Artificial Intelligence and Firms' Systematic Risk

Tania Babina[a], Anastassia Fedyk[b,], Alex He[c], James Hodson[d]

[a]*University of Maryland, College Park, MD, USA, NBER, and CEPR*
[b]*University of California, Berkeley, Berkeley, CA, USA*
[c]*University of Maryland, College Park, MD, USA*
[d]*AI for Good Foundation, Berkeley, CA, USA*

Abstract

We provide direct evidence that firms' investments in new technologies affect the composition of firms' risk profiles. Leveraging comprehensive data on firm-level artificial intelligence (AI) investments, we document that firms that invest more in AI experience increases in their systematic risk, measured by market beta. Our results are consistent with AI investments creating growth options: AI-investing firms become more growth-like, and the effect on market betas concentrates during market upswings and periods of increased news and attention around AI advances. Other already established technologies (e.g., non-AI IT and Robotics) and capital expenditures do not display similar effects. Our evidence supports theories arguing that emerging technologies can be an important source of growth options and new investment opportunities.

Keywords: Artificial intelligence, technology, systematic risk, market beta, asset pricing, growth options, cost of capital

*This draft: February 2, 2026 (first draft: November 18, 2023.) Email addresses: tbabina@umd.edu (Tania Babina), fedyk@berkeley.edu (Anastassia Fedyk), axhe@umd.edu (Alex He), hodson@ai4good.org (James Hodson). We are grateful for the helpful comments of Simona Abis (discussant), Jan Bena (discussant), Leland Bybee (discussant), John Campbell, Lauren Cohen (discussant), Kent Daniel, Winston Dou (discussant), Andrea Eisfeldt, Andrei Gonçalves, Leonid Kogan, Serhiy Kozak, Eben Lazarus, Martin Lettau, Jun Li, Semyon Malamud, Dimitris Papanikolaou (discussant), Tano Santos, Sean Shin, Gregor Schubert (discussant), Mike Simutin, David Sraer, Paul Tetlock, Laura Veldkamp, Johan Walden, Baozhong Yang (discussant); Ben Zhang (discussant), and participants at AI in Finance Conference 2026 in Barcelona; AIEA Seminar; American Economic Association; American University; Association of Financial Economists; Arizona State University; Bank of Italy; Bundesbank; CEPR CAFFE (online) Seminar; Central European University; Columbia University's Women Applied Micro Seminar; European Central Bank; European Finance Association; Federal Reserve Board; Financial Intermediation Research Society; Fordam University; Foundation for Advancement of Research in Financial Economics (FARFE) Conference, Frankfurt School of Finance; Georgetown University; Georgia State University; Georgia Tech University; Georgia Tech AI Conference; IMF-WIFPR Conference on Financial and Real Implications of Technologies, AI, and Cyber Risks; Michigan State University; MIT Initiative on the Digital Economy Seminar; NBER Productivity Innovation, and Entrepreneurship Meeting; Notre Dame Investment Management conference; Rutgers University; SFS Cavalcade; Conference on AI in Corporate Finance; Temple University; UC Berkeley; UC Irvine; University of British Columbia; University of Delaware; University of Georgia; University of Southern California; University of Saint Andrews; University of Toronto; Webinar on Applied Machine Learning, Economics, and Data Science (AMLEDS); Wharton AI and the Future of Work Conference; and York University. We thank Andrei Gonçalves and Eben Lazarus for sharing their equity duration data. All errors are our own.

Technological advances are a major source of economic growth (Aghion and Howitt, 1992). For firms, investments in technology can bring substantial benefits in the form of increased scale, productivity, and valuations (Kogan et al., 2017). At the same time, investments in new and untested technologies involve inherent risks, incurring upfront costs with highly uncertain payoffs. As the value of investments in a new technology depends on whether the technology proves to be widely important, firms' investments in new technologies can carry systematic risk (Pástor and Veronesi, 2009). This has important implications for firms' cost of capital, investment, capital allocation, and market stability.

The notion of new technologies transforming firms' systematic risk is especially salient for the latest technological revolution unfolding over the past decade: artificial intelligence (AI).[1] While early AI-adopting firms have reaped benefits in the form of increased sales, valuations, and market share (Rock, 2019; Eisfeldt et al., 2025; Babina et al., 2024), how this transformation has affected firms' systematic risk remains an open question. On the one hand, theoretical work has argued that significant new technologies such as AI can increase firms' systematic risk through growth options: if the new technology proves to be widely important, investing firms will end up with many investment opportunities (Carlson et al., 2004, 2006, 2010; Pástor and Veronesi, 2009; Kumar and Li, 2016). On the other hand, as a prediction technology (Agrawal et al., 2019), AI can help firms better adjust to market conditions, reducing their systematic risk.

This paper uses the AI revolution as a laboratory to empirically assess the effect of new technologies on systematic risk. Unlike prior general purpose technologies, the AI revolution unfolded at a time when digitization and AI tools themselves made it possible to construct detailed firm-level data on AI investments. Focusing on the early adoption years when it was uncertain how valuable this technology could be,[2] we examine how an

[1] Mihet and Philippon (2019) provide an overview of AI technologies and their key economic properties.

[2] Our period, 2010–2018, focuses on the initial rise of AI before OpenAI released GPT-3 in June 2020, a massive 175-billion parameter model that brought widespread attention to large language models.

emerging general purpose technology transforms firms' risk profiles.

To evaluate changes in systematic risk associated with firms' AI investments, we use a measure of firm investments in AI technologies based on AI-skilled human capital (e.g., machine learning engineer), following the methodology proposed and validated by Babina et al. (2024). We link firm-level AI investments to measures of firm systematic risk—market betas computed for U.S. public firms using the Capital Asset Pricing Model (CAPM) and the Carhart (1997) four-factor model.[3] Our main empirical specification is a long-differences regression, which is especially well-suited to gradual processes such as technological change (e.g., Acemoglu and Restrepo, 2020). Specifically, we estimate how changes in firm betas from 2010 to 2018 relate to concurrent changes in firm-level AI investments. This specification also controls for time-invariant firm characteristics by first-differencing both the dependent and independent variables.

As our main result, we document that firms that invest more in AI experience an increase in their systematic risk: a one-standard-deviation increase in the growth of a firm's share of AI workers corresponds to a 0.05 increase in the firm's market beta. To put this magnitude in perspective, this increase in market beta corresponds to approximately 20% of the standard deviation of the change in beta over the time period. While previous theoretical work has argued that important emerging technologies can increase the systematic risk of early adopter firms (e.g., Pástor and Veronesi 2009), to the best of our knowledge, ours is the first paper to show this connection empirically using AI as a test ground.

We show that the positive association between AI investment and systematic risk is not explained by reverse causality. First, firms' initial betas do not predict subsequent growth of firms' AI investments, and the main results are robust to controlling for initial firms' betas. Second, we find similar results when looking at early adopters—firms investing heavily in AI in the first half of the sample. To further bolster causal interpretation, we follow Babina et al. (2024) and instrument for firm-level AI investments using vari-

[3] A firm's market beta is the covariance of the firm's stock returns with aggregate stock market returns.

ation in firms' ex-ante exposure to the subsequent supply of AI talent from universities that are historically strong in AI research. As AI-research-strong universities have been able to train more AI-skilled students, firms that historically hired from those universities have better access to the supply of AI trained graduates. We find that instrumented AI investments predict increases in firms' market betas.

Our main finding is consistent with firms using AI technology to create growth options that enable future expansion. As modeled by Carlson et al. (2004, 2006, 2010), Pástor and Veronesi (2009), and Kumar and Li (2016) in different settings, growth opportunities are associated with increasing market beta as the exercise of those opportunities becomes more likely.[4] If those growth options become in-the-money and get exercised, they can help firms expand through improved labor productivity (e.g., Kogan et al. 2024) and increased product innovation (Babina et al. 2024). Bena et al. (2023) examine nearly a century of patent activity to show that innovator firms have different dynamics from non-innovator firms, consistent with growth options—that is, *expected* growth (Hou et al., 2021). Our results suggest the potential for new technologies, such as AI, to reflect investments in future growth options, rather than immediate changes to firm operations.

The growth options channel has several additional predictions that we test in the data. First, consistent with AI-investing firms loading positively on growth options, these firms become more growth-like, experiencing a significant decrease in the value (high-minus-low, or HML) factor. AI-investing firms become less correlated with value firms and more correlated with growth firms, with significant effects on both sides. In this way, our paper speaks to technology as a *source* of growth opportunities and a driver of firm characteristics, complementing recent work on how firms with (pre-existing) growth opportunities react to subsequent technological shocks (Kogan and Papanikolaou, 2014).

Second, we examine whether AI-investing firms' increased correlation with market

[4]Empirically, Bernardo et al. (2007) document that growth opportunities have higher beta than assets-in-place in virtually all industries.

returns is driven by upside risk (market going up) or downside risk (market going down). The hypothesis is that growth options offered by AI become more in-the-money during market upswings, leading to a greater increase in upside beta than downside beta. To test this, we decompose firm beta into upside and downside beta following the methodology of Ang et al. (2006). The results reveal that AI-investing firms experience a significantly larger increase in upside beta than downside beta.

Third, conceptual frameworks such as Pástor and Veronesi (2009) predict that market betas of firms that leverage a new exploratory technology should increase with learning positive information about the new technology. We directly test this mechanism in the data, by focusing on times when AI-driven growth opportunities are likely to become more valuable: periods of heightened media and investor attention to advances in AI. We use the comprehensive RavenPack news data to separate each year into days with above-median and below-median AI news. As an alternative measure, we leverage Google Trends data to identify spikes in search attention around "artificial intelligence." For both measures, the increase in AI-investing firms' betas is about twice larger during high AI news times than during low AI news times.

We further test the channel of new technologies creating growth options in early stages of their adoption by considering several foils. We leverage our detailed data to measure firms' investments in what are arguably the most related technologies: (non-AI) information technology (IT) and robotics. By the time of the AI revolution, these technologies were already established; their growth options had been harvested and converted into assets in place. Empirically, we confirm that both of these non-AI technologies have a null relationship with changes in firms' betas during our sample period. Moreover, we find no significant association between firms' systematic risk and organizational capital, capital expenditures, or R&D investments, which also capture firms' realization and development of existing growth options in addition to the creation of future growth options. These results highlight that AI has had a unique relationship with firms' systematic risk

during our sample period, when AI technologies were emerging.

We demonstrate that our results cannot be explained by several alternative channels. First, the increased systematic risk is not driven by mechanical effects of AI-investing firms capturing a larger share of the market. Second, the relationship between firms' AI investments and their market betas is not driven by changes in financial or operating leverage. Third, the results are not due to issues with infrequent trading (Dimson, 1979). Fourth, the increased beta of AI-investing firms is not driven by equity duration (Lettau and Wachter, 2007; Gonçalves, 2021; Gormsen and Lazarus, 2023) and cannot be explained by the investment factor (Fama and French, 1993). Finally, our key finding is not consistent with a mechanism where AI-investing firms' betas increase due to correlated investor shocks or behaviors (Barberis and Shleifer, 2003): the results remain unchanged when we measure market returns using only non-AI investing firms; and the relationship between firms' AI investments and changes in their market beta is the same for firms with high and low shares of institutional ownership.

In addition, we test whether the increased systematic risk of AI-investing firms can be explained by either (i) these firms' increased correlation with the tech sector (if AI-investing firms from across different industries become more similar to "tech firms") or (ii) these firms' increased correlation with their own industry (due to becoming more dominant players in their own industry). Neither of these possibilities appears to be the main driver of our results. Remarkably, AI-investing firms experience very similar increases in betas to their own industry, the tech sector, and other industries. The ubiquitous effect, where AI-investing firms experience increased covariance with all parts of the market, supports theories such as Pástor and Veronesi (2009): as the market learns about a new technology, increasing the probability of eventual large-scale adoption, early adopters see increases in their systematic risk and comovement with other (non-adopting) firms.

In our final tests, we augment the results on systematic risk with a look at idiosyncratic volatility. Theory predicts that when the market is learning about a new emerging

technology, with corresponding increases in the probability of large-scale adoption, risk associated with the technology for early adopters turns from idiosyncratic to systematic (Pástor and Veronesi, 2009). This is exactly what we observe empirically for AI-investing firms in the 2010s. We document that firms that invest more in AI experience declines in idiosyncratic volatility. Although the effects on idiosyncratic volatility are statistically insignificant in some specifications, their economic magnitude is sufficient to offset the increase in systematic risk: despite increasing market betas, firms that invest more in AI see no changes in their total stock return volatility.

Overall, our evidence points to a significant shift in firms' risk profiles as they invest in artificial intelligence. AI-investing firms experience a reallocation of risk from idiosyncratic to systematic during the 2010s, when the technology was new and early AI investments created growth options. Further supporting this growth option mechanism, AI-investing firms become more growth-like, and the increased market covariance is larger on the market upside and during periods of intensive AI news.

Our paper contributes to the literature on the economic effects of technological change by documenting that investments in new technologies such as AI affect not only firm growth (i.e., the first moment) but also change firms' risk profiles (i.e., the second moment). These findings complement the results on excess returns, alpha, and potential bubbles associated with firms' technology investments and skilled human capital.[5] Prior work has shown positive abnormal returns and performance for firm investments in AI in general (e.g., Rock 2019; Eisfeldt et al. 2025; Hampole et al. 2025; Sheng et al. 2026) and in specific settings, such as asset management (e.g., Sheng et al. 2026; Chen et al. 2025). Our results are the first to show that AI affects not only firms' "alpha," but also their "beta," influencing the correlation structure between firms in the economy. In doing so, we speak to the growing literature on the effects of emerging AI technologies on firms, investors,

[5] E.g., Aboody and Lev (2000); Kogan et al. (2017); Gómez-Cram and Lawrence (2025); Fedyk and Hodson (2023).

and markets,[6] providing a novel angle centered on the composition of AI-investing firms' risk profiles.

We also contribute to the literature that examines how the emergence of growth options affects firms' systematic risk (Berk et al., 2004; Carlson et al., 2004, 2006, 2010; Pástor and Veronesi, 2009; Kumar and Li, 2016). Due to our granular firm-level measure of AI investments during a period when the technology was emerging, our results offer support to the notion that new technologies create growth options and affect the systematic risk profiles of AI-investing firms. To our knowledge, our paper is the first to directly measure the relationship between firm-level investments in an emerging technology and the systematic risk of firms investing in it. This complements the evidence on growth options from other innovation activities, such as patents (e.g., Bena et al. 2023).

1. Data and Measurement

Motivated by the heavy reliance of AI implementation on AI-skilled human capital, we measure firms' AI investments using their intensity of hiring AI-skilled labor. To construct these measures, we leverage two datasets: individual worker resumes from Cognism and job postings from Burning Glass Technologies. Below, we briefly describe each of these two datasets and present our measures of firms' AI investments and market betas.

1.1. Employment Profiles from Cognism

We use a dataset of approximately 535 million individual employee resumes to measure the stock of AI workers at each firm at each point in time. These data come from Cognism, an aggregator of employment profiles for lead generation and client relation-

[6] In finance, researchers have examined the impact of AI technologies in various settings: robo-advising (D'Acunto et al., 2019), loan underwriting (Fuster et al., 2022; Jansen et al., 2025), trading and price efficiency (Dou et al. 2024; Bonelli and Foucault 2023), fintech innovation (Chen et al., 2019), financial analysts (Grennan and Michaely, 2019; Abis and Veldkamp, 2024; Cao et al., 2024), venture capital and entrepreneurship (Gofman and Jin, 2024; Bonelli, 2025), and household finance (Blank et al. 2025).

ship management services, which obtains individual profiles from a variety of sources including publicly available online data, collaborations with recruiting agencies, and third-party resume aggregators.[7] The Cognism data are introduced and described in detail in Fedyk and Hodson (2023). Cognism data boast excellent coverage, accounting for approximately 64% of the entire U.S. workforce as of 2018, with a representative breakdown across industries.[8] In each resume, we observe the start and end dates, job title, company name, and job description of each listed job, as well as additional information provided by individuals on their resumes such as patents, awards, and publications.

Cognism's AI Research department uses techniques from machine learning and natural language processing to enrich the resume data by normalizing job titles and occupations, associating employees with functional divisions and teams within firms, identifying institutions, degrees, and majors from education records, and matching employer names in the Cognism data to the company names in the Compustat database.[9] This yields a sample of 101 million person-firm-years matched to U.S. public firms between 2010 and 2018, which includes 19 million distinct individual employees.

1.2. Job Postings from Burning Glass

We supplement the resume data from Cognism with over 180 million job postings in the United States in 2007 and 2010–2018, provided by Burning Glass Technologies. These data are drawn from a large set of sources, including more than 40,000 online job boards and company websites. Burning Glass aggregates the job posting data, parses them into a machine-readable form, and creates labor market analytics. The Burning Glass dataset covers approximately 60–70% of all vacancies posted in the U.S., either online or offline,

[7] The processing of all profiles is compliant with the applicable GDPR and CCPA regulations.

[8] Our data snapshot is from July of 2021, but we follow Tambe et al. (2020) and Babina et al. (2024) and use only the years through 2018 to avoid any noise from workers updating their resumes with a lag. The focus on the 2010–2018 time period is also motivated by our interest in examining the effect of AI as a new emerging technology, before its impact was widely visible.

[9] The matching of individual resumes to firm entities is performed dynamically to account for acquisitions and divestitures.

and its representativeness at the occupation level has remained stable over time (Hershbein and Kahn, 2018). For each job posting, Burning Glass records the job title, job location, occupation, and employer name.[10] Furthermore, the job postings are tagged with thousands of specific skills standardized from the open text in each job opening. This detailed taxonomy of skills in the job posting data is key to empirically identifying highly AI-relevant skills to measure firms' investments in AI-skilled human capital. We also leverage the job posting data to identify firms' investments in other related technologies: (non-AI) IT and robotics.

We restrict the sample to job postings with non-missing employer names (65% of all job postings) and at least one required skill (93% of all job postings). We drop all job postings that are internships and match the employer firms in the remaining job postings to Compustat firms following the fuzzy matching procedure outlined in Babina et al. (2024). The resulting sample consists of 42 million job postings matched to Compustat firms.

1.3. Additional Data Sources

To measure firms' betas, idiosyncratic volatility, and total volatility, we merge Cognism resume data and Burning Glass job posting data to stock return data from the Center for Research in Security Prices (CRSP). We add firm-level operational information (sales, assets, operating expenses, capital expenditures, cost of goods sold, cash flows, and R&D expenditures) from Compustat. We also collect commuting-zone-level wage and education data from the Census American Community Surveys (ACS) and industry-level wages and employment data from the Census Quarterly Workforce Indicators (QWI). Equity duration data come from Gonçalves (2021) and Gormsen and Lazarus (2023).

Comprehensive news data come from RavenPack, which provides real-time news analytics based on the Dow Jones (DJ) Newswire. RavenPack identifies entities mentioned

[10]Burning Glass employs a sophisticated deduplication algorithm to avoid double counting vacancies posted on multiple job boards.

in the news, measures characteristics such as sentiment, and classifies events and topics covered by the news. We use a sample of all DJ Newswire articles between 2010 and 2018 that RavenPack identifies as being related to artificial intelligence. We also use information on search for artificial intelligence terms from Google Trends, available at the monthly level.

1.4. Measures of Firm-Level AI Investments

We adopt the measures of firm-level AI investments introduced in Babina et al. (2024), which leverages the detailed skill taxonomy in the job posting data to empirically determine the terms that are most related to AI jobs. These measures are motivated by our research question and exhibit desirable characteristics within its context (Babina, 2026). Our motivating research question—on whether firms' risk changes as they invest in AI—calls for data: (i) on firms that are AI users rather than inventors (since we are interested in wider AI adoption); (ii) capturing internal AI development rather than outsourcing (to capture firms investing in the new technology); (iii) with broad firm coverage; (iv) with comprehensive AI use cases; (v) capturing actual AI capabilities rather than perceptions thereof; and (vi) reflecting all AI efforts whether successful or not. Our data-driven method also circumvents issues such as having to pre-specify lists of keywords to search, which may suffer from both Type I (incorrectly labeling tangentially related jobs as AI jobs) and Type II (missing actual AI jobs) errors.

Our measures of firm-level AI investments are constructed in three steps. First, we look at the 15,000 required skills listed in the job postings and measure the co-occurrence of each required skill with four core AI skills: *artificial intelligence*, *machine learning*, *natural language processing*, and *computer vision*. Specifically, for each required skill s that appears in the job postings, we compute the following measure:

$$w_s^{AI} = \frac{\text{\# of jobs requiring skill } s \text{ and (ML, NLP, CV, or AI in required skills or in job title)}}{\text{\# of jobs requiring skill } s} \tag{1}$$

This measure captures how frequently each skill appears together with the core AI skills. For example, the skill "Long Short-Term Memory (LSTM)" has a co-occurrence measure of 0.971, meaning that out of all job postings that have "Long Short-Term Memory (LSTM)" as a required skill, 97.1% of them explicitly include at least one of "Artificial Intelligence," "Machine Learning," "Computer Vision," and "Natural Language Processing" as a required skill. By contrast, the skill "Microsoft Office" has a co-occurrence measure of only 0.003, because the vast majority of job postings requiring "Microsoft Office" skills are not related to AI. Similarly, "Snow Removal" skills are not at all related to AI skills and have zero co-occurrence with the core AI skills.

In the second step of measuring firm-level AI investments, we use the terms identified as most related to AI in the job postings (i.e., terms with the highest measure w_s^{AI}) to locate AI-related employees in the Cognism resume data. Specifically, we search for these terms in the employees' job titles, job descriptions, and any patents, publications, and awards produced on the job. If any of these fields include at least one of the highly AI-relevant terms, then that employee at that firm at that time is considered an AI worker; otherwise, the employee is not considered an AI worker. For example, if an employee's job title is "Senior Machine Learning Developer," that employee is considered an AI worker, since "machine learning" is a highly AI-relevant term. Similarly, if an employee's job description includes "develop Chatbots using Python deep learning models," that employee is considered an AI worker, since "deep learning" is a highly AI-relevant term.

The final step aggregates the identified AI job postings and AI employees to the firm level. Our main firm-level measure is based on the Cognism resumes: the fraction of employees at each firm in each year who are classified as AI-skilled. We also compute a secondary firm-level measure based on job postings: the fraction of the job postings at each firm in each year that have an average AI-relatedness measure (across all required skills of the job posting) above 0.1. Since our empirical analyses focus on U.S.-listed firms, we include only employees who are based in the U.S. when computing the measures of

firms' AI investments.[11] These firm-level measures are described in detail and validated in Babina et al. (2024).

1.5. *Measures of Firms' Systematic Risk*

We follow the long literature in asset pricing and measure firms' systematic risk using market beta, which measures the covariance of the firm's stock returns with aggregate stock market returns. Our primary specification is the standard single-factor Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966). We are interested in understanding how firms' market betas change with their AI investments from 2010 to 2018. To do so, we estimate beta separately in each year, using daily return data (Frazzini and Pedersen, 2014; Hong and Sraer, 2016; Levi and Welch, 2017). Specifically, for each firm i in year T, we calculate

$$\beta_{i,T} = \frac{cov(r_{i,t}, r_{m,t})}{var(r_{m,t})} \text{ for days } t \text{ in year } T, \tag{2}$$

where $r_{i,t}$ is the time series of daily returns on security i during year T, and $r_{m,t}$ is the time series of the value-weighted return of all CRSP firms incorporated in the US, which we use as a proxy for the market portfolio. We estimate $\beta_{i,T}$ by regressing the daily stock returns against the daily market returns.

To examine the robustness of the market beta result and delve into the growth options mechanism, we also compute each security's market beta based on the Carhart (1997) four-factor model. Specifically, for each firm i in year t, we estimate the following regression using daily data:

$$r_{i,t} = \alpha_{i,T} + \beta_{i,T} r_{m,t} + \beta_{i,T}^{SMB} r_{SMB,t} + \beta_{i,T}^{HML} r_{HML,t} + \beta_{i,T}^{UMD} r_{UMD,t} \text{ for days } t \text{ in year } T, \tag{3}$$

[11] We restrict the sample to only those firms that have at least 20 U.S.-based employees in both 2010 and 2018, to ensure sufficient data coverage.

where $r_{SMB,t}$ is the daily premium on the small-minus-big factor as defined by Fama and French (1993), $r_{HML,t}$ is the daily premium on the high-minus-low factor from Fama and French (1993), and $r_{UMD,t}$ is the daily premium on the up-minus-down factor from Carhart (1997). The estimate of $\beta_{i,T}$ is the market beta, while $\beta_{i,T}^{SMB}$, $\beta_{i,T}^{HML}$, and $\beta_{i,T}^{UMD}$ provide additional information about how much AI-investing firms comove with three other key risk factors: size, value, and momentum, respectively.

It is worth pointing out that our main dependent variable—changes in firms' daily market beta from 2010 to 2018—does not require high-frequency information or updating regarding firms' hiring and AI investments. AI investments are slow-moving and positively correlated over time, and what we capture as the change in a firm's AI investment from 2010 to 2018 can be conceptualized as a firm characteristic (being an "AI-investing firm"). Changes in this firm characteristic can induce changes in the comovement of the firm's return with the overall market return, in the same way as characteristics such as size and value exhibit certain patterns of comovement in firms' returns, incuding firms' responses to future technological innovations (Kogan and Papanikolaou, 2014). As long as investors perceive firms' overall (low-frequency) AI investments, this will be reflected in the daily comovement of the firms' returns with market factors.

Table 1 presents the summary statistics for all variables included in the analysis: the dependent variables (measures of firm-level betas and their changes), independent variables (changes in AI investments and related technologies such as IT and robotics), and firm-level controls. On average, the increase in AI workers at firms is less than 0.1% of all firm workers, and the increase in the share of AI-related job postings is approximately 0.3%. A one-standard-deviation change in the resume-based (job-posting-based) measure of AI investments is 0.26% (0.95%). The average market beta of the firms in our sample in 2010 is 1.2 based on the CAPM and 1.0 based on the Carhart (1997) four-factor model.

2. Main Results: AI Investments, Market Beta, and Industry Betas

We begin by documenting our key finding: firm-level investments in artificial intelligence are associated with increases in systematic risk (market betas), and show robustness to several potential concerns. Next, we examine the trends of the main result over time. We then show that the positive relationship between firms' AI investments and market betas is ubiquitous: AI-investing firms increase covariance with many sectors of the economy (their own industry, the tech sector, and other industries). Finally, we find that the results are unique to AI during our sample period when AI was an emerging technology: robotics, (non-AI) IT, capital expenditures, organizational capital, and general R&D investments do not display similar changes in firms' systematic risk.

2.1. AI Investments and Market Beta

We begin our analysis by investigating how firm-level AI investments relate to changes in firms' CAPM betas from 2010 to 2018. We focus the analysis on firms in non-tech sectors to understand how firms' adoption and use of AI technologies affect systematic risk, rather than focusing on the particular firms that create AI solutions for others. Our focus on the users (rather than producers) of AI technology is motivated by the goal of understanding how the trend of technology adoption reshapes overall risk in the market, rather than a case study of a handful of exceptional firms. The exclusion of the tech sector also means that our sample does not include firms like Nvidia and Google, which have earned disproportionate attention and returns in recent years.

Columns 1 and 2 of Table 2 estimate the following model:

$$\Delta\beta_{i,[2010,2018]} = \alpha + b\Delta ShareAIWorkers_{i,[2010,2018]} + Controls'_{i,2010}\gamma + SectorFE + \epsilon_i, \quad (4)$$

where the main dependent variable, $\Delta\beta_{i,[2010,2018]}$, is the change in the firm's market beta from 2010 ($\beta_{i,2010}$) to 2018 ($\beta_{i,2018}$), calculated according to equation (2). In Panel A of Table 2, the main independent variable, $\Delta ShareAIWorkers_{i,[2010,2018]}$, is the change in the share

of AI workers at firm i from 2010 to 2018 based on the Cognism resume data. In Panel B, the main independent variable, $\Delta ShareAIWorkers_{i,[2010,2018]}$, is the change in the share of AI job postings at firm i from 2010 to 2018 based on the Burning Glass job posting data. Both measures are described in Section 1.4. In both cases, $\Delta ShareAIWorkers_{i,[2010,2018]}$ is standardized to have a mean of zero and a standard deviation of one. $SectorFE$ are 2-digit NAICS industry fixed effects. In Column 1, we include only industry fixed effects to examine the unconditional relationship between changes in AI investments and firms' market beta. In Column 2, we add a rich set of controls that are all measured at the start of the sample period in 2010: (i) initial firm-level characteristics that might relate to AI investments (log sales, cash/assets, R&D/sales, log markups computed following De Loecker et al. (2020)), and the log of the firm's total Cognism employment[12]; (ii) characteristics of the commuting zones (CZ) where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers)[13]; and (iii) the log industry-average wage. We keep the same number of observations in Column 1 as in Column 2 (where all controls are included) to avoid changes in estimates due to sample size differences; however, re-estimating Column 1 with all available observations does not affect our results. To account for differences in precision in the measurement of AI investments across firms with different numbers of available worker observations, the estimating equation is weighted by the number of worker resumes in Cognism in 2010 in Panel A and the number of job postings in Burning Glass in 2010 in Panel B. In Appendix Table A.1, we weight the regressions by firms' market capitalization in 2010 and obtain similar results.

[12]The control for log employment addresses the concern that the share of AI workers may be more volatile in firms with fewer total workers. The control ensures that the variation in the share of AI workers is between firms with similar total employment in Cognism but different numbers of AI workers.

[13]When firms span multiple commuting zones, we use the commuting zone that accounts for the highest number of job postings.

The results show that firms' investments in AI are accompanied by increases in these firms' market beta. This is equally true whether firms' AI investments are measured from employee resumes or from firms' job postings. With all controls included in Column 2, a one-standard-deviation increase in a firm's share of AI workers or job postings translates into a 0.05 increase in the firm's CAPM beta (Table 2 Panels A and B). This increase in market beta corresponds to 17% of the standard deviation of the changes in beta. These effects are significant at the 1% level and robust to the inclusion of a rich set of controls.

2.2. Robustness

We perform several robustness tests on our main result. First, we re-estimate equation (4) with the outcome variable being betas estimated from the Carhart (1997) four-factor model (according to equation (3)). Columns 3–4 in Table 2 show the effects on the beta to the market factor in the four-factor model. These effects are remarkably similar to the market beta from the single-factor CAPM model. Specifically, with all controls included in Column 4, a one-standard-deviation increase in either the resume-based AI investment measure or the job-posting-based measure translates into a 0.05–0.06 increase in market beta (which corresponds to 22–24% of the standard deviation of the changes in beta).

We then further augment the Carhart (1997) four-factor model with two additional factors: profitability (robust minus weak, RMW) and investment (conservative minus aggressive, CMA), following Fama and French (2015). Columns 1–2 of Appendix Table A.2 show the effects on the beta to the market factor in the six-factor model. These effects remain the same as in the CAMP model and the four-factor model, confirming that our results are not driven by differential profitability or investment patterns of AI-investing firms.

Second, we estimate betas using a three-year window and look at changes in firms' market betas from the period of 2009 to 2011 to the period of 2017 to 2019. Appendix Table A.3 shows that the results are similar to the main results in Table 2, suggesting that the relationship between AI investment and firms' systematic risk is not sensitive to the

choice of beta estimation window.

Third, the increased systematic risk is not driven by mechanical effects of AI-investing firms capturing a larger share of the market. In Appendix Table A.4, we confirm that the results are unchanged if we drop each AI-investing firm from the market portfolio when calculating its beta. Even more powerfully, we find that AI investments are associated with increasing beta to a market portfolio consisting only of *non*-AI investing firms (see Table 9 described in Section 3.2).

Fourth, we show that our results are robust to changes in firm financial and operating leverage. Since financial leverage increases equity betas, changes in firm leverage can mechanically create a positive relationship between AI investments and estimates of market beta. In Appendix Table A.5, we consider two values of the tax rate when calculating unlevered betas: a statutory tax of 35% in 2010 and 21% in 2018 for all firms in Columns 1–2, and a firm-specific marginal tax rate from Blouin et al. (2010) in Columns 3–4; we find strong increases in unlevered beta in both cases.[14] Our results are also not driven by AI-investing firms increasing their operating leverage. We calculate operating leverage following two methods: first, we follow Kogan et al. (2023) and define operating leverage as SG&A expenses divided by gross profit (revenue minus cost of goods sold); second, we consider the definition of operating leverage in Novy-Marx (2011) as cost of goods sold and SG&A expenses scaled by assets. Appendix Table A.6 shows that firm-level AI investments are not associated with increases in either measure of operating leverage. The key regression coefficients are negative in most specifications, statistically insignificant in all but one specification, and economically small across the board.

Fifth, since our estimates of beta are based on daily data, we address the potential concern that our results are affected by infrequent or asynchronous trading (Dimson, 1979). This concern is most likely to impact beta estimates of small, less liquid firms. There-

[14]Since the Blouin et al. (2010) data only go until 2016, we use the 2016 tax rates to approximate the tax rates in 2018.

fore, we begin by examining whether our estimated effects are driven predominantly by smaller firms. Appendix Table A.7 sorts firms into terciles based on 2010 total employment and estimates our main specification (4) separately within each subsample of firm size. The positive relationship between firms' AI investments and changes in firms' market betas is ubiquitous across the firm size distribution, with varying degrees of precision. Thus, it is not the case that our results are driven by small firms subject to infrequent or asynchronous trading where the incorporation of market-wide news is likely to occur with a delay. Nonetheless, as an additional check, we repeat our analysis with Dimson-adjusted betas following Hou et al. (2020). The results, tabulated in Table A.8, are similar to our baseline results, albeit with attenuated coefficients because averaging beta estimates across several days introduces noise and creates a downward bias for larger firms with faster trading.

Finally, we address the potential concern that our results are driven by selection bias of only the best AI-investing firms surviving from 2010 to 2018. We require all firms in the sample to have adequate data in both 2010 and 2018. This selection criterion applies equally to firms with higher and lower AI investments. However, as a new technology, AI might be associated with a higher incidence of tail outcomes. In this case, more AI-investing firms would exit the sample, and the remainder would incorrectly represent only the "best" AI-investing firms. Empirically, this is not the case. Larger AI investments are associated with slightly *lower* (not always significant) firm exit rates, assuaging the concern that the results are driven by a selective sample of AI-investing firms (Appendix Table A.9).

2.3. Instrumental Variable Estimates

To establish a causal interpretation of our results, we adopt an instrumental variable strategy following Babina et al. (2024). We instrument for AI investment using firm-level exposure to the supply of AI-skilled labor from universities. The core idea is that the limited supply of AI-trained labor is among the most important constraints on firms' adop-

tion of AI technologies. Universities with longstanding strengths in AI research have, in recent years, produced a larger number of AI-skilled graduates than less AI-strong universities, allowing firms that had traditionally recruited from these institutions to more easily attract AI talent. Since commercial interest in AI only became widespread around 2012, it is unlikely that firms' ties to AI-strong universities in 2010 have been motivated by demand for AI-skilled workers, particularly for the non-technology firms that constitute our main sample.[15] Therefore, the instrument captures quasi-exogenous variation in firms' AI investments stemming from the supply of AI labor, reducing bias from demand shocks that jointly influence AI investment and firm growth.

We define the instrument as: $IV_i = \sum_u s_{iu}^{2010} AIStrong_u$, where s_{iu}^{2010} is the share of STEM workers in firm i in 2010 who graduated from university u computed using the Cognism data, and $AIStrong_u$ is an indicator variable equal to one if university u is identified as an AI-strong university based on its pre-2010 publications in the Open Academic Graph (OAGv2) dataset.

To address the concern that AI-strong universities may also be different in other dimensions, we control for firms' ex-ante exposure to Computer Science (CS)-strong and top-10 universities constructed analogously: $sum_u s_{iu}^{2010} CSStrong_u$ and $sum_u s_{iu}^{2010} Top10_u$, where $CSStrong_u$ is the pre-2010 share of (non-AI) CS researchers at university u, and $Top10_u$ equals one if a university is among the top 10 universities ranked by the U.S. News & World Report.

Table 3 presents the 2SLS estimates of the effect of firms' AI investments on their market betas. Column 1 controls for exposure to CS-strong universities, top-10 universities, and the firm's industry fixed effects. In column 2, we add controls for state fixed effects to control for local labor market characteristics that might drive both firms' AI hiring and their growth. In column 3, we add controls for pre-period (2000–2008) sales and employ-

[15] Babina et al. (2024) perform a number of validation tests on the instrument and confirm that there are no pre-trends in terms of AI-skilled hiring *prior* to 2010 at firms connected to AI-strong universities.

ment growth to mitigate concerns that pre-exising firm trends jointly affect AI investments and betas. In column 4, we add all the baseline firm-, industry-, and commuting-zone-level controls. In all columns, the coefficient on AI investment remains positive and significant, suggesting that AI investment leads to an increase in firms' market beta.[16]

2.4. Time Trends in Market Betas

Our baseline specification uses an 8-year long-differences regression, because AI investments are gradual over time, and the effects of AI, as a new emerging technology, are likely to not be immediate. To test the robustness of our results, we consider an overlapping 4-year long-differences specification following Bloom et al. (2016):

$$\Delta\beta_{i,[t,t+4]} = \alpha + b\Delta ShareAIWorkers_{i,[t,t+4]} + Controls'_{i,t}\gamma + \gamma_{st} + \epsilon_i, \tag{5}$$

where Δ denotes the 4-year long difference operator. We maximize the use of the data by using overlapping 4-year differences (2010–2014, 2011–2015, etc.). We control for sector fixed effects interacted with period fixed effects. Appendix Table A.10 presents the results. The coefficients on AI investment remain positive and significant, although the magnitudes are smaller with the shorter time period, suggesting that the effects of AI investment grow over time.

We examine even more granular time trends in the increase in market betas of AI-investing firms by constructing an "AI factor": a long-short portfolio with the long side comprised of firms that rank above the median (weighted by market capitalization) change in AI investment from 2010 to 2018 and the short side comprised of all other firms.[17] We compute the daily return of the factor portfolio from 2010 to 2024 and calculate its annual

[16] It is worth noting that the F-statistics from the first stage reported in Table 3 in row "F Statistic" are somewhat smaller than those reported in Babina et al. (2024), which is mainly driven by a smaller sample size due to requiring market returns.

[17] Note that this object is not a tradable strategy since it has inherent look-ahead bias. The purpose of this non-tradable long-short portfolio is simply to explore the timing of our headline result.

betas ($\beta^{(AI)}$) by regressing the daily factor return on the daily market return:

$$ret_t^{(AI)} = \alpha^{(AI)} + \beta^{(AI)} r_{m,t} + \epsilon_t, \tag{6}$$

where $ret^{(AI)}$ is the return on the AI factor portfolio on day t, and $r_{m,t}$ is the day-t market return. We estimate equation (6) separately for each year from 2010 to 2024.

Figure 1 shows the time series of the estimates of the AI factor's market beta ($\beta^{(AI)}$), which is indistinguishable from zero in 2010 but then steadily increases and turns positive and significant for most of the years.[18]

2.5. *AI Investments and Industry Betas*

We explore whether firms using AI become more similar to technology firms, driving the results in Table 2. That would make the stock returns of AI-investing firms comove more with the stock returns of the tech sector part of the market. Another possibility is that the systematic risk of AI-investing firms goes up from their increased dominance in their own sector, as AI-investing firms gain greater market share in their industry (e.g., Babina et al. 2024). To address these possibilities, we compute each firm's beta separately to the tech sector, the firm's own sector, and all other sectors. In particular, for each firm i and industry sector j in year T, we calculate

$$\beta_{i,j,T} = \frac{cov(r_{i,t}, r_{j,t})}{var(r_{j,t})} \text{ for days } t \text{ in year } T, \tag{7}$$

where $r_{i,t}$ is the time series of daily stock returns for firm i during year T, and $r_{j,t}$ is the value-weighted daily return of stocks in industry sector j during that year. For each firm i, we consider three industry benchmarks j: (i) the tech sector (the high-tech sector in Fama-French-10 industry classification), (ii) firm i's own sector, and (iii) all other sectors.

[18] There is a drop in the beta of the AI factor during the market downturn in 2020. This is consistent with AI investments being associated with lower downside risk than upside risk, as we discuss later in Section 3.1.

As before, we estimate the results with and without controls measured in 2010.

Table 4 presents the results. Columns 1 and 2 show the results for industry betas with respect to the tech (IT) sector, columns 3 and 4 show the results for industry betas with respect to the firm's own sector, and columns 5 and 6 show the results for the industry betas with respect to all other industry sectors. The relationship between individual firms' AI investments and industry betas is positive and significant for all industry sectors with similar magnitudes across sectors. For example, using the resume data, a one-standard-deviation increase in firm-level AI investments is associated with a 0.05 increase in the tech sector beta, a 0.04 increase in the firm's own industry beta, and a 0.05 increase in the beta to all other sectors. This suggests that the positive relationship between AI investments and market betas is not driven by a single sector, but rather reflects similar increases in comovement in returns across industry sectors.

3. Mechanisms

In this section, we explore potential mechanisms for our results. First, we outline the conceptual framework of emerging new technologies creating growth options for early-investing firms and show that the key predictions of this framework are supported by the data. We then consider three alternative explanations and show that they are not consistent with the data: (i) our results do not reflect reverse causality whereby firms with higher systematic risk are more likely to invest in AI, (ii) the results are not due to increased equity duration of AI-investing firms, and (iii) the results do not appear to be driven by correlated shocks to investor demand for AI firms.

3.1. Innovation and Growth Options

During 2010–2018, AI emerged as an exciting new technology with thrilling but uncertain commercial applications. While research in artificial intelligence has been ongoing for decades, commercial interest in AI appeared following the ImageNet challenge in 2012.

Throughout the 2010s, firms became progressively more enthusiastic about this technology, but its adoption remained limited (McElheran et al., 2024). It was not until the release of OpenAI's GPT-3 in June 2020 that the widespread applicability of AI became evident. As a result, the early years (2010–2018) offer a unique opportunity to examine technology adoption during the learning phase about its potential. Pástor and Veronesi (2009) offer a theoretical framework to conceptualize the effects on the early adopting firms. The framework predicts that AI-investing firms should experience an increase in systematic risk (market beta), especially as the probability of widespread adoption of AI increases, and a decline in idiosyncratic risk, as these firms' idiosyncratic volatility transforms into systematic risk.

In addition, existing empirical evidence on the impact of AI on firm operations shows that the main effects of commercial AI across industries have manifested themselves through increased product innovation, rather than immediate labor displacement or productivity gains (Rock, 2019; Babina et al., 2024). Examples of AI-driven product and service innovation include the use of AI in drug and vaccine development (e.g., Tranchero 2024 and see here), increased vehicle safety through built-in computer vision (see here), and customized financial products (Babina et al., 2025). Innovation as the main use case of AI technology is consistent with this new technology creating growth opportunities for the early-adopting firms. Innovation tends to be pro-cyclical (Comin and Gertler, 2006; Broda and Weinstein, 2010), and the power of AI to produce a greater variety of new products is likely to pay off during market booms. Empirically, Bernardo et al. (2007) document that growth opportunities have higher beta than assets-in-place in virtually all industries. Kumar and Li (2016) take this reasoning to firms with innovative capacity (IC) and uncertain growth option generation and exercise. Analogous logic applies to AI investments: as firms invest in AI, they have the potential to experiment more effectively and expand through new products if and when warranted by market conditions.

The challenge of testing the growth options channel is that growth options are un-

observable and not possible to measure directly. However, the channel of AI as a new emerging technology creating growth options for early-adopting firms gives five additional predictions, in addition to the increasing market betas documented in the previous section: (i) that the increase in market beta is specific to *emerging* technology, and we should not see analogous effects for established technologies, (ii) that AI-investing firms should load heavily on growth, (iii) that their comovement with the market should be especially high during market upswings, when the prospect of realizing the growth options goes up, (iv) that their comovement with the market should increase with the emergence of news about AI advances, consistent with models of learning about a new technology and its rising likelihood of adoption (Pástor and Veronesi, 2009), and (v) that AI-investing firms' idiosyncratic volatility should decline as their idiosyncratic risk transforms into systematic risk. We test each of these additional predictions in turn.[19]

First, we explore whether increased systematic risk during the 2010s is a feature of all technological investments or specific to firms' investments in AI. To answer this question, we leverage our detailed human capital data to measure firms' investments in two other related technologies: (non-AI) IT and robotics. Table 5 shows that neither of these technologies is related to increases in firms' market betas. The table re-estimates equation (4), but the main independent variable is the change in the share of a firm's job postings that require non-AI IT (Panel A) or robotics (Panel B) skills. The results confirm that at the time when AI was a new and emerging technology, firms' AI investments exhibited a unique association with increased systematic risk. Adjacent but more mature technologies such as IT and robotics do not display the same pattern at that time. Similarly, the increased betas associated with firms' AI investments do not reflect the effect of capital expenditures (investment over assets, in Panel C of Table 5), R&D investments (Panel D of Table 5), or firms' organizational capital (measured as cumulative SG&A expenses following Eisfeldt

[19] An additional prediction is that AI-investing firms' market betas will eventually decline as these firms will realize their AI-enabled growth options; however, the time trends in Figure 1 underscore that it is still too early in the adoption curve of AI technology to test this empirically.

and Papanikolaou 2013, in Panel E of Table 5).

The lack of a significant relationship between firm market betas and other technologies or investments—IT, robotics, capital expenditures, R&D, and organizational capital—is consistent with their different life cycle phases compared to AI technology. In our sample period during the 2010s, AI was a new emerging technology with uncertain potential for transformative impact and large-scale adoption. Firms investing in this new technology in the early stages effectively invested in future growth opportunities. By contrast, IT and robotics are more developed technologies, and further investments into these technologies mostly reflect the realization rather than the creation of growth options. Similarly, capital expenditures and organizational capital may capture the ability of firms to leverage existing growth opportunities as much as create new ones, and R&D also comprises both *research* (creation of future growth options) and *development* (realization of existing growth options).[20] Overall, firms' adoption of AI offers a unique laboratory to study the effects of technology at the onset, when it creates future growth opportunities for firms and raises their systematic risk as the probability of large-scale adoption increases (Pástor and Veronesi, 2009).

Second, the growth options channel suggests that AI investments should be associated with the investing firms looking increasingly like growth firms rather than value firms. We test this directly in Columns 5–10 of Table 2, which show how AI investments relate to other factors in the Carhart (1997) four-factor model. Consistent with the prediction, AI-investing firms experience declining loadings on the high-minus-low (β^{HML} in Columns 7 and 8) value factor, with the negative effect both statistically significant and economically large. With all controls, a one-standard-deviation increase in the resume-based measure of AI investments is associated with a 0.11 decline in β^{HML}, and a one-standard-deviation increase in the job-posting-based measure of AI investments is associated with a 0.14

[20]Changes in R&D are driven not only by incentives to create investment opportunities, but also by changes in government R&D incentives (e.g., Bloom et al. 2013; Babina and Howell 2024) and accounting rules, making a firm's R&D expense a hodgepodge of different drivers.

decline in β^{HML} (Column 8 of Panel A and Panel B, respectively). This result means that AI-investing firms become less like value and more like growth firms. The relationship with the other factors (size and momentum) is weaker. The size factor, in particular, displays a null effect, despite AI investments favoring larger firms (Acemoglu et al., 2022). The association between AI investments and the momentum factor (β^{UMD}) is negative but not consistently statistically significant.

We further decompose the effect on the high-minus-low value factor into changes in AI-investing firms' correlations with value firms and growth firms, separately. The results, presented in Appendix Table A.11, reveal that the effect is present on both sides: firms that invest more in AI become *more* correlated with growth firms and *less* correlated with value firms, both statistically significant and economically large (especially on the growth side). When all controls are included, a one-standard-deviation increase in the resume-based (job-posting-based) measure of AI investments is associated with a 0.12 (0.16) reduction in beta to the index of value firms (the top quintile of firms based on the book-to-market ratio) and a 0.35 (0.40) increase in beta to the index of growth firms (the bottom quintile of firms based on the book-to-market ratio).

Third, we examine whether the increasing return covariance of AI-investing firms with the stock market is driven by the upside (market going up) or the downside (market going down) risk. Upside risk can capture the (positive) option value of AI investments, for example, through pro-cyclical product innovation. Segal et al. (2015) show that, in general, good (positive) uncertainty is associated with higher growth and larger investments in areas such as R&D. If AI investments create the potential for greater growth through innovation, their returns will be especially responsive to positive market news. To test this, we follow the methodology in Ang et al. (2006) to separate each firm's beta into upside beta and downside beta. Specifically, for each firm i in year t, we calculate:

$$\beta_{i,t}^{-} = \frac{cov(r_{i,t}, r_{m,t} | r_{m,t} < \mu_{m,t})}{var(r_{m,t} | r_{m,t} < \mu_{m,t})} \quad and \quad \beta_{i,t}^{+} = \frac{cov(r_{i,t}, r_{m,t} | r_{m,t} > \mu_{m,t})}{var(r_{m,t} | r_{m,t} > \mu_{m,t})}, \tag{8}$$

where $\mu_{m,t}$ is the average daily return on the market during year t. $\beta^{-}_{i,t}$ represents firm i's equity return beta on days when the daily market return is below the annual average ("downside beta") and $\beta^{+}_{i,t}$ on days when the daily market return is above the annual average ("upside beta"). For each firm i, we take the difference between $\beta^{-}_{i,2018}$ and $\beta^{-}_{i,2010}$, which captures the change in firm i's downside beta. Similarly, the difference between $\beta^{+}_{i,2018}$ and $\beta^{+}_{i,2010}$ gives the change in firm i's upside beta. As in Table 2, we regress these changes against $\Delta ShareAIWorkers_{i,[2010,2018]}$ in a long-differences specification using equation (4).

The results, presented in Table 6, reveal that AI-investing firms experience much larger increases in upside than downside beta, by about a factor of two. For example, when using the resume-based AI measure (Panel A) and including all controls, a one-standard-deviation increase in AI investments is associated with a 0.08 increase in upside beta (Column 2) and a 0.04 increase in downside beta (Column 4). The difference between the effect on upside beta and the effect on downside beta is statistically significant at the 1% level (Column 6). AI-investing firms comove more with market returns when the stock market is going up, but do not drop as much when the stock market is doing poorly. Therefore, while AI investments increase firms' systematic risk, the effect concentrates mostly on upside risk rather than downside risk. This finding reinforces the notion that AI is benefiting firms and their investors.

Fourth, we leverage extensive news and search data to examine how the increase in AI-investing firms' betas relates to news regarding the promise of (and advances in) AI technology. First, we obtain a dataset from RavenPack that identifies all events in the comprehensive Dow Jones Newswire that cover AI from 2010 to 2018. For each day, we compute the number of AI-related news stories on that day and the preceding week (to account for potential lags in market reactions) and split the days in each year into those with above- and below-median numbers of AI news. We then estimate the relationship between AI investments and changes in beta separately for AI-news days and non-AI-

news days, analogously to the regressions of upside and downside beta in Table 6. The results reported in Panel A of Appendix Table A.12 show that AI investments are associated with a twice-larger increase in market beta on AI-news days than on non-AI-news days. This finding is consistent with increased comovement in returns of AI-investing firms with the aggregate market reflecting new information about the potential of AI technologies (Pástor and Veronesi, 2009). Panel (a) of Figure 2 shows the effects by year, similar to Figure 1 but separately for AI-news and non-AI-news days in each year. The figure reveals that the divergence concentrates in the latter half of the sample period.

For additional validation, we repeat the analysis using an alternative measure of information regarding the potential of AI technology—Google search volumes. Specifically, we examine monthly Google search trends for the term "artificial intelligence" from 2010 to 2018 and estimate a smooth function of search interest over time using kernel regression. We define abnormal AI-search months as those with a spike in search interest (i.e., when monthly search interest is above the predicted value from the kernel regression). Panel B of Appendix Table A.12 conducts our baseline regression separately on abnormal AI-search months and other months, showing that the increase in beta is at least 1.5 times larger during times of elevated search attention to artificial intelligence. Panel (b) of Figure 2 shows the results by year, displaying similar patterns to the news-based results in Panel (a). Overall, both RavenPack news and Google search volumes show that the increase in AI-investing firms' beta is stronger during times of heightened media coverage and public attention to AI, when AI-driven growth options are likely to be more in-the-money, consistent with the results on upside and downside beta.

Finally, Pástor and Veronesi (2009) predict that early adopters of a new emerging technology should experience a reallocation of risk from idiosyncratic volatility to systematic risk. We examine whether AI investments are associated with any changes in idiosyncratic (return) volatility and total (return) risk. To calculate idiosyncratic volatility, we estimate the Capital Asset Pricing Model and the Carhart (1997) four-factor model us-

ing daily stock returns over a year and compute the standard deviation of the residuals. The first four columns of Table 7 present the results from regressing the changes in the annual measures of idiosyncratic volatility from 2010 to 2018 against contemporaneous changes in the measure of firm-level AI investments (i.e., re-estimating equation (4) with changes in idiosyncratic volatility as the dependent variable). When using the resume-based measure of AI investments (Panel A), we find negative and insignificant effects on idiosyncratic volatility. When using the job-posting-based measure of AI investment (Panel B), we find larger negative effects, significant at the 10% level.

The last two columns of Table 7 consider changes in firms' total volatility, computed as the standard deviation of a firm's daily stock returns over a year. We estimate the long-differences specification in equation (4), with the change in the annual total volatility measure from 2010 to 2018 as the dependent variable. The association between a firm's AI investments and its total equity return volatility is close to zero, statistically insignificant, and directionally ambiguous. These results suggest that while AI investments are associated with an increase in firms' systematic market risk, they are (weakly) associated with a decrease in firms' idiosyncratic risk. The two effects somewhat offset each other, and there is no association between AI investments and total equity return risk. Thus, AI investments do appear to prompt a reallocation of equity return risk from idiosyncratic to systematic for the early-adopting firms.

3.2. Alternative Explanations

Beyond the extensive robustness tests performed in Section 2.2, we consider three alternative explanations for our results. The first is that firms that invest in AI have different risk profiles, leading to a reverse causality relationship between AI investments and changes in firm beta. To examine this possibility, we run predictive regressions of the changes in firms' share of AI workers from 2010 to 2018 on their starting betas in 2010:

$$\Delta ShareAIWorkers_{i,[2010,2018]} = \alpha + b\beta_{i,2010} + Controls'_{i,2010}\gamma + SectorFE + \epsilon_i, \qquad (9)$$

where the controls include firm-specific characteristics measured as of 2010: log sales, cash/assets, R&D/sales, and the two measures of markups.

The results, presented in Table A.13, show that firms with higher market betas do not invest more in AI. In the table, odd columns show unconditional relationships between starting values of firm betas and subsequent AI investments, without any controls except sector fixed effects; even columns add firm-level controls. The resume-based measure of AI investments (Panel A of Table A.13) is positively but insignificantly associated with CAMP beta in 2010 when all controls are included in Column 2 (the relationship is negative and insignificant without controls in Column 1) and negatively but insignificantly associated with market beta in the Carhart (1997) four-factor model, both with and without controls (Columns 3–4). Similarly, Panel B shows that the job-posting-based measure of AI investments is negatively predicted by starting market beta in most specifications, significant in two out of four specifications. Overall, it is not the case that firms with greater systematic market risk are more likely to invest in AI.

To further address concerns regarding reverse causality and mean reversion, we conduct several tests. First, the results in Appendix Table A.14 show that the association between firms' AI investments and changes in market beta is consistent across different levels of starting beta. Second, Appendix Table A.15 shows that the results are robust to directly controlling for firms' market beta in 2010. Finally, we look at earliest adopters of AI—firms that invested heavily in AI in the first half of the sample period from 2010 to 2014. Appendix Table A.16 shows that these firms also experienced an increase in market beta. These findings further indicate that our main results are not driven by firms with higher risks simply investing more in AI.

The second alternative explanation we examine is that AI investments lead to changes in firms' effective equity duration, which may in turn change these firms' risk and return profiles (Lettau and Wachter, 2007). In Columns 1 and 2 of Appendix Table A.17, we regress changes from 2010 to 2018 in duration estimated following Gonçalves (2021)

against firms' AI investments, with the same set of controls as in our other analyses. The results show a small and insignificant decrease in the duration of AI-investing firms. In Columns 3 and 4, we perform the same analysis but using the Gormsen and Lazarus (2023) measure of duration. The results reveal an insignificant and mostly negative relationship between AI investments and changes in equity duration. Overall, AI investments display no consistent relationship with changes in equity duration, indicating that pure changes in equity duration are unlikely to explain increases in betas of AI-investing firms.

Finally, we investigate whether AI-investing firms' increasing betas are due to correlated behavior of investors holding the shares of those firms. Specifically, institutional investors may have greater demand for AI-investing stocks because of the rising popularity of AI technology. If these investors have similar tastes and behavior, this can create comovement among the AI-investing firms due to the shared investor base (Barberis and Shleifer, 2003). If this comovement is sufficiently strong, it can lead to increased estimates of beta for the AI-investing firms.

We conduct two tests to assess this potential channel. First, Table 8 examines the relationship between the changes in the share of firms' AI workers and the changes in firms' market betas, separately for firms that have above versus below median shares of institutional ownership. Institutional ownership is measured at the start of the sample period, in 2010. The results reveal a very consistent increase in market beta for AI-investing firms in both subsamples. Thus, AI investments are related to increased systematic market risk, regardless of institutional ownership. Second, Table 9 shows that AI investments are associated with increasing beta even to a market index that consists only of *non*-AI-investing firms. The effect sizes are similar to the baseline estimates in Table 2. Thus, AI-investing firms are becoming more correlated not only with each other but also with other (non-AI-investing) parts of the market. This runs counter to the investor capital mechanism, which would imply that capital flowing toward AI-investing firms would induce greater comovement specifically between those firms. Together, the results in Tables 8 and 9 sug-

gest that the investor capital channel is unlikely to be the main driver of our results.

The evidence in Table 9 helps further clarify the relationship between AI investments, technological shocks, and growth opportunities. Kogan and Papanikolaou (2014) show that investment-specific technological shocks can give rise to the value factor by inducing comovement among firms with similar (pre-existing) growth opportunities. By contrast, our results show that firms investing in AI increase comovement not just with each other, but also with non-AI investing firms, demonstrating a broad correlation with the overall market as predicted by Pástor and Veronesi (2009). AI-investing firms *become* more like growth firms, as AI creates new growth opportunities. Thus, AI is a technology that creates opportunities for further investment, which can then be complemented by investment-specific technological shocks examined by Kogan and Papanikolaou (2014).

4. Conclusion

This paper fills a gap in our empirical understanding of how new technologies affect firms' systematic risk by looking at firm investments in artificial intelligence during the 2010s. We document that firms that invested more in AI experienced increased systematic risk. This finding is robust across many model specifications and is most consistent with the notion that AI, as an emerging technology with exciting but uncertain potential for widespread adoption, created growth opportunities for the early-adopting firms (Pástor and Veronesi, 2009; Kumar and Li, 2016).

Our paper contributes to the literature on the economic effects of technological change by showing that investments in new technologies such as artificial intelligence not only affect firm growth (i.e., the first moment) but also change firms' risk profiles (i.e., the second moment). Our evidence points to a significant shift in firms' risk profiles as they invest in AI. The overall risk level (total volatility) of AI-investing firms does not change significantly, but there is a reallocation from idiosyncratic risk to systematic risk. AI-investing firms experience increases in comovement with all sectors of the economy—including

their own sector, the tech sector, and other industry sectors. This increased market covariance mostly reflects increased upside, as AI-investing firms experience much larger increases in upside market beta than downside market beta. These patterns are consistent with AI-investing firms innovating and producing more new products, which allows them to capture larger market share during good market conditions.

Overall, our findings suggest a novel market implication of firms' AI investments: they are associated with increased systematic market risk. These findings have implications for firms' cost of capital, investment, employment, capital allocation, and market stability.

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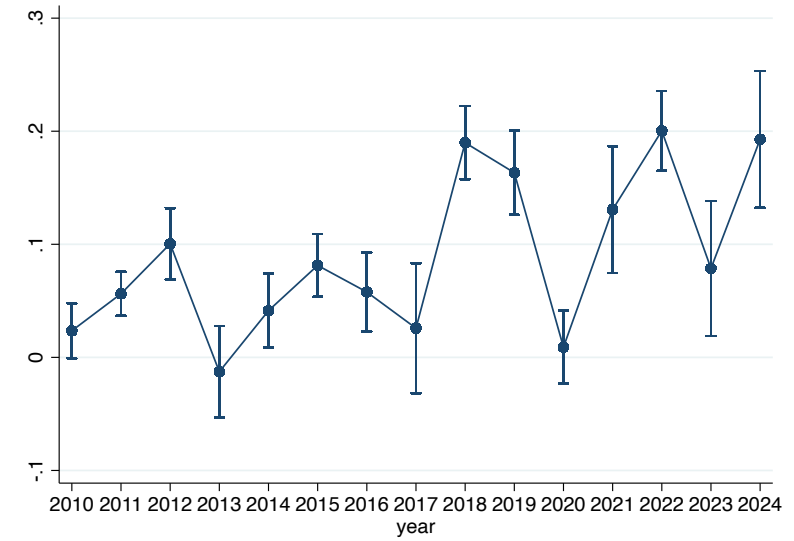
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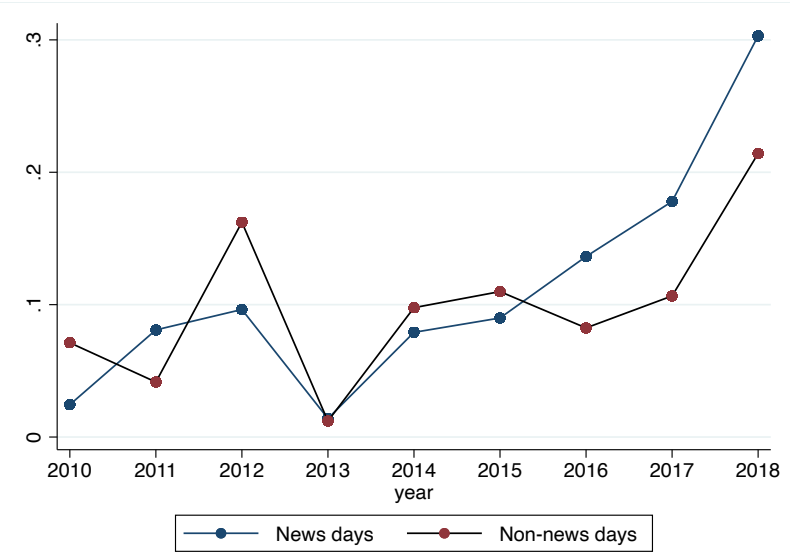
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Figure 1. Beta of the AI Factor Over Time

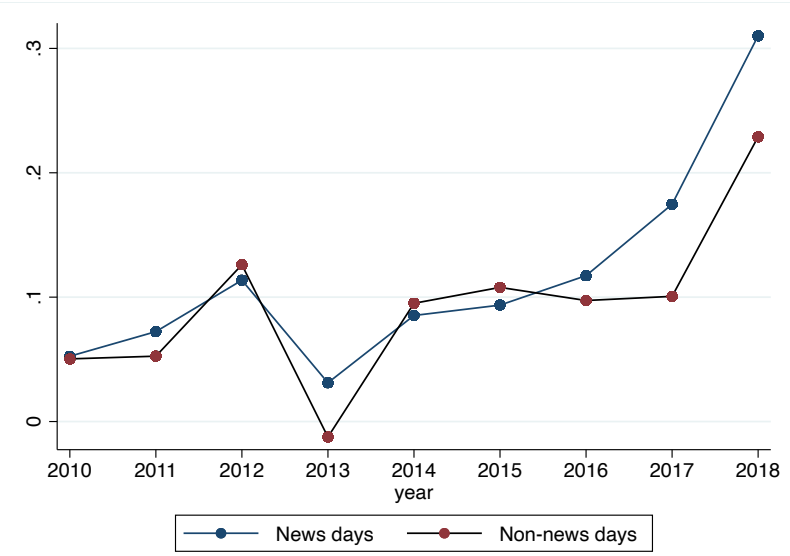


This figure plots the beta of the AI factor and the associated 95% confidence intervals in each year between 2010 and 2024. The AI factor is the average value-weighted return on a portfolio of AI-investing firms (firms with above-median AI investment between 2010 and 2018) minus the average value-weighted return on a portfolio of non-AI-investing firms (firms with below-median AI investments between 2010 and 2018). The market beta of the AI factor is calculated based on the Capital Asset Pricing Model in each year.

Figure 2. Beta of the AI Factor on AI News and Non-AI News Days



(a) Ravenpack news



(b) Google search trends

This figure plots the (annualized) beta of the AI factor on days with and without AI news in each year between 2010 and 2018. The AI factor is the average value-weighted return on a portfolio of AI-investing firms (firms with above-median AI investment between 2010 and 2018) minus the average value-weighted return on a portfolio of non-AI-investing firms (firms with below-median AI investment between 2010 and 2018). In Panel (a), AI news counts are measured using AI-related news events from RavenPack. In Panel (b), AI news counts are measured using Google search trends. In each panel, we plot the market beta annually of the AI factor based on the Capital Asset Pricing Model computed over days with AI news and days without AI news.

Table 1. Summary Statistics

Variable Name	N	Mean	Std. Deviation	p1	p5	p10	p25	p50	p75	p90	p95	p99
Change in share of AI workers (Cognism)	846	.00099	.0026	-.0019	0	0	0	0	.001	.0025	.005	.018
Change in share of AI workers (Burning Glass)	829	.0033	.0095	0	0	0	0	0	.0017	.0077	.019	.06
Change in share of IT workers	829	-.0056	.19	-.58	-.36	-.24	-.093	.0046	.086	.22	.31	.49
Change in share of robotics workers	829	.00083	.005	-.017	-.00011	0	0	0	0	.003	.0067	.031
R&D / Sales in 2010	846	.034	.09	0	0	0	0	0	.024	.11	.17	.66
Change in organization capital / sales	689	.0019	1	-3.2	-1.4	-.87	-.34	-.065	.23	.86	1.5	4.5
Change in CAPM beta	846	-.29	.42	-1.5	-1	-.82	-.52	-.29	-.017	.22	.37	.75
Change in four-factor market beta	846	-.014	.36	-.86	-.6	-.47	-.24	-.028	.2	.45	.61	1
Change in β^{SMB}	846	-.01	.54	-1.5	-.88	-.69	-.34	-.031	.31	.64	.91	1.6
Change in β^{HML}	846	.088	.57	-1.5	-.95	-.68	-.25	.12	.46	.75	.97	1.3
Change in β^{UMD}	846	-.057	.69	-1.6	-1.2	-.89	-.52	-.11	.41	.91	1.2	1.6
Change in unlevered beta (statutory tax)	840	-.37	.5	-2.4	-1.2	-.93	-.59	-.31	-.071	.17	.35	.63
Change in unlevered beta (marginal tax)	700	-.34	.47	-2	-1.2	-.89	-.58	-.29	-.05	.17	.32	.82
CAPM beta in 2010	846	1.2	.44	.09	.52	.67	.91	1.2	1.5	1.8	2	2.3
Four-factor market beta in 2010	846	1	.33	-.11	.48	.62	.83	1	1.2	1.4	1.5	1.7
β^{SMB} in 2010	846	.64	.63	-.44	-.25	-.14	.13	.57	1.1	1.5	1.7	2
β^{HML} in 2010	846	.19	.53	-.76	-.5	-.37	-.16	.12	.48	.83	1.1	2
β^{UMD} in 2010	846	-.058	.52	-1.3	-1	-.75	-.37	-.045	.26	.58	.8	1.2
Log sales in 2010	846	7.4	1.7	3.8	4.8	5.3	6.3	7.4	8.6	9.5	10	11
Cash / Assets in 2010	846	.16	.15	.00037	.007	.015	.039	.11	.22	.36	.48	.68
Log markup in 2010	846	.55	.44	-.08	.098	.14	.25	.42	.72	1.2	1.5	2.3
Log markup (total expenditure based) in 2010	846	.21	.22	-.4	-.0064	.035	.086	.16	.28	.45	.59	1.1
Change in idiosyncratic volatility (CAPM)	823	.12	.98	-2.8	-1.1	-.79	-.35	.029	.45	1.1	1.9	4.2
Change in idiosyncratic volatility (four-factor model)	846	.062	.81	-2.7	-1.1	-.8	-.36	.049	.43	.99	1.5	2.6
Change in total volatility	823	-.17	1	-2.9	-1.5	-1.2	-.68	-.24	.21	.83	1.6	4
Change in equity duration (Gonçalves, 2021)	513	-1.7	35	-184	-57	-27	-7.2	2.8	12	23	38	86
Change in equity duration (Gormsen and Lazarus, 2023)	826	-1.2	10	-25	-18	-15	-7	-1.1	5.2	12	15	24
Change in operating leverage (Kogan et al., 2023)	627	-.024	.24	-1.3	-.28	-.19	-.082	-.015	.044	.14	.24	.89
Change in operating leverage (Novy-Marx, 2011)	726	-.052	.33	-1.4	-.58	-.41	-.18	-.022	.1	.31	.51	.86
Institutional ownership share in 2010	699	.72	.21	.084	.29	.42	.61	.76	.86	.94	.98	1

This table reports summary statistics for the sample of firms in our baseline regressions (including 846 firms in the regressions with the resume-based measure and 829 firms in the regressions with the job-posting-based measure). All changes in variables are computed over 2010–2018. For each variable, we report the number of observations, the mean, the standard deviation, the median, and 1st, 5th, 10th, 25th, 75th, 90th, 95th, and 99th percentiles.

Table 2. AI Investments and Firms' Systematic Risk

Panel A: Cognism

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.110***	0.054***	0.052***	0.057***	-0.006	-0.003	-0.084**	-0.109***	-0.036	-0.076**
	(0.018)	(0.015)	(0.011)	(0.012)	(0.044)	(0.043)	(0.033)	(0.039)	(0.037)	(0.035)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.234	0.372	0.207	0.260	0.275	0.344	0.294	0.401	0.534	0.615
Observations	846	846	846	846	846	846	846	846	846	846

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.085***	0.052***	0.046***	0.063***	-0.041	-0.047	-0.100***	-0.138***	-0.023	-0.054**
	(0.021)	(0.017)	(0.012)	(0.011)	(0.035)	(0.038)	(0.034)	(0.038)	(0.028)	(0.027)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.225	0.395	0.279	0.337	0.297	0.390	0.405	0.500	0.502	0.567
Observations	829	829	829	829	829	829	829	829	829	829

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2, changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4, changes in β^{SMB} (size factor) in Columns 5 and 6, changes in β^{HML} (value factor) in Columns 7 and 8, and changes in β^{UMD} (momentum factor) in Columns 9 and 10. All changes are measured from 2010 to 2018. The main independent variable is the growth in the share of AI workers from 2010 to 2018 standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B as of 2010. All specifications control for industry sector fixed effects. Columns 2, 4, 6, 8, and 10 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. AI Investments and Firms' Systematic Risk: IV Estimates

Panel A: Cognism

	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.161***	0.167***	0.164***	0.113*
	(0.042)	(0.047)	(0.052)	(0.068)
Industry FE	Y	Y	Y	Y
CS Control	Y	Y	Y	Y
Top 10 Control	Y	Y	Y	Y
State FE	N	Y	Y	Y
Control Pre-trend	N	N	Y	Y
Baseline Controls	N	N	N	Y
F Statistic	7.5	11.4	11.5	10.7
Observations	837	834	669	669

Panel B: Burning Glass

	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.135***	0.176***	0.149***	0.129**
	(0.045)	(0.061)	(0.056)	(0.065)
Industry FE	Y	Y	Y	Y
CS Control	Y	Y	Y	Y
State FE	N	Y	Y	Y
Control Pre-trend	N	N	Y	Y
Baseline Controls	N	N	N	Y
F Statistic	8.6	11.0	11.1	7.2
Observations	863	861	683	683

This table estimates the relationship between AI investments and firms' systematic risks from 2010 to 2018 for U.S. public firms (in non-tech sectors), where firm AI investments are instrumented with ex-ante firm-level exposure to AI-skilled graduates from AI-strong universities. The dependent variable is the change in market beta based on the Capital Asset Pricing Model from 2010 to 2018. The independent variable is the growth in the share of AI workers from 2010 to 2018 standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. (see the definition of the instrument in Section 2.3). The independent variable and the instrument are standardized to mean zero and standard deviation of one. All specifications control for industry sector fixed effects and ex-ante exposure to universities that are strong in computer science research as well as top 10 universities. Columns 2 to 4 also control for state fixed effects. Columns 3 and 4 additionally control for firm-level changes in log sales and log employment from 2000 to 2008. Column 4 controls for the baseline controls all measured as of 2010: log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers). Standard errors are clustered at the 5-digit NAICS industry level. The first-stage F-statistics of the instrument are reported for all specifications. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. AI Investments and Industry Beta

Panel A: Cognism

	$\Delta\beta_IT$		$\Delta\beta_Industry$		$\Delta\beta_Other$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.090***	0.050***	0.063***	0.040**	0.111***	0.053***
	(0.017)	(0.016)	(0.019)	(0.018)	(0.017)	(0.014)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.197	0.338	0.190	0.319	0.280	0.410
Observations	845	845	845	845	845	845

Panel B: Burning Glass

	$\Delta\beta_IT$		$\Delta\beta_Industry$		$\Delta\beta_Other$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.067***	0.047***	0.061***	0.054***	0.084***	0.053***
	(0.019)	(0.016)	(0.021)	(0.020)	(0.021)	(0.017)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.199	0.363	0.225	0.376	0.285	0.444
Observations	828	828	828	828	828	828

This table reports the coefficients from long-differences regressions of changes in industry-specific beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in (value-weighted) industry beta with the tech sector in Columns 1 and 2, changes in industry beta with the firm's own sector in Columns 3 and 4, and changes in industry beta with the other sectors in Columns 5 and 6. The calculation of industry betas is detailed in Section 2.5. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Other (Non-AI) Technological Investments and Firms' Systematic Risk

Panel A: IT

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share Other IT Workers	-0.057	-0.056	-0.033	-0.036	-0.196**	-0.192***	-0.062	-0.034	0.017	0.004
	(0.047)	(0.037)	(0.040)	(0.039)	(0.092)	(0.062)	(0.058)	(0.048)	(0.074)	(0.072)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.156	0.381	0.250	0.296	0.336	0.424	0.369	0.445	0.500	0.561
Observations	829	829	829	829	829	829	829	829	829	829

Panel B: Robotics

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share Robot Workers	0.065	0.042	0.009	0.025	-0.052	-0.036	-0.136**	-0.140**	0.028	0.045
	(0.047)	(0.034)	(0.021)	(0.023)	(0.055)	(0.043)	(0.063)	(0.058)	(0.032)	(0.027)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.162	0.379	0.247	0.295	0.292	0.384	0.387	0.466	0.501	0.563
Observations	829	829	829	829	829	829	829	829	829	829

Panel C: Capital Expenditure

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Investment/Assets	-0.024	-0.024	-0.007	0.003	-0.012	-0.015	-0.112**	-0.115***	-0.062	-0.081*
	(0.025)	(0.021)	(0.019)	(0.018)	(0.044)	(0.035)	(0.047)	(0.033)	(0.048)	(0.044)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.152	0.373	0.140	0.183	0.228	0.254	0.257	0.365	0.461	0.541
Observations	949	949	949	949	949	949	949	949	949	949

Panel D: R&D

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ R&D/Sales	0.045	0.108	0.011	0.052	0.039	-0.061	-0.036	-0.226	0.054**	0.148**
	(0.041)	(0.067)	(0.017)	(0.039)	(0.054)	(0.157)	(0.071)	(0.204)	(0.022)	(0.069)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.150	0.378	0.246	0.293	0.289	0.383	0.366	0.451	0.501	0.563
Observations	829	829	829	829	829	829	829	829	829	829

Panel E: Organization Capital

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Organization Capital/Assets	-0.032	-0.014	0.008	0.012	0.120***	0.105***	0.008	0.015	-0.017	-0.063**
	(0.031)	(0.030)	(0.027)	(0.025)	(0.034)	(0.026)	(0.044)	(0.032)	(0.038)	(0.028)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.121	0.372	0.129	0.175	0.334	0.417	0.260	0.352	0.544	0.625
Observations	687	687	687	687	687	687	687	687	687	687

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on the contemporaneous firm-level changes in IT investments, robotics investments, capital expenditure, R&D, and organization capital among U.S. public firms (in non-tech sectors). The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2, changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4, changes in β^{SMB} (size factor) in Columns 5 and 6, changes in β^{HML} (value factor) in Columns 7 and 8, and changes in β^{UMD} (momentum factor) in Columns 9 and 10. β^{SMB}, β^{HML}, and β^{UMD} are defined in equation 3, and all changes are measured from 2010 to 2018. In Panel A, the main independent variable is the growth in the share of non-AI IT jobs from 2010 to 2018, standardized to mean zero and standard deviation of one. In Panel B, the main independent variable is the growth in the share of robotics jobs from 2010 to 2018, standardized to mean zero and standard deviation of one. In Panel C, the main independent variable is the change in capital expenditure (investment over assets) from 2010 to 2018, standardized to mean zero and standard deviation of one. In Panel D, the main independent variable is the growth in R&D over sales from 2010 to 2018, standardized to mean zero and standard deviation of one. In Panel E, the main independent variable is the growth in organization capital over sales from 2010 to 2018, standardized to mean zero and standard deviation of one. Organization capital is calculated based on SG&A expenses following Eisfeldt and Papanikolaou (2013). Regressions are weighted by the number of Burning Glass job postings in 2010. All specifications control for industry sector fixed effects. Columns 2, 4, 6, 8, and 10 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. AI Investments and Upside and Downside Beta

Panel A: Cognism

	Δ Upside Beta		Δ Downside Beta		Δ Upside-Downside Beta	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.160***	0.079***	0.075***	0.037**	0.086***	0.044***
	(0.029)	(0.026)	(0.017)	(0.016)	(0.016)	(0.017)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.196	0.328	0.139	0.304	0.145	0.241
Observations	846	846	846	846	846	846

Panel B: Burning Glass

	Δ Upside Beta		Δ Downside Beta		Δ Upside-Downside Beta	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.122***	0.068**	0.061***	0.041**	0.060**	0.026
	(0.043)	(0.031)	(0.017)	(0.016)	(0.030)	(0.022)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.238	0.356	0.191	0.368	0.213	0.304
Observations	829	829	829	829	829	829

This table reports the coefficients from long-differences regressions of changes in firms' upside and downside beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are firm upside beta in Columns 1 and 2, changes in firm downside beta in Columns 3 and 4, and changes in the difference between firm upside beta and downside beta in Columns 5 and 6. The calculation of upside and downside betas follows Ang et al. (2006) and is described in Section 3.1. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. AI Investments, Idiosyncratic Volatility, and Total Volatility

Panel A: Cognism

	Δ IVOL CAPM		Δ IVOL FF4		Δ Total Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	-0.057	-0.017	-0.027	0.010	-0.002	0.013
	(0.071)	(0.076)	(0.058)	(0.058)	(0.059)	(0.067)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.273	0.311	0.264	0.298	0.293	0.327
Observations	828	828	846	846	828	828

Panel B: Burning Glass

	Δ IVOL CAPM		Δ IVOL FF4		Δ Total Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	-0.099	-0.136*	-0.074*	-0.081*	-0.056	-0.104
	(0.065)	(0.080)	(0.041)	(0.044)	(0.062)	(0.076)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.285	0.414	0.323	0.390	0.274	0.418
Observations	806	806	829	829	806	806

This table reports the coefficients from long-differences regressions of changes in idiosyncratic equity volatility and total equity volatility from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in idiosyncratic volatility based on the Capital Asset Pricing Model in Columns 1 and 2, changes in idiosyncratic volatility based on the Carhart (1997) four-factor model in Columns 3 and 4, and changes in total volatility in Columns 5 and 6. All changes are measured from 2010 to 2018. Dependent variables are scaled up by 100 for readability. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. AI Investments and Systematic Risk Interacted with Institutional Ownership

Panel A: Cognism

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers*High Institutional Ownership	0.134***	0.088***	0.015	0.030
	(0.032)	(0.030)	(0.021)	(0.019)
Δ Share AI Workers*Low Institutional Ownership	0.097***	0.042***	0.051***	0.051***
	(0.018)	(0.014)	(0.011)	(0.012)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.288	0.417	0.252	0.322
Observations	699	699	699	699

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers*High Institutional Ownership	0.053*	0.058***	0.043***	0.073***
	(0.031)	(0.017)	(0.011)	(0.021)
Δ Share AI Workers*Low Institutional Ownership	0.094***	0.052***	0.041**	0.060***
	(0.018)	(0.019)	(0.016)	(0.015)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.284	0.440	0.274	0.343
Observations	673	673	673	673

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors), separately for firms with above-median institutional ownership (High Institutional Ownership) and below-median institutional ownership (Low Institutional Ownership). Firms are divided equally into two groups based on the percentage of institutional ownership obtained from the Thompson Reuters 13F data in 2010. The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2 and changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. AI Investments and Market Beta to Market Excluding AI-Investing Firms

Panel A: Cognism

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.096***	0.053***	0.052***	0.058***
	(0.013)	(0.012)	(0.010)	(0.011)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.255	0.356	0.203	0.259
Observations	846	846	846	846

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.073***	0.047***	0.046***	0.063***
	(0.018)	(0.014)	(0.012)	(0.011)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.248	0.391	0.277	0.335
Observations	829	829	829	829

This table reports the coefficients from long-differences regressions of changes in market beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The market returns are calculated excluding AI-investing firms (firms with positive AI investment between 2010 and 2018). The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2, and changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix

Table A.1. AI Investments and Firms' Systematic Risk: Weight By Market Capitalization in 2010

Panel A: Cognism

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.084***	0.045***	0.037***	0.047***	-0.019	-0.018	-0.074***	-0.100***	-0.032	-0.101***
	(0.017)	(0.014)	(0.013)	(0.013)	(0.031)	(0.037)	(0.020)	(0.022)	(0.044)	(0.037)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.305	0.430	0.265	0.339	0.275	0.306	0.305	0.454	0.425	0.553
Observations	846	846	846	846	846	846	846	846	846	846

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.072***	0.038***	0.035***	0.034***	-0.021	-0.033	-0.040**	-0.065***	-0.043	-0.097***
	(0.011)	(0.010)	(0.009)	(0.008)	(0.015)	(0.022)	(0.019)	(0.019)	(0.035)	(0.024)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.327	0.431	0.266	0.309	0.236	0.264	0.319	0.460	0.435	0.577
Observations	829	829	829	829	829	829	829	829	829	829

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2, changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4, changes in β^{SMB} (size factor) in Columns 5 and 6, changes in β^{HML} (value factor) in Columns 7 and 8, and changes in β^{UMD} (momentum factor) in Columns 9 and 10. All changes are measured from 2010 to 2018. The main independent variable is the growth in the share of AI workers from 2010 to 2018 standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the market capitalization as of 2010. All specifications control for industry sector fixed effects. Columns 2, 4, 6, 8, and 10 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.2. AI Investments and Firms' Systematic Risk (Six-Factor Model)

Panel A: Cognism

	$\Delta\beta$ (6-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$		$\Delta\beta^{RMW}$		$\Delta\beta^{CMA}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Share AI Workers	0.038***	0.056***	0.026	0.034	-0.035	-0.071***	-0.031	-0.083***	0.020	-0.002	-0.026	-0.080**
	(0.015)	(0.012)	(0.037)	(0.031)	(0.022)	(0.014)	(0.029)	(0.025)	(0.026)	(0.034)	(0.039)	(0.033)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.233	0.275	0.260	0.297	0.274	0.344	0.290	0.375	0.441	0.492	0.336	0.471
Observations	955	955	955	955	955	955	955	955	955	955	955	955

Panel B: Burning Glass

	$\Delta\beta$ (6-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$		$\Delta\beta^{RMW}$		$\Delta\beta^{CMA}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Share AI Workers	0.043**	0.046***	-0.002	0.003	-0.052***	-0.071***	-0.074***	-0.063*	-0.030	-0.030	-0.032	-0.062
	(0.019)	(0.016)	(0.039)	(0.029)	(0.015)	(0.021)	(0.025)	(0.036)	(0.019)	(0.045)	(0.041)	(0.041)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.412	0.501	0.525	0.601	0.595	0.663	0.331	0.429	0.696	0.760	0.438	0.618
Observations	678	678	678	678	678	678	678	678	678	678	678	678

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in factor betas from the six-factor model, which augments the Carhart (1997) four-factor model with profitability (RMW) and investment (CMA) factors from Fama and French (2015). Profitability (for the RMW factor) is measured as revenue minus the cost of goods sold, minus SG&A, minus interest expense, all scaled by book equity. Investment (for the CMA factor) is measured as the change in total assets from the fiscal year ending in year $t-2$ to the fiscal year ending in $t-1$, scaled by $t-2$ total assets. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2, 4, 6, and 8 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.3. AI Investments and Firms' Systematic Risk: Three-Year Window

Panel A: Cognism

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.102***	0.057***	0.052***	0.049***	-0.020	-0.048**	-0.077***	-0.074*	-0.001	0.009
	(0.020)	(0.016)	(0.011)	(0.008)	(0.016)	(0.020)	(0.023)	(0.040)	(0.021)	(0.025)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.499	0.583	0.229	0.260	0.337	0.486	0.409	0.485	0.582	0.613
Observations	810	810	810	810	810	810	810	810	810	810

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.063***	0.023	0.033**	0.029***	-0.023	-0.043	-0.070***	-0.088***	0.023	0.038
	(0.022)	(0.017)	(0.013)	(0.011)	(0.023)	(0.031)	(0.018)	(0.033)	(0.025)	(0.028)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.450	0.566	0.176	0.257	0.310	0.485	0.490	0.553	0.533	0.608
Observations	792	792	792	792	792	792	792	792	792	792

This table reports the coefficients from long-differences regressions of changes in three-year-window firm beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in 3-year-rolling-window market beta based on the Capital Asset Pricing Model in Columns 1 and 2, changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4, changes in β^{SMB} (size factor) in Columns 5 and 6, changes in β^{HML} (value factor) in Columns 7 and 8, and changes in β^{UMD} (momentum factor) in Columns 9 and 10. All changes are measured from 2009–2011 to 2017–2019. The main independent variable is the growth in the share of AI workers from 2010 to 2018 standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B as of 2010. All specifications control for industry sector fixed effects. Columns 2, 4, 6, 8, and 10 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.4. AI Investments and Firms' Market Beta (to Market Excluding Own Firm)

Panel A: Cognism

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.109***	0.054***	0.054***	0.058***
	(0.018)	(0.015)	(0.011)	(0.012)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.240	0.371	0.219	0.275
Observations	846	846	846	846

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.084***	0.053***	0.048***	0.064***
	(0.021)	(0.017)	(0.013)	(0.011)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.230	0.397	0.281	0.343
Observations	829	829	829	829

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The market returns are calculated excluding the firm's own returns. The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2, and changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.5. AI Investments and Unlevered Beta

Panel A: Cognism

	Δ Unlevered Beta Statutory Tax		Δ Unlevered Beta Marginal Tax	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.111***	0.103**	0.113***	0.080**
	(0.027)	(0.046)	(0.026)	(0.036)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.075	0.286	0.134	0.270
Observations	840	840	700	700

Panel B: Burning Glass

	Δ Unlevered Beta Statutory Tax		Δ Unlevered Beta Marginal Tax	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.100***	0.091**	0.093***	0.065*
	(0.029)	(0.041)	(0.023)	(0.033)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.108	0.295	0.146	0.350
Observations	823	823	692	692

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in unlevered beta using the statutory tax (35% in 2010 and 21% in 2018) in Columns 1 and 2, and changes in unlevered beta using firm-specific marginal tax rates from Blouin et al. (2010) in Columns 3 and 4. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.6. AI Investments and Firms' Operating Leverage

Panel A: Cognism

	Δ Operating Leverage (Kogan et al.)		Δ Operating Leverage (Novy-Marx)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	0.008*	0.009	-0.010	-0.007
	(0.005)	(0.007)	(0.027)	(0.025)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.110	0.183	0.092	0.220
Observations	690	690	804	804

Panel B: Burning Glass

	Δ Operating Leverage (Kogan et al.)		Δ Operating Leverage (Novy-Marx)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	-0.000	-0.012	-0.016	-0.045
	(0.005)	(0.008)	(0.031)	(0.027)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.079	0.372	0.371	0.497
Observations	662	662	780	780

This table reports the coefficients from long-differences regressions of changes in firm operating leverage from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in operating leverage from 2010 to 2018. In Columns 1 and 2, firm operating leverage is defined as SG&A expenses divided by gross profit (revenue minus cost of goods sold) following Kogan et al. (2023). In Columns 3 and 4, firm operating leverage is defined as the cost of goods sold and SG&A expenses scaled by assets following Novy-Marx (2011). The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.7. AI Investments and Systematic Risk: Heterogeneity by Initial Firm Size

Panel A: Cognism

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers*Size Tercile 1	0.061*	0.017	0.034	0.032
	(0.035)	(0.032)	(0.028)	(0.029)
Δ Share AI Workers*Size Tercile 2	0.124***	0.036	0.018	0.029
	(0.045)	(0.043)	(0.036)	(0.033)
Δ Share AI Workers*Size Tercile 3	0.112***	0.058***	0.054***	0.060***
	(0.019)	(0.016)	(0.011)	(0.012)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.233	0.371	0.206	0.259
Observations	846	846	846	846

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers*Size Tercile 1	0.154**	0.068	0.081	0.077
	(0.074)	(0.060)	(0.052)	(0.054)
Δ Share AI Workers*Size Tercile 2	0.123***	0.083***	0.014	0.045***
	(0.014)	(0.026)	(0.009)	(0.014)
Δ Share AI Workers*Size Tercile 3	0.064***	0.038***	0.061***	0.071***
	(0.023)	(0.013)	(0.015)	(0.015)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.232	0.398	0.285	0.338
Observations	829	829	829	829

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on contemporaneous changes in AI investments among US public firms (in non-tech sectors), separately for each tercile of initial firm size. Firms in each 2-digit NAICS sector are divided into terciles based on employment in 2010. The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2 and changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.8. AI Investments and Adjusted Beta

Panel A: Cognism

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.085***	0.026	0.033**	0.038**	-0.036	-0.060	-0.118**	-0.148***	-0.022	-0.043
	(0.024)	(0.020)	(0.016)	(0.018)	(0.035)	(0.036)	(0.047)	(0.054)	(0.051)	(0.051)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.173	0.331	0.160	0.187	0.166	0.297	0.171	0.260	0.374	0.444
Observations	846	846	846	846	846	846	846	846	846	846

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.078***	0.042*	0.044***	0.062***	-0.032	-0.054	-0.152***	-0.174***	-0.001	-0.022
	(0.025)	(0.023)	(0.016)	(0.020)	(0.051)	(0.052)	(0.052)	(0.054)	(0.047)	(0.046)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.212	0.364	0.293	0.317	0.319	0.422	0.406	0.453	0.292	0.375
Observations	829	829	829	829	829	829	829	829	829	829

This table reports the coefficients from long-differences regressions of changes in firms' adjusted market beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). Market betas are adjusted for nonsynchronous price movements following the methodology in Dimson (1979) and Hou et al. (2020). In particular, we include the current value as well as the one-day lead and one-day lag of the market and factor returns in the regressions, estimating beta as the sum of the slopes on all three (current, leading, and lagging) market and factor returns. The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2, changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4, changes in β^{SMB} (size factor) in Columns 5 and 6, changes in β^{HML} (value factor) in Columns 7 and 8, and changes in β^{UMD} (momentum factor) in Columns 9 and 10. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2, 4, 6, 8, and 10 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.9. AI Investments and Firm Exit

Panel A: Cognism

	Exit	
	(1)	(2)
Δ Share AI Workers	-0.028***	-0.009
	(0.009)	(0.009)
NAICS2 FE	Y	Y
Controls	N	Y
Adj R-Squared	0.098	0.165
Observations	1,213	1,213

Panel B: Burning Glass

	Exit	
	(1)	(2)
Δ Share AI Workers	-0.032**	-0.023*
	(0.013)	(0.013)
NAICS2 FE	Y	Y
Controls	N	Y
Adj R-Squared	0.232	0.285
Observations	1,191	1,191

This table reports the coefficients from long-differences regressions of firm exit between 2010 and 2018 on the contemporaneous firm-level changes in AI investments from 2010 to 2018 among U.S. public firms (in non-tech sectors). The dependent variable is a dummy variable for a firm exiting between 2010 and 2018, where the firm exists in the Compustat data in 2010 but not 2018. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Column 2 also controls for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.10. Overlapping 4-year Long Differences: 2010–2014, 2011–2015..., 2014–2018

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.030**	0.027**	0.019**	0.020**	-0.038**	-0.024*	-0.024	-0.008	0.035**	0.036**
	(0.014)	(0.012)	(0.009)	(0.009)	(0.017)	(0.012)	(0.018)	(0.012)	(0.018)	(0.017)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.036	0.046	0.024	0.033	0.065	0.080	0.095	0.122	0.073	0.077
Observations	7,856	7,856	7,856	7,856	7,856	7,856	7,856	7,856	7,856	7,856

This table reports the coefficients from overlapping 4-year long-differences regressions of changes in firm beta (2010–2014, 2011–2015, 2012–2016, 2013–2017, 2014–2018) on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2, changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4, changes in β^{SMB} (size factor) in Columns 5 and 6, changes in β^{HML} (value factor) in Columns 7 and 8, and changes in β^{UMD} (momentum factor) in Columns 9 and 10. The main independent variable is the growth in the share of AI workers in the Cognism resume data during the same 4-year period standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes as of 2010. All specifications control for industry sector fixed effects interacted with period fixed effects. Columns 2, 4, 6, 8, and 10 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups measured at the beginning of each period, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers) measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.11. AI Investments and Firms' Value and Growth Betas

Panel A: Cognism

	$\Delta\beta_{value}$		$\Delta\beta_{growth}$	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	-0.105***	-0.119***	0.142	0.348***
	(0.037)	(0.043)	(0.103)	(0.123)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.237	0.345	0.270	0.373
Observations	846	846	846	846

Panel B: Burning Glass

	$\Delta\beta_{value}$		$\Delta\beta_{growth}$	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	-0.121***	-0.158***	0.240*	0.403***
	(0.038)	(0.042)	(0.123)	(0.122)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.351	0.445	0.413	0.505
Observations	829	829	829	829

This table reports the coefficients from long-differences regressions of changes in firms' value and growth betas from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in value beta (the coefficient of regressing firm returns on the average return of the value firms) in Columns 1 and 2, and changes in growth beta (the coefficient of regressing firm returns on the average return of the growth firms) in Columns 3 and 4. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.12. AI Investment and Betas on AI News and Non-AI News Days

Panel A: RavenPack News

	Δ Beta News Days		Δ Beta Non-News Days		Δ News - Non-News Beta	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.126***	0.070***	0.084***	0.026*	0.042**	0.044*
	(0.025)	(0.023)	(0.013)	(0.015)	(0.021)	(0.023)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.257	0.353	0.212	0.345	0.242	0.276
Observations	830	830	830	830	830	830

Panel B: Google Search Interest

	Δ Beta News Days		Δ Beta Non-News Days		Δ News - Non-News Beta	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.132***	0.065***	0.094***	0.042***	0.038*	0.023
	(0.024)	(0.020)	(0.020)	(0.014)	(0.022)	(0.015)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Squared	0.252	0.415	0.204	0.318	0.211	0.362
Observations	830	830	830	830	830	830

This table reports the coefficients from long-differences regressions of changes in firm beta on days with or without AI news from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in market beta based on the Capital Asset Pricing Model computed over days with AI news in Columns 1 and 2, changes in market beta based on the Capital Asset Pricing Model computed over days without AI news in Columns 3 and 4, and changes in the difference between the beta on days with AI news and the beta on days without AI news in Columns 5 and 6. Panel A measures AI news using RavenPack AI news counts, while Panel B uses Google search interest. The main independent variable is the growth in the share of AI workers in the resume data from 2010 to 2018, standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes as of 2010. All specifications control for industry sector fixed effects. Columns 2, 4, and 6 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10

Table A.13. Predicting AI Investments Using 2010 Betas

Panel A: Cognism

	Δ Share of AI Workers, 2010–2018									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CAPM Beta 2010	-0.154	0.107								
	(0.110)	(0.093)								
FF4 Beta 2010			-0.157	-0.012						
			(0.211)	(0.150)						
SMB Factor 2010					-0.339***	0.284**				
					(0.114)	(0.120)				
HML Factor 2010							-0.276*	-0.125		
							(0.141)	(0.100)		
UMD Factor 2010									0.592**	0.414**
									(0.250)	(0.178)
Log Sales 2010		0.149***		0.143***		0.203***		0.142***		0.154***
		(0.032)		(0.031)		(0.051)		(0.030)		(0.032)
Cash/Assets 2010		2.995***		3.021***		3.039***		2.956***		2.665***
		(0.767)		(0.773)		(0.772)		(0.739)		(0.672)
R&D/Sales 2010		3.882**		3.748**		4.030**		3.591**		3.704**
		(1.769)		(1.739)		(1.749)		(1.762)		(1.700)
Log Markup (COGS) 2010		-0.501**		-0.491**		-0.493**		-0.473**		-0.311*
		(0.200)		(0.196)		(0.199)		(0.187)		(0.162)
Log Markup (Total Exp) 2010		2.179**		2.118**		2.322**		2.104**		1.803**
		(0.891)		(0.868)		(0.923)		(0.869)		(0.810)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj R-Squared	0.112	0.372	0.110	0.371	0.133	0.379	0.126	0.374	0.153	0.389
Observations	1,429	1,429	1,429	1,429	1,429	1,429	1,429	1,429	1,429	1,429

Panel B: Burning Glass

	Δ Share of AI Workers, 2010–2018									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CAPM Beta 2010	-0.261**	0.011								
	(0.126)	(0.123)								
4-factor Beta 2010			-0.375	-0.461**						
			(0.251)	(0.203)						
SMB Factor 2010					-0.424***	0.025				
					(0.102)	(0.143)				
HML Factor 2010							-0.152	-0.003		
							(0.209)	(0.139)		
UMD Factor 2010									0.621**	0.574***
									(0.276)	(0.218)
Log Sales 2010		0.178***		0.187***		0.183***		0.177***		0.189***
		(0.044)		(0.043)		(0.059)		(0.041)		(0.043)
Cash/Assets 2010		3.277**		3.328**		3.274**		3.274***		3.112**
		(1.303)		(1.298)		(1.309)		(1.229)		(1.259)
R&D/Sales 2010		1.860***		1.830***		1.875***		1.859***		1.753***
		(0.668)		(0.652)		(0.665)		(0.659)		(0.617)
Log Markup (COGS) 2010		-0.408		-0.414		-0.404		-0.408		-0.328
		(0.366)		(0.364)		(0.382)		(0.373)		(0.338)
Log Markup (Total Exp) 2010		2.405***		2.328***		2.416***		2.403***		2.314***
		(0.911)		(0.878)		(0.893)		(0.892)		(0.828)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj R-Squared	0.132	0.315	0.132	0.323	0.154	0.315	0.131	0.315	0.156	0.340
Observations	1,061	1,061	1,061	1,061	1,061	1,061	1,061	1,061	1,061	1,061

This table reports the coefficients from regressions of cross-sectional changes in AI investments by U.S. public firms (in non-tech sectors) from 2010 to 2018 on the following ex-ante firm characteristics measured in 2010: market beta based on the Capital Asset Pricing Model in Columns 1 and 2, market beta based on the Carhart (1997) four-factor model in Columns 3 and 4, β^{SMB} (size factor) in Columns 5 and 6, changes in β^{HML} (value factor) in Columns 7 and 8, and changes in β^{UMD} (momentum factor) in Columns 9 and 10. β^{SMB}, β^{HML}, and β^{UMD} are defined in equation 3. All specifications control for industry sector fixed effects. Columns 2, 4, 6, 8, and 10 also control for log sales, cash/assets, R&D/sales, log markup measured following De Loecker et al. (2020), and log markup measured following Traina (2018) in 2010. The dependent variable is the growth in the share of AI workers from 2010 to 2018 using the resume data from Cognism in Panel A, and the growth in the share of AI jobs from 2010 to 2018 using the job postings data from Burning Glass in Panel B. The dependent variable is normalized to have a mean of zero and a standard deviation of one. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. Standard errors are clustered at the 5-digit NAICS industry level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.14. AI Investments and Systematic Risk: Heterogeneity by Initial Level of Beta

Panel A: Cognism

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers*Beta Tercile 1	0.108***	0.057***	0.057***	0.062***
	(0.015)	(0.013)	(0.010)	(0.011)
Δ Share AI Workers*Beta Tercile 2	0.150***	0.070**	0.027	0.031
	(0.031)	(0.034)	(0.022)	(0.027)
Δ Share AI Workers*Beta Tercile 3	0.071*	0.024	0.057**	0.061***
	(0.038)	(0.035)	(0.023)	(0.023)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.237	0.372	0.207	0.260
Observations	846	846	846	846

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers*Beta Tercile 1	0.083***	0.039**	0.049***	0.049***
	(0.017)	(0.017)	(0.015)	(0.015)
Δ Share AI Workers*Beta Tercile 2	0.129***	0.083***	0.033*	0.059***
	(0.013)	(0.029)	(0.017)	(0.015)
Δ Share AI Workers*Beta Tercile 3	0.035	0.042*	0.055***	0.086***
	(0.031)	(0.024)	(0.019)	(0.016)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.238	0.398	0.278	0.339
Observations	829	829	829	829

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on contemporaneous changes in AI investments among US public firms (in non-tech sectors), separately for each tercile of initial beta. Firms in each 2-digit NAICS sector are divided into terciles based on the market beta (based on the Capital Asset Pricing Model) in 2010. The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2, and changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4. The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.15. AI Investments and Firms' Systematic Risk: Controlling for Starting Beta

Panel A: Cognism

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.085***	0.053***	0.047***	0.029***	-0.005	0.004	-0.102**	-0.074*	-0.043	-0.060*
	(0.016)	(0.014)	(0.008)	(0.009)	(0.045)	(0.044)	(0.040)	(0.043)	(0.033)	(0.033)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.685	0.725	0.510	0.540	0.276	0.348	0.468	0.557	0.556	0.634
Observations	846	846	846	846	846	846	846	846	846	846

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.068***	0.049***	0.036***	0.026**	-0.039	-0.040	-0.106**	-0.102**	-0.023	-0.040
	(0.016)	(0.014)	(0.008)	(0.012)	(0.036)	(0.037)	(0.042)	(0.041)	(0.026)	(0.028)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.712	0.759	0.577	0.627	0.300	0.400	0.528	0.610	0.502	0.573
Observations	829	829	829	829	829	829	829	829	829	829

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2, changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4, changes in β^{SMB} (size factor) in Columns 5 and 6, changes in β^{HML} (value factor) in Columns 7 and 8, and changes in β^{UMD} (momentum factor) in Columns 9 and 10. All changes are measured from 2010 to 2018. The main independent variable is the growth in the share of AI workers from 2010 to 2018 standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B as of 2010. All specifications control for industry sector fixed effects and the market beta (based on the CAPM model) as of 2010. Columns 2, 4, 6, 8, and 10 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.16. AI Investments and Firms' Systematic Risk: Early Adopters

Panel A: Revelio

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.114***	0.065***	0.037**	0.036*	-0.029	-0.042	-0.065**	-0.081**	0.022	-0.027
	(0.015)	(0.021)	(0.015)	(0.021)	(0.047)	(0.041)	(0.026)	(0.033)	(0.027)	(0.024)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.197	0.271	0.129	0.152	0.241	0.289	0.296	0.357	0.433	0.522
Observations	1,041	1,041	1,041	1,041	1,041	1,041	1,041	1,041	1,041	1,041

Panel B: Burning Glass

	$\Delta\beta$ (CAPM)		$\Delta\beta$ (4-factor)		$\Delta\beta^{SMB}$		$\Delta\beta^{HML}$		$\Delta\beta^{UMD}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.076***	0.047**	0.041***	0.054***	-0.016	-0.008	-0.069**	-0.086**	-0.038	-0.034
	(0.019)	(0.022)	(0.011)	(0.013)	(0.037)	(0.035)	(0.033)	(0.034)	(0.024)	(0.021)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Squared	0.199	0.300	0.222	0.266	0.246	0.318	0.346	0.418	0.470	0.550
Observations	1,212	1,212	1,212	1,212	1,212	1,212	1,212	1,212	1,212	1,212

This table reports the coefficients from long-differences regressions of changes in firm beta from 2010 to 2018 on firm-level changes in AI investments from 2010 to 2014 among U.S. public firms (in non-tech sectors). The dependent variables are changes in market beta based on the Capital Asset Pricing Model in Columns 1 and 2, changes in market beta based on the Carhart (1997) four-factor model in Columns 3 and 4, changes in β^{SMB} (size factor) in Columns 5 and 6, changes in β^{HML} (value factor) in Columns 7 and 8, and changes in β^{UMD} (momentum factor) in Columns 9 and 10. All changes are measured from 2010 to 2018. The main independent variable is the growth in the share of AI workers from 2010 to 2014 standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B as of 2010. All specifications control for industry sector fixed effects. Columns 2, 4, 6, 8, and 10 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.17. AI Investments and Equity Duration

Panel A: Cognism

	Δ Duration (Gonçalves)		Δ Duration (Gormsen and Lazarus)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	-1.470	-0.873	-0.234	0.102
	(1.185)	(1.552)	(1.349)	(1.386)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.286	0.340	0.135	0.184
Observations	512	512	851	851

Panel B: Burning Glass

	Δ Duration (Gonçalves)		Δ Duration (Gormsen and Lazarus)	
	(1)	(2)	(3)	(4)
Δ Share AI Workers	-0.868	-2.679	-0.740	-1.358
	(1.445)	(1.779)	(0.776)	(0.898)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Squared	0.368	0.495	0.271	0.355
Observations	509	509	836	836

This table reports the coefficients from long-differences regressions of changes in firms' equity duration from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among U.S. public firms (in non-tech sectors). The dependent variables are changes in equity duration in Columns 1 and 2 and changes in log equity duration in Columns 3 and 4. In Columns 1 and 2, equity duration is measured following Gonçalves (2021). In Columns 3 and 4, equity duration is measured following Gormsen and Lazarus (2023). The main independent variable is the growth in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. Panel A considers the resume-based measure of the share of AI workers, while Panel B uses the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in Panel A and Burning Glass job postings in Panel B, as of 2010. All specifications control for industry sector fixed effects. Columns 2 and 4 also control for log employment, cash/assets, log sales, log industry wages, R&D/Sales, and log markups, as well as characteristics of the commuting zones where the firms are located (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industries, the share of workers in IT-related occupations, and the share of female and foreign-born workers), all measured as of 2010. Standard errors are clustered at the 5-digit NAICS industry level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.