Artificial Intelligence and Firms' Systematic Risk

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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. This is unique to AI: robotics, IT, organizational capital, and R&D investments do not display similar effects. 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.

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

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Over the past decade, there has been a significant market shift as substantial developments in artificial intelligence (AI) technologies have spurred their widespread commercial adoption by U.S. firms.[1] Motivated by AI's potential to generate investment opportunities and stimulate growth, recent studies have focused on the firm performance implications of AI investments.[2] However, little is known about the potential risks of investments in AI: does the systematic risk of firms increase or decrease when they invest in AI? Answering this question has implications for firms' cost of capital, investment, employment, capital allocation, and market stability.

This paper takes the first steps to explore how investments in artificial intelligence relate to changes in firms' systematic risk. We focus on the most commonly used measure of systematic risk: firms' market beta, which captures the covariance between firms' equity returns and the returns on the stock market portfolio. Theoretically, the relationship between firms' betas and their AI investments is ex-ante ambiguous. On the one hand, as a prediction technology (Agrawal et al., 2019), AI can help firms better adjust to market conditions, lowering their systematic risk. On the other hand, several mechanisms predict an increase in firms' systematic risk due to AI investments. First, AI investments can lead to increased fragility and elevated systematic risk during market downturns.[3] Second, AI can increase firms' systematic risk by creating growth options, which make firms comove more with the market, especially on the upside (Carlson et al., 2004, 2006, 2010; Pástor and Veronesi, 2009). This mechanism is consistent with the primary use of AI to date being product innovation.[4]

[1]Mihet and Philippon (2019) and Babina et al. (2024b) provide an overview of AI technologies and their key economic properties.

[2]Firms innovating in AI technologies have benefited from increased growth and productivity (Alderucci et al., 2020), and firms using AI in their operations have experienced increased growth in sales (Rock, 2019), greater product innovation (Cockburn et al., 2018; Babina et al., 2024b), improved product quality (Fedyk et al., 2022), and increased productivity in certain tasks (Brynjolfsson et al., 2023; Eloundou et al., 2023).

[3]Increased fragility during market downturns can arise due to common risks stemming from shared reliance on the same datasets, third-party dependencies (e.g., cloud computing), and similar models tested on short-term time series (Financial Stability Board, 2017).

[4]Early predictions that AI's main impact will be labor displacement (e.g., Frey and Osborne 2017) have not materialized more than a decade after the onset of commercial interest and large-scale investments in AI

To empirically 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, following the methodology proposed and validated by Babina et al. (2024b). Specifically, we leverage comprehensive employer-employee matched data from Cognism, Inc., and job posting data from Burning Glass Technologies, Inc. We identify the most AI-relevant keywords from the required skills in the job postings data, then use these keywords to identify AI-skilled employees or job postings. We calculate the share of AI-skilled workers and job postings at each firm in each year. We link these measures of firm-level AI investments to market betas computed for U.S. public firms using the Capital Asset Pricing Model (CAPM) and the Carhart (1997) four-factor model. 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. An additional benefit of this specification is that (by taking the first differences of both dependent and independent variables) we control for time-invariant firm characteristics.

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 measured using the CAPM or the Carhart (1997) four-factor model. This finding suggests a novel market implication of firms' AI investments: they are associated with changing composition of firms' risk profiles through increased systematic risk.

Our main result is consistent with firms using AI technology to create growth op-

(Acemoglu et al. 2022b; Alderucci et al. 2020; Handel 2022; Babina et al. 2023; Autor 2024). Instead, the most common use of AI to date has been product innovation (Cockburn et al. 2018; Babina et al. 2024b): creating, improving, and customizing products and services. Examples of AI-aided product and service innovation include the use of AI for drug and vaccine development (e.g., Tranchero 2024 and see here), safer cars through built-in computer vision (see here), and financial products customized to each customer's data (Babina et al., 2024a).

tions by enabling expansion through product innovation. As modeled by Carlson et al. (2004, 2006, 2010) and Pástor and Veronesi (2009), growth opportunities are associated with increasing market beta as the exercise of those opportunities becomes more likely, followed by a drop in market beta when the growth options are eventually exercised and converted into assets-in-place.[5] This channel has several additional predictions that we test in the data. First, consistent with AI-investing firms loading positively on growth options, these firms should become more growth-like, experiencing a significant decrease in the value (high-minus-low, or HML) factor. This is exactly what we observe in the data: a one-standard-deviation increase in AI investments corresponds to a 0.11 reduction in the HML factor beta. AI-investing firms become less correlated with value firms and more correlated with growth firms, with significant effects on both sides.

Second, we examine whether AI-investing firms' increased correlation with market 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)—computing each firm's beta separately on days when the market return is above-median ("upside beta") and on days when the market return is below-median ("downside beta"). The results reveal that AI-investing firms experience a much larger increase in upside beta than downside beta. Specifically, a one-standard-deviation increase in firms' AI investments is associated with a 0.08 increase in upside beta and a 0.04 increase in downside beta.

Third, we consider another measure of 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

[5]Theoretically, Carlson et al. (2004, 2006) model growth options as being riskier than assets-in-place due to the implicit additional leverage. Empirically, Bernardo et al. (2007) document that growth opportunities have higher beta than assets-in-place in virtually all industries.

into days with above-median and below-median AI news. We find that a one-standard-deviation increase in firms' AI investments is associated with a 0.07 increase in beta during AI-news days, compared to a mere 0.03 increase in beta during non-AI-news days. As an alternative measure, we leverage Google Trends data to identify spikes in search attention around "artificial intelligence." A one-standard-deviation increase in firms' AI investments corresponds to a 0.07 increase in beta during search spikes, compared to a 0.04 increase outside of search spikes.

These results are consistent with AI-driven innovation offering firms growth options, which highlights a key feature of AI investments: while they increase firms' systematic risk, this effect concentrates mostly in upside risk and during times of elevated news about AI technologies. Investors demand higher compensation for downside risk (Ang et al., 2006), which has been used to explain the value premium (Zhang, 2005). Therefore, the concentration of the risk on the upside coupled with generally good returns of AI-investing firms (e.g., Eisfeldt et al. 2023; Babina et al. 2024b) reinforces the notion that AI is benefiting firms and their investors.

The positive relationship with market betas is unique to artificial intelligence during the 2010s. We leverage our detailed data to measure firms' investments in what are arguably the most related technologies: (non-AI) information technology (IT) and robotics. Both of these have a null relationship with changes in firms' betas. Moreover, organizational capital and R&D investments also display a statistically insignificant association with firms' market betas, highlighting that AI has had a unique relationship with firms' systematic risk during our sample period.

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);

smaller firms (where the issues of infrequent trading are most acute) do not drive the results, and the results are robust to adjusting beta estimation following Hou et al. (2020). Fourth, firms' initial betas measured in 2010 are *not* positively predictive of firms' investments in AI from 2010 to 2018, challenging explanations based on reverse causality. Fifth, the increased beta of AI-investing firms is not driven by equity duration: we show that firms' AI investments are not associated with significant changes in their equity duration (Lettau and Wachter, 2007; Gonçalves, 2021; Gormsen and Lazarus, 2023).

Moreover, additional tests show that our key result is not consistent with a mechanism where the investor base of AI-investing firms drives increased betas, which can occur when investors experience correlated shocks or behaviors (Barberis and Shleifer, 2003). Our first test for this demonstrates that 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 our second test, we find similar increases in market betas of AI-investing firms when we measure market returns using only non-AI investing firms. Thus, AI-investing firms are becoming more correlated not only with each other, but with other parts of the market, too. In contrast, the investor channel would induce increased comovement specifically among AI-investing firms. Together, these tests suggest that the investor channel is unlikely to be the main driver of our results.

In addition, we explore whether the positive relationship between firms' AI investments and market betas is driven by AI-investing firms' particular focus or whether it is more ubiquitous. Specifically, 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 (an increase of 0.04 for a one-standard-deviation increase in AI investments), the tech sector (an increase of 0.05), and other industries (an increase of 0.05). Thus, although AI investments are unevenly distributed across firms, favoring larger firms (Acemoglu et al., 2022a), this is not the main driver of AI-investing firms' increased systematic risk. Instead, AI-investing firms are becoming more correlated with *all* industries: their own, tech, and others.

In supplementary analyses, we augment the results on the increased systematic risk associated with AI by examining AI-investing firms' total risk, idiosyncratic volatility, and cash flow risk. First, 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 a null effect on their total stock return volatility. Second, we augment our analysis of equity return comovement with an analysis of firm cash flows. We use quarterly financial data to compute the annual volatility of return on assets (ROA), return on equity (ROE), and cash flows over assets (CFOA). All three of these variables show statistically significant *declines* with firms' AI investments. Thus, AI investments are associated with less volatility in the firm's fundamentals (return on assets, return on equity, and cash flows over assets) and a null effect on total return volatility, but a redistribution of return volatility, with less loading on idiosyncratic volatility and more on market beta.

Overall, our evidence points to a significant shift in firms' risk profiles as they invest in artificial intelligence. The overall risk level (total volatility) of AI-investing firms does not change significantly, but there is a reallocation of risk from idiosyncratic to systematic (higher market beta). The positive relationship between firms' AI investments and market betas is ubiquitous: AI-investing firms increase covariance with all sectors of the economy (their own industry, the tech sector, and other industries) and are becoming more correlated not only with each other but with non-AI-investing firms as well. Consistent with AI investments being used by firms to create growth options, AI-investing firms also become more growth-like. Furthermore, the increased market covariance mostly reflects increased upside, as AI-investing firms experience a twice larger increase in upside market beta than downside market beta, and the effects are much larger during periods of intensive AI news. These patterns are consistent with firms using AI to create new investment opportunities and, eventually, new products and services. Thus, our paper shines a light on the black box that is the origin of new projects and investment opportunities.

Our paper contributes to the literature on the economic effects of technological change by documenting that investments in new technologies such as artificial intelligence 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.[6] While several studies have documented positive abnormal returns associated with AI (e.g., Rock 2019; Eisfeldt et al. 2023; Babina et al. 2024b), 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 effect of emerging AI technologies on firms, investors, and markets,[7] 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 (Carlson et al., 2004, 2006, 2010; Pástor and Veronesi, 2009). Due to our granular firm-level measure of AI investments, our results offer direct support to the notion that new technologies such as AI create growth options and affect the systematic risk profiles of AI-investing firms. To the best of our knowledge, our paper is the first to directly measure the relationship between firm-level investments in an

[6]E.g., Aboody and Lev (2000); Kogan et al. (2017); Gomez Cram and Lawrence (2022); Fedyk and Hodson (2023).

[7]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., 2020; Jansen et al., 2020), 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, 2020; Cao et al., 2021), and venture capital and entrepreneurship (Gofman and Jin, 2020; Bonelli, 2022).

emerging technology and the systematic risk of firms investing in it.

More broadly, this paper builds on emerging work examining financial risks of the new data economy. Mihet et al. (2024) consider whether companies that are highly exposed to data risk experience significant changes to their financial and innovation outcomes. Cybersecurity risk and corporate data breaches lead to the loss of firm value and damage corporate reputation (e.g., Akey et al. 2023; Florackis et al. 2022). Bian et al. (2023) find that curbing firms' collection of consumers' personal data mitigates financial fraud. We complement these studies by focusing on the systematic risk implications of artificial intelligence technologies for AI-investing firms.

The remainder of the paper is organized as follows. Section 1 describes our data and how we use them to measure firms' investments in AI. Section 2 presents our key finding of increased betas associated with firms' AI investments, demonstrates the robustness of this result, and explores aspects such as time trends and industry betas. Section 3 investigates potential mechanisms driving the main result. Section 4 supplements the main result by examining other aspects of firms' risk profiles, and Section 5 concludes.

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 do so, 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 relationship 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.[8] 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.[9] 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.[10] 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 postings 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, 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,

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

[9]Our data snapshot is from July of 2021, but we follow Tambe et al. (2020) and Babina et al. (2024b) and use only the years through 2018 to avoid any noise from workers updating their resumes with a lag.

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

job location, occupation, and employer name.[11] 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 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. (2024b). 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, 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 RavePnack, which provides real-time news analytics based on the Dow Jones (DJ) Newswire. RavenPack identifies entities mentioned 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

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

monthly level.

1.4. Measures of Firm-Level AI Investments

We adopt the measure of firm-level AI investments introduced in Babina et al. (2024b), which leverages the detailed skill taxonomy in the job posting data to empirically determine the terms that are most related to AI jobs. This data-driven method 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 measure of firm-level AI investments is 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.[12] These firm-level measures are described in detail and validated in Babina et al. (2024b).

1.5. Measures of Firms' Systematic Risk

We follow the long literature in asset pricing and measure firms' systematic risk using market beta. 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,

[12] 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.

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.

In robustness analysis, 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:

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

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.

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 market betas. 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: robotics, (non-AI) IT, 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 Nvidia, which has 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 log markups computed following Traina (2018) and the log of the firm's total Cognism employment[13]; (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)[14]; 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.

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 the share of AI workers based on the resume data translates into a 0.05 increase in the CAPM beta (Table 2 Panel A). This increase in market beta corresponds to about 17% of the standard deviation of the changes in beta (shown in

[13]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.

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

the row called "Coeff Norm by Sd" at the bottom of the table). Similarly, a one-standard-deviation increase in the share of AI job postings is associated with a 0.05 increase in the CAPM beta (Table 2 Panel B), which is about 16% of the standard deviation of the changes in beta. Both 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 corresponds to a 0.05–0.06 increase in market beta (which corresponds to 22–24% of the standard deviation of the changes in beta).

Second, 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.1, 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 8 described in Section 3.2).

Third, we also confirm that the results are not due to mean-reversion in beta. Appendix Table A.2 conducts the analysis separately for each tercile of firms based on starting (2010) beta and documents very similar results across subsamples.

Fourth, we test the robustness of our results to changes in firm financial or 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. Appendix Table A.3 shows that the leverage channel does not explain our results, because AI investments are associated with increases in unlevered beta that are just as noticeable as the increases in levered beta reported in Table 2. 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.[15] Our results are also not driven by AI-investing firms having increased operating leverage. Appendix Table A.4 shows that firm-level AI investments are not associated with increased 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. 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. Therefore, we begin by examining whether our estimated effects are driven predominantly by smaller firms. Table 3 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 firm 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 are similar to our baseline results (see Appendix Table A.5),

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

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.6).

2.3. Time Trends

We explore the time trends in the increase in market betas of AI-investing firms to see whether the effects are driven mostly by earlier or later years. To do so, we construct an "AI factor": a long-short portfolio with the long side comprised of firms that rank above the median among firms with non-zero AI investments and the short side comprised of all other firms.[16] We compute the daily return of the factor portfolio and calculate its annual alpha ($\alpha^{(AI)}$) and beta ($\beta^{(AI)}$) by regressing the daily factor return on the daily market return:

$$ret_t^{(AI)} = \alpha^{(AI)} + \beta^{(AI)} r_{m,t} + \epsilon_t, \tag{5}$$

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 (5) separately for each year from 2010 to 2018 using a three-year moving average.

[16] 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.

Figure 1 shows the time series of the estimates of the AI factor's market alpha ($\alpha^{(AI)}$) in Panel A and beta ($\beta^{(AI)}$) in Panel B. Panel A does not show statistically significant alpha, but the returns to AI-investing firms have been consistently positive (albeit not statistically significant) during the later part of the sample, consistent with the evidence in (Babina et al., 2024b). Panel B shows that the beta of the AI factor has been relatively low in the first few years of the sample, but starts to increase in the middle and becomes especially high at the end (in 2017 and 2018), consistent with the increasing potential to realize AI-related growth options over time.

2.4. AI Investments and Industry Betas

We explore the drivers of the increase in market betas following AI investments by breaking down the correlations with the market return into correlations with different industry returns. For example, one possible explanation for the results in Table 2 is that firms using AI become more similar to technology firms. That would make the stock returns of AI-investing firms comove more with the stock returns of the tech sector, leading to higher market betas given that the tech sector comprises a large fraction of the overall stock market. Another possibility is that the systematic risk of AI-investing firms comes from their dominance in their own sector, as AI investments tend to be associated with increasing market share of AI-investing firms (e.g., Babina et al. 2024b).

To address these possibilities, we compute each firm's beta separately to its own industry, the tech sector, and all other sectors. In particular, for each firm i and industry sector j in year T, we calculate

$$\beta_{i,j,T} = \frac{cov(r_{i,t}, r_{j,t})}{var(r_{j,t})} \text{ for days } t \text{ in year } T, \tag{6}$$

where $r_{i,t}$ is the time series of daily returns on security i during year T, and $r_{j,t}$ is the value-weighted daily returns of stocks in industry sector j during that year (the results are robust to using equal-weighted returns). For each firm i, we consider three industry benchmarks j: (i) i's own sector (using the Fama-French-10 industry classification), (ii) the tech sector (the high-tech sector in Fama-French-10 industry classification), and (iii) all other sectors. We estimate $\beta_{i,j,T}$ by regressing the firm's daily stock returns against the weighted average daily returns of each of the three industry benchmarks. 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 Fama-French-10 industry 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, and the magnitudes are also similar across industry 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 such as the tech sector or the firm's own sector, but rather reflects similar increases in comovements in returns with all industry sectors.

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

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. Firms' investments in non-AI IT jobs are negatively and insignificantly related to changes in firms' market betas from 2010 to 2018. Firms' investments in robotics are positively but insignificantly related to changes in firms' market betas. Overall, AI technology appears to be unique in its robust and significant link to increases in firm market beta during the sample period. Adjacent technologies such as IT and robotics do not display the same pattern of increasing firms' systematic market risk.

Moreover, the increased betas associated with firms' AI investments are not simply reflecting common patterns of R&D investments or acquisition of organizational capital. In Panel C of Table 5, we examine how increases in R&D investments (changes in R&D/Sales) from 2010 to 2018 translate into changes in firms' market betas and find a null result. Increases in R&D investments are associated only with increases in momentum beta but have an insignificant association with market beta measured using either CAMP or the Carhart (1997) 4-factor model, and no increases in either size or value beta. Similarly, Panel D of Table 5 shows that increases in firms' organizational capital, measured as cumulative SG&A expenses following Eisfeldt and Papanikolaou (2013), are not associated with increases in firms' market beta.

The lack of a significant relationship between beta and these other technologies—IT, robotics, R&D, and SG&A expenditures—potentially reflects their different life cycle phases compared to AI technology. In our sample period, AI-driven product innovation creates growth options for AI-investing firms that are still early in their realization. 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, R&D comprises both *research* (creation of future growth options) and *development* (realization of existing growth options). Furthermore, 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 Forthcoming) and accounting rules, making a firm's R&D expense a hodgepodge of different drivers. Overall, firms' adoption of AI offers a unique laboratory to study the effects of technology at the onset of adoption, when it creates future growth opportunities for firms, with sharper effects than traditional measures of innovation investments such as R&D expenditures.

3. Mechanisms

In this section, we explore potential mechanisms for our results. First, we outline the conceptual framework of the growth-options-based mechanism and show that its key predictions 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 cash flow duration of AI-investing firms (Gonçalves, 2021; Gormsen and Lazarus, 2023), and (iii) the results do not appear to be driven by correlated shocks to investor demand for AI firms, as in style investing (Barberis and Shleifer, 2003).

3.1. Innovation and Growth Options

Prior evidence shows that the main uses of commercial AI across industries have not comprised productivity gains or labor displacement, but rather product innovation (Rock, 2019; Babina et al., 2024b). AI-investing firms receive more trademarks and product (but not process) patents, increase their product variety, and scale up both sales and employment. 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., 2024a). 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.

Thus, AI investments can be thought of as generating growth options for the firm. Carlson et al. (2004, 2006, 2010) point out that in the setting of seasoned equity offerings (SEOs), growth options are riskier than assets-in-place and can lead to rising betas as the prospects of realizing the options increase. Moreover, Bernardo et al. (2007) document that growth opportunities have higher beta than assets-in-place in virtually all industries. 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. This would yield the pattern of increasing market betas that we observe for AI-investing firms in the data, plus three additional predictions: (i) that AI-investing firms should load heavily on growth, (ii) that their comovement with the market should be especially high during market upswings, when the prospect of realizing the growth options goes up, and (iii) that their comovement with the market should increase with the emergence of news about AI advances, as such news makes the AI growth options more in-the-money. We test each of these additional predictions in turn.[17]

First, 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}) 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 decline in β^{HML} (Column 10 of Panel A and Panel B, respectively). The relationship with the other factors (size and momentum) is much weaker. The size factor effect in particular is small and statistically insignificant, despite AI investments favoring larger firms (Acemoglu et al., 2022a). The association between AI investments and the momentum factor (β^{UMD}) is not consistently statistically significant.

We further decompose the effect on the high-minus-low factor into changes in AI-

[17] An addition prediction is that AI-investing firms' 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.

investing firms' correlations with value firms and growth firms, separately. The results, presented in Appendix Table A.7, 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 (bottom quintile of firms based on the book-to-market ratio).

Second, we examine whether the increasing return covariance of AI-investing firms with the 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:

$$\beta_{i,t}^{-} = \frac{cov(r_{i,t}, r_{m,t} | r_{m,t} < \mu_{m,t})}{var(r_{m,t} | r_{m,t} < \mu_{m,t})} \quad and \quad \beta_{i,t}^{+} = \frac{cov(r_{i,t}, r_{m,t} | r_{m,t} > \mu_{m,t})}{var(r_{m,t} | r_{m,t} > \mu_{m,t})}, \tag{7}$$

where $\mu_{m,t}$ is the average daily return on the market during year t. $\beta_{i,t}^{-}$ represents a firm'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). This demonstrates that the stock returns of 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, coupled with the generally positive returns of AI-investing firms, reinforces the notion that AI is benefiting firms and their investors.

Finally, 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 news 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.8 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. 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.

Second, 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.8 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 from RavenPack 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.

3.2. Alternative Explanations

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:

$$\Delta ShareAIWorkers_{i,[2010,2018]} = \alpha + b\beta_{i,2010} + Controls'_{i,2010}\gamma + SectorFE + \epsilon_i, \quad (8)$$

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.9, 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 (Table A.9 Panel A) 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, helping to assuage concerns regarding reverse causality. Furthermore, the results in Appendix Table A.2 show that the effects are consistent across different levels of starting beta, further indicating that the results are not driven by mechanical reverse causality such as mean reversion.

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). Table A.10 tests the premise of the potential explanation that AI investments are associated with changes in firms' equity duration. First, in Columns 1 and 2 we regress changes from 2010 to 2018 in duration estimated following Gonçalves (2021) against contemporaneous changes in firms' share of AI workers, 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. Second, 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 changes in equity duration do not appear 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 7 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 8 considers firms' beta to a market index that consists only of *non*-AI investing firms. The results show that AI investments are associated with increasing beta even to this market index 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 7 and 8 suggest that the investor capital channel is unlikely to be the main driver of our key result.

The evidence in Table 8 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. 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). The value and realization of the growth opportunities created through AI investments correlate with market conditions, resulting in increased comovement with the overall market index.

4. Additional Analyses: Idiosyncratic Risk, Total Risk, and Cash Flow Risk

We supplement our main analysis of AI-investing firms' systematic risk by considering other aspects of their risk profile. Specifically, we examine whether AI investments are associated with any changes in idiosyncratic (return) volatility and total (return) risk, as well as measures of cash flow risk.

4.1. Idiosyncratic and Total Equity Return Volatility

We begin by exploring whether AI investments are associated with increases in firms' overall equity return risks, to understand whether AI-investing firms are becoming generally riskier or experiencing a reallocation of risk towards a more systematic component.

First, we examine idiosyncratic volatility. To calculate idiosyncratic volatility, we estimate the Capital Asset Pricing Model and the Carhart (1997) four-factor model using daily stock returns over a year and compute the standard deviation of the residuals from these models. The first four columns of Table 9 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. For example, when all controls are included, a one-standard-deviation change in the job-posting-based measure of AI investments is associated with a 0.136 reduction in idiosyncratic volatility based on the CAPM model and a 0.081 reduction in idiosyncratic volatility based on the Carhart (1997) four-factor model.

The last two columns of Table 9 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 often negative. 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 are associated with a reallocation of equity return risk from idiosyncratic to systematic.

4.2. Cash Flow Risk

Increasing betas of AI-investing firms may also reflect increased cash flow risks (Campbell and Vuolteenaho, 2004). To evaluate this possibility, Table 10 considers three measures of cash flows at the quarterly level: return on assets (ROA), return on equity (ROE), and cash flow over assets (CFOA).[18] For each measure, we calculate cash flow volatility as the standard deviation of the corresponding cash flow measure across all quarters over a 3-year or 5-year period surrounding 2010 or 2018. We then take the change in cash flow

[18] CFOA is defined as: (Net Income + Depreciation - Δ Working Capital - Capital Expenditures)/ Lagged Total Assets.

volatility from 2010 to 2018 as the dependent variable in the long-differences specification. For example, in Column 1, the dependent variable is the volatility of ROA across all quarters from 2016 to 2020 minus the volatility of ROA across all quarters from 2008 to 2012. In Column 7, the dependent variable is the volatility of ROA across all quarters from 2017 to 2019 minus the volatility of ROA across all quarters from 2009 to 2011.

Overall, the negative coefficients across Table 10 suggest that AI investments are associated with a decline in the volatility of cash flows. The effects are mostly statistically significant for the resume-based measure of AI investments. AI investments are also typically associated with lower cash flow volatility when using the job-posting-based measure, although those estimates are not statistically significant. Overall, we find that AI-investing firms have *less* volatile cash flows. Therefore, the higher return beta of these AI-investing firms is not associated with increased cash flow risks.

5. Conclusion

This paper fills a gap in our understanding of the potential risks of investments in artificial intelligence. We examine how the risk profile of firms changes when they invest in AI. We document that firms that invest more in AI experience increased systematic risk. This finding is robust across many model specifications and is most consistent with the notion that AI creates growth options for firms through increased potential for product innovation.

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 risks to systematic risks (higher market beta). 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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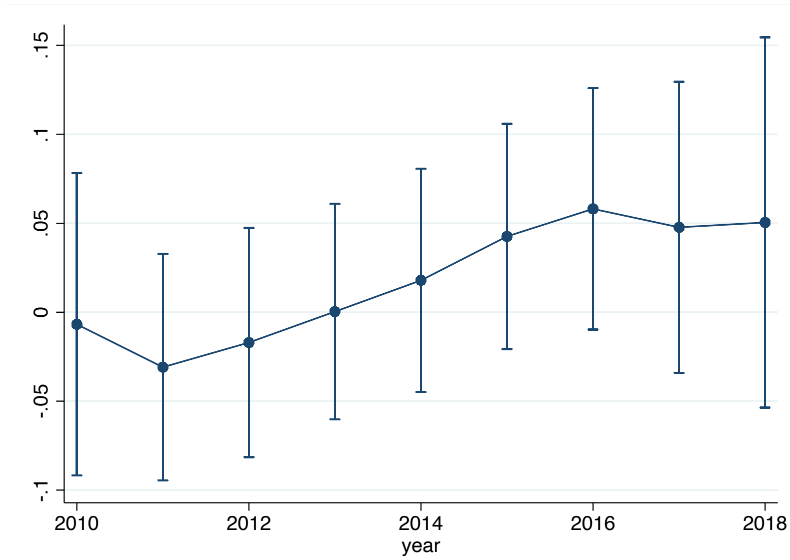
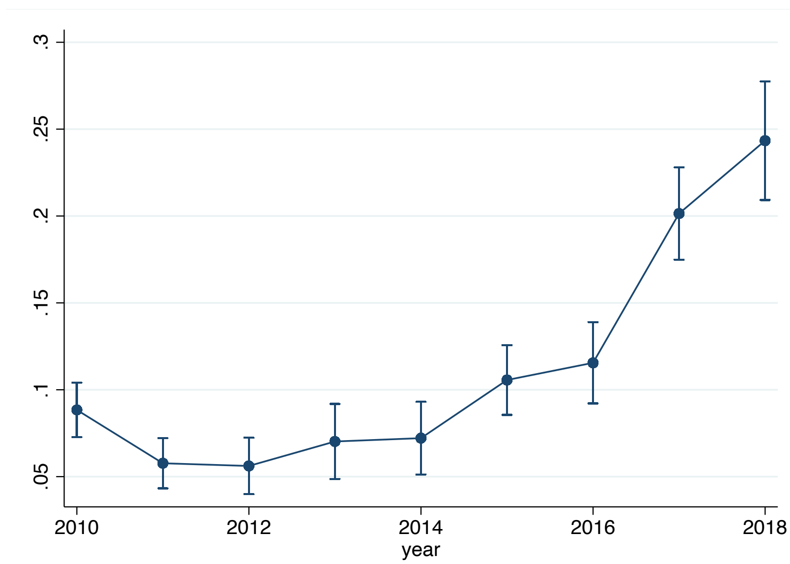
Figure 1. Alpha and Beta of the AI Factor Over Time



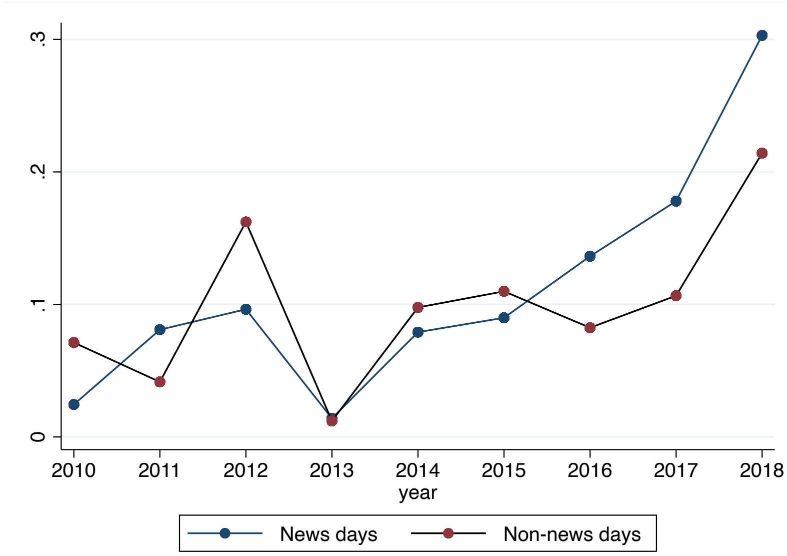
(a) Alpha of AI factor



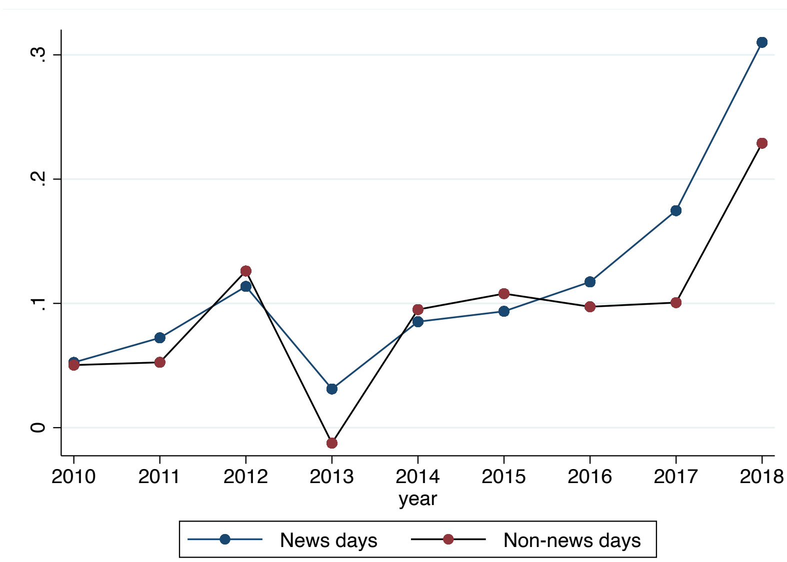
(b) Beta of AI factor

This figure plots the (annualized) alpha and beta of the AI factor and the associated 95% confidence intervals 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 investments between 2010 and 2018). Panel (a) plots the alpha of the AI factor based on the Capital Asset Pricing Model computed over a 3-year window around each year, and Panel (b) plots the market beta of the AI factor based on the Capital Asset Pricing Model computed over a 3-year window around 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
Mean of Dep Var	-0.169	-0.169	-0.008	-0.008	0.115	0.115	0.135	0.135	-0.056	-0.056
S.d. of Dep Var	0.326	0.326	0.261	0.261	0.446	0.446	0.537	0.537	0.642	0.642
Interquartile range Dep Var	0.462	0.462	0.348	0.348	0.512	0.512	0.637	0.637	0.892	0.892
Coeff Norm by Sd	0.337	0.167	0.198	0.218	-0.014	-0.006	-0.157	-0.203	-0.057	-0.119
Coeff Norm by Interquartile	0.238	0.118	0.148	0.163	-0.012	-0.005	-0.132	-0.171	-0.041	-0.086
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
Mean of Dep Var	-0.162	-0.162	0.025	0.025	0.180	0.180	0.163	0.163	-0.015	-0.015
S.d. of Dep Var	0.321	0.321	0.266	0.266	0.463	0.463	0.526	0.526	0.632	0.632
Interquartile range Dep Var	0.512	0.512	0.386	0.386	0.413	0.413	0.606	0.606	0.900	0.900
Coeff Norm by Sd	0.264	0.163	0.172	0.236	-0.089	-0.101	-0.190	-0.262	-0.036	-0.086
Coeff Norm by Interquartile	0.165	0.102	0.118	0.163	-0.100	-0.114	-0.165	-0.227	-0.025	-0.060
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. In this and other tables, Mean of Dep Var shows the (weighted) mean of the dependent variable; S.d. of Dep Var shows the standard deviation of the dependent variable; Interquartile range Dep Var shows the interquartile range of the dependent variable; Coeff Norm by Sd and Coeff Norm by Interquartile reflect the main regression coefficient divided by the standard deviation or the interquartile range of the dependent variable. 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 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
Mean of Dep Var	-0.169	-0.169	-0.008	-0.008
S.d. of Dep Var	0.326	0.326	0.261	0.261
Interquartile range Dep Var	0.462	0.462	0.348	0.348
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
Mean of Dep Var	-0.162	-0.162	0.025	0.025
S.d. of Dep Var	0.321	0.321	0.266	0.266
Interquartile range Dep Var	0.512	0.512	0.386	0.386
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 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
Mean of Dep Var	-0.337	-0.337	-0.164	-0.164	-0.194	-0.194
S.d. of Dep Var	0.277	0.277	0.320	0.320	0.342	0.342
Interquartile range Dep Var	0.394	0.394	0.399	0.399	0.479	0.479
Coeff Norm by Sd	0.325	0.179	0.197	0.125	0.325	0.156
Coeff Norm by Interquartile	0.229	0.126	0.158	0.100	0.232	0.111
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
Mean of Dep Var	-0.324	-0.324	-0.187	-0.187	-0.185	-0.185
S.d. of Dep Var	0.271	0.271	0.330	0.330	0.340	0.340
Interquartile range Dep Var	0.421	0.421	0.393	0.393	0.549	0.549
Coeff Norm by Sd	0.247	0.173	0.185	0.163	0.246	0.155
Coeff Norm by Interquartile	0.159	0.111	0.155	0.137	0.152	0.096
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 2.4. 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, 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
Mean of Dep Var	-0.162	-0.162	0.025	0.025	0.180	0.180	0.163	0.163	-0.015	-0.015
S.d. of Dep Var	0.321	0.321	0.266	0.266	0.463	0.463	0.526	0.526	0.632	0.632
Interquartile range Dep Var	0.512	0.512	0.386	0.386	0.413	0.413	0.606	0.606	0.900	0.900
Coeff Norm by Sd	-0.179	-0.174	-0.125	-0.135	-0.423	-0.414	-0.117	-0.065	0.026	0.007
Coeff Norm by Interquartile	-0.112	-0.109	-0.086	-0.093	-0.475	-0.465	-0.102	-0.057	0.019	0.005
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
Mean of Dep Var	-0.162	-0.162	0.025	0.025	0.180	0.180	0.163	0.163	-0.015	-0.015
S.d. of Dep Var	0.321	0.321	0.266	0.266	0.463	0.463	0.526	0.526	0.632	0.632
Interquartile range Dep Var	0.512	0.512	0.386	0.386	0.413	0.413	0.606	0.606	0.900	0.900
Coeff Norm by Sd	0.204	0.131	0.035	0.093	-0.113	-0.078	-0.258	-0.266	0.045	0.071
Coeff Norm by Interquartile	0.128	0.082	0.024	0.064	-0.127	-0.088	-0.223	-0.230	0.032	0.050
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: 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
Mean of Dep Var	-0.162	-0.162	0.025	0.025	0.180	0.180	0.163	0.163	-0.015	-0.015
S.d. of Dep Var	0.321	0.321	0.266	0.266	0.463	0.463	0.526	0.526	0.632	0.632
Interquartile range Dep Var	0.512	0.512	0.386	0.386	0.413	0.413	0.606	0.606	0.900	0.900
Coeff Norm by Sd	0.140	0.337	0.042	0.194	0.085	-0.132	-0.069	-0.431	0.085	0.235
Coeff Norm by Interquartile	0.087	0.211	0.029	0.133	0.095	-0.149	-0.060	-0.373	0.060	0.165
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 D: 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
Mean of Dep Var	-0.169	-0.169	-0.008	-0.008	0.115	0.115	0.135	0.135	-0.056	-0.056
S.d. of Dep Var	0.326	0.326	0.261	0.261	0.446	0.446	0.537	0.537	0.642	0.642
Interquartile range Dep Var	0.462	0.462	0.348	0.348	0.512	0.512	0.637	0.637	0.892	0.892
Coeff Norm by Sd	-0.099	-0.043	0.030	0.045	0.270	0.235	0.015	0.028	-0.026	-0.098
Coeff Norm by Interquartile	-0.070	-0.031	0.023	0.034	0.235	0.205	0.012	0.023	-0.019	-0.070
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, 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 growth in R&D over sales from 2010 to 2018, standardized to mean zero and standard deviation of one. In Panel D, 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
Mean of Dep Var	-0.197	-0.197	-0.137	-0.137	-0.058	-0.058
S.d. of Dep Var	0.438	0.438	0.334	0.334	0.359	0.359
Interquartile range Dep Var	0.567	0.567	0.438	0.438	0.420	0.420
Coeff Norm by Sd	0.365	0.180	0.223	0.111	0.239	0.122
Coeff Norm by Interquartile	0.282	0.139	0.170	0.085	0.204	0.105
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
Mean of Dep Var	-0.189	-0.189	-0.143	-0.143	-0.045	-0.045
S.d. of Dep Var	0.450	0.450	0.308	0.308	0.383	0.383
Interquartile range Dep Var	0.507	0.507	0.421	0.421	0.386	0.386
Coeff Norm by Sd	0.270	0.151	0.199	0.133	0.157	0.067
Coeff Norm by Interquartile	0.240	0.134	0.146	0.098	0.156	0.066
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 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
Mean of Dep Var	-0.169	-0.169	-0.008	-0.008
S.d. of Dep Var	0.326	0.326	0.261	0.261
Interquartile range Dep Var	0.462	0.462	0.348	0.348
Coeff Norm by Sd	0.412	0.269	0.059	0.115
Coeff Norm by Interquartile	0.291	0.190	0.044	0.086
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
Mean of Dep Var	-0.162	-0.162	0.025	0.025
S.d. of Dep Var	0.321	0.321	0.266	0.266
Interquartile range Dep Var	0.512	0.512	0.386	0.386
Coeff Norm by Sd	0.164	0.180	0.161	0.273
Coeff Norm by Interquartile	0.103	0.112	0.111	0.188
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 8. 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
Mean of Dep Var	-0.024	-0.024	-0.028	-0.028
S.d. of Dep Var	0.288	0.288	0.260	0.260
Interquartile range Dep Var	0.401	0.401	0.343	0.343
Coeff Norm by Sd	0.334	0.183	0.200	0.222
Coeff Norm by Interquartile	0.240	0.132	0.152	0.169
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
Mean of Dep Var	-0.013	-0.013	0.004	0.004
S.d. of Dep Var	0.283	0.283	0.265	0.265
Interquartile range Dep Var	0.413	0.413	0.385	0.385
Coeff Norm by Sd	0.257	0.168	0.175	0.239
Coeff Norm by Interquartile	0.176	0.115	0.120	0.165
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.

Table 9. 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
Mean of Dep Var	0.212	0.212	0.133	0.133	-0.070	-0.070
S.d. of Dep Var	0.770	0.770	0.621	0.621	0.790	0.790
Interquartile range Dep Var	0.711	0.711	0.683	0.683	0.783	0.783
Coeff Norm by Sd	-0.075	-0.023	-0.044	0.016	-0.003	0.016
Coeff Norm by Interquartile	-0.081	-0.024	-0.040	0.014	-0.003	0.016
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
Mean of Dep Var	0.261	0.261	0.148	0.148	-0.022	-0.022
S.d. of Dep Var	0.942	0.942	0.703	0.703	0.940	0.940
Interquartile range Dep Var	0.859	0.859	0.707	0.707	0.852	0.852
Coeff Norm by Sd	-0.105	-0.144	-0.105	-0.115	-0.059	-0.111
Coeff Norm by Interquartile	-0.116	-0.158	-0.104	-0.114	-0.066	-0.122
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 10. AI Investments and Cash Flow Volatility

Panel A: Cognism

	Δ Volatility ROA 5 year		Δ Volatility ROE 5 year		Δ Volatility CFOA 5 year		Δ Volatility ROA 3 year		Δ Volatility ROE 3 year		Δ Volatility CFOA 3 year	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Share AI Workers	-0.001	-0.002**	-0.009*	-0.021**	-0.004*	-0.007**	-0.001	-0.002**	-0.009*	-0.022***	-0.002	-0.005**
	(0.001)	(0.001)	(0.005)	(0.011)	(0.002)	(0.003)	(0.001)	(0.001)	(0.005)	(0.007)	(0.001)	(0.002)
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
Mean of Dep Var	0.002	0.002	0.030	0.030	0.012	0.012	0.003	0.003	0.026	0.026	0.009	0.009
S.d. of Dep Var	0.014	0.014	0.149	0.149	0.038	0.038	0.013	0.013	0.159	0.159	0.041	0.041
Interquartile range Dep Var	0.011	0.011	0.050	0.050	0.030	0.030	0.009	0.009	0.036	0.036	0.024	0.024
Coeff Norm by Sd	-0.039	-0.125	-0.062	-0.144	-0.104	-0.194	-0.047	-0.172	-0.057	-0.136	-0.048	-0.122
Coeff Norm by Interquartile	-0.049	-0.156	-0.183	-0.428	-0.130	-0.242	-0.069	-0.251	-0.254	-0.604	-0.080	-0.204
Adj R-Squared	0.098	0.146	0.134	0.196	0.036	0.116	0.083	0.144	0.129	0.199	0.019	0.124
Observations	886	886	885	885	712	712	898	898	897	897	709	709

Panel B: Burning Glass

	Δ Volatility ROA 5 year		Δ Volatility ROE 5 year		Δ Volatility CFOA 5 year		Δ Volatility ROA 3 year		Δ Volatility ROE 3 year		Δ Volatility CFOA 3 year	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Share AI Workers	-0.000	-0.001	0.003	-0.008	-0.005	-0.006	0.000	-0.001	0.007	-0.002	-0.000	-0.002
	(0.001)	(0.001)	(0.008)	(0.009)	(0.003)	(0.004)	(0.000)	(0.001)	(0.005)	(0.007)	(0.001)	(0.003)
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
Mean of Dep Var	-0.000	-0.000	0.069	0.069	0.007	0.007	0.001	0.001	0.051	0.051	0.007	0.007
S.d. of Dep Var	0.017	0.017	0.191	0.191	0.036	0.036	0.018	0.018	0.185	0.185	0.037	0.037
Interquartile range Dep Var	0.011	0.011	0.068	0.068	0.030	0.030	0.009	0.009	0.047	0.047	0.027	0.027
Coeff Norm by Sd	-0.002	-0.060	0.014	-0.040	-0.134	-0.178	0.008	-0.066	0.038	-0.010	-0.007	-0.049
Coeff Norm by Interquartile	-0.003	-0.095	0.038	-0.113	-0.162	-0.215	0.016	-0.135	0.150	-0.041	-0.009	-0.066
Adj R-Squared	0.209	0.317	0.201	0.325	0.076	0.130	0.278	0.381	0.157	0.269	0.041	0.113
Observations	868	868	868	868	706	706	878	878	878	878	699	699

This table reports the coefficients from long-differences regressions of changes in cash flow 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 5-year ROA volatility in Columns 1 and 2, changes in 5-year ROE volatility in Columns 3 and 4, changes in 5-year CFOA volatility in Columns 5 and 6, changes in 3-year ROA volatility in Columns 7 and 8, changes in 3-year ROE volatility in Columns 9 and 10, and changes in 3-year CFOA volatility in Columns 11 and 12. We use 3-year or 5-year windows centered around 2010 or 2018 to calculate the cash flow volatility. 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. The control variables are the same as Table 2. 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' 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
Mean of Dep Var	-0.142	-0.142	0.009	0.009
S.d. of Dep Var	0.321	0.321	0.265	0.265
Interquartile range Dep Var	0.452	0.452	0.348	0.348
Coeff Norm by Sd	0.340	0.169	0.205	0.220
Coeff Norm by Interquartile	0.241	0.120	0.156	0.167
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
Mean of Dep Var	-0.133	-0.133	0.041	0.041
S.d. of Dep Var	0.316	0.316	0.269	0.269
Interquartile range Dep Var	0.508	0.508	0.423	0.423
Coeff Norm by Sd	0.267	0.166	0.178	0.237
Coeff Norm by Interquartile	0.166	0.104	0.113	0.151
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.2. 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
Mean of Dep Var	-0.169	-0.169	-0.008	-0.008
S.d. of Dep Var	0.326	0.326	0.261	0.261
Interquartile range Dep Var	0.462	0.462	0.348	0.348
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
Mean of Dep Var	-0.162	-0.162	0.025	0.025
S.d. of Dep Var	0.321	0.321	0.266	0.266
Interquartile range Dep Var	0.512	0.512	0.386	0.386
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.3. 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
Mean of Dep Var	-0.168	-0.168	-0.164	-0.164
S.d. of Dep Var	0.478	0.478	0.373	0.373
Interquartile range Dep Var	0.452	0.452	0.424	0.424
Coeff Norm by Sd	0.232	0.216	0.303	0.215
Coeff Norm by Interquartile	0.245	0.228	0.266	0.189
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
Mean of Dep Var	-0.195	-0.195	-0.192	-0.192
S.d. of Dep Var	0.452	0.452	0.375	0.375
Interquartile range Dep Var	0.534	0.534	0.483	0.483
Coeff Norm by Sd	0.220	0.201	0.248	0.172
Coeff Norm by Interquartile	0.186	0.170	0.193	0.134
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.4. 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
Mean of Dep Var	-0.020	-0.020	-0.049	-0.049
S.d. of Dep Var	0.134	0.134	0.308	0.308
Interquartile range Dep Var	0.079	0.079	0.273	0.273
Coeff Norm by Sd	0.059	0.071	-0.031	-0.021
Coeff Norm by Interquartile	0.100	0.120	-0.035	-0.024
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
Mean of Dep Var	-0.023	-0.023	-0.066	-0.066
S.d. of Dep Var	0.163	0.163	0.420	0.420
Interquartile range Dep Var	0.097	0.097	0.352	0.352
Coeff Norm by Sd	-0.002	-0.074	-0.038	-0.107
Coeff Norm by Interquartile	-0.003	-0.125	-0.046	-0.127
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.5. 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
Mean of Dep Var	-0.119	-0.119	0.034	0.034	0.164	0.164	0.178	0.178	-0.031	-0.031
S.d. of Dep Var	0.411	0.411	0.351	0.351	0.613	0.613	0.690	0.690	0.754	0.754
Interquartile range Dep Var	0.509	0.509	0.445	0.445	0.729	0.729	0.843	0.843	0.897	0.897
Coeff Norm by Sd	0.208	0.064	0.093	0.109	-0.059	-0.097	-0.170	-0.215	-0.029	-0.057
Coeff Norm by Interquartile	0.168	0.052	0.073	0.086	-0.049	-0.082	-0.139	-0.176	-0.025	-0.048
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
Mean of Dep Var	-0.136	-0.136	0.049	0.049	0.214	0.214	0.227	0.227	0.039	0.039
S.d. of Dep Var	0.428	0.428	0.375	0.375	0.659	0.659	0.804	0.804	0.757	0.757
Interquartile range Dep Var	0.524	0.524	0.456	0.456	0.892	0.892	0.919	0.919	0.924	0.924
Coeff Norm by Sd	0.181	0.098	0.118	0.166	-0.048	-0.082	-0.188	-0.216	-0.001	-0.029
Coeff Norm by Interquartile	0.148	0.080	0.097	0.137	-0.035	-0.061	-0.165	-0.189	-0.001	-0.023
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.6. 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
Mean of Dep Var	0.096	0.096
S.d. of Dep Var	0.295	0.295
Coeff Norm by Sd	-0.093	-0.032
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
Mean of Dep Var	0.119	0.119
S.d. of Dep Var	0.324	0.324
Coeff Norm by Sd	-0.098	-0.072
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.7. 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
Mean of Dep Var	0.148	0.148	-0.465	-0.465
S.d. of Dep Var	0.629	0.629	1.663	1.663
Interquartile range Dep Var	0.767	0.767	2.202	2.202
Coeff Norm by Sd	-0.167	-0.190	0.086	0.209
Coeff Norm by Interquartile	-0.137	-0.155	0.065	0.158
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
Mean of Dep Var	0.172	0.172	-0.588	-0.588
S.d. of Dep Var	0.597	0.597	1.858	1.858
Interquartile range Dep Var	0.569	0.569	2.959	2.959
Coeff Norm by Sd	-0.203	-0.264	0.129	0.217
Coeff Norm by Interquartile	-0.213	-0.278	0.081	0.136
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.8. 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
Mean of Dep Var	-0.180	-0.180	-0.154	-0.154	-0.026	-0.026
S.d. of Dep Var	0.351	0.351	0.350	0.350	0.268	0.268
Interquartile range Dep Var	0.433	0.433	0.491	0.491	0.342	0.342
Coeff Norm by Sd	0.360	0.199	0.242	0.074	0.157	0.165
Coeff Norm by Interquartile	0.292	0.161	0.172	0.052	0.122	0.129
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
Mean of Dep Var	-0.233	-0.233	-0.123	-0.123	-0.110	-0.110
S.d. of Dep Var	0.401	0.401	0.315	0.315	0.281	0.281
Interquartile range Dep Var	0.592	0.592	0.350	0.350	0.359	0.359
Coeff Norm by Sd	0.329	0.162	0.299	0.135	0.135	0.084
Coeff Norm by Interquartile	0.223	0.110	0.269	0.121	0.105	0.065
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.9. 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.10. 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
Mean of Dep Var	-4.892	-4.892	-2.941	-2.941
S.d. of Dep Var	32.279	32.279	9.788	9.788
Interquartile range Dep Var	17.086	17.086	13.358	13.358
Coeff Norm by Sd	-0.046	-0.027	-0.024	0.010
Coeff Norm by Interquartile	-0.086	-0.051	-0.018	0.008
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
Mean of Dep Var	-4.755	-4.755	-2.293	-2.293
S.d. of Dep Var	34.822	34.822	10.955	10.955
Interquartile range Dep Var	18.939	18.939	14.371	14.371
Coeff Norm by Sd	-0.025	-0.077	-0.068	-0.124
Coeff Norm by Interquartile	-0.046	-0.141	-0.051	-0.094
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.