI laws. We next investigate the channels behind this finding and document that firms hire more AI-related top managers and are subject to less employment-related corporate misconducts after the adoption of AI laws. Overall, our findings suggest that investors benefit from AI mandates through real actions taken by managers in reducing firms' exposure to AI risk.

JEL Classifications: G31; K22

Keywords: artificial intelligence, artificial intelligence regulation, artificial intelligence risk, cost of capital

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Abstract

Artificial intelligence (AI) is the new frontier in humankind's quest for creating intelligent systems to improve human capabilities. However, there are concerns that AI could harm consumers and employees exposing firms to AI risk. Some state- and local-level jurisdictions in the U.S. recently enacted laws intended to safeguard the rights of consumers and employees against AI-induced risk. We conjecture that these laws incentivize firms to address AI related concerns and thereby help lower investor risk. We find that investor risk, proxied by cost of equity, decreases following the passage of AI laws. We next investigate the channels behind this finding and document that firms hire more AI-related top managers and are subject to less employment-related corporate misconducts after the adoption of AI laws. Overall, our findings suggest that investors benefit from AI mandates through real actions taken by managers in reducing firms' exposure to AI risk.

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The First Law of Robotics: "A robot may not injure a human being or, through inaction, allow a human being to come to harm."

–Isaac Asimov; I, Robot (1950, p.117)

1. Introduction

One of the most exciting technological developments of the last decade is artificial intelligence (AI). AI uses machine learning techniques and computational power to process huge data sets to create intelligent algorithms which can improve and expand human capabilities in various tasks (Acemoglu 2022). These algorithms are now widely used in various online platforms across different industries (Ford 2015; Agrawal, Gans, and Goldfarb 2018; Russell 2019). Worldwide AI investment is expected to reach $200 billion by 2025[1] and generate a $1.3 trillion market by 2032.[2]

Many authorities are grappling with how to regulate the ever-expanding proliferation of AI given the loud and growing chorus of concern about the rapid development and deployment of AI. These concerns can broadly be classified as AI: (i) replacing humans (Paolillo et al. 2022; Gervais and Nay 2023), (ii) enabling human actors to engage in misconduct (Bengio et al. 2024), (iii) engaging in misconduct directly (Calvano, Calzolari, Denicolo, and Pastorello 2020), or (iv) unintentionally causing harm due to bias or irrationality (Ahmed, Wahed, and Thompson (2023); Parkes and Wellman 2015).[3] Some U.S. states and local jurisdictions have taken the first steps toward addressing the potential risks AI presents by enacting laws to inhibit specific types of AI-related intentional and unintentional harm. Initial enacted laws generally seek to curtail one of two problems thought to be the result of AI use, namely harm to consumers and employees (please

[1] https://www.goldmansachs.com/intelligence/pages/ai-investment-forecast-to-approach-200-billion-globally-by-2025.html

[2] https://www.bloomberg.com/company/press/generative-ai-to-become-a-1-3-trillion-market-by-2032-research-finds/

[3] In a recent example highlighting potential harm of AI to individuals, a woman was murdered by her husband although AI suggested that the woman was safe. See https://www.nytimes.com/interactive/2024/07/18/technology/spain-domestic-violence-viogen-algorithm.html for this news story.

refer to Appendix A for details of these laws). It is unclear whether these laws reduce potential risks AI use poses. In this paper, we undertake a risk management perspective of regulation and examine whether AI laws reduce investors' risk and the channels through which AI laws affect investor risk.

This study has two primary sources of motivation. First, many stakeholder groups assert that AI regulation is necessary. For example, in a recent survey Boston Consulting Group (BCG) finds that managers are optimistic about the potential benefits of AI but approximately 79% of the employees feel that AI regulation would be beneficial (BCG 2023). These sentiments are echoed by the leaders in the development of AI such as OpenAI chief executive Sam Altman who asserted that, "If this technology goes wrong, it can go quite wrong" (Altman 2023).[4] Globally individuals are most concerned with whether AI can be used intentionally to perpetrate misconduct or negatively impact jobs (The AI Index Report 2024). One example of intentional use of AI to perpetrate misconduct is using AI to detect and exploit human vulnerabilities and manipulate their decisions (Acemoglu 2022). Further, AI can replicate and amplify historical human biases and prejudices (Lee, Resnick, and Barton 2019). This stems either from unrepresentative data AI is trained on (i.e., AI trained only on white job applicants in employment decisions) or biased data reflecting historical inequalities (i.e., AI trained only on people of color in sentencing and bail decisions).

Second, given the extensive attention that AI is receiving from regulators and legislators it is critical to provide empirical evidence about existing AI-related laws. Without such evidence regulators and legislators will likely rely upon intuition to craft laws and regulations which may

[4] Consistent with the increasing concern of AI misuse, there is an upward trend of reported AI incidents, where AI causes harm to individuals. See Chapter 3 of the AI Index Report: https://aiindex.stanford.edu/wp-content/uploads/2024/04/HAI_2024_AI-Index-Report.pdf

or may not effectively achieve their objectives (Madsen 2011). Therefore, it is important to provide evidence regarding whether and to what extent AI-related laws address the risk firms are subject to due to widespread AI adoption.

SEC Chairman Gary Gensler argues that AI algorithms can create a system-wide risk in an economy due to herding and network interconnectedness as most AI algorithms are based on a small number of AI models (Sorkin, Mattu, Kessler, de la Merced, and Livni 2023). This creates the issue that various economic actors may make similar (perhaps flawed) decisions as they receive a similar signal from a base AI model. AI affects all individuals, firms, and governments and creates a non-diversifiable risk. Therefore, firms with high AI investments have higher systematic risk as measured by equity market beta (Babina, Fedyk, He, and Hodson 2024a).

Theory suggests that AI related issues are not due to technology but related to how AI is developed and deployed by firms (and governments) against consumers, employees, and society (Acemoglu 2022). Acemoglu (2022) concludes that competition increasing market mechanisms are unlikely to address AI related issues and suggests the need for regulation. In fact, for revolutionary technologies such as AI, theory posits that as the potential for severe negative outcomes increases, it will be desirable to slow down or prohibit the adoption of the technology to allow regulation to catch up and prevent negative outcomes (Acemoglu and Lensman 2023). As with the adoption of other emerging technologies, there is a limit as to how informed managers will be about the potential cost and harm that adoption of AI could cause (Simon 1973).

We expect that AI-related laws that inhibit the use of AI from harming consumers or employees will be perceived as beneficial by shareholders. Our expectation is consistent with prior research which asserts that shareholders will perceive laws which induce real actions to mitigate bad news will be viewed favorably (Ashraf and Sunder 2023) and with the large literature on risk

management that argues reducing risks will reduce costs to firms (Baxter, Bedard, Hoitash, and Yezegel 2013).

When considering firms' management of AI-related risk, the endogenous nature of AI adoption and deployment makes it challenging to establish a causal link between AI risk and investors' perceptions of the risk of a given firm. By exploiting the staggered adoption of laws against AI risks among states and local jurisdictions, our research design mitigates concerns about endogeneity and self-selection. We rely upon two sources, The Council of State Governments and BCLP which is a legal service firm that tracks regulatory AI bills in the United States, to identify laws addressing AI. During the period spanning 2018 through 2021, we observe three states and one local jurisdiction that enacted AI-related laws. We note that these laws address different potential AI-related problems thus limiting concerns about an underlying common shock that gave rise to the laws. Using the staggered variation in state and local laws constraining AI use, we employ a difference-in-difference design to examine the impact of these laws on investor risk as proxied by cost of equity. Consistent with prior literature, we use the cost of equity to measure shareholders' perceptions of firm risk (Ashraf and Sunder 2023). On average, we find a statistically significant 6.7 percent decrease in the cost of equity capital following the enactment of AI-related laws.

We conduct a series of robustness tests to check the sensitivity of our results to alternative explanations, research designs, and variable measurement. First, we address the concern that our results are driven by some pre-treatment effects and find support for the validity of the parallel trends assumption in our setting. Second, we conduct a placebo-test using randomly assigned event dates for the enactment of each law to address potential concerns that our results are driven by confounding factors. We fail to find any association between the cost of equity and our placebo

dates. Third, to address the concern that clustering of firms belonging to certain industries in some states can drive our results, we employ an alternative fixed-effects structure in which we include industry-year fixed effects and find qualitatively similar results. Fourth, we explore whether our results are affected by how we adjust for correlations arising from observed clusters by double-clustering standard errors by state and year. Results are qualitatively similar. Fifth, we utilize two alternative measures for the cost of equity capital, the unmodified Easton methodology and a factor comprised of the four cost of equity measures that we average in our main analysis. We find qualitatively similar results. Sixth, we check the sensitivity of our results against the concern of time-varying treatment effects and add each treatment effect one at a time. We find qualitatively similar results. Seventh, we confirm that our results are driven by firms with relatively more AI investment as defined by Babina et al. (2024b). This finding increases our confidence that our results are due to AI adoption rather than some other correlated omitted variables. Eighth, the laws that we examine are enacted to protect customers and employees of that state. We are not able to measure the extent of customer or employee dispersion within as compared to outside of a given state. In line with prior research, we assign exposure to AI laws based on the state in which firms are headquartered (Kamiya, Kang, Kim, Milidonis, and Stulz 2021; Huang and Wang 2021; Ashraf and Sunder 2023). To alleviate concerns about this research design choice, we estimate our model after splitting the sample at the median firm size. Consistent with our expectation that smaller firms will have a smaller geographic footprint and thus be relatively more affected by these laws, we find that the negative association holds for the small firm subsample but not the large firm subsample. Ninth, in another attempt to mitigate the concern that we assign whether a firm is subject to AI laws based on firm headquarter location, we follow Garcia and Norli (2012) and Ashraf and Sunder (2023) and measure geographic concentration based on the ratio of the

mentions of a specific state in a firm's 10-K to the mentions of all states. We find similar results when we use a continuous geographic concentration measure of AI regulation as our independent variable of interest.

We argue that the reduction in shareholders' perception of risk is driven by real actions that firms take in response to AI laws. We conduct two sets of analysis to shed light on whether firms take real actions to ensure compliance with these laws. First, we find that firms are more likely to hire a Chief Information Officer, Chief Information Security Officer, or Chief Security Officer after enactment of AI laws. Second, we find that firms are less likely to violate labor laws after the enactment of AI laws. Taken together, this evidence suggests that AI regulations have real effects on firms, which reduce their AI related risks on investors. Our findings provide empirical support for the theoretical argument that regulation can increase welfare by prohibiting the use of transformative technologies until the harmful effects of these technologies are fully assessed (Acemoglu and Lensman 2023).

We make several contributions to the prior literature. First, we contribute to the emerging literature examining AI and its relation to firm performance and reporting. Prior research finds that AI is positively associated with innovation (Cockburn, Henderson, and Stern 2018), operating performance (Babina et al. 2024b), firm value (Chen and Srinivasan 2023), and financial reporting quality (Ashraf 2024; Ding, Lev, Pen, Sun, and Vasarhelyi 2020; Fedyk, Hodson, Khimich, and Fedyk 2022). While the literature largely examines and documents the benefits of AI, we take a risk management perspective and explore whether AI regulation is associated with investors' perceptions of firm risk. Our results suggest that investors respond positively to laws that curtail potential misuse of AI likely due to the real actions taken by firms to ensure proper oversight of AI.

Second, we contribute to the large literature that examines risk management. This literature examines whether risk management initiatives improve firm outcomes and largely finds that risk management is positively related to firm performance (Hoyt and Liebenberg 2011; Baxter et al. 2013). For example, Cassar and Gerakos (2017) find that hedge funds that utilize risk management in their decision-making avoid relatively more extremely negative outcomes. Our study extends this literature by documenting that regulation can reduce investor risk by imposing restrictions on harmful activities.

Our study has important implications for regulators, legislators, and managers. Regulators and legislators are currently considering AI-related regulations and laws aimed at establishing "guard rails" to prevent AI-related misuse (Gensler 2024; Biden 2023). The majority of U.S. states as well as the federal government have yet to enact any AI-related laws. Our study suggests that laws to curb AI-related misuse are perceived favorably by shareholders and appear to spur real actions by firms to comply with these laws. Other states and jurisdictions could consider enacting similar laws to the extent that they seek to mitigate these AI-related risks. Managers have also been calling for regulation of AI and have expressed concerns about the risks that AI poses (BCG 2023). Our results suggest that regulation can be an effective mechanism to mitigate AI-related risk.

2. Background and Hypothesis Development

2.1 Artificial Intelligence and Firm Risk

AI usage has grown twice as much as compared to 2017 levels and firms across various industries are investing in AI (McKinsey 2022). AI technologies such as machine learning, natural language processing, and computer vision learn from large quantities of, often, unstructured data to capture complex (nonlinear) patterns and generate predictions (Agrawal, Gans, and Goldfarb 2018; Davenport and Ronanki 2018). These predictions, in turn, have the potential to improve

organizational decision-making (Agrawal, Gans, and Goldfarb 2024). Existing work largely focuses on and documents the benefits of AI technologies to firm-level outcomes. Babina et al. (2024b) study the impact of AI investments on human capital and find that AI investing firms achieve higher sales growth, employment, and market value. Brown, Louis, Rozario, and Zhang (2024) examine the effect of actual use of AI technologies by firms on the quality of earnings forecasts and find that AI improves the accuracy and precision of forecasts. Similarly, Anantharaman, Rozario, and Zhang (2024) study the actual use of AI by firms and its effect on financial reporting quality. They document benefits of AI adoption in relation to lower discretionary accruals and tighter mapping of accruals to cash flows. Lastly, studying the effect of AI on tax planning, Krupa and Mullaney (2024) find that AI investments enable firms to exercise more aggressive tax positions.

Investments in AI technologies, however, come with their own challenges. First, as with the adoption of other scientific advancements, human capital is a critical input that will drive the success of adoption (Stephan 1996). Scientific expertise is hard for individuals to develop and the demand for qualified individuals to develop and deploy complex technologies generally outstrips supply (Matolcsy and Wyatt 2008). Second, Gary Gensler, Chair of the Securities and Exchange Commission cautioned that AI is a significant threat to the financial system (Sorkin et al. 2023). Broadly, concerns regarding AI adoption focus on the potential to harm consumers or employees. Two common types of harm raised by critics of AI are that it will produce misinformation or facilitate discrimination. Misinformation would include efforts to alter social media sentiment while discrimination would include instances where AI generate predictions based on data reflecting historical biases perpetuating social inequalities (Villasenor 2019; Surden 2023; Bengio et al. 2024).

2.2 Artificial Intelligence Regulation

As the world grapples with the rapid development of AI and the societal and business risks associated with the technology, lawmakers have proactively proposed, and some have enacted legislation to ensure safe and trustworthy AI systems. In February 2024, The European Union (EU) passed legislation on AI, referred to as the AI Act. The law places compliance requirements in the design and use of AI systems and affects companies that operate within the EU (Blackman and Vasiliu-Feltes 2024; Gibney 2024). Efforts to regulate AI are also taking place in the U.S. at the federal, state, and local level. At the federal-level, President Biden signed an executive order directing users of AI tools to address and manage its risks (The White House 2023). To date, however, there are no federal laws governing the use of AI in the U.S. AI statutes, on the other hand, have been enacted at the state- and local-level as California, Illinois, Maryland, and New York City have passed AI laws between 2018 and 2021 (The Council of State Governments 2023; BCLP LLP 2023).[5]

California was the first jurisdiction to enact an AI law in 2018. Proponents of the law at the time argued that autonomous programs, or bots, spread misinformation. During a session of the Committee on Privacy and Consumer Protection, California State Senator Hertzberg argued that bots were being used to manipulate elections as well as consumer sentiment (Hertzberg 2018).[6] The problem with manipulating consumer sentiment is that it will cause certain products or services to appear more desirable or of higher quality than they actually are.

In contrast to California, Illinois, Maryland, and New York City enacted AI-related laws focused on possible harm to potential employees. In an Economic Matters Committee session,

[5] See Appendix A for a summary of each law.
[6] Senator Hertzberg also argued that for some firms looking to go public at the time bots allowed these firms to inflate their appeal driving up their valuations. His comments can be viewed from the recording of this session at: https://digitaldemocracy.calmatters.org/hearings/255297?t=1369&f=5be42e2261be7d85e875540965bdac91.

Maryland Delegate Fisher argued that AI could be abused to marginalize individuals with certain political views and prevent them from obtaining a job simply because of their political affiliation.[7] Concern that AI could lead to discrimination was also raised by commenters during the solicitation for public comment of proposed Local Law 144 in New York City. For example, the nonprofit organization Data & Society cited scholarly research which finds that AI is prone to bias because it is based upon prior decisions which embed bias.[8]

Generally speaking, the enacted AI regulation across these local jurisdictions restricts the use of AI to (i) prevent companies from manipulating consumers, and (ii) limit AI-based discrimination against customers, employees, or job candidates (The Council of State Governments 2023; BCLP LLP 2023). While there are differences in the laws, they follow similar objectives and impose similar obligations (International Association of Privacy Professionals 2024).[9] The laws require firms to disclose the use of AI to affected persons (i.e., consumers and employees), offer individuals the right to opt-out from being "profiled" by AI systems based on sensitive personal information, and conduct impact assessments of AI tools to ensure against the misuse of sensitive personal information and discrimination. The laws also require the impact assessments to be shared with government agencies. Consequently, the primary intent of the laws is to protect the rights of consumers and employees. In the following section, we argue that state

[7] The commentary related to this bill is at: https://mgaleg.maryland.gov/mgawebsite/Committees/Media/false?cmte=ecm&ys=2020RS&clip=ECM_3_3_2020_meeting_1&url=https%3A%2F%2Fmgahouse.maryland.gov%2Fmga%2Fplay%2Fb1a53053117f4baa82035cac7ea37fdf1d%3Fcatalog%2F03e481c7-8a42-4438-a7da-93ff74bdaa4c%26playfrom%3D9623673.

[8] The public comment letters can be accessed here: https://www.nyc.gov/assets/dca/downloads/pdf/about/PublicComments-Proposed-Rules-Related-to-Automated-Employment-Decision-Tools-Updated.pdf. Please refer to pages 35 – 42 for the comment letter from Data & Society.

[9] For example, the Illinois Artificial Intelligence Video Interview Act of 2019 mandates firms to destroy interview videos within 30 days after a job applicant has submitted a request to opt-out of being subject to AI tools. Similarly, the New York City Local Law 244 of 2021 requires firms to accommodate a job candidate's request to not have their application evaluated by an AI system within 10 business days.

and local AI laws encourage managers to address and manage AI risks, thereby improving oversight of firms' use of AI systems. In turn, actions taken to mitigate firms' AI risk will be viewed favorably by investors.

2.3 Artificial Intelligence Regulation and Cost of Equity

Despite the evidence that AI investments yield significant benefits, the implications of AI risk are nontrivial. The head of the SEC, Gary Gensler, contends that "a few A.I. companies will build the foundational models that underpin the tech tools that lots of businesses will come to rely on…" and that this in turn, could be the next big systemic risk to the financial system (Sorkin et al. 2023). Supporting the notion that AI risk is a systematic (market-wide) risk, a contemporary paper by Babina et al. (2024a) finds that firms' investments in AI are associated with increases in market beta. If AI risk reflects market risk, it is nondiversifiable by investors and should be a priced source of risk (Francis, LaFond, Olsson, and Schipper 2004; Ashraf and Sunder 2023) leading to an increase in cost of equity. Consequently, firms with greater AI risk will experience a higher cost of equity and firms that undertake real activities to limit their exposure to AI risk will benefit from a decrease in the cost of equity.

There is significant concern that firms are adopting AI without exercising appropriate care or even being aware of its risks (McKinsey 2023). Prior literature asserts that when an emerging technology is adopted or when a decision requires the collection of relatively more information, it can be difficult for a manager to consider all possible consequences of the decision (Simon 1973; Chen, Correia, and Urcan 2023). Consistent with this assertion, Cuellar, Larsen, Lee, and Webb (2024) conduct an online survey experiment to study managers' perceptions of AI-related issues. They randomly assigned managers to different proposed AI regulations and find that AI regulation increases managers' awareness of AI-related issues such as bias/discrimination, privacy, safety,

and transparency. This suggests that AI regulation curtailing the misuse of AI should increase managers' awareness of AI-related risks. This line of reasoning is consistent with prior literature which argues that changes in accounting disclosure regulation prompt changes in firms' actions including the amount of effort expended to acquire more information to improve decision-making (Roychowdhury, Shroff, and Verdi 2019). Since AI laws can increase managers' awareness of AI issues, they can incentivize managers to engage in real activities to decrease a firm's exposure to AI risk.

To the extent that AI regulation encourages managers to take real actions to improve oversight of AI systems and this is viewed favorably by investors, we expect it to be associated with a decrease in cost of equity. As such, we state our hypothesis in the alternative form.

H1: Cost of equity decreases following the passage of AI laws.

Our hypothesis is not without tension. Long-standing theory posits that regulation can impose costs leading to suboptimal outcomes for regulated firms (Peltzman 1976; Peltzman 1989). The regulation of AI is challenging due to the fast-changing nature of AI technology. Moreover, opposition to AI developments can have negative effects on economic growth as AI investment is associated with higher growth in sales, employment, market valuation, and product innovation (Babina et al. 2024b). Furthermore, it is not easy to determine the optimal amount of AI regulation and firms can be subject to more regulation than necessary stifling innovation and firm growth. Taken together, the regulatory risk can increase the cost of doing business and cost of capital (Brennan and Schwartz 1982; Prager 1989).

3. Research Design

3.1. Identifying Firms Affected by Artificial Intelligence Regulation

We identify AI regulation and the dates in which the laws were passed from (i) The Council of State Governments (The Council of State Governments 2023), a nonpartisan organization that "champion[s] excellence in state government" and (ii) BCLP (BCLP LLP 2023). Next, at least two researchers read the corresponding AI bills from the legislative websites of each state and local government. We identify that three states (California, Illinois, Maryland) and a local jurisdiction (New York City) have passed AI regulation between 2018 and 2021. Although some states have enacted legislation targeting data privacy safeguards, we do not identify these laws as AI legislation since they do not explicitly refer to AI and cover broader aspects of data privacy that may or may not extend to AI, i.e., data privacy laws cover *any* form of manual or automated data collection and processing of personal information).[10,11] As a result, we exclude these laws from our design to more directly examine the impact of AI regulation. We define an affected firm as a firm that has its business address in California, Illinois, Maryland or New York City.[12,13] Further, we note that the four AI-related laws are distinct as they pertain to varying AI-related concerns thus there does not appear to be a common shock that triggered these laws.

[10] For example, the California Consumer Privacy Act of 2018, the Colorado Privacy Act of 2021, and the Connecticut Privacy Act of 2022 include provisions for "automated decision-making systems". Although AI and non-AI automation are increasingly integrated, not all automated decision-making systems involve AI (BCLP LLP 2023).
[11] We note that the U.S. FTC Act of 1914 also prohibits the use of unfair business practices but similarly does not include any explicit mention of AI.
[12] We identify a firm's business address from 10-K filings – this data is provided by Loughran-McDonald in the University of Notre Dame's online repository. See: https://sraf.nd.edu/sec-edgar-data/
[13] Colorado passed an AI law in 2021 that deals with protecting consumers from AI-induced discrimination in insurance practices. Due to the narrow scope of this law, we do not include it in our sample of treated firms as there are no firm-years that belong to the insurance industry in Colorado during our sample period.

3.2. Sample Selection

Table 1, Panel A shows our sample construction process. We start with 35,013 firm-year observations from U.S. firms in Compustat between 2017 and 2022 for which we have business address information. We next remove 27,859 observations that have missing earnings forecasts from Institutional Brokers' Estimate System (I/B/E/S), since this data is necessary to estimate cost of equity measures. We then remove 933 observations with missing data to compute the control variables used in the main tests and 219 singleton observations. Our final sample includes 6,002 observations, comprising 1,285 unique firms.[14]

Table 1, Panel B shows that about 17 percent of the sample clusters in the state of California, followed by other largely populated states, such as Texas (11 percent), New York (6 percent), Massachusetts (6 percent), Florida (5 percent), Illinois (5 percent), and Pennsylvania (5 percent). Furthermore, using the Fama-French industry classification, Table 1, Panel C shows that 23 percent of firm-year observations conduct business in the Business Equipment industry, followed by the Healthcare industry (16 percent), the Other industry (14 percent), which comprises mining, construction, hotels, services, and business services, the Wholesale, Retail, and Some Services industry (13 percent), and Manufacturing (12 percent).

[14] Sample attrition in our study is similar to attrition reported in prior literature. For example, Jing, Myers, Ng, and Su (2023) loses roughly 85% of its sample due to data requirements and the authors note that such attrition is consistent with prior literature. Further, Call, Hewitt, Watkins, and Yohn (2021) find that for the same sample period the number of observations available to researchers decreases with larger lags prior to downloading the data. Such a finding makes it more difficult to compare sample attrition across studies. Finally, Ellahie, Hayes, and Plumlee (2022) show that the number of observations for which cost of capital can be measured appears to be declining over time.

3.3. Model Specification

Drawing from prior research (e.g., Dhaliwal, Judd, Serfling, and Shaikh 2016; Ashraf and Sunder 2023), we estimate the following model to examine the effect of AI regulation on a firm's cost of equity capital:

$$\begin{aligned} COC_{it} = {} & b_0 + b_1 AILAW_{it} + b_2 ROA_{it} + b_3 LEVERAGE_{it} + b_4 SIZE_{it} + b_5 MTB_{it} + b_6 BETA_{it} \\ & + b_7 LNDISP_{it} + b_8 LTG_{it} + b_9 MOMENTUM_{it} + b_{10} RISK_{it} \\ & + Firm\ Fixed\ Effects + Year\ Fixed\ Effecs \\ & + \varepsilon \qquad (1) \end{aligned}$$

where the subscripts *i* and *t* stand for firm and year, respectively. *COC* is the average of the implied cost of equity capital as per the Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001), modified Easton (2004), and Ohlson and Juettner-Nauroth (2005) measures less the risk-free rate, i.e., the yield on 10-year Treasury bonds.[15] We follow prior literature and use the average cost of equity from the four models to reduce the concern of measurement error coming from a particular model (Hail and Leuz 2006; Dhaliwal, Krull, and Li 2007; Li, 2010; Dhaliwal et al. 2016; Ashraf and Sunder 2023). *COC* is estimated for firm *i* in year *t* using stock prices and analyst forecasts in June of the following year (Dhaliwal et al. 2016; Ashraf and Sunder 2023).

The main variable of interest is *AILAW*. *AILAW* is an indicator variable equal to 1 in the year after an AI law is adopted in firm *i*'s state address (or the local jurisdiction of New York City) and thereafter and 0 otherwise.[16] To mitigate the confounding effects of firm characteristics, we follow prior literature and include *ROA, LEVERAGE, SIZE, MTB, BETA, LNDISP, LTG, MOMENTUM*, and *RISK* as control variables (Dhaliwal et al. 2016; Ashraf and Sunder 2023).

[15] Refer to Dhaliwal et al. (2016) for more details on the estimation of cost of equity capital measures.
[16] The main variable of interest is forward-oriented to match the estimation of cost of equity capital. For example, for AI regulation in California, enacted in 2018, the AILAW indicator is equal to 1 in 2019 and in subsequent years.

Their descriptions are provided in Appendix B. Equation 1 includes firm and year fixed effects to mitigate the effects of time-invariant firm characteristics and macroeconomic shocks. Since we employ firm and year fixed effects, *AILAW* captures the differential impact of AI laws on cost of equity capital between control and treatment firms (Bertrand and Mullainathan 2003). Following Ashraf and Sunder (2023), we cluster standard errors by state because the treatment variable is at the state-level. H1 predicts that $b_1 < 0$.

4. Results

4.1. Descriptive Statistics

The descriptive statistics of the variables used in our analysis are presented in Table 2. The Pearson correlations are presented in Table 3. All variables are winsorized at the top and bottom one percent. Table 2, Panel A shows that 15 percent of firm-year observations are subject to AI regulation. The average *COC* in excess of the risk-free rate is 6.1 percent, which is comparable to the *COC* reported in prior studies (e.g., Dhaliwal et al. 2016; Ashraf and Sunder 2023; Jing, Myers, Ng, and Su 2023).

Table 2, Panel B shows the descriptive statistics separately for firms that are affected by AI regulation and those that are not. Sample companies that are affected by AI regulation have lower *COC*, lower profitability (*ROA*), lower leverage (*LEVERAGE*), are larger (*SIZE*), have higher growth opportunities (*MTB*), and are riskier in terms of market beta (*BETA*), and idiosyncratic risk (*RISK*), relative to firms that are not affected by AI regulation.

Table 3 shows Pearson correlations among our variables of interest. We find that *COC* is higher for firms with high leverage and firm risk and lower for larger firms and firms with high growth opportunities. Overall, we note that the descriptive statistics and correlations are largely

consistent with prior literature (e.g., Dhaliwal et al. 2016; Ashraf and Sunder 2023; Jing et al. 2023).

4.2. Main Results

Table 4 presents the results for our main analysis. We use ordinary least squares (OLS) regression to estimate the effect of AI regulation on cost of equity capital. The coefficient on *AILAW* is significantly negative at the 5 percent level. The coefficient on *AILAW* of -0.41 percent translates to a 6.7 percent decrease in the cost of equity capital.[17] Overall, the result provides support for our hypothesis that AI laws decrease firm risk.

For control variables, the associations are comparable to prior work (e.g. Dhaliwal et al. 2016; Ashraf and Sunder 2023; Jing et al. 2023). The implied cost of equity is positively associated with firm profitability (*ROA*), financial leverage (*LEVERAGE*), equity risk (*BETA*), and analysts' long-term growth forecasts (*LTG*), while the cost of equity is negatively associated with stock return momentum (*MOMENTUM*).

4.3. Robustness Tests

4.3.1. Validity of the Parallel Trends Assumption

The difference-in-differences analysis we employ in the main analysis is based on the assumption that the average change in the cost of equity capital between control and treatment groups would have been insignificantly different, in the absence of the treatment. To test the validity of the parallel trends assumption, we conduct a dynamic analysis, i.e., an event-time

[17] Calculated as the coefficient of interest divided by the sample mean (0.0041/0.0613). The economic significance of *AILAW* is similar to that of other cost of capital determinants. For example, Dhaliwal et al. (2016) report similar economic significance (4.8 percent) for a concentrated customer base and a supplier's cost of equity. The economic significance of tax avoidance on cost of equity in Goh, Lee, Lim, and Shevlin (2016), estimated as the coefficients of interest divided by the sample mean, ranges between 9 percent and 24 percent.

specification, and capture the progression of changes in cost of equity capital two years before, the year of, and two years after the enactment of AI laws (Atanasov and Black 2016). If the parallel trends assumption holds, we would observe the coefficients on pre- AI law period to be statistically insignificant and those in the post- AI law period to be significantly negative.

We replace the variable of interest *AILAW* with indicator variables: $AILAW_{t-2}$, $AILAW_{t-1}$, $AILAW_{t}$, $AILAW_{t+1}$ and $AILAW_{t+2}$. Table 5 presents the results. Overall, the results suggest that the parallel trends assumption holds as indicated by the insignificant coefficients in the pre- AI law periods relative to the significantly negative coefficient in year t+2. In terms of the timing of the laws affecting cost of equity, this result suggests that it takes some time for AI regulation to have real effects which will be priced by shareholders.

4.3.2. Placebo Analysis

Our identification strategy of capturing a series of shocks from the staggered adoption of the fair use of AI laws and the difference-in-differences research design mitigate the concern that our finding is attributable to omitted correlated variables. To further address the concern that our results are driven by unobservable factors, we conduct a falsification test by introducing a placebo treatment in randomized periods (Cornaggia, Mao, Tian, and Wolfe 2015; Atanasov and Black 2016). We randomly assign the actual years of adoption of AI regulation. Therefore, $AILAW_PLACEBO_{it}$ is an indicator variable that is equal to 1 when there is a randomly assigned adoption of AI regulation in the state of the firm's address that is not the actual year of AI law adoption and 0 otherwise. For example, if a firm is affected by state-level AI regulation in 2020 as is the case for firms in Maryland, $AILAW_PLACEBO_{it}$ is set to 1 for that same firm in 2019. If there are confounding factors that drive the results on cost of capital, we expect the coefficient on $AILAW_PLACEBO_{it}$ to load significantly negative. As shown in Table 6, Column 1,

AILAW_PLACEBO$_{it}$ is not significantly associated with *COC*, providing support that our main findings are unlikely to be attributable to omitted correlated variables.[18]

4.3.3. Industry-Year Fixed Effects

In our main analysis we include firm and year fixed effects to account for time-invariant firm characteristics and macroeconomic shocks. Firms belonging to certain industries within specific states might have higher exposure to AI. For example, technology firms headquartered in California might have higher exposure to AI due to the nature of their business models compared to firms headquartered in Maryland. As a result, industry-specific trends in the same years that AI laws are passed might be driving the observed reduction in *COC*. To reduce this concern, we add industry-year fixed effects along with firm fixed effects to Equation 1 to control for correlated omitted variables at the industry-year level. The results in Table 6, Column 2, show that the *AILAW* continues to be significantly associated with a reduction in COC (the coefficient is equal to -0.0037 and is significant at the 1 percent level).

4.3.4. Clustering by State and Year

We next cluster standard errors by state and year, instead of only clustering by state, to account for within-year correlations in addition to serial correlations. Table 6, Column 3, shows that after applying double clustering to standard errors in Equation 1, the coefficient on *AILAW* is negative and significant (the coefficient is equal to -0.0041 and is significant at the 5 percent level).

[18] In untabulated analysis, we artificially reverse the actual years of adoption of AI regulation by two years. That is, *AILAW_PLACEBO*$_{it}$, is an indicator variable that is equal to 1 when there is a "seeded", (i.e., falsified), adoption of AI regulation in the state of the firm's address two years before the actual adoption of the law and 0 otherwise; we continue to find an insignificant association between the placebo treatment and cost of equity capital.

4.3.5. Alternative Measures of Cost of Capital

Prior research suggests that cost of capital is subject to measurement error. To mitigate this concern, we use the average of the implied cost of equity capital from Claus and Thomas (2001), Gebhard et al. (2001), modified Easton (2004), and Ohlson and Juettner-Nauroth (2005) measures in our main specification. To offer additional evidence that our findings remain robust regardless of the proxy we choose for cost of equity, we estimate cost of equity using two alternative methodologies: (i) the unmodified Easton (2004) estimation, a measure suggested by Botosan, Plumlee, and Wen (2011) and (ii) a factor comprised of the four cost of equity proxies. As shown in Table 6, Columns 4 and 5, our inferences remain unchanged using these two alternative measures for cost of equity (the coefficients are equal to -0.0069 and -0.1462 and they are significant at the 1 percent level, respectively).

4.3.6. Time-Varying Treatment Effects

A limitation of the staggered difference-in-differences design is that the early-treated units act as controls for the later-treated units and because of this "dynamic" nature of the treatment, the coefficient of the treatment effect can be biased. This bias can be reflected as a coefficient estimate with the wrong sign and magnitude (Goodman-Bacon 2021; Baker, Larcker, and Wang 2022). In our setting, since we find an on-average effect of a reduction in cost of equity, the concern would be that the actual effect is positive or less economically significant.

To address this concern, we follow Ashraf and Sunder (2023) and conduct a diagnostic analysis by adding each treatment event *one at a time* to check whether time-varying treatment effects are a valid concern. We start by estimating the effect of AI laws on cost of equity on the sample period for the first treatment event (2017 to 2018), then expand it for the second treatment

event (2017 to 2019) and so on.[19] This analysis is reported in Appendix C. In three of the four treatment windows, we observe that the coefficient on *AILAW* is consistently negative (p-values ranging between 5 percent level and 1 percent level of significance) and of similar magnitude (ranging from -0.41 percent to -0.51 percent). Together, these results suggest that a biased coefficient on *AILAW* driven by time-varying treatment effects is unlikely to be a significant threat to our inferences.

4.3.7. Investments in AI

We examine whether the effect of AI regulation on cost of equity is amplified for firms that have more investments in AI. To the extent that shareholders' perceptions of a firm's AI risk decrease after AI laws are passed, we expect the reduction to cost of equity to be more pronounced (muted) for firms that have more (less) investments in AI because these firms have to exert more effort into enhancing oversight of AI systems. Following Babina et al. (2024b), we capture investment in AI by a firm as the level of human capital with AI skills, *AIWORKERS*.[20] *AIWORKERS* is equal the number of AI-skilled employees scaled by the total number of employees. The more (less) investment in AI sample consists of firm-years with *AIWORKERS* above (below) the median. We report the results in Table 7. Consistent with our expectations, we find that firms that have more investments in AI technology experience a significant reduction to cost of equity ($p<0.01$). This finding reinforces our confidence that our results are more likely to be related to AI rather than some other corelated omitted variable.

[19] In our setting we have the following treatment event periods: 2018, 2019, 2020, and 2021, refer to Appendix A for more details.
[20] Data for *AIWORKERS* is publicly available from Babina et al. (2024b). The mean (median) of *AIWORKERS* is equal to 0.0024 (0.0005)

4.3.8. Smaller Firms

Our main analysis relies on the assumption that firms headquartered in a state where AI laws are passed will be affected by the laws. Firms may operate in states other than the state in which they are headquartered, potentially subjecting them to exposure to AI laws coming from other states *prior* to their home state enacting such a law (Ashraf and Sunder 2023). Although this is less likely to be a concern in our setting since AI laws are not yet pervasive, i.e., only 4 states and cities have passed AI laws, we nevertheless address the exposure concern by investigating whether smaller firms have a more pronounced effect to their cost of equity compared to larger firms. To the extent that smaller firms have a customer and employee base that is more geographically concentrated than larger firms we expect a more pronounced reduction in the cost of equity for these firms following the passage of AI laws. We use firm size to partition the sample into smaller firms versus larger firms. The smaller (larger) firm sample comprises firm-years with *SIZE* below (above) the median. We report the results for this test in Table 8. Consistent with our expectations, we find that smaller firms have a statistically significant decrease to cost of equity capital once AI laws are passed compared to larger firms ($p<0.01$).[21]

4.3.9. Alternative Measure of Geographic Concentration

In all of our analyses so far, we assign a firm to the treatment sample based on its headquarter location. However, firms might have exposure to AI laws based on the location of their customers and employees. Unfortunately, we do not have data on the location of customers and employees. To alleviate this concern, we follow an approach used in prior literature (e.g., Garcia and Norli, 2012) and estimate geographic concentration from 10-K annual reports for firm

[21] In untabulated analyses, we use the upper (lower) quartiles as well as the upper (lower) quintiles of firm size to partition the sample and find qualitatively similar results.

i in year *t*. Geographic concentration is measured as the ratio of the mentions of a specific state in firm *i*'s 10-K for year *t* to the mentions of all states in firm *i's* 10-K for year *t*. The greater the ratio the higher the geographic concentration in a particular state. Next, we multiply geographic concentration by *AILAW* to measure the geographic concentration of states that have passed AI laws, captured as *AILAW_GEOCON*. In essence, *AILAW_GEOCON* is a continuous measure of AI law adoption. We replace *AILAW* with *AILAW_GEOCON* and re-estimate Equation 1. The results, presented in Table 9, continue to support our main inferences that AI laws decrease cost of equity capital ($p<0.05$).

4.4. Real Effects of AI Laws

4.4.1. Technology Officer on the Top Management Team

We argue that the passage of AI laws incentivizes managers to undertake real activities to manage AI-related risks; this in turn, reduces firm risk – as documented by the decrease in cost of equity. To provide evidence that managers take real actions to improve the governance over AI systems, we examine whether firms are more likely to have a technology officer following the passage of AI laws. The primary objective of AI laws is to ensure the protection of consumers and employee rights by curtailing the misuse of AI by firms. Therefore, the laws can serve as an external mechanism to promote equitable use of firms' AI systems by imposing compliance requirements aimed at mitigating risks associated with such systems.

Prior literature suggests that Chief Information Officers (CIOs), Chief Security Officers (CSOs), or Chief Information Security Officers (CISOs) have responsibilities that are closely related to the oversight of AI systems (Taddeo, McCutcheon, and Floridi 2019; Li, Li, Wang and Thatcher 2021). For example, CIOs are generally in charge of deploying the strategy for emerging technologies such as AI (Li et al. 2021) and because AI systems can leverage personally

identifiable information, the oversight of AI systems may fall under the purview of CSOs and CISOs. Therefore, these top managers may influence the strategy for AI risk mitigation (Singh and Hess 2017; Rosiek 2018; Schafer, Schneider, Drechsler, and vom Brocke 2022). This is likely because of the multifaceted nature of AI applications (Babina et al. 2024b), which can present implications for multiple aspects of the firm's technology strategy for risk mitigation.[22] CIOs, CISOs, or CSOs have technological expertise in different areas and can contribute to mitigating the risk associated with the use of AI systems. To the extent that the laws encourage managers to enhance the governance over AI systems, we expect that firms will be more likely to have a technology officer on the top management team once AI laws are passed.

We employ a Linear Probability Model (LPM) to predict the firm's likelihood to have a technology officer:[23]

$$
\begin{aligned}
CIO_CSO_CISO_{it} \\
&= b_0 + b_1 AILAW_{it} + b_2 ROA_{it} + b_3 LEVERAGE_{it} + b_4 SIZE_{it} + b_5 MTB_{it} \\
&+ b_6 AGE_{it} + b_7 IO_{it} + b_8 SEGMENTS_{it} + b_9 FOREIGN_{it} + b_{10} ACQUISITION_{it} \\
&+ b_{11} RESTRUCTURE_{it} + Firm\ Fixed\ Effects + Year\ Fixed\ Effecs \\
&+ \varepsilon, \qquad (2)
\end{aligned}
$$

Using data from BoardEx, we measure $CIO_CSO_CISO_{it}$ as a binary variable that equals to 1 if the firm has a CIO, CSO, or CISO on the top management team in year t and 0 otherwise. Approximately 4.4 percent of firm-year observations (n = 7,965) have top managers

[22] For example, Walmart uses natural language processing (NLP) to understand orders placed by customers and machine learning to predict customer demand for products. See: https://tech.walmart.com/content/walmart-global-tech/en_us/news/articles/three-ways-we-are-using-conversational-ai-at-walmart.html; https://tech.walmart.com/content/walmart-global-tech/en_us/news/articles/walmarts-ai-powered-inventory-system-brightens-the-holidays.html

[23] It is common practice to use LPMs for a binary dependent variable when fixed effects are included in the model (Greene 2004; Hanlon and Hoopes 2014; Francoeur, Li, Singer, and Zhang 2023).

with technology expertise (untabulated). Following Ashraf and Sunder (2023), we control for firm characteristics which have been found to affect the decision to have a technology officer on the top management team. These variables are defined in Appendix B. Table 10 reports the results of our analysis. We observe that the coefficient on *AILAW* is positive and significant ($p<0.01$) suggesting that the AI regulation incentivizes managers to enhance oversight on the equitable use of AI systems. [24] This enhanced oversight, presumably, decreases the perceived riskiness of firms' use of AI systems as reflected in cost of equity.

4.4.2. Consumer- and Employment- Related Misconduct

Building on the notion that AI laws encourage managers to take real actions to manage AI-related risks, we posit that a firm's legal exposure due to misuse of customer data in AI systems and unfair hiring practices from AI-induced biases will decrease after the passing of AI laws.[25] To the extent that managers take real actions that in turn, ensure compliance with AI laws, we expect a negative association between the adoption of AI laws and firms' consumer- and employment-related violations. We obtain data on corporate misconduct from Violation Tracker to capture firms' legal exposure related to consumer- and employee-related offenses. Violation Tracker is a data repository that covers a wide-range of facility-level violations and penalties issued by federal agencies and has been used in prior research examining corporate misconduct (Heese and Perez-

[24] CIOs, CSOs, and CISOs are top managers that arguably have technology expertise that is relevant to deploying AI strategy. We also capture technology expertise on the top management team broadly, by including Chief Technology Officers (CTOs) in addition to CIOs, CSOs, and CISOs. In untabulated analyses, we observe a positive but insignificant coefficient for *AILAW*. The lack of significance is not unexpected as CTOs may have responsibilities related to the governance of AI systems but likely take on additional responsibilities as well.

[25] An unintended consequence of AI use by firms is the increasing trend in AI-related incidents. The term "incidents" refers to events where AI systems cause harm to individuals or certain groups. See: https://www.aiaaic.org/aiaaic-repository and https://aiindex.stanford.edu/report/. For example, three former Estee Lauder employees sued the company claiming that they were wrongfully fired after their interviews were scored by an AI system that discriminated against them based on their gender. Estee Lauder settled the lawsuit out-of-court by paying an undisclosed amount.

Cavazos 2020; Raghunandan 2021). We estimate the following model to study the effect of AI regulation on firms' legal exposure due to consumer- and employment-related offenses:

$$
\begin{aligned}
VIOLATION/PENALTIES_{it} \\
&= b_0 + b_1 AILAW_{it} + b_2 ROA_{it} + b_3 LEVERAGE_{it} + b_4 SIZE_{it} + b_5 SALES_{it} \\
&+ b_6 EMPLOYEES_{it} + b_7 ADVERTISING_{it} + b_8 SEGMENTS_{it} \\
&+ b_9 LAG_VIOLATION/LAG_PENALTIES_{it} + Firm\ Fixed\ Effects \\
&+ Year\ Fixed\ Effecs \\
&+ \varepsilon, \qquad (3)
\end{aligned}
$$

VIOLATION/PENALTIES$_{it}$ captures four industry-adjusted (at the four-digit SIC level) measures related to firm-level consumer- and employment-related offenses. First, we measure whether the firm engaged in consumer (employment) offenses. *CVIOLATION (EVIOLATION)* is equal to 1 if firm *i* engaged in a consumer (employment) related violation in year *t* and 0 otherwise. We also measure the monetary amount of consumer (employment) offenses incurred by the firm. *CPENALTIES (EPENALTIES)* is equal to the natural logarithm of the total penalties for firm-level consumer (employment) misconduct for firm *i* in year *t*. In our sample, approximately 2 percent of firm-year observations (n = 7,369) are subject to consumer violations and the average penalty amount is around $28 million (untabulated). Moreover, we observe that 4.1 percent of firm-year observations in our sample (n = 7,369) are subject to employment violations with an average penalty amount of $5.4 million (untabulated). The test variable in this analysis is *AILAW*. We also control for the following firm characteristics: *ROA, LEVERAGE, SIZE, SALES, EMPLOYEES*, *ADVERTISING*, and *SEGMENTS* which have been found to be associated with the corporate violations (Christensen 2016; Heese and Perez-Cavazos 2020). We additionally control for prior firm related consumer- and employment-related offenses (*LAG_CVIOLATION,*

LAG_EVIOLATION, LAG_CPENALTIES, and *LAG_EPENALTIES*) as they can be informative of future misconduct. The variable descriptions are provided in Appendix B.

We report the results of our analysis in Table 11. In Columns 1 and 2, we find no evidence of AI laws decreasing litigation exposure for firms engaging in consumer-related offenses. In contrast, in Columns 3 and 4 we find a decrease in litigation exposure for firms that engage in employment-related offenses following the adoption of the laws ($p<0.05$).[26] These results suggest that a reduction in firms' employment-related litigation risk, i.e., a "real outcome" is a channel through which AI laws negatively affect investor risk.

5. Conclusion

This paper examines whether AI regulation to decrease firms' AI-related risk benefits shareholders. As AI use by firms increases, so have the incidents related to its misuse. Regulators, legislators, and practitioners grapple with how to regulate AI. While the regulation of AI at the federal level is in its nascent stage, some U.S. states and local governments have enacted legislation aimed at reducing intentional or unintentional harm to customers or employees as a result of AI use. Using the staggered adoption of AI laws implemented in three states and one local jurisdiction, we find that investor risk, measured by cost of equity, decreases following the passage of these laws. This finding is robust to a series of additional tests including alternative fixed effects structures, double clustering of standard errors, alternative measures of cost of equity, and a placebo analysis. Further, we find evidence consistent with real actions taken by firms to reduce the problematic use of AI. Specifically, we find that firms are more likely to have a Chief Information Officer, Chief Information Security Officer, or Chief Security Officer after AI laws

[26] In untabulated analysis, we exclude the lagged misconduct-related variables and find qualitatively similar results.

are passed. Similarly, we find that firms are less likely to have employment-related corporate misconduct after AI laws are passed. Taken together, our findings support the theoretical predictions of Acemoglu and Lensman (2023) that transformative technologies should be adopted slowly to reduce disaster risk and sometimes regulation should be used to prohibit the use of new technology until the disaster risk of the transformative technology is proven to be low.

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Appendix A			
State (City)	**State and Local Legislation**	**Date Passed**	**Excerpts from the Legislation**
CA	Senate Bill No. 1001 CHAPTER 892	Sep-18	It shall be unlawful for any person to use a **bot** to communicate or interact with another person in California online, with the intent to mislead the other person about its artificial identity for the purpose of knowingly deceiving the person about the content of the communication in order to incentivize a purchase or sale of goods or services in a commercial transaction or to influence a vote in an election. A person using a bot shall not be liable under this section if the person discloses that it is a bot.
IL	(820 ILCS 42/) Artificial Intelligence Video Interview Act.	Aug-19	An employer that asks applicants to record video interviews and uses an **artificial intelligence** analysis of the applicant-submitted videos shall do all of the following when considering applicants for positions based in Illinois before asking applicants to submit video interviews: (1) Notify each applicant before the interview that artificial intelligence may be used to analyze the applicant's video interview and consider the applicant's fitness for the position. (2) Provide each applicant with information before the interview explaining how the artificial intelligence works and what general types of characteristics it uses to evaluate applicants. (3) Obtain, before the interview, consent from the applicant to be evaluated by the artificial intelligence program as described in the information provided. An employer may not use artificial intelligence to evaluate applicants who have not consented to the use of artificial intelligence analysis.
MD	HOUSE BILL 1202	May-20	An act concerning Labor and Employment – Use of **Facial Recognition** Services – Prohibition. For the purpose of prohibiting an employer from using certain facial recognition services during an applicant's interview for employment unless the applicant consents under a certain provision of this Act; authorizing an applicant to consent to the use of certain facial recognition service technologies during an interview by signing a waiver; providing for the contents of a certain waiver; defining certain terms; and generally relating to employer use of facial recognition service technologies during job interviews.
NYC	Local Law 144	Dec-21	In the city, it shall be unlawful for an employer or an employment agency to use an **automated employment decision tool** to screen a candidate or employee for an employment decision unless such tool has been the subject of a bias audit conducted no more than one year prior to the use of such tool; and a summary of the results of the most recent bias audit of such tool as well as the distribution date of the tool to which such audit applies has been made publicly available on the website of the employer or employment agency prior to the use of such tool. An AEDT is a computer-based tool that: Uses **machine learning**, statistical modeling, data analytics, or **artificial intelligence**.

Appendix B		
Variable	**Definitions**	**Source**
ACQUISITION	An indicator variable that equal 1 if firm i's had an acquisition in year t that affects revenues or income	Compustat
ADVERTISING	The natural logarithm of advertising expenses for firm i in year t	Compustat
AGE	The number of years since firm i first appeared in Compustat as of year t	Compustat
AILAW	An indicator variable equals to 1 in year t after firm i's home state (or city) j adopts regulation to ensure the responsible use of AI systems and thereafter and 0 otherwise.	Manually Collected
AILAW_PLACEBO	An indicator variable that equals 1 if firm i's year t actual passing of AI regulation is randomly assigned, and 0 otherwise.	Seeded
AILAWt	An indicator variable that equals to 1 if firm i's year t is in the year firm i's home state (or city) j passes AI law, i.e., when the law is enacted, and 0 otherwise	Manually Collected
AILAWt+1	An indicator variable that equals to 1 if firm i's year t is in the year after firm i's home state (or city) j passes AI law, i.e., when the law is enacted, and 0 otherwise	Manually Collected
AILAWt+2	An indicator variable that equals to 1 if firm i's year t falls two years after firm i's home (or city) state j passes AI law, i.e., when the law is enacted, and 0 otherwise	Manually Collected
AILAWt-1	An indicator variable that equals to 1 if firm i's year t is in the year before firm i's home state (or city) j passes AI law, i.e., when the law is enacted, and 0 otherwise	Manually Collected
AILAWt-2	An indicator variable that equals to 1 if firm i's year t falls within two years before firm i's home state (or city) j passes AI law, i.e., when the law is enacted, and 0 otherwise	Manually Collected
AILAW_GEOCON	The ratio of the mentions of a specific state for firm i's 10-K in year t to the mentions of all states in firm i's 10-K in year t multiplied by AILAW.	Manually Collected
AIWORKERS	The number of employees with AI-related skills scaled by the total number of employees for firm i in year t obtained from resume aggregator Cognism as per Babina et al. (2024)	Babina et al. (2024)
BETA	The coefficient from regressing daily returns for firm i over year t on contemporaneous value equally-weighted market returns; this measure is corrected for nonsynchronous trading following Scholes and Williams (1977)	CRSP
CIO_CISO_CSO	An indicator variable that equals to 1 if firm i has a Chief Information Officer, Chief Information Security Officer, or Chief Security Officer in year t and 0 otherwise	BoardEx
COC	The average of the four implied cost of equity estimates, in excess of the risk-free rate, calculated following the methodologies in Claus and Thomas (2001), Gebhardt et	I/B/E/S

	al. (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005)	
COC_FACTOR	The first factor from a principal component analysis of the four implied cost of equity estimates, in excess of the risk-free rate, calculated following the methodologies in Claus and Thomas (2001), Gebhardt et al. (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005)	I/B/E/S, Principal Component Analysis
COC_PEG	The implied cost of equity capital, in excess of the risk-free rate, estimated using the unmodified Easton (2004) model	I/B/E/S
CPENALTIES	The natural logarithm of the total consumer-related penalties for firm i in year t and 0 otherwise	Violation Tracker
CVIOLATION	An indicator variable equals to 1 if firm i had a consumer-related violation in year t and 0 otherwise	Violation Tracker
EMPLOYEES	The natural logarithm of the total number or employees for firm i in year t and 0 otherwise	Compustat
EPENALTIES	The natural logarithm of the total employment-related penalties for firm i in year t and 0 otherwise	Violation Tracker
EVIOLATION	An indicator variable equals to 1 if firm i had an employment-related violation in year t and 0 otherwise	Violation Tracker
FOREIGN	An indicator variable equals to 1 if firm i has positive foreign income in year t and 0 otherwise	Compustat
IO	The percentage of firm i's shares held by institutional investors in year t	Thomson Reuters
LAG_CVIOLATION	An indicator variable equals to 1 if firm i had a consumer-related violation in year t-1 and 0 otherwise	Violation Tracker
LAG_CPENALTIES	The natural logarithm of the total consumer-related penalties for firm i in year t-1	Violation Tracker
LAG_EVIOLATION	An indicator variable equals to 1 if firm i had an employment-related violation in year t -1 and 0 otherwise	Violation Tracker
LAG_EPENALTIES	The natural logarithm of the total employment-related penalties for firm i in year t-1 and 0 otherwise	Violation Tracker
LEVERAGE	Long-term debt divided by total assets for firm i in year t	Compustat
LNDISP	The natural logarithm of 1 plus the standard deviation of analysts' forecasts divided by the consensus analyst forecast for firm i in year t	I/B/E/S
LTG	The median analyst forecast of the long-term earnings growth rate for firm i in year t	I/B/E/S
MOMENTUM	The stock return over the fiscal year	CRSP
MTB	Market capitalization divided by book value of equity for firm i in year t	Compustat
RESTRUCTURE	An indicator variable that equals 1 if firm i recognized positive restructuring charges in year t and zero otherwise	Compustat
RISK	The annualized standard deviation of the residuals from regressing daily stock returns for firm i over year t on the contemporaneous value-weighted market returns; this measure is corrected for nonsynchronous trading following Scholes and Williams (1977)	CRSP

ROA	Income divided by total assets for firm i in year t	Compustat
SALES	The natural logarithm of sales for firm i in year t	Compustat
SEGMENTS	The natural logarithm of the total number of geographic and operating segments for firm i in year t	Compustat
SIZE	The natural logarithm of total market capitalization for firm i in year t	Compustat
TECHOFFICER	An indicator variable that equals to 1 if firm i has a Chief Technology Officer, Chief Information Officer, Chief Information Security Officer, or Chief Security Officer in year t and 0 otherwise	BoardEx

Appendix C

Robustness Check for Time-Varying Treatment Effects

		COC	COC	COC	COC
	Expected Sign	**(1)**	**(2)**	**(3)**	**(4)**
AILAW	-	-0.0038	-0.0051***	-0.0045**	-0.0041**
		(-1.59)	(-3.09)	(-2.31)	(-2.65)
ROA	?	-0.0115	0.0051	0.0177***	0.0126**
		(-1.66)	(0.93)	(3.09)	(2.36)
LEVERAGE	+	0.0114	0.0240***	0.0258***	0.0257***
		(1.00)	(3.68)	(3.76)	(3.83)
SIZE	-	0.0033	0.0017	-0.0021	-0.0007
		(0.70)	(0.57)	(-1.00)	(-0.26)
MTB	-	-0.0002***	-0.0001**	-0.0001	-0.0001
		(-2.72)	(-2.08)	(-1.52)	(-1.04)
BETA	+	0.0121***	0.0096***	0.0104***	0.0110***
		(4.40)	(4.41)	(4.06)	(3.85)
LNDISP	+	-0.0138**	-0.0053	-0.007	-0.0052
		(-2.14)	(-0.87)	(-1.41)	(-1.13)
LTG	+	0.0077**	0.0069***	0.0066***	0.0073***
		(2.66)	(3.16)	(2.86)	(3.15)
MOMENTUM	-	-0.003	-0.0050**	-0.0046**	-0.0032**
		(-1.33)	(-2.61)	(-2.48)	(-2.38)
RISK	+	0.0098	0.0016	0.0189	0.0161
		(0.34)	(0.11)	(1.30)	(1.36)
Firm FE		YES	YES	YES	YES
Year FE		YES	YES	YES	YES
Adj.R2		0.5019	0.5116	0.5047	0.4968
N		2998	4015	5025	6002

This table presents the robustness check for whether time-varying treatment effects are a significant threat to inferences. Column 1 presents the results for the first treatment event (2018). Column 2 presents the results for the second treatment event (2019). Column 3 presents the results for the third treatment event (2020). Column 4 presents the results for the fourth treatment event (2021). Standard errors are clustered by state unless otherwise indicated. t-statistics are presented in parentheses. Significance is assessed using two-tailed tests p-values. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 1

Panel A: Sample Selection

	Observations
Firm-year observations from Compustat between 2017 to 2022 with available state location information	35013
Less: Data missing earnings forecasts from IBES	27859
Less: Data missing control variables	933
Less: Singleton observations in fixed-effect model	219
Total sample size	6002

This table reports our sample selection procedure.

Panel B: Sample Distribution by State

State	Observations	State	Observations
Alabama	30	Montana	6
Arkansas	32	North Carolina	154
Arizona	150	Nebraska	28
California	1008	New Hampshire	25
Colorado	185	New Jersey	189
Connecticut	111	New Mexico	2
District of Columbia	20	Nevada	66
Delaware	29	New York	385
Florida	284	Ohio	208
Georgia	179	Oklahoma	42
Hawaii	12	Oregon	40
Iowa	15	Pennsylvania	274
Idaho	20	Puerto Rico	6
Illinois	275	Rhode Island	25
Indiana	71	South Carolina	36
Kansas	19	South Dakota	3
Kentucky	40	Tennessee	80
Louisiana	29	Texas	663
Massachusetts	372	Utah	68
Maryland	89	Virginia	181
Maine	6	Washington	96
Michigan	114	Wisconsin	135
Minnesota	134	West Virginia	4
Missouri	51	Total	6002
Mississippi	11		

This table reports the sample distribution by state.

Panel C: Sample Distribution by Industry

Fama-French (12) Industries	Observations
Business Equipment -- Computers, Software, and Electronic Equipment	1380
Chemicals and Allied Products	211
Consumer Durables -- Cars, TV's, Furniture, Household Appliances	173
Consumer NonDurables -- Food, Tobacco, Textiles, Apparel, Leather, Toys	334
Finance	85
Healthcare, Medical Equipment, and Drugs	984
Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	714
Oil, Gas, and Coal Extraction and Products	344
Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment	829
Telephone and Television Transmission	161
Utilities	22
Wholesale, Retail, and Some Services (Laundries, Repair Shops)	765
Total	6002

This table reports the sample distribution by industry.

Table 2

Panel A: Descriptive Statistics

Variable	Observations	Mean	Std. dev	Median	Min	Max
AILAW	6,002	0.1503	0.3574	0.0000	0.0000	1.0000
COC	6,002	0.0613	0.0497	0.0541	-0.0309	0.6317
ROA	6,002	0.0013	0.2130	0.0403	-4.8769	0.4492
LEVERAGE	6,002	0.2971	0.2293	0.2744	0.0000	1.4189
SIZE	6,002	8.1008	1.7275	8.0950	1.3772	11.6098
MTB	6,002	4.3083	10.8799	2.8914	-51.5005	61.5752
BETA	6,002	1.1808	0.4215	1.1507	0.1227	2.4476
LNDISP	6,002	0.0760	0.1646	0.0227	0.0000	1.1394
LTG	6,002	0.1257	0.7591	0.1200	-4.0000	4.2143
MOMENTUM	6,002	0.1600	0.4659	0.1732	-1.7274	2.0706
RISK	6,002	0.2514	0.1275	0.2205	0.0639	1.0225

Panel B: Descriptive Statistics by AILAW=1 and AILAW=0

	AILAW=1			AILAW=0				
Variable	Mean	Std. dev	Median	Mean	Std. dev	Median	Difference	
COC	0.0513	0.0484	0.0443	0.0630	0.0497	0.0562	-0.0117	***
ROA	-0.0142	0.2530	0.0363	0.0040	0.2050	0.0406	-0.0182	*
LEVERAGE	0.2643	0.2098	0.2416	0.3029	0.2321	0.2794	-0.0386	***
SIZE	8.4141	1.8688	8.3757	8.0454	1.6954	8.0442	0.3687	***
MTB	5.8345	12.9032	4.0566	4.0383	10.4597	2.7294	1.7962	***
BETA	1.2398	0.4558	1.2049	1.1704	0.4144	1.1425	0.0694	***
LNDISP	0.0838	0.1673	0.0267	0.0746	0.1641	0.0220	0.0092	
LTG	0.1206	0.8709	0.1366	0.1266	0.7376	0.1164	-0.0060	
MOMENTUM	0.1598	0.5368	0.1832	0.1600	0.4523	0.1721	-0.0002	
RISK	0.2803	0.1280	0.2516	0.2463	0.1267	0.2145	0.0340	***
Observations	902			5100			6002	

This table shows the descriptive statistics. All continuous variables are winsorized at the 1st and 99th percentiles. Panel A presents statistics for the pooled sample. Panel B presents statistics for firm-years affected by AI regulation (AILAW=1) and firm-years not affected by AI regulation (AILAW=0). All variables are defined in Appendix B.

Table 3
Pearson Correlations

	COC	ROA	LEVERAGE	SIZE	MTB	BETA	LNDISP	LTG	MOMENTUM	RISK
COC	1.00									
ROA	**0.11**	1.00								
LEVERAGE	**0.16**	**-0.04**	1.00							
SIZE	**-0.12**	**0.42**	**0.04**	1.00						
MTB	**-0.11**	0.02	**-0.11**	**0.13**	1.00					
BETA	**0.11**	**-0.14**	**0.06**	**-0.11**	**0.03**	1.00				
LNDISP	**0.05**	**-0.11**	**0.03**	**-0.19**	0.00	**0.11**	1.00			
LTG	**0.14**	**0.13**	0.01	**0.06**	0.01	0.01	**0.05**	1.00		
MOMENTUM	**-0.03**	**0.12**	**-0.05**	**0.14**	**0.10**	-0.01	0.02	0.01	1.00	
RISK	**0.08**	**-0.49**	**0.04**	**-0.55**	**-0.03**	**0.30**	**0.25**	**-0.08**	**0.15**	1.00

This table shows the Pearson correlations for the sample. Correlations that are significant at the 0.05 level or better are highlighted in bold. All variables are defined in Appendix B.

Table 4
The Effect of AI Laws for the Responsible Use of AI and Cost of Capital

		COC
	Expected Sign	**(1)**
AILAW	-	**-0.0041****
		(-2.65)
ROA	?	0.0126**
		(2.36)
LEVERAGE	+	0.0257***
		(3.83)
SIZE	-	-0.0007
		(-0.26)
MTB	-	-0.0001
		(-1.04)
BETA	+	0.0110***
		(3.85)
LNDISP	+	-0.0052
		(-1.13)
LTG	+	0.0073***
		(3.15)
MOMENTUM	-	-0.0032**
		(-2.38)
RISK	+	0.0161
		(1.36)
Firm FE		YES
Year FE		YES
Adj.R2		0.497
N		6002

This table presents the results of estimating Equation (1) for H1. Standard errors are clustered by state. t-statistics are presented in parentheses. Significance is assessed using two-tailed tests p-values. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 5
Validity of the Parallel Trends Assumption

		COC
	Expected Sign	**(1)**
AILAWt-2	Not significant	-0.0006
		(-0.34)
AILAWt-1	Not significant	0.0017
		(0.78)
AILAWt	-	-0.0034
		(-1.53)
AILAWt+1	-	-0.004
		(-1.08)
AILAWt+2	-	-0.0057***
		(-2.96)
ROA	?	0.0128**
		(2.39)
LEVERAGE	+	0.0254***
		(3.78)
SIZE	-	-0.0008
		(-0.30)
MTB	-	-0.0001
		(-1.01)
BETA	+	0.0111***
		(3.89)
LNDISP	+	-0.0053
		(-1.16)
LTG	+	0.0073***
		(3.13)
MOMENTUM	-	-0.0031**
		(-2.20)
RISK	+	0.0156
		(1.33)
Firm FE		YES
Year FE		YES
Adj.R2		0.497
N		6002

This table presents the results for the leads and lags analysis to validate the parallel trends assumption. Standard errors are clustered by state. t-statistics are presented in parentheses. Significance is assessed using two-tailed tests p-values. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 6
Sensitivity Analyses

		COC	COC	COC	COC_PEG	COC_FACTOR
	Expected Sign	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
AILAW_PLACEBO	**Not significant**	0.0012				
		(0.75)				
AILAW	**-**		**-0.0037*** **	**-0.0041** **	**-0.0069*** **	**-0.1462*** **
			(-3.05)	**(-2.30)**	**(-3.23)**	**(-3.28)**
ROA	?	0.0135**	0.0079	0.01	-0.0168	-0.2655
		(2.47)	(1.55)	(1.63)	(-0.94)	(-0.61)
LEVERAGE	+	0.0267***	0.0200***	0.0257***	0.0416***	1.5586***
		(4.12)	(2.80)	(5.30)	(5.48)	(9.18)
SIZE	-	-0.001	-0.0011	(0.00)	-0.0130***	-0.3406***
		(-0.39)	(-0.37)	(-0.22)	(-5.16)	(-6.27)
MTB	-	0.0000*	-0.0001	-0.0001	0.0000	-0.0025*
		(1.86)	(-1.17)	(-1.11)	(0.91)	(-1.68)
BETA	+	0.0106***	0.0106***	0.0110***	0.0231***	0.6089***
		(3.39)	(3.70)	(4.55)	(5.96)	(7.70)
LNDISP	+	-0.0022	-0.0028	-0.0052	-0.0038	-0.4045***
		(-0.67)	(-0.65)	(-1.18)	(-0.57)	(-2.83)
LTG	+	0.0008	0.0065***	0.0073**	0.0036	0.7853***
		(1.36)	(2.91)	(3.31)	(1.06)	(8.39)
MOMENTUM	-	-0.0026*	-0.0026*	-0.0032	-0.0086***	-0.2860***
		(-1.88)	(-1.98)	(-1.77)	(-4.80)	(-6.22)
RISK	+	0.0149	0.0119	0.0161	0.0051	-0.0646
		(1.24)	(0.97)	(1.26)	(0.35)	(-0.19)
Firm FE		YES	YES	YES	YES	YES
Year FE		YES	NO	YES	YES	YES
Industry*Year FE		NO	YES	NO	NO	NO
Adj.R2		0.4868	0.5118	0.4968	0.5633	0.6988
N		6002	5972	6002	4395	4246

This table presents sensitivity analyses. Column 1 shows the results of AI regulation placebo treatment and cost of equity. Column 2 shows the results of AI regulation and cost of equity with industry-year fixed effects. Column 3 shows the results of AI regulation and cost of equity with double-clustered standard errors by state and year. Column 4 shows the results of AI regulation and the implied cost of equity estimation based on the unmodified Easton methodology. Column 5 shows the results of AI regulation and a factor comprised of the four cost of equity estimations as per the Claus and Thomas (2001), Gebhard et al. (2001), modified Easton (2004), and Ohlson and Juettner-Nauroth (2005) measures. Standard errors are clustered by state unless otherwise indicated. t-statistics are presented in parentheses. Significance is assessed using two-tailed tests p-values. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 7
The Effect of AI Laws for the Responsible Use of AI and More AI Investment

		Less AI Investment COC	More AI Investment COC
	Expected Sign	**(1)**	**(2)**
AILAW	-	-0.0038	-0.0071***
		(-0.78)	(-4.44)
ROA	?	0.0407***	0.0015
		(3.84)	(0.11)
LEVERAGE	+	0.0179	0.0194**
		(1.25)	(2.63)
SIZE	-	-0.0019	0.0016
		(-0.37)	(0.43)
MTB	-	-0.0001	-0.0001
		(-1.14)	(-1.09)
BETA	+	0.0111**	0.0108***
		(2.49)	(2.99)
LNDISP	+	0.0026	-0.0072
		(0.30)	(-1.08)
LTG	+	0.0052*	0.0073**
		(1.76)	(2.28)
MOMENTUM	-	-0.0070*	-0.0085***
		(-1.87)	(-3.44)
RISK	+	0.0057	-0.0237
		(0.30)	(-0.92)
Firm FE		YES	YES
Year FE		YES	YES
Adj.R2		0.5078	0.5412
N		1690	1825

This table presents the results for the effects of AI laws on cost of equity for the subsample of firms with more versus less investments in AI. Standard errors are clustered by state. t-statistics are presented in parentheses. Significance is assessed using two-tailed tests p-values. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 8
The Effect of AI Laws for the Responsible Use of AI and Firm Size

		Smaller Firms COC	Larger Firms COC
	Expected Sign	**(1)**	**(2)**
AILAW	-	-0.0081***	-0.0001
		(-2.73)	(-0.05)
ROA	?	0.008	0.0047
		(1.28)	(0.47)
LEVERAGE	+	0.0264**	0.0221***
		(2.65)	(2.89)
SIZE	-	0.005	-0.0067***
		(1.30)	(-4.22)
MTB	-	-0.0002*	0.000
		(-1.98)	(-0.50)
BETA	+	0.0084*	0.0160***
		(1.80)	(7.18)
LNDISP	+	-0.002	-0.0155*
		(-0.40)	(-1.97)
LTG	+	0.0077***	0.0056***
		(2.92)	(2.75)
MOMENTUM	-	-0.0033	-0.0043***
		(-1.55)	(-2.75)
RISK	+	0.0303*	-0.0134
		(1.72)	(-0.94)
Firm FE		YES	YES
Year FE		YES	YES
Adj.R2		0.4444	0.5805
N		2801	3078

This table presents the results for the effects of AI laws on cost of equity for the subsample with smaller firms and larger firms. Standard errors are clustered by state. t-statistics are presented in parentheses. Significance is assessed using two-tailed tests p-values. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 9

The Effect of AI Laws, Geographic Concentration, and Cost of Capital

		COC
	Expected Sign	**(1)**
AILAW_GEOCON	-	-0.0064**
		(-2.41)
ROA	?	0.0126**
		(2.34)
LEVERAGE	+	0.0256***
		(3.81)
SIZE	-	-0.0007
		(-0.26)
MTB	-	-0.0001
		(-1.05)
BETA	+	0.0110***
		(3.89)
LNDISP	+	-0.0051
		(-1.12)
LTG	+	0.0073***
		(3.14)
MOMENTUM	-	-0.0032**
		(-2.34)
RISK	+	0.0162
		(1.36)
Firm FE		YES
Year FE		YES
Adj.R2		0.4966
N		6002

This table presents the results for the geographic concentration (based on 10-K mentions) of firms that are affected by AI laws on cost of equity. Standard errors are clustered by state. t-statistics are presented in parentheses. Significance is assessed using two-tailed tests p-values. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 10
The Effect of AI Laws for the Responsible Use of AI and Technology Expertise in Top Management

		CIO_CISO_CSO
	Expected Sign	**(1)**
AILAW	+	**0.0271*** **
		(3.82)
ROA	?	0.0004
		(0.32)
LEVERAGE	?	0.0117
		(0.68)
SIZE	+	0.0073***
		(4.65)
MTB	?	0.0001
		(0.49)
AGE	?	0.0101
		(0.49)
IO	?	-0.0034
		(-1.07)
SEGMENTS	?	0.0037*
		(1.93)
FOREIGN	?	0.0073
		(0.52)
ACQUISITION	?	0.0082
		(0.86)
RESTRUCTURING	?	0.0064
		(0.77)
Firm FE		YES
Year FE		YES
Adj.R2		0.1026
N		7965

This table presents the results for the effects of AI laws and technology expertise on the top management team. Column 1 shows the results of AI regulation and CIO_CISO_CSO (whether the firm has a Chief Information Officer, Chief Information Security Officer, or Chief Security Officer). Standard errors are clustered by state. t-statistics are presented in parentheses. Significance is assessed using two-tailed tests p-values. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 11
The Effect of AI Laws for the Responsible Use of AI and Firm Violations

		CVIOLATION	CPENALTIES	EVIOLATION	EPENALTIES
	Expected Sign	**(1)**	**(2)**	**(3)**	**(4)**
AILAW	-	0.0011	0.0185	-0.0110**	-0.1312**
		(0.15)	(0.21)	(-2.07)	(-2.45)
ROA	?	(0.00)	(0.01)	(0.00)	(0.00)
		(-1.57)	(-1.33)	(-0.08)	(-0.15)
LEVERAGE	?	0.01	0.06	(0.01)	(0.13)
		(0.95)	(0.76)	(-1.09)	(-1.27)
SIZE	?	0.00	0.01	0.0013*	0.01
		(0.78)	(0.46)	(2.07)	(1.48)
SALES	?	0.0054	0.0691*	0.0035	0.0387
		(1.99)	(2.13)	(1.05)	(1.01)
EMPLOYEES	?	0.00	0.00	0.01	0.10
		(0.15)	(0.11)	(1.11)	(1.27)
ADVERTISING	?	-0.0017	-0.021	-0.0001	-0.0101
		(-0.96)	(-1.06)	(-0.02)	(-0.35)
SEGMENTS	?	-0.0007	-0.008	0.0016	0.0181
		(-0.50)	(-0.49)	(0.98)	(0.93)
LAG_CVIOLATION	?	-0.1793***			
		(-5.72)			
LAG_CPENALTIES	?		-0.1739***		
			(-5.75)		
LAG_EVIOLATION	?			-0.1229***	
				(-4.13)	
LAG_EPENALTIES	?				-0.1020***
					(-3.72)
Firm FE		YES	YES	YES	YES
Year FE		YES	YES	YES	YES
Adj.R2		0.245	0.241	0.322	0.33
N		7369	7369	7369	7369

This table presents the results for the effects of AI laws on consumer- or employee-related firm violations. Column 1 shows the results of AI regulation and consumer-related firm violations. Column 2 shows the results of AI regulation and consumer-related firm penalty amounts. Column 3 shows the results of AI regulation and employee-related firm violations. Column 4 shows the results of AI regulation and employee-related firm penalty amounts. Standard errors are clustered by state. t-statistics are presented in parentheses. Significance is assessed using two-tailed tests p-values. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.