Artificial Intelligence, Firm Growth, and Industry Concentration*

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Abstract

Which firms invest in artificial intelligence (AI) technologies, and how do these investments affect individual firms and industries? We provide a comprehensive picture of the use of AI technologies and its impact among US firms over the last decade, using a unique combination of job postings and individual-level employment profiles. We introduce a novel measure of investments in AI technologies based on human capital and document that larger firms with higher sales, markups, and cash reserves tend to invest in AI more. Firms that invest more in AI experience faster growth in both sales and employment, which translates into analogous growth at the industry level. The positive effects are concentrated among the largest firms, leading to a positive correlation between AI investments and an increase in industry concentration. However, increases in concentration are not accompanied by either increased mark-ups or increased productivity. Our results are robust to instrumenting firm-level AI investments with foreign industry-level AI investments and local variation in industry-level AI investments, and we document consistent patterns across measures of AI using firms' demand for AI talent (job postings) and actual AI talent (resumes). Overall, our findings support the view that new technologies, such as AI, increase the scale of the most productive firms and contribute to the rise of superstar firms.

Keywords: artificial intelligence, technological change, technology adoption, economic growth, human capital, superstar firms, industry concentration

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Technological advances are key drivers of economic growth. The past decade has seen a new technological shift: advances in computing power and data availability have led to substantial improvements in artificial intelligence (AI) technologies, enabling their commercial applications across a broad landscape of firms, industries, and countries.[1] Yet, whether artificial intelligence can transform economies and spur economic growth remains an open question. On the one hand, as a potential new general purpose technology, AI can generate growth through product innovations and increased productivity (Aghion et al., 2017; Cockburn et al., 2018). On the other hand, aggregate productivity growth over the past decade has slowed significantly, leading to concerns that AI may not deliver growth or take a much longer time to reach its potential (Brynjolfsson et al., 2019). So far, little systematic evidence exists on AI investments and their economic impact.

In this paper, we examine the adoption and impact of artificial intelligence technologies (machine learning, natural language processing, and computer vision) on the growth of US firms and industries over the past decade. According to OECD (2019), an AI system is *"Machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments."* Artificial intelligence technologies have economic features that can affect outcomes through different channels and lead to different implications. First, AI technologies can help streamline tasks such as decision-making, prediction, and anomaly identification and improve forecast accuracy (Agrawal et al., 2019; Mihet and Philippon, 2019; Tanaka et al., 2019; Brynjolfsson et al., 2011). This type of automation can potentially stimulate growth by streamlining production processes and increasing productivity. Second, one of the primary use cases of AI is the ability to tailor product offerings, which can potentially be applied to price discriminate and increase firms' market power (Chase, 2013; Mihet and Philippon, 2019). Third, AI has a unique reliance on big data. Since firms with larger operations are likely to accumulate larger datasets, this can favor ex ante larger, more productive firms and increase the scale of these firms (Farboodi et al., 2019).

A major challenge to studying the impact of AI on firms is the lack of firm-level data on the use of AI technology. We overcome this challenge by developing a novel measure of AI investments based on detailed data on firms' human capital, motivated by the heavy reliance of AI on human rather than physical capital. We use a unique combination of datasets to measure firms'

[1]For example, a third of companies surveyed globally by Deloitte in 2018 have a comprehensive AI strategy. See here. Bughin et al. (2018) and Furman and Seamans (2019) provide an overview of investments in the private sector. When it comes to public investments, the US government seeks to double its non-defense AI R&D (Executive Office of the President, 2019), while the European Union has called for $24 billion per year to be invested in AI research by 2020 (European Commission, 2020), and China aims $150 billion investments in domestic AI market by 2030 (Mou, 2019).

AI-related human capital: job postings data from Burning Glass Technologies, which include the near-universe of online job vacancies, and resume data from Cognism Inc, which offer job histories for millions of individual employees. These datasets enable us to construct firm-level measures of investment in AI by observing the stock and hiring of AI-related employees.

We offer a novel approach to measure AI-relatedness of jobs, which consists of several steps. First, we measure AI-relatedness of each skill using the job postings data. The measure is based on an intuitive idea that if a given skill is related to AI, then jobs requiring that skill should also require some basic AI skills, such as machine learning. We identify four basic AI skills: “machine learning”, “natural language processing”, “computer vision”, and “artificial intelligence”. Our measure of AI-relatedness of each skill is the fraction of jobs requiring that skill that also require one of the four basic AI skills.[2] Second, we average the scores across all required skills listed in a given job posting to obtain a continuous measure of AI-relatedness of jobs that ranges from 0 to 1. We define AI jobs as jobs whose AI-relatedness measure is over a certain cutoff (e.g., 0.1). Next, we adapt this measure to define AI jobs in the less structured resume data. For each employee, at each point in time, we consider whether terms with the highest AI-relatedness measures (e.g. “deep learning”) appear either in the current job description, in any patents or publications produced during the current job, or in any awards received during the current job. This gives us a classification of each employee of each firm at each point in time.

Our measure of AI jobs offers several advantages over previous studies. First, compared to previous studies using a bag-of-words approach with job-postings data, our method does not require researchers to pre-specify a list of AI-related keywords and instead learns the most relevant terms empirically. Second, our measure is built on a continuous (rather than binary) classification, which allows us to capture a wide range of AI-related skills and differentiate more AI-related skills (e.g., deep learning) from less AI-related skills (e.g., information retrieval). Our paper is also the first one to cross-validate AI demand identified in job postings with the resume data. Importantly, our methodology for identifying AI-skilled jobs can also be applied to identify jobs related to a wide range of technologies or skills (e.g., programming, cognitive, communication, research), especially those centering on human expertise.

We confirm that measures of AI investment constructed from both datasets display intuitive properties. In both datasets, the fraction of AI workers has monotonically increased over time,

[2] For example, the score for “deep learning” is 0.86, meaning that 86% of jobs that require deep learning also require one of the four basic AI skills. In contrast, the score for “information retrieval” is 0.37, the score for “regression analysis” is 0.09, and the score for “communication skills” is 0.003.

growing more than five-fold from 2010 to 2018. Although AI investments rise most in the Information Technology sector, firms in all sectors invest in AI, consistent with AI being a general purpose technology (Goldfarb et al., 2019; Klinger et al., 2019). Encouragingly, the two measures of AI investments based AI-skilled labor—based on a firm's *current* employees (from resumes) and the demand for *additional* AI employees (from job postings)—are highly correlated, and all subsequent tests in the paper yield consistent results across the two datasets.

We begin our empirical analysis by examining which firms invest in AI. We aggregate both job postings data and resume data to the firm level and match to public firms in Compustat. We predict grwoth in the share of AI-related employees between 2010 and 2018 based on firm characteristics measured as of 2010. Our results indicate that larger firms, in terms of both sales and market share, are more likely to invest in AI, consistent with Alekseeva et al. (2020). Furthermore, AI investment is stronger among firms with higher cash reserves and higher mark-ups, and among firms with higher R&D intensity. Looking at the local market conditions, we observe that higher-wage and more educated areas experience higher growth in AI-skilled hiring.

We then address the fundamental question of whether artificial intelligence is able to stimulate growth for the adopting firms. Given that AI investment is gradual in the data, and that we do not expect to observe its effects on firms immediately, we estimate a long-differences regression of changes in firm-level outcomes on contemporaneous changes in the share of AI workers from 2010 to 2018 as in Autor et al. (2013). We find a strong and consistent pattern: firms that invest in AI grow more. Specifically, a one-standard-deviation increase in the share of AI workers based on the resume data corresponds to a 14.6% increase in sales, a 13.3% increase in employment, and a 1.3 percentage point increase in market share. The results are similar using the job-postings-based measure of AI investments. The results on the increased employment are surprising, given wide-spread concerns of the potential for AI to replace labor (Frank et al., 2019).

In order to address endogeneity concerns around firms' decisions to invest in AI, we employ two different instruments for AI investments. First, we employ a strategy similar to Autor et al. (2013) and Acemoglu et al. (2020) and instrument each firm's change in AI workers using the change in the share of AI workers by European public firms in the same 5-digit NAICS industry. Our unique resume data, which include consistent coverage of resumes in Europe, enables the detailed measurement of firm- and industry-level AI investment rates in Europe. Second, we instrument for firm-level AI investments using a shift-share design with weighted average of national industry-level AI investment rates, where the weights are given by the industry share at the location(s) where the firm operates. These instruments are motivated by the substantial heterogeneity in AI investments across industries, highlighted by the following argument made in industry reports (Bughin et al., 2017): differences in AI investments across industries are largely driven by differences in availability of data and technical capabilities, rather than individual firms' demand and growth trajectories. Both instruments have a strong first stage for both measures of AI investments, with F-statistics above 10, and we confirm that firms and industries that invest in AI more are not on different growth trajectories prior to 2010. The IV results confirm the patterns documented in OLS regressions.

We next turn to whether firm-level growth translates into industry-level changes in sales and employment. It is possible that the positive effects on employment and sales at the firm level could be offset or even dominated by negative spillovers to competitors within the industry as output and labor are reallocated from other firms to the AI-investing firms (Acemoglu et al., 2020). Contrary to this idea, we find that industries that invest in AI more experience an overall increase in sales and employment. This highlights the differences between AI and previous technologies, such as robots and automation. Although larger firms are also more likely to adopt robots (Humlum, 2019; Acemoglu et al., 2020), many papers find that robot adoption leads to lower aggregate employment (Autor and Salomons, 2018; Acemoglu and Restrepo, 2019; Zator, 2019).[3]

AI investments spur not only industry growth in sales and employment, but also increased industry concentration. Slicing our analysis by initial firm size, we show that the positive relationship between AI investments and growth concentrates among the largest firms. For example, a one-standard-deviation increase in the share of AI workers based on resume data increases sales by 16.4% in the top tercile of initial firm size, 7.3% in the middle tercile, and 0.8% in the bottom tercile. Furthermore, industry-level growth in AI investments is associated with increased industry concentration measured by the Herfindahl-Hirschman Index (HHI) or the fraction of sales accruing to the single largest firm.

Conceptually, we outline three broad channels through which investments in AI technologies can generate the empirical patterns we observe in increased firm-level growth and higher industry concentration. First, we consider whether the observed effects stem form AI improving productivity. Empirically, we do not find much support for this hypothesis, at least in the short run. We find

[3]Recent evidence in Aghion et al. (2020) suggests that automation can also increase aggregate employment. For theoretical treatments of the impact of automation and labor displacement, see Korinek and Stiglitz (2017), Acemoglu and Restrepo (2019), Agrawal et al. (2019). See also Brynjolfsson et al. (2018b) and Athey et al. (2020) for task allocation across human and artificial intelligence.

small, statistically insignificant, and even slightly negative relationship between AI investments and sales per worker or revenue TFP. Second, since big data and AI enable granular product tailoring that can potentially facilitate price discrimination, we evaluate whether the AI-fueled growth is driven by increased market power captured by the AI-investing firms. We find statistically insignificant and economically small effects on firm-level markups (on the order of +/-1% change in markups for a one-standard-deviation change in AI investments).

Instead, our combination of results appear most consistent with AI facilitating greater scalability of the most ex ante productive firms (Aghion et al., 2019; Autor et al., 2020; Lashkari et al., 2018): large firms are more likely to invest in AI, and these investments allow the firms to grow even larger, without measurable impact upon either productivity or markups. We perform two additional tests of this mechanism. First, we find that the positive effects of AI on firm growth are concentrated in the most ex ante productive firms, with large effects for firms in the highest productivity tercile back in 2010, and small and insignificant effects for firms in lower terciles. Second, we look into drivers of scale directly and document that AI investments are related to firms' expansion across geographic regions (measured as the number of counties accounting for at least 1% of the firm's job postings) and products (measured as the firm's demand for product managers). Concurrently, we also find large increases in research & development (R&D) investment by AI-investing firms, both in absolute terms and as a fraction of sales.

Our paper contributes to the literature on adoption and economic impact of new technologies. Specifically, we contribute to the growing literature on the adoption of artificial intelligence and its impact on the economy. While a number of theories have been proposed about how artificial intelligence and big data could affect the economy (Mihet and Philippon, 2019; Brynjolfsson et al., 2019; Brynjolfsson et al., 2018a; Farboodi et al., 2019), there has been a dearth of empirical evidence until recently due to the lack of data (Brynjolfsson and Mitchell, 2017; Seamans and Raj, 2018). Most empirical evidence to date focuses on the effect of AI on the labor market (Webb, 2020; Grennan and Michaely, 2019). The papers closest to ours are Rock (2019), who studies the contribution of AI skills to the market value of firms, and Alderucci et al. (2020), who explore the effect of investment in AI on firm outcomes using AI-related patents as a measure of AI investments. Our measure of AI investments using a combination of job postings and resumes complements the skill-based and patent-based measures, and allows us to measure AI investments in a wide range of firms and industries and estimate its effect on both firm-level and industry-level outcomes.

We also contribute to the literature on the causes and consequences of increasing industry concentration. A growing literature documents the rise of concentration and market power in the US (Grullon et al., 2019; Barkai, 2020; De Loecker et al., 2020; Gutiérrez and Philippon, 2017). Our results suggest that, while AI technologies contribute to increased concentration, they do not tend to increase firms' market power, at least in the short-run. Instead, our results lend support to the hypothesis that new technologies, such as AI, can disproportionately favor big firms by enabling the most productive firms to scale more easily, supporting the mechanisms proposed by Farboodi et al. (2019) and Aghion et al. (2017). Our findings are also consistent with the novel evidence in Abis and Veldkamp (2020) who show that machine learning technologies can increase the returns to scale.[4] Nevertheless, we do not find that firms become more productive upon investing in AI, which is consistent with (Brynjolfsson et al., 2019) who argue that the productivity benefits of AI investments can take a long time to materialize.

The remainder of the paper proceeds as follows. Section 1 develops our main hypotheses. We introduce the two primary datasets (on job postings and resumes) in Section 2 and detail our methodology to construct the measures of AI investments from these data in Section 3. Section 4 addresses the question of which firms choose to invest in AI, while Section 5 considers the impact of AI investments on firm growth and industry concentration. Section 6 explores the mechanisms. Section 7 concludes.

1 Conceptual Framework

It is an open question whether AI investments fuel firms' expansion. On the one hand, investments in AI can spur firm growth: as a general purpose technology, AI can be widely applicable across firms' operations, empowering the creation of new products and services or facilitating entry into new markets.[5] This would lead to the expansion of the firm's operations and growth in sales. On the other hand, current attention to AI investments may be over-hyped (Mihet and Philippon, 2019), or AI may still be too early in the adoption cycle to have a meaningful impact on firm growth (Brynjolfsson et al., 2018a). Moreover, even if the AI investments are already benefiting firms via faster sales growth, the impact of AI on employment, which is of first-order

[4]Other explanations for growing concentration include increasing barriers to entry and lax antitrust enforcement (e.g., Grullon et al., 2019 and Covarrubias et al., 2019), low interest rates (Liu et al., 2019); and globalization (e.g.,Elsby et al., 2013).

[5]Consistent with the broad applicability of AI, JP Morgan's 2017 annual report says: *"Artificial intelligence, big data and machine learning are helping us reduce risk and fraud, upgrade service, improve underwriting and enhance marketing across the firm."*

importance (Frank et al., 2019), is ambiguous. Since AI capabilities have the potential to displace a large share of occupations, employment may decline even as sales increase.

At a broader level, we are also interested in whether investments in AI technologies affect industry concentration. Following a well-documented increase in industry concentration over the past several decades (Grullon et al., 2019; Furman and Orszag, 2015), an active debate emerged about the causes and consequences of the increased industry concentration (see Syverson, 2019 and Covarrubias et al., 2019 for a review). One proposed channel driving this and other important trends, including the decrease in the labor share, is improvements in information technology (IT) (e.g., Karabarbounis and Neiman, 2014; Crouzet and Eberly, 2019; Lashkari et al., 2018; Aghion et al., 2019). Empirically, Bessen (2017) finds a positive relationship between the rise of industry concentration and the use of proprietary IT systems in the U.S. He stresses that the scalability of intangibles is advantageous to firms that are already large. However, in the case of AI, the effect of this new technology on concentration is ex ante ambiguous. On the one hand, AI can democratize adoption among smaller firms. Unlike proprietary IT systems that require large upfront investments, AI implementation is largely dependent on data storage and computing, which are variable costs, since firms can purchase these services from specialized providers on a per use basis (Van Ark, 2016; OECD, 2015). On the other hand, big data and AI technologies have scale effects that favor large firms and industry leaders with large amounts of data, which can contribute to the increase in industry concentration and winner-take-all dynamics (Farboodi et al., 2019).

Finally, we discuss specific channels through which investments in artificial intelligence can lead to firm growth and higher industry concentration. First, as a technological advancement, AI can potentially stimulate growth by streamlining production processes and increasing productivity. Second, some of the specific use cases of AI can potentially be applied to price discriminate and increase firms' market power. Third, AI has unique features that can favor ex ante larger, more productive firms and increase the scale of these firms. While all three channels lead to higher growth of individual firms, they have different implications for competitive industry dynamics and varying predictions for firm-level productivity and markups, leading to different economic implications associated with "good" vs. "bad" concentration (Covarrubias et al., 2019).

1.1 AI as a Driver of Productivity Growth

Technological innovations aim at streamlining operations and improving productivity. Artificial intelligence can increase productivity in at least two ways. First, AI can potentially replace human labor for some tasks (Webb, 2020; Agrawal et al., 2019) and cut labor costs. Research studying automation technologies and robots finds that these technologies increase the productivity of adopting firms (Acemoglu et al., 2020; Graetz and Michaels, 2018).

Second, big data and AI can increase efficiency through better forecasts (Mihet and Philippon, 2019). This aspect is explored in depth by Tanaka et al. (2019), who present a model of firm input choice under uncertainty and costly adjustment, where forecast errors result in under- or over-investment.[6] The forecasting applications of artificial intelligence are indeed prevalent in the data. Chase (2013) draws on executive interviews to point out that big data can streamline demand-driven forecasting, leading to more efficient inventory management. Our detailed resume data highlight how AI-enabled forecasting is implemented across a variety of industries: for example, AI workers at JP Morgan Chase model default of non-performing loans; ExxonMobil invests in assessment and mitigation of risks in oil exploration; and General Electric uses AI in decision support for jet engines.

Prediction 1 (Productivity Channel). *Productivity gains from artificial intelligence would be observed empirically as:*

1. *AI-investing firms see increases in productivity (TFP) and labor productivity (sales per worker).*
2. *AI-investing firms potentially see decreases in total costs or employment.*

1.2 AI as a Driver of Price Discrimination and Market Power

One of the primary use cases through which data can enable successful implementation of artificial intelligence is through the greater ability to tailor product offerings to customers' tastes. For example, a consumer product company may use machine learning to build more specialized products tailored to certain customers and shield competition from other producers, which allows the company to charge higher prices. Mihet and Philippon (2019) highlight the uses of artificial intelligence by companies such as Amazon to improve matching of products with consumers and to deliver more tailored recommendations. Detailed consumer data can enhance not only product design but also pricing (Varian, 2018). Mihet and Philippon (2019) point out that detailed data

[6]Their empirical evidence supports the prediction that forecast accuracy is associated with higher profitability among Japanese firms. Other empirical evidence includes Brynjolfsson et al. (2011), who use detailed survey data from 179 large public firms to document a positive link between the use of "data driven decision making" and firm-level output and productivity.

enable firms to set prices based on a large number of features including consumers' demographics. Moreover, data on individual behaviors such as web browsing history enable approximations of individual demand functions that can generate significantly greater profit increases than pure demographics and would lead to large heterogeneity in prices charged to different consumers (Shiller, 2016). If this effect is present, than the ability to tailor products (thereby making them less substitutable) and price discriminate would grant greater market power to firms investing in AI, enabling them to extract more consumer surplus.[7] Empirically, this greater market power would appear in the form of higher markups charged by the AI-investing firms (Syverson, 2019).

Prediction 2 (**Market Power Channel**). *Applications of artificial intelligence that enable price discrimination would generate the following effects:*

1. *Investments in AI lead to higher firm-level markups without increases in productivity.*

1.3 AI and Scale

As an information good, AI can also have scale effects that would facilitate higher growth of large firms and industry leaders even without increases in productivity or market power. If this is the case, then AI can contribute to the rise of superstar firms (Autor et al., 2020).

Big data and artificial intelligence are intangible assets (Mihet and Philippon, 2019). Crouzet and Eberly (2019) highlight that intangible assets are more "scalable" than physical capital, and De Ridder (2019) conceptualizes intangible assets as a shift towards fixed costs and away from variable costs. In particular, successful implementation of AI technology relies strongly on data availability (Fedyk, 2016), and there is a positive feedback loop between firm size (and the amount of accumulated economic activity) and the firm's data assets, driven by the fact that data are a "by-product of economic activity" (Farboodi et al., 2019). This induces economies of scale even when the technology of physical production has constant returns. For example, while implementing an AI system to analyze the risks of a single credit card applicant would be costlier than relying on a human analyst, the average cost would decline sharply in the number of applications processed, leading to lower costs for banks with more data.

As a general purpose technology, AI may also allow firms to expand more easily across different markets. In our data, we find that similar methods and skillsets were used to leverage

[7] At the same time, the transparency of online pricing may limit firms' ability to successfully price discriminate (Cavallo, 2017; Ater and Rigby, 2018).

AI in different business segments, and when firms began investing in AI, they tended to do so concurrently on multiple fronts. For example, investments in AI by JP Morgan Chase spanned applications from fraud detection in the risk modeling divisions to applying data science techniques in the quantitative research space. This means that AI can potentially reduce the overhead costs of entering new markets, which can lead to the expansion of the most efficient firms across different markets (Aghion et al., 2019).[8]

At the individual level, scalability of AI implies that larger firms should both (a) be more willing to invest in AI, and (b) benefit more from this investment. At the broader level, firms' ability to scale and span more markets can lead to greater market share accruing to the most ex ante productive firms.

Prediction 3 (**Scalability Channel**). *Scale effects from AI generate the following predictions:*

1. *Larger firms are more likely to invest in AI.*
2. *AI investments lead to largest and most productive firms growing more and accruing greater market share.*
3. *AI investments are associated with expansion into new markets.*

2 Data

We provide a uniquely comprehensive perspective on firm-level AI investments by simultaneously measuring *demand* for AI skills through job postings and the *stock* of AI skills through employment profiles. We detail each dataset in turn and describe our sample construction.

2.1 Job Postings from Burning Glass

The first dataset we use is a proprietary dataset covering over 180 million electronic job postings in the United States in 2007 and 2010–2018. The dataset is provided by Burning Glass Technologies (BG in short) and draws from a rich set of sources. Burning Glass examines more than 40,000 online job boards and company websites to aggregate the job postings data, parse them into a

[8]Relatedly, Hsieh and Rossi-Hansberg (2019) model the ongoing transformation of the services industry as technological innovation that increases fixed costs but reduces variable costs, allowing productive firms to expand into new markets.

systematic, machine-readable form, and create labor market analytic products. The company employs a sophisticated deduplication algorithm, to avoid double counting vacancies that post on multiple job boards. Hershbein and Kahn (2018) provide detailed description of the BG data.

The main advantages of the BG data are the breadth of its coverage and the detail of the individual jobs in the sample. The dataset captures a near-universe of jobs that were posted online and covers approximately 60–70% of vacancies posted in the US, either online or offline (Carnevale et al., 2014). The broad coverage of the database presents a substantial strength over datasets based on a single vacancy source, such as CareerBuilder.com. Hershbein and Kahn (2018) show that the representativeness of Burning Glass is stable over time at the occupation level. In other words, although BG over-represents some occupations relative to the CPS, the degree to which these occupations are over-represented does not change over the sample period.

The BG data contain detailed information for each vacancy, including job title, job location, occupation, and employer name. Importantly, the codified skills include thousands of specific skills standardized from open text in each job posting.[9] In Section 3.1 we describe the methodology we employ to characterize AI-related job postings based on the skills data.

We focus on jobs with non-missing employer names and at least one required skill. About 65% of the job listings have employer information[10] and 93% of the job listings are linked to at least one skill. We also drop job listings that are internships. We then match the employer firms in the job postings to Compustat firms. This step is necessary to aggregate job postings to firm level and merge with other firm-level variables. We fuzzy-match firm names in BG and Compustat after stripping out common endings in firm data (e.g., "Inc" and "L.P."). For observations that do not match exactly on firm name, we manually assess the top ten potential matches by looking at the firm name, industry, and location.[11] Out of 112 million job postings with non-missing employer names and skills, 42 million (38%) are matched to Compustat firms. This is consistent with the fact that publicly listed firms constitute about one-third of U.S. employment in the non-farm business sector (Davis et al., 2006).

[9]For example, a job ad might ask for a worker who is bilingual or who can organize and manage a team. BG cleans and codes these and other skills into a taxonomy of thousands of unique but standardized requirements. Beginning with a set of predefined possible skills, BG does a fuzzy search of the ad text for an indication that the skill is required. For example, for team work, they search for the key words "team work" but also look for variations such as "ability to work in a team."

[10]The job postings with missing employer names are primarily from those listed on recruiting websites that typically do not reveal the employer.

[11]Observations without an exact match fall into the following three scenarios: 1) the employer name in BG matches to several firms in Compustat; 2) different suffixes (e.g., "Corp" vs."Inc"); 3) extra words (e.g., "X company" vs. "X company international").

2.2 Employment Profiles from Cognism

While job postings data provide an important look at the firms' *demand* for certain types of employees, vacancies data represent just one margin through which a firm may adjust labor inputs: through stated, but not necessarily realized, demand (Hershbein and Kahn, 2018). This is a less complete view of the firm's labor inputs than the actual firm employees. To address this concern, we validate our job postings data with comprehensive information on the actual individuals employed at each firm. To do so, we leverage a novel dataset of approximately 145 million individual profiles provided by Cognism, an aggregator of employment profiles for the Lead Generation and Client Relationship Management industries.

For each individual in our sample, we have the following general information: a unique identifier, city and country level location, an approximate age derived from the individual's educational record, gender classified based on the first name, the size of the individual's professional network, and a short bio sketch (where provided). For each employment record listed by the individual, we see the start and end dates, the job title, the company name, and the job description (where provided). Similarly, each education record includes start and end dates, the name of the institution, and the degree (major). In addition, individuals may volunteer self-identified skills and list their patents, courses, awards, and publications. The individuals may also have recommendations provided by their peers.

We perform several steps to disambiguate self-reported employer names in the profile data to official company names of publicly traded firms. First, we follow the procedure outlined in Fedyk and Hodson (2019): (i) begin with a comprehensive list of publicly traded companies from the exchanges (NASDAQ, NYSE) and common datasets (CRSP and Compustat), (ii) strip out common endings (e.g., "Inc" and "L.P."); (iii) run a fuzzy matching algorithm from the self-reported employer names to the official company names; and (iv) augment the algorithm by mapping the self-reported employer names to semantic entities in the WikiData project. In addition, for the set of Compustat firms that are not mapped to any companies in the employment data, we perform a manual attempt at finding matches. Similar to our match of BG job postings to Compustat firms, we manually check potential matches when the firm names do not match exactly.

2.3 Additional Data Sources

We merge the Burning Glass job postings data and the Cognism resume data to several additional data sources. We use commuting-zone-level wage and education information from the Census American Community Surveys (ACS) and industry-level wage data from the Census Quarterly Workforce Indicators (QWI). Operational variables such as sales, employment, assets, net income, cash, costs of goods sold, operating expenses, R&D expenditures, and SG&A expenses come from annual accounting data available through Compustat.

3 Methodology: AI Investments by Firms

In this section, we introduce a new methodology to measure firm-level AI investments from the job postings data. We provide summary statistics of our AI investments measure and validate the (job-postings-based) measure using the resume data. The two measures—based on job openings versus current employees–display analogous trends over time and across industries and show high correlations with each other.

3.1 AI Investments in Job Postings (Burning Glass)

We take advantage of the detailed information on required skills in the job postings data to propose a new methodology for identifying AI-related jobs. Previous work classifies job postings as requiring certain skills by pre-specifying a list of search terms that need to occur among the required skills.[12] This methodology presents significant measurement challenges, as pre-specified word lists require judgment and are likely to suffer from both Type I (incorrectly labeling tangentially-related employees as AI-related) and Type II (missing real AI skills that did not make the initial dictionary) errors. In a quickly-evolving domain such as AI, identifying well-structured bag-of-words search terms is especially challenging, as newer emerging skills can be missed. Our methodology circumvents these challenges by not requiring researchers to impose any subjective assessments on which skills are AI-related ex ante, instead learning the AI-relatedness of each of approximately 15,000 unique skills directly from the job postings data, based on their empirical co-occurrence with core AI concepts. We then aggregate the skill-level measure to the job level to

[12]For example, Hershbein and Kahn (2018) identify jobs requiring cognitive skill if any listed skills include at least one of the following terms: "research," "analy," "decision," "solving," "math," "statistic," or "thinking." Similar bag-of-words approaches with pre-specified search terms are used to identify AI-related employees (see, for example, Alekseeva et al., 2020).

generate a continuous measure of AI relatedness for each job, from which we can classify employees into AI-workers and non-AI-workers.

We consider four core AI concepts: Artificial Intelligence (AI), Machine Learning (ML), Natural Language Processing (NLP), and Computer Vision (CV). For each skill w, we define a metric that captures the relatedness of that skill to these four core AI technologies (AI, ML, CV and NLP):

$$w_s^{AllAI} = \frac{\text{\# of jobs with skill } s \text{ and \{ML, NLP, CV, or AI\} in job title or in skills}}{\text{\# of jobs with skill } s}$$

Intuitively, this measure captures how "close" each skill is to AI skills by measuring the overlap between the skill and core AI concepts (AI, ML, NLP, and CV). For example, the skill "Tensorflow" has a value of 0.9, which means that 90% of job postings with Tensorflow as a required skill also requires one of the core AI skills or contain one of the core AI skills in the job title. Hence, requiring "Tensorflow" as a skill for a job is very informative about a job being AI-related. On the other hand, "Communication" skill is required in a large share of jobs across the board, so its AI-relatedness measure equals 0.3% and is not very informative about a job being AI-related.

We define the job-level AI-relatedness measure for a given job as the mean (skill-level) measure across all skills required for that job. Letting N denote the number of required skills listed for job j, we define the job-level AI-relatedness measure as:

$$\omega_j^{AllAI} = \frac{1}{N}\sum_{i=1}^{N} w_i^{AllAI}$$

To further refine our measure and screen out general skills (e.g., the programming language "R", which has a value of 0.25), we manually categorized all skills with the AI-relatedness measure, w_s^{AllAI}, above 0.05 and that are required in at least 50 jobs into narrow AI skills and skills more broadly related to AI. The threshold of 0.05 is set sufficiently low to ensure that we do not miss any ex-ante important AI-skills. There are about 700 skills with $w_s^{AllAI} > 0.05$ and at least 50 jobs. We group these skills into nine categories: computing (e.g. GPU), data (e.g. NoSQL), general programming (e.g. Python), AI software (e.g. Tensorflow), AI methodology or algorithm (e.g. supervised learning), AI application (e.g. Chatbot), AI core (AI, ML, CV, NLP), statistics (e.g. linear regression), and other. Of these we consider "computing", "data", "AI software", "AI methodology or algorithm", "AI application", and "AI core" as narrow AI skills, while "general programming", "statistics", and "other" represent more general skills.

We can decompose the measure ω_j^{AllAI} into components corresponding to these categories:

$$\begin{aligned} w_j^{AllAI} &= \omega_j^{computing} + \omega_j^{data} + \omega_j^{AIsoftware} + \omega_j^{AImethodology} + \omega_j^{AIapplication} + \omega_j^{AIcore} \\ &\quad + \omega_j^{programming} + \omega_j^{other} + \omega_j^{statistics} + \omega_j^{w<0.05} \\ &= \omega_j^{NarrowAI} + \omega_j^{programming} + \omega_j^{statistics} + \omega_j^{other} + \omega_j^{w<0.05} \end{aligned} \tag{1}$$

For the remainder of the paper, we use $\omega^{NarrowAI}$ as the primary continuous measure of AI-relatedness of jobs. We transform this continuous measure into a discrete indicator by defining each job j as AI-related if and only if the measure $\omega_j^{NarrowAI}$ is above 0.1, which upon careful examination captures the majority of AI-jobs. The firm-level measure $Share_{f,t}^{NarrowAI}$ is the fraction of job postings by firm f in year t whose $\omega_j^{NarrowAI}$ measure exceeds the 0.1 threshold. The reason for using a discrete classification of each job as AI or non-AI is twofold. First, this increases the interpretability of the firm-level measure, with each job posting classified as either an AI employee or not. Second, we apply the same binary classification to the firm's current employees when constructing the resume-based measure in Section 3.2, leading to consistent approaches and interpretations across the two datasets. In Section 5.1, we confirm that our key results are robust to: (i) averaging the continuous narrow-AI measure $\omega^{NarrowAI}$ across all jobs in a given firm, and (ii) averaging the continuous measure using all skills (ω_j^{AllAI}) across all jobs in a given firm.

3.1.1 Summary Statistics

Our firm-level measure displays intuitive properties: the overall share of AI workers rises over time, concentrates in the "Information" sector, and captures relevant job titles such as "Artificial Intelligence Researcher" and "Deep Learning Engineer".

Specifically, the trends over time are displayed in Figure 1. The average job-level measure $\omega_j^{NarrowAI}$ starts out close to zero, at 0.02%, at the beginning of the sample in 2007. The average AI-relatedness of job postings rises monotonically over time, with the increase speeding up from 2014 to 2018. The measure peaks at 0.2% at the end of the sample in 2018.[13] The increase in AI jobs is ubiquitous across industries, as can be seen from Figure 2, in line with the notion that AI is a general purpose technology (Goldfarb et al., 2019). This figure plots the average AI-relatedness

[13] In unreported results, we confirm that the rise in $\omega_j^{NarrowAI}$ accounts for almost all of the rise in w_j^{AllAI} over time, which means that the increase in AI-relatedness of jobs is entirely driven by the increase in the frequency of required skills that we manually categorize as "Narrow AI" skills instead of other less AI-specific skills (e.g. statistics or programming languages) or skills that have AI-relatedness measure below 0.05.

measure of job postings in each of the NAICS sectors, separately for the years [2007, 2008–2014] and 2005–2018. The figure highlights that AI investments are highest in the "Information" sector, growing from 0.19% in the early years of 2007–2014 to 0.49% in the later period of 2015–2018. AI investments in nearly all sectors show a substantial (two- to three-fold) increase during the later period. The heterogeneity in AI investments across industries is consistent with supply-side arguments made in industry reports (Bughin et al., 2017): AI adoption across industries is largely driven by availability of data and technical capabilities, which are crucial inputs for the AI production function.

Additional checks on the data confirm that our measure is indeed capturing the essence of AI investments by firms. For example, Table A.1 shows that the job titles associated with the highest job-level measure of AI-relatedness, $\omega_j^{NarrowAI}$, are all very relevant postings: "Artificial Intelligence Engineer" (average AI-relatedness measure of 0.476), "Senior Data Scientist - Machine Learning Engineer" (0.367), "AI Consultant" (0.365), and "AI Senior Analyst" (0.354). Similarly, Table A.2 shows that the (more common) job titles that contribute the highest number of AI-classified job postings (defined as jobs with $\omega_j^{NarrowAI}$ measure above 0.1) are relevant titles such as "Data Scientist", "Senior Data Scientist", "Software Engineer", "Principal Data Scientist", and "Data Engineer". AI jobs are also concentrated in the BLS occupations "Computer and Information Research Scientists", "Software Developers, Applications", and "Computer Occupations" (Table A.3).

In all of our analyses, we consider only jobs that are matched to Compustat firms. Figure A.1 plots the share of all jobs and the share of AI jobs that are matched to Compustat in each year. Although publicly listed firms constitute 38% of all job postings, they account for about half of all AI-related job postings. This suggests that publicly-listed firms hire more AI workers than private firms on average.

3.2 AI Investments from Resumes (Cognism)

We validate our job-postings-based measure of firms' investments in AI against an analogous measure using profiles of all firm employees with available resume records. This helps address concerns that the job postings data are not fully representative of firm activities—for example, if a firm is not able to hire despite active job postings, or if a firm posts numerous job openings due to high employee turnover. This type of data issue does not appear to drive our job-postings-based measure. Instead, the measure using resumes displays very similar trends (e.g., across industries and over time) to the measure using job postings and, as we show in Section 3.3, the two measures are highly correlated.

We use resume data to identify individuals skilled in the area of Artificial Intelligence through a holistic approach covering each person's entire profile. We search for AI-related terms in the following sections of each individual's profile: job roles and descriptions, patents, publications, and awards. We define AI-related employees as those whose current positions are directly related to AI. Specifically, in each section of the profile, we use regular expressions to identify the keywords that were identified as having an AI-relatedness measure w_s^{AllAI} above 0.70 in the Burning Glass data. This include the 73 skills that are most relevant for AI-skilled jobs.

The classification is performed at the level of each individual job record of each person. For a particular job record, we consider four aspects when classifying someone as a direct AI employee: 1) whether that job (role and description) is AI-related; 2) whether any patents obtained during the year of interest or the two following years (to account for the time lag between the work and the patent grant) are AI-related; 3) whether any publications during the year of interest or the following year are AI-related; 4) whether any AI-related awards were received during the year of interest or the following year. If any of these conditions are met, then that person at that firm at that time is classified as being an AI employee. If none of the conditions are met, then the employee is considered non-AI-related at that point in time.

Having classified each individual at each point in time, we aggregate the AI and non-AI employment variables up to the firm level: for each firm in each year, we compute the percentage of employees of that firm in that year who are classified as AI-related.

3.2.1 Summary Statistics

The general patterns of AI investment are very similar using the resume-based measure and the job-postings based measure. Figure 3 displays the time trends of the resume-based measure, plotting the fraction of all employees in each year who are classified as directly AI-related. Figure 4 shows the distribution of the fraction of AI employees across industries, separately for the 2007–2014 and the 2015–2018 sub-periods.

The rise in the fraction of AI employees (Figure 3) is very similar to the contemporaneous rise in AI job postings (Figure 1), beginning very close to zero, at 0.03%, in 2007 and reaching 0.24% in 2018. The one notable distinction is that the increase ramps up sooner in the resume data, with the steepest slope between 2014 and 2017, and slows down in the final year (from 2017 to 2018). The patterns across industries are also similar for the two measures (compare Figure 4 to Figure 2). Analogous to the job postings measure, the resume-based measure increases from earlier (2007–2014) to later (2015–2018) in the sample period for all sectors. The measure is higher for the "Information" sector than for any other sector in both sub-periods, although the difference between this sector and others is more pronounced in the measure constructed from job postings data.

3.3 Correlations between AI Investment Measures from Job Postings (Burning Glass) and Resumes (Cognism)

The two measure of AI investments—using job postings and resumes—are highly but imperfectly correlated. The two measures capture different aspects of AI investment: the job-postings-based measure captures the extent to which firms *seek* to hire AI talent, while the resume-based measure reflects the extent to which firms are *able* to actually onboard AI talent. As a result, these measures are closely related but with substantial heterogeneity across the two.

Table 1 displays the cross-sectional correlations between the two measures for each year when job postings data are available, {2007,2010–2018}. We report correlations for three variable pairs: (i) the absolute number of AI job postings in Burning Glass against the absolute number of AI employees in Cognism; (ii) the fractions of AI employees in the two datasets; and (iii) the fraction of AI employees in the Cognism resume dataset against the firm-average continuous measure of AI-relatedness from the Burning Glass job postings data, $\omega_j^{NarrowAI}$. Panel 1 presents Pearson correlations, while Panel 2 tabulates Spearman (rank) correlations. In each year, the cross-sectional correlations are computed for the sample of all firms that have observations in both Burning Glass job postings data and Cognism resume data, with at least 50 total employees in Cognism. This avoids small firms or firms with small coverage (e.g., 1 or 2 employees in the resume data) skewing the relationship if just 1 employee happens to be AI-related.

The correlations are quite high in the recent years: e.g., in 2018, we see a Pearson correlation of 0.83 for absolute numbers of AI jobs, 0.61 for the fractions, and 0.65 for the Cognism fraction against the continuous Burning Glass measure. The relationship between the AI investment metrics computed from the two datasets is weaker in the earlier part of the sample; while the absolute numbers of AI jobs still displayed a Spearman correlation of 0.65 in 2007, the correlation for fractions was only 0.21. Reflecting this pattern, the time series relationship between the measures across the entire sample period is somewhat weaker (all time series correlations are estimated by including firm fixed effects): a Spearman correlation coefficient of 0.73 between the absolute numbers of AI jobs, 0.34 between the fractions, and 0.37 between the Cognism fraction and Burning Glass continuous measure. Given the low correlation in the measures in 2007, we limit all our analysis to the BG data available from 2010 onward.

4 Which Firms Invest in AI?

We document differential patterns of investment in artificial intelligence technology across firm characteristics. Investment rates are larger among superstar-like firms. First, larger firms—with more employees, higher sales, and larger market share—see greater levels of investment in AI between 2010 and 2018. Second, firms with larger markups tend to invest in AI more aggressively. Moreover, firms with higher cash reserves are also more likely to invest in AI technologies. On a broader level, AI investments tend to concentrate in geographic locations with higher wages and more well-educated workers.

4.1 AI Investments and Firm Characteristics

The firm-level investment patterns are presented in Table 2. Panel 1 displays the results using the changes in the number of *actual* AI employees, using the Cognism resume data. Panel 2 presents the results for changes in the firms' *demand* for AI talent, using the job postings data from Burning Glass. Since firms in the information technology (IT) sector are likely to be suppliers of AI and, hence, can have differential dynamics than other sectors, we exclude these firms in throughout our empirical analyses.[14] For each measure of AI investment, we estimate the following specification:

$$\Delta ShareAIWorkers_{i,[2010,2018]} = FirmVar'_{i,2010}\beta + IndustryFE + \epsilon_i, \tag{2}$$

where $\Delta ShareAIWorkers_{i,[2010,2018]}$ denotes the change in the share of firm i's AI employees from 2010 to 2018 in the regressions in Panel 1, and the change in the share of firm i's AI-related job postings in Panel 2. All regressions include 4-digit NAICS industry fixed effects. Here and throughout all subsequent analyses, the $\Delta ShareAIWorkers_{i,[2010,2018]}$ variables are standardized to mean zero and standard deviation one to aid in economic interpretation. $FirmVar_{i,2010}$ represents one of

[14] IT sectors include NAICS 2-digit industry codes 51 (Information) and 54 (Professional, Scientific, and Technical Services).

the firm variables of interest: log firm employment in column 1, firm market share in the corresponding 4-digit NAICS industry in column 2, log sales in column 3, the ratio of cash to assets (Cash/Assets) in column 4, the ratio of R&D expenditures to Sales (R&D/Sales) in column 5, return on sales (ROS) measured as the ratio of net income plus interest expense to sales as in Fracassi and Tate (2012) in column 6, log markup measured as the log of the ratio of sales to cost of goods sold following De Loecker et al. (2020) in column 7, and log markup measured as the log of the ratio of sales to operating expense following Traina (2018) in column 8.[15] Column 9 includes all variables in a multivariate specification, except for employment and market share, which are highly correlated with sales. All independent variables and controls are measured as of 2010.

The results reported in Table 2 highlight that larger firms, as measured by sales or market share, experience higher levels of AI investment. For example, using the Cognism-based measure in Panel 1, a one-standard-deviation increase in sales in 2010 corresponds to the share of AI workers increasing by 9% of the standard deviation from 2010 to 2018, significant at the 1% level. A 10% increase in the firm's market share in 2010 translates into the share of AI workers increasing by 5% of the standard deviation. In addition, firms with higher starting Cash/Assets and higher R&D/Sales also see greater investment in AI, which is consistent with contemporaneous work of Alekseeva et al. (2020), who use Burning Glass data to measure firms' AI demand. While overall return on sales is not predictive of future AI investments, the COGS-based markups positively predict future AI investments in the Cognism data.

Importantly, the results for firm-level demand for AI talent measured with Burning Glass data are very consistent with the patterns using actual firm-level AI-hiring from Cognism data, reinforcing the high correlations documented in Table 1. This consistency suggests that, in the absence of firm-worker matched data, our measure of AI investments using Burning Glass data can be a good proxy for firms' actual AI hiring.

4.2 AI Investments and Local Conditions

We now turn to examining how AI investment patterns relate to conditions at the local level, which further helps validate our measure of firm-level AI investments based on AI-skilled human capi-

[15]Since we are interested in changes, the change in log markups measures the percent change in markups. Log markups is also considered in De Loecker and Warzynski (2012). In De Loecker et al. (2020), firm-level markups are equal to $\mu_i = \theta_s \frac{Revenue_i}{Varriable\ Cost_i}$, where θ_s is the degree of returns to scale in industry s and is constant within each industry. When taking the logs, $\log \mu_i = \log(\theta_s) + \log(Revenue_i / VariableCost_i)$, the term $\log(\theta_s)$ is absorbed by the industry fixed effects, and therefore we only need to consider the change in $\log(Revenue_i / VariableCost_i)$.

tal. AI investments are larger in locations with highly-educated and higher-paid workforce, since AI-skilled labor is the most critical input to successful deployment of AI programs (Bughin et al., 2018). This contrasts with investments in Robotics, which concentrate in areas with larger shares of manufacturing employment (Acemoglu et al., 2020). We document this empirically by estimating the following specification, which aggregates firm-level AI investments for all Compustat firms to commuting-zone-level and links the commuting-zone-level measure to commuting-zone-level education and wages:

$$\Delta ShareAIWorkers_{i,[2010,2018]} = \alpha + LogCommutingZoneVariable_{i,2010} + \epsilon_i, \tag{3}$$

where $\Delta ShareAIWorkers_{i,[2010,2018]}$ measures the change in the share of AI workers in commuting zone i from 2010 to 2018.[16] The independent variable, $LogCommutingZoneVariable_{i,2010}$ is either the starting log average wage for commuting zone i in 2010, , or the share of college-educated workers, calculated from the Census American Community Survey.

Figure 5 (a) presents a binscatter plot of the change in the share of AI workers from 2010 to 2018 against the average log wage in 2010, and the red line is the fitted regression line. The regression is weighted by commuting zone population as of 2010. We find a strong positive relationship between the the average wage of a region and the local growth in AI jobs—the R-squared of the regression is 0.43. Figure **5** (b) plots the relationship between the change in the share of AI workers from 2010 to 2018 and the share of college-educated workers in 2010. We see a very similar pattern: growth in AI workers is concentrated in commuting zones with a large fraction of college-educated workers. These results highlight that regional variation in the available skilled labor is an important determinant of local AI investments, and suggest that it is important to control for the workforce composition of the local labor markets when examining the impact of AI investments on economic outcomes. Finally, Figure **6** displays a heat map of the growth in the average job-level AI measure from 2010 to 2018 across all commuting zones. The figure shows that there is significant variation in AI investments across the commuting zones.

[16] The share of AI workers is based on job postings data from Burning Glass, because the coverage of job-level location information in job postings is better than in resumes, which tend to report an employee's current location rather than the location of all prior job records.

5 AI Investment, Growth, and Industry Concentration

We present our main results on the effects of AI investment on firm- and industry-level growth. We document that firms and industries investing in AI technologies grow more, and that this result is robust to using two distinct instruments for AI investments in an instrumental variables (IV) strategy. The growth of AI-investing firms is concentrated among largest firms and contributes to the increase in industry concentration.

5.1 Firm Growth

We begin the analysis by exploring the impact of AI investments on growth of individual firms, first in OLS regressions and then in the IV setting.

5.1.1 Ordinary Least Squares (OLS) Results

We examine the relationship between firms' investments in artificial intelligence from 2010 to 2018 and a number of firm-level outcomes measuring growth over the same time period. Given that we do not expect to observe the effects of AI investments on firms immediately, we use a long-differences specification. In Table 3, we report the estimates from the following specification:[17]

$$\Delta FirmVariable_{i,[2010,2018]} = \beta \Delta ShareAIWorkers_{i,[2010,2018]} + Controls'_{i,2010}\gamma + IndustryFE + \epsilon_i, \quad (4)$$

where the main independent variable, $\Delta ShareAIWorkers_{i,[2010,2018]}$, captures the change in firm-level AI-skilled hiring from 2010 to 2018, standardized to mean 0 and standard deviation 1. $IndustryFE$ are 2-digit NAICS fixed effects. In Panel 1, we report the coefficients for the resume-based measure of AI investments, while Panel 2 considers the job-postings-based measure. To account for differences in precision in the measurement of AI investments due to the number of observations available to calculate the measure for each firm, the estimating equation is weighted by each firm's number of resumes (job postings) available to calculate each measure.[18] In columns 1, 3, and 5 we include only industry fixed effects to examine the unconditional relationship between AI investments and firm growth. In columns 2, 4, and 6, we include additional controls that are all mea-

[17] In the baseline regressions, we include only firms that are observed in the Compustat sample both in 2010 and 2018. We consider entry and exit in industry-level results in Section 5.2.

[18] Since the number of worker resumes and job postings are highly correlated with the size of the firm, this weighting scheme also roughly weights firms in accordance to their contribution to the economy. The results are robust to weighting each firm by its sales or employment in 2010.

sured at the start of the period in 2010: (a) firm-level characteristics that predict investment in AI, including the log of the total number of jobs (or job postings), cash/assets, log sales, log industry wages, and log markups; and (b) a rich set of controls for the characteristics of commuting zones where the firms are located, which might independently affect the AI employment share or be correlated with investments in other technologies: log average wage, the share of college-educated workers, 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.[19]

In columns 1 and 2, the dependent variable is the firm-level change in log sales from 2010 to 2018. Both measures of AI investment are associated with a significant and economically large increase in sales growth: a one-standard-deviation increase in the share of AI workers predicts an additional 11% to 15% growth in sales, depending on the specification. In columns 3 and 4, we examine how AI investments are associated with changes in employment. The effect of AI investments on employment is of particular interest, since its sign is ex ante ambiguous, with AI having the potential to displace a large fraction of jobs, as discussed in Section 1.1. We find a positive effect on employment of similar magnitude to the effect on sales: a one-standard-deviation increase in the share of AI workers predicts a 10% to 15% increase in firm-level employment. Columns 5 and 6 show that AI-investing firms grow more than their industry peers: a one-standard-deviation increase in the share of AI workers is associated with to a 1.2–1.5 percentage points increase in a firm's market share in its 4-digit NAICS industry, although the effect is not statistically significant except in one specification.[20] Overall, we observe that investments in AI appear to be associated with economically significant increases in firms' operations.

5.1.2 Instrumental Variables (IV) Results

In this section, we confirm that the results presented in the previous section are robust to using two different instruments for AI investment. Although we control for factors that predict firms'

[19]For example, the share of routine workers is correlated with adoption of automation technologies (Autor and Dorn, 2013), and the share of workers in IT-related occupations is correlated with general IT technologies. When firms span multiple commuting zones, we calculate these variables as the weighted average number of job postings in Burning Glass in each commuting zone as weights. The results are similar in magnitude and economic significance if we only include firm-level controls enumerated in list (a). We estimate all columns on the sample with all non-missing control variables. The results of the regressions without additional controls are similar if we estimate based on the entire available sample.

[20]In Table A.4 and Table A.5, we show that the results are robust to using continuous measures of average AI-relatedness of job postings, which are defined at the end of Section 3.1).

investment in AI, the OLS estimates may still be biased if there are other omitted variables that correlate with both AI investments and firm growth. The direction of the bias is ex ante ambiguous. On the one hand, the OLS estimates may be biased upwards if firms investment in AI are already on a faster growth trajectory or have more efficient managers that also improve other aspects of the firm. On the other hand, if firms have fewer growth opportunities or anticipate negative shocks, they may have a lower opportunity cost to engage in large-scale innovation and adopt new technologies (Bloom et al., 2013b). In this case, the endogenous choice to adopt AI may be correlated with lower future growth. Furthermore, measurement error can attenuate the bias in OLS estimates, which creates further downward bias. Leveraging two distinct instruments, our IV results are consistent with those from the OLS regressions, lending further credence to the estimated link between AI investments and firm growth.

Foreign Industry Instrument. We instrument for a firm's change in the share of AI workers using the change from 2010 to 2018 in the share of AI workers of foreign firms in the firm's 5-digit NAICS industry. This instrument is similar to those in Autor et al. (2013) and Acemoglu and Restrepo (2020), where a weighted average of US industry-level changes is instrumented by a weighted average of changes in corresponding foreign industries. The identifying assumption underlying this strategy is that the common within-industry component of the rising share of AI workers is due to differences in data availability and technological feasibility across industries. Industry reports, such as Bughin et al. (2017) argue that AI adoption across industries is largely driven by the availability of data and technical capabilities, which are crucial inputs for the AI production function.

In particular, we include all firms that are listed on stock exchanges in Europe.[21] We focus on European firms for three reasons. First, similar to the US, Europe also experienced a surge in AI investment in recent years.[22] Second, Cognism has good coverage of job resumes in Europe, while the coverage is sparser for other countries, e.g. China. Third, focusing on Europe helps to capture inherent cross-industry heterogeneity that is likely similar to that in the U.S. because, as a developed economy, Europe is likely to have similar technological development and data

[21]The European exchanges include Euronext Paris, Frankfurt Stock Exchange, Borsa Italiana (Milan), SIX Swiss Exchange, NASDAQ Stockholm, NASDAQ Copenhagen, Oslo Stock Exchange, Warsaw Stock Exchange, Vienna Stock Exchange, and Madrid Stock Exchange. Similar to our US Cognism analysis, we include firms with at least 50 European employees in the Cognism data in at least one year. We exclude European workers of US multinational firms that are listed in the US, and the US workers of European firms.

[22]EU has the third largest number of AI researchers right behind US and China. See for example https://macropolo.org/digital-projects/the-global-ai-talent-tracker/.

availability to the U.S. The main threat to the validity of our instrument is that industries with higher rates of AI investment (in the United States and Europe) could be on a different trend because of, for example, increasing demand. We discuss pre-trend tests to address this concern at the end of this subsection.

We begin by reporting the first stage of the IV regressions: the relationship between the instrument and our two measures of AI investments. The results are reported in columns 1 and 2 of Table 4 Panel 1 displays the results using the resume-based AI investment measure, and Panel 2 uses the job-postings-based measure. As in OLS regressions, we include NAICS-2 industry fixed effects. The specifications in column 1 includes only industry fixed effects, while column 2 also includes the same set of additional controls as in the OLS regressions. The instrument has a strong first stage for both AI measures, with F-statistics ranging from 16 to 36, depending on the specification.

Next, we report the instrumented effect of AI investments on firm growth in columns 3 through 8 of Table 4. We consider the same three outcomes and controls as in the OLS regressions, with the outcomes being change in log sales in columns 3 and 4, change in log employment in columns 5 and 6, and change in market share in columns 7 and 8. A one-standard-deviation increase in the resume-based measure of AI investment corresponds to a 27% increase in sales, 33% increase in employment, and 5 percentage point increase in market share, with all of the coefficients being statistically significant. Similarly, a one-standard-deviation increase in the job-postings-based measure translates to a 20% increase in sales, 23% increase in employment, and 4 percentage points increase in the firm's market share. Overall, the findings are consistent across the OLS and IV specifications with higher point estimates in the IV regressions. The difference could be potentially due to measurement errors in our AI measures or the lower opportunity cost of innovation and lower growth prospects of firms investing in AI. It's important to note, however, that the OLS and IV coefficients are not statistically different. This suggests that the difference between the point estimates could also be driven by estimation error.

To address the concern that industries that firms investing in AI more are on a different trend prior to these investments, we test the pre-trends in Table A.6. Specifically, we regress the changes in the outcome variables of interest (log employment, log sales, and market share) from 2000 to 2008 on subsequent change in the two measures of AI investments from 2010 to 2018.[23] The coefficients are all statistically insignificant and flip signs across different AI measures, indicating

[23]We look at 2000–2008 to avoid the confounding effect of the financial crisis between 2008 and 2010.

that industries that invest in AI more are not on a different pre-trend.

Geographic Shift-share Instrument. In an alternative instrumental variables strategy, we use a shift-share instrument for a firm's change in the share of AI workers using a weighted average of U.S. national industry-level changes in the share of AI workers, where the weights are given by the industry employment share at the locations of the firm's operations. Let s_{ic} denote the share of U.S. employment of firm i that falls within commuting zone c. Analogously, let the share of each industry j's employment within commuting zone c be θ_{cj}. Our instrument for firm i's change in the share of AI workers from 2010 to 2018 ($\Delta ShareAIWorkers_{i,[2010,2018]}$) is:

$$\sum_c s_{ic} \left(\sum_j \theta_{cj} \Delta A_{j,[2010,2018]} \right),$$

where $\Delta A_j^{2010-2018}$ is industry j's change in the share of AI workers from 2010 to 2018.

The instrument is similar to a Bartik-style shift-share instrument (Bartik, 1991), where firm-level AI investment is instrumented by a weighted average of national industries' average AI investments. The difference from a canonical Bartik instrument is that our instrument not only assigns positive weights to the industries a firm operates in, but also assigns positive weights to the industries geographically close to the firm. For example, a technological shock that enables firms in the finance industry to adopt AI would not only affect financial firms in New York City, but also positively affect non-financial firms in New York City because of the increase in AI labor supply in the city.

The identifying assumption is that firms' industry shares ($\sum_c s_{ic}\theta_{cj}$) are uncorrelated with errors in changes in firm sales, employment, and market shares. In other words, whether a firm is geographically close to industries that subsequently invest in AI should be pre-determined and uncorrelated with changes in firm outcomes. Goldsmith-Pinkham et al. (2019) suggest that one way to test the plausibility of this assumption is to check whether there are pre-trends before the shocks. We test for pre-trends in Table A.8 and find no relationship between future shocks to AI investments and past changes in firm outcomes. Specifically, we regress the changes in the outcome variables of interest (log employment, log sales, and market share) from 2000 to 2008 on the subsequent changes in the two AI investment measures from 2010 to 2018. Columns 1–3 of Table A.8 consider the resume-based measure of AI investment, while columns 4–6 use the job-postings-based measure. The relationships are all statistically insignificant.

In table A.7, we report the results of this instrumental variables approach for both measures of AI investments (the resume-based measure in Panel 1 and job-postings-based measure in Panel 2). Columns 1 and 2 display the results from the first stage regression, while columns 3 through 8 show the second stage results for the log changes in sales in columns 3–4, log changes in employment in columns 5–6, and changes in market share in columns 7–8. As in OLS regressions, we include NAICS-2 industry fixed effects. The specifications in odd columns only include industry fixed effects, while even columns include all controls, analogous to the OLS analysis. The results of the first stage regressions show that the instrument's F-statistic ranges from 8 to 16, depending on the specification. The second stage regressions show a robust and significant effect of AI investments on sales. The effect on employment is also positive and significant in 3 out of 4 specifications. The instrumented AI investments also have a positive albeit insignificant effect on the firms' market share.

Overall, the results of our second IV analysis are consistent with the OLS results and the first IV specification: all three analyses show that AI investments measured through the human capital lens predict robust and economically meaningful growth at the firm-level. Moreover, we document strikingly similar magnitudes of the effects across the two IV strategies, which are constructed from very different datasets. This lends further credence to the IV estimation capturing the causal impact of AI investments. We next examine whether this relationship aggregates to the industry-level.

5.2 Industry Growth

To shed light on the aggregate effects of AI investments, we examine the relationship between industry-level variation in AI investments and industry growth. Firm-level growth does not have to translate into industry-level growth., since firm investments in innovation can lead to business-stealing, whereby innovating firms gain sales and market share from their competitors Bloom et al. (2013a). When it comes to employment, Acemoglu et al. (2020) find that the adoption of robots increases employment at the firm level, but the overall effect on employment at the industry level is negative. This stems from a reallocation of output and labor towards firms that reduce their costs relative to their competitors, and the negative spillover effects dominate at the aggregate level.

To examine whether AI investments at the firm level translate into significant changes in industry-level growth, we first estimate the following industry-level variant of our baseline long-differences regression:

$$\Delta \ln y_{i,[2010,2018]} = \beta \Delta ShareAIWorkers_{i,[2010,2018]} + SectorFE + \epsilon_i \quad (5)$$

where $\Delta ShareAIWorkers_{i,[2010,2018]}$ is the change in the share of AI workers from 2010 to 2018 among Compustat firms in industry i. We focus on industry employment and sales as the dependent variables and (analogous to the firm-level tests) on the estimates weighted by the industry total number of resumes (or job postings). We also use the IV strategy described in Section 5.1.2. Specifically, we instrument industry-level AI investments with AI investments in the same industries in Europe. All industry-level regressions are at the NAICS-5 level, which is the level of the instrument and provides the most granular measure of AI investments at the industry level.[24]

Table 5 shows that AI investments are associated with a robust increase in employment and sales across industries. We report the coefficients for the resume-based measure of AI investment in Panel 1, and job-postings-based measure in Panel 2. In both panels, columns 1–3 present OLS estimates, and columns 4–6 show the second stage IV results. Odd columns show the unconditional relationship (with sector fixed effects only), and even columns add controls for initial industry employment and sales, as well as employment and sales growth from 2000 to 2008 to control for pre-existing growth trends. At the industry level, the instrument is generally strong with F-statistics ranging from 10 to 14 when all controls are included in columns 6 and 8. In Panel 1 estimated with the resume data, the estimates including all controls suggest that a one-standard-deviation increase in the share of AI workers in an industry is associated with a 15% increase in industry sales (column 2) and a 16% increase in employment (column 4). The IV estimates suggest larger effects by an order of 40 to 60%.

The results on industry growth are based on the same sample of firm as in the firm-level analysis in Section 5.1. To take into account entry and exit of firms, in Table A.9 we include all public firms in 2010 and 2018, including those that entered the sample after 2010 or exited before 2018. This yields similar positive and significant effects of AI investment on total industry sales and employment of all public firms. Combined, these results imply that the negative spillovers on competitors, if any, are small in magnitude. The effects of AI investments on industry sales and employment are both positive and similar in magnitude, suggesting that contrary to robots, AI does not reduce aggregate employment.

[24]We only consider the first IV strategy for industry-level regressions. The second instrument (Bartik IV) relies on firm-level variation and does not directly map to an industry-level instrumental variable.

5.3 AI Investments and Industry Concentration

Our results so far show that larger firms are invest more in AI, and that AI fuels firm and industry growth. We next examine whether AI investments are related to changes in industry concentration. As we discuss in Section 1, AI can reduce the barriers to growth among small firms or contribute to the growth of larger, "superstar firms" documented in Autor et al. (2020).

To explore these hypotheses, we start by looking at how the effect of AI investments on firm growth varies along the firm size distribution. If AI leads to the highest growth among the smallest firms, then it will reduce overall concentration; on the other hand, if AI leads to greater growth among the largest firms, then it will increase overall concentration. Table 6 shows the effect of AI investments on firm growth by firms' initial size, measured as firm employment as of 2010. The independent variables are changes in the firm-level share of AI workers (resume-based in Panel 1 and job-postings-based in Panel 2) from 2010 to 2018 interacted with dummy variables indicating which size tercile the firm falls into in 2010. For employment, sales, and market share, the effect of AI investments is monotonically increasing in the firm's initial size. For example, using the resume-based measure, the results in column 2 indicate that a one-standard-deviation increase in the share of AI workers is associated with a 16% increase in sales of firms in the top size tercile, 7% increase for the firms in the middle tercile, and an insignificant 0.8% increase for the firms in the bottom tercile. The t-test statistic indicates that the differential effect of AI on sales between the top and bottom size terciles is statistically significant at the 1% level.

To examine whether AI-fueled firm-level growth in size is large enough to translate into increased industry concentration, we link industry-level growth in the share of AI job postings to contemporaneous changes in industry concentration from 2010 to 2018, while controlling for NAICS-2 fixed effects. Following Autor et al. (2020), we use the Herfindahl-Hirschman Index (HHI) to measure industry concentration. To examine winner-take-all dynamics, we also measure the fraction of sales accruing to the largest Compustat firm in each 5-digit NAICS industry. Figure 7 shows that growth in both measures of concentration is positively correlated with growth in the share of AI job postings. While these industry-level regressions do not have causal interpretations, they show a strong relationship between industry growth in AI investments and increases in concentration. This result is consistent with Bessen (2017), who argues that investments in proprietary technology systems are likely responsible for the rise in industry concentration observed in the U.S. data. Our results suggest that, as a general purpose technology that can be applied across many industries, AI has the potential to further increase concentration across a broad range of industries.

6 Mechanisms

In this section, we examine three non-mutually exclusive mechanisms described in Section 1 that can explain the AI-fueled growth and the increase in industry concentration. We find no evidence of higher productivity or market power. Instead, our results point to more nuanced effects of AI investments, with AI increasing the scale of the most productive firms by facilitating expansion into new geographies and products.

6.1 Productivity

First, we explore whether the increase in firm growth from AI investments is driven by AI technologies making firms more productive, consistent with the mechanism outlined in Section 1.1. Contrary to Prediction 1.1, Table **7** shows that investments in AI are associated with slightly lower sales per worker and revenue TFP, although the effect is not statistically significant.[25] We also do not observe any evidence of a decrease in costs (Prediction 1.2): costs of goods sold (COGS) and operating expenses both increase with AI investments, as does total employment (as shown in Section 5). For example, a one-standard-deviation increase in the share of AI workers measured in resume data corresponds to a 14% increase in operating expenses when all controls are included in column 8 of Panel 1 in Table **7**, comparable to the effect of AI on sales growth in 5.

As a result, we do not find evidence that investments in AI make firms more productive, at least in the short term. Brynjolfsson et al. (2018a) point out that because complementary investments are necessary to obtain the full benefit of a new technology like AI, productivity growth will follow a J-curve, where firms investing in AI can have low measured productivity growth in the short run and high measured growth in the future. In Table A.10, we look at the effect of AI investments in the first half of the period (2010–2014) on productivity growth through 2018 and do not find any significant positive effect. This highlights the extent of the puzzle presented by Brynjolfsson et al. (2019): even with a lag of a few years, AI is not yet associated with productivity gains. If AI does bring productivity gains in the future, our results indicate that the time lag in the

[25]The Revenue TFP is the residual from regressing log revenue on log employment and log capital (constructed using perpetual inventory method), with separate regressions for each industry sector.

J-curve between adoption and productivity growth must be longer than a few years.

6.2 Market Power

As described in Section 1.2, an alternative explanation for AI-fueled growth is that artificial intelligence grants firms more market power in the product market, enabling firms to expand and increase markups without improving productivity. To test this mechanism, we look at the effect of AI investments on markups. We consider three measures of markups: the first two measures are based on De Loecker et al. (2020) and Traina (2018) and use Cost of Goods Sold (COGS) and Operating Expenses, respectively, as the measure of variable costs. For both measures, the markup is the log of revenues divided by the corresponding variable cost measure. In addition, we also look at the operating profit rate, termed the "Lerner Index" (Gutiérrez and Philippon, 2017). The Lerner Index is defined as operating income before depreciation and amortization (OIBDA) minus depreciation, scaled by sales. As in previous analyses, we include industry fixed effects in all regressions to absorb sector-specific variation.

Table 8 shows that for all three markup measures, the effect of AI investments is a precisely estimated zero. This is consistent with the significant increase in variable costs (COGS or Operating Expenses) reported in Table 7. The increase in costs associated with AI investments has a similar magnitude to the increase in sales (both on the order of 14% per one-standard-deviation change in the share of AI workers in OLS regressions), suggesting that firms grow sales and variable costs at approximately the same rate.

6.3 Scale

Lastly, we explore the possibility that investments in artificial intelligence allow firms to scale up their operations, as outlined in Section 1.3. The results presented so far are consistent with this mechanism. First, Table 2 shows that large firms invest in AI more, consistent with Prediction 3.1. Second, the positive effects of AI investments are greatest among the ex ante largest firms (Table 6), consistent with Prediction 3.2.

We perform two additional tests to further investigate the scalability channel. First, in addition to the slicing by initial firm size performed in Table 6, we slice firms based on ex ante productivity, as also suggested by Prediction 3.2. Specifically, in Table 9, we group firms into terciles based on revenue TFP measured as of 2010 and, within each group, examine the relationship between AI-skilled hiring and the growth in sales (column 1), employment (column 2), market share (column 3), sales per worker (column 4), and revenue TFP (column 5).[26] The results indicate that even though AI does not appear to improve firms' productivity, the growth fueled by AI is mostly concentrated among the most ex ante productive firms. For the firms in the top tercile of ex ante productivity, a one-standard-deviation increase in the share of AI workers predicts a 5% increase in market share from 2010 to 2018 (column 3 of Panel 1). This result highlights that the increased industry concentration observed in Figure 7 reflects the growth of the most ex ante productive firms.

Second, we look into the drivers of scale (Prediction 3.3) directly, by exploring whether AI allows firms to expand their product offerings across markets. Specifically, we estimate the relationship between a firm's investment in AI and changes in: (1) the geographic reach of the firm, measured as the number of counties with at least 1% of the firm's job postings in Burning Glass in 2010; (2) the number of industries at the most granular (6-digit NAICS) level with at least 1% of the firm's job postings; and (3) the number of product manager jobs posted by the firm. Since product managers align the firm's product capabilities to specific market segments and are responsible for product innovation, the number of product managers hired by a given firm is a direct measure of the firm's expansion of its product offerings.

The results, reported in Table 10, are consistent with AI-adopting firms innovating across new geographic markets and products. A one-standard-deviation increase in the share of AI workers measured in the resume data is accompanied by a 13% increase in job openings for product managers (column 6) and an 8% increase in the number of different counties with a non-negligible share of job postings (column 2), both statistically significant.[27] The effect on the number of different industries spanned is milder at only 2% and not statistically significant, suggesting that AI investments are less associated with expansion across industries. Consistent with AI enabling more product innovations, investment in AI is also associated with increased R&D investment, as can be seen in columns 7–10 of Table 10. This increase in R&D investment is significant even accounting for the overall expansion in size: R&D investment as a fraction of sales also increases significantly.

[26] For robustness, Table A.11 shows similar results when using sales per worker to measure productivity.

[27] In unreported results we also divide the number of product managers by the number of all job postings, and find that a one-standard-deviation increase in the share of AI workers increases the share of product manager job listings by about 15% of the mean, although not always statistically significant.

7 Conclusion

We introduce a novel measure of AI investment by firms using two detailed datasets on human capital: job postings from Burning Glass Technologies, which indicate each firm's demand for different skills, and resume data from Cognism, which reveal the actual composition of a firm's workforce. Our measure of AI investment takes advantage of co-occurrence of different skills with fundamental concepts such as "machine learning" to empirically determine each skill's AI-relatedness, which avoids relying on ex ante specified lists of keywords. Our measures demonstrate the steep growth in AI over the last decade across the full landscape of industries.

We examine both determinants and consequences of firm-level investments in AI. Consistent with conceptual features of AI technologies, investments concentrate among the largest firms. As a firm invests in AI, it grows larger, gaining sales, employment, and market share. This firm-level AI-fueled growth is concentrated among larger firms and is associated with increased concentration at the industry level. AI facilitates scalability of the most ex ante productive ("superstar") firms, allowing them to expand product offerings and into new markets, with no observed productivity gains in the short run, potentially reflecting the productivity J-curve proposed by (Brynjolfsson et al., 2019). The null result on productivity is also consistent with recent evidence in Juhász et al. (2020) who, in the context of mechanized cotton spinning during the Industrial Revolution in France, show that technology adoption by firms is associated with high uncertainly on how to apply the new technology effectively, This high uncertainty necessitates experimentation with potentially inefficient early use and resulting in slow accrual of productivity benefits for the average firm. Our findings point to a gradual impact of important technologies, such as cotton spinning, electricity, and IT in the earlier waves and AI in the present, on firm and industry productivity (Hall and Khan, 2003). Indeed, industry reports emphasize that firms are still in an experimental mode learning how to apply AI and big data technologies effectively (Bughin et al., 2018). Further understanding how AI diffuses through the economy, how it affects the production processes, strategies, and product innovation of firms, and whether the technology spurs productivity growth in the longer term, will be an area for fruitful future research.

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Figure 1. Time Series of the AI Measure from Job Posting Data

This figure shows the time series of the job-posting-based AI measure. The figure reports averages for 2007 and 2010-2018, based on the sample of public firms in Burning Glass. The sample includes all job postings that are matched to Compustat. The solid line shows the average job-level continuous measure based on narrow AI skills ($w_j^{NarrowAI}$) (left Y axis), and the dashed line tracks the fraction of jobs with (narrow AI) continuous measure above 0.1 (right Y axis).

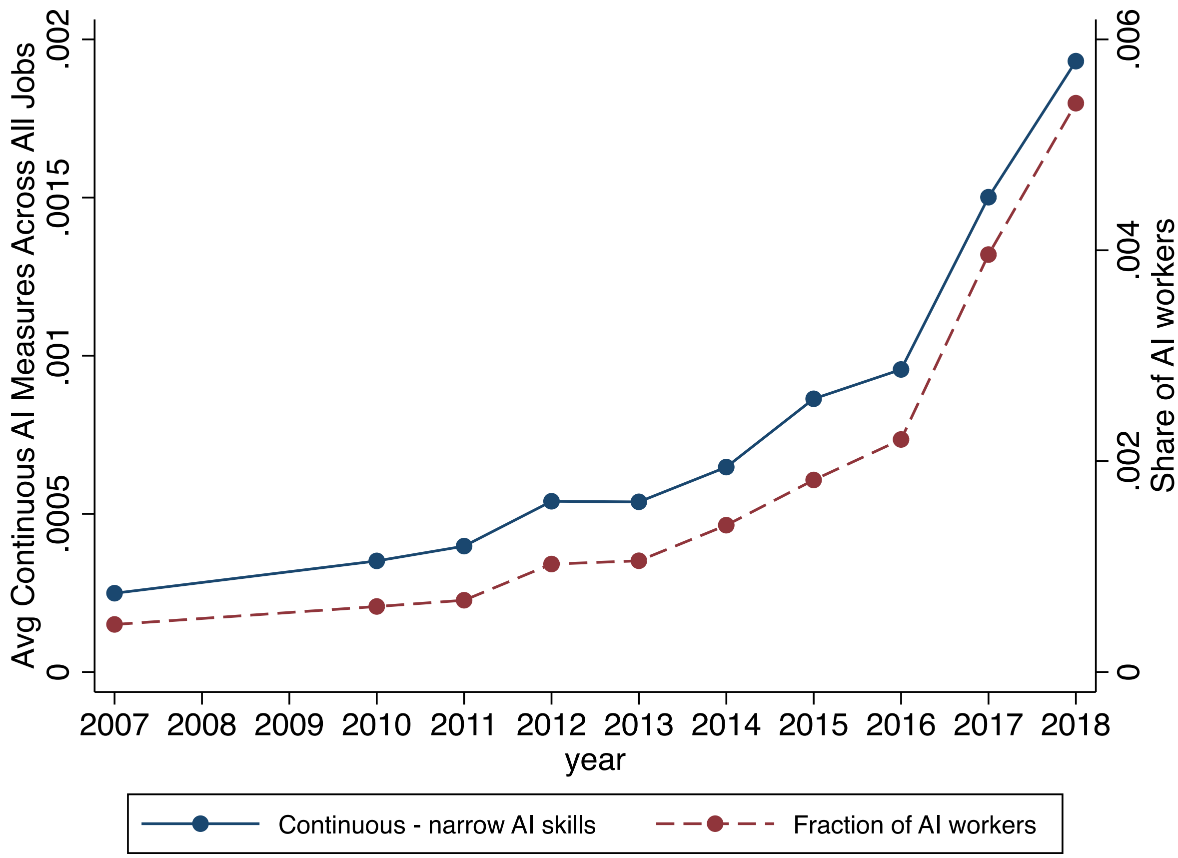


Figure 2. AI Measure by Industry Sector from Job Posting Data

This figure presents the job-posting-based AI measure using Burning Glass (based on the sample of public firms) at the industry level. For each sector (based on NAICS–2 digit industry codes), we compute the average job-level continuous measure across all jobs posted by firms in that sector across two sub-periods: 2007–2014 and 2015–2018.

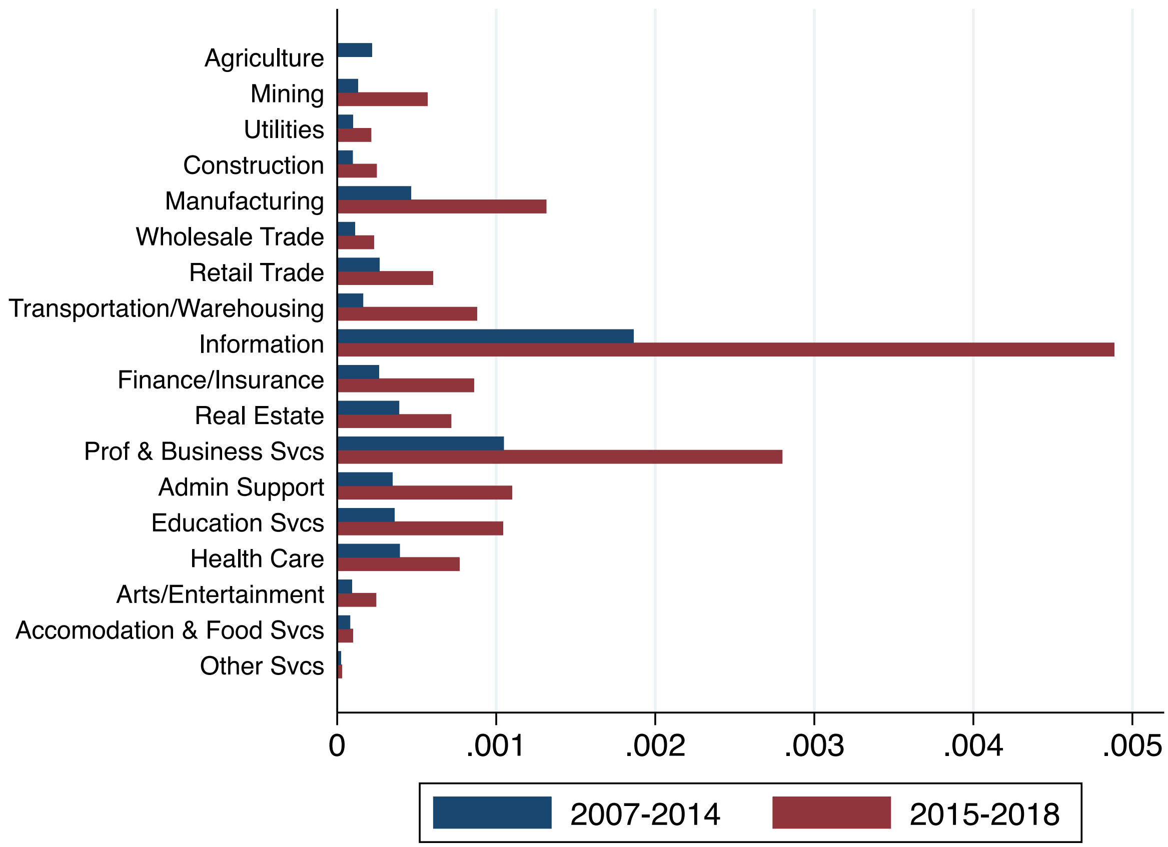


Figure 3. Time Series of the Share of AI Workers from Resume Data

This figure shows the time series of the resume-based share of AI workers using the sample of public firms in Cognism data, computed as the fraction of all employees (across all firms) in a given year who are classified as holding directly AI-related positions. The figure reports the fraction for each year from 2007 to 2018.

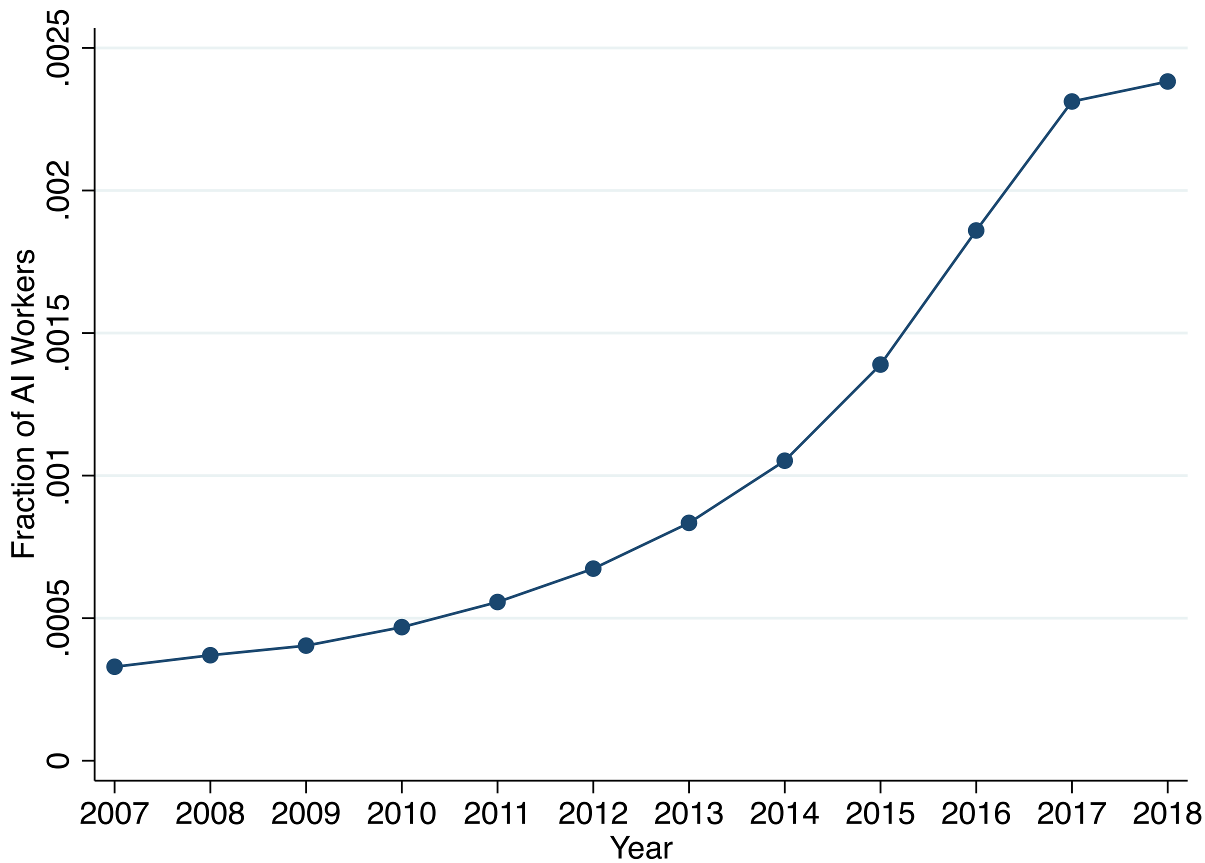


Figure 4. Share of AI Workers by Industry Sector from Resume Data

This figure presents the resume-based share of AI workers using Cognism data (based on the sample of public firms) at the industry level. For each of the sectors (based on NAICS–2 digit industry codes), we compute the fraction of all individuals employed at the firms within that sector who are classified as AI-related employees. This is done separately for two sub-periods: 2007–2014 and 2015–2018.

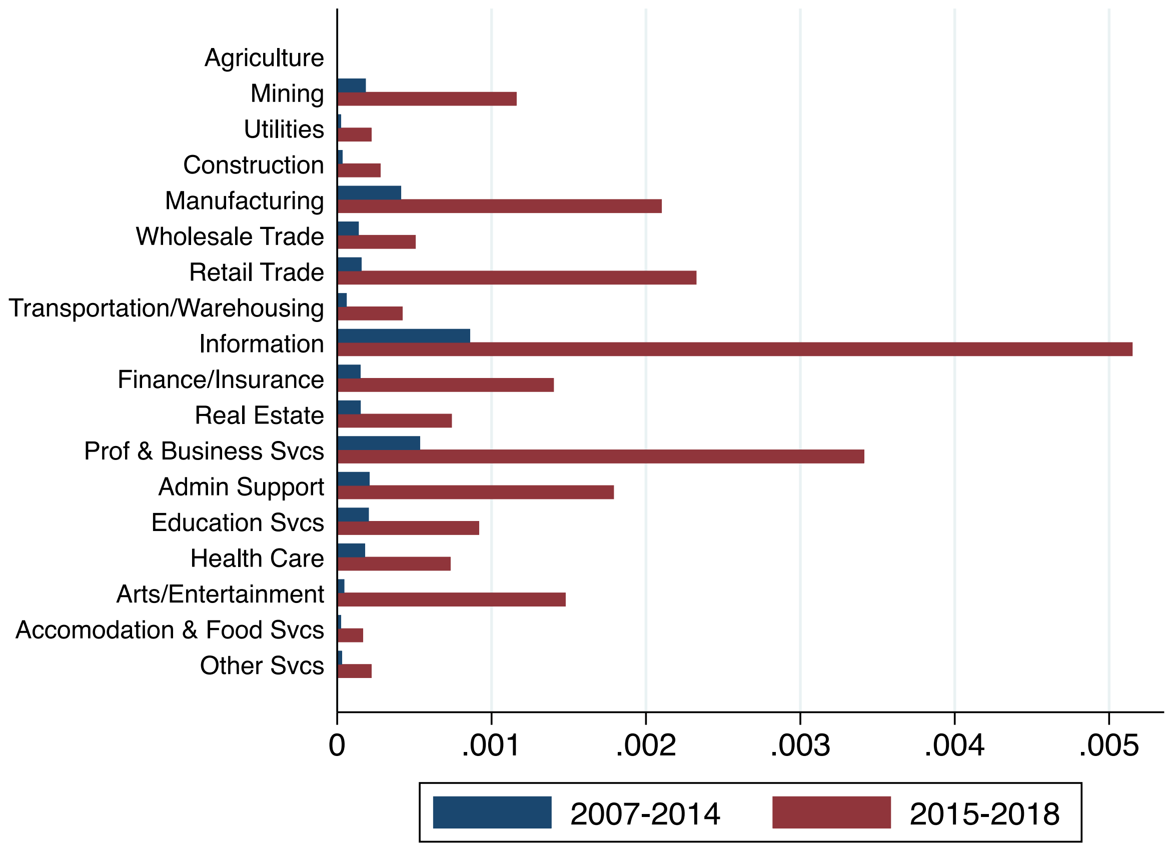
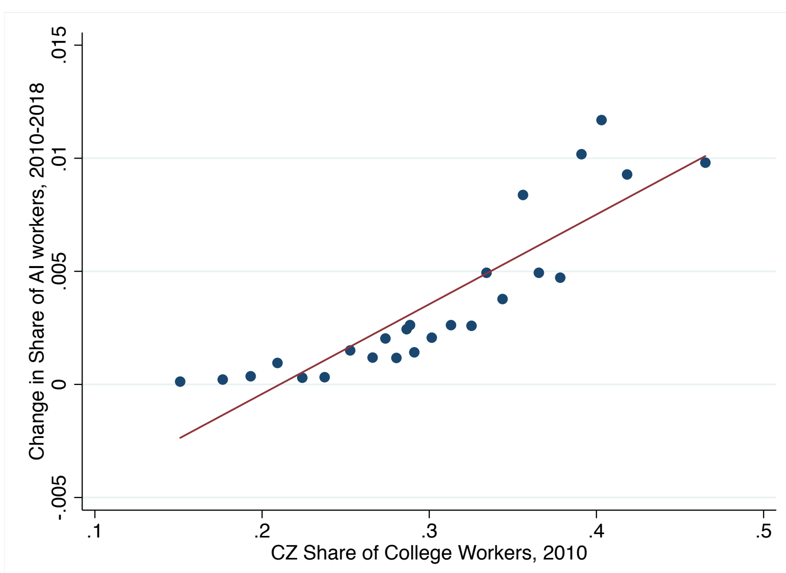


Figure 5. AI Investment and Local Conditions

This figure is a binscatter of commuting-zone-level AI investments against local conditions. The solid line is the fitted regression line, where regressions are weighted by commuting zones' population in 2010. The y-axis is the change in the AI investments (measured as the share of AI workers) from 2010 to 2018, using the Burning Glass data (based on the sample of public firms). The x-axis in the top figure is average log wage of a commuting zone in 2010. The x-axis in the bottom figure is the share of college educated workers in a commuting zone in 2010. The log wage and the share of college-educated workers are from the Census American Community Survey. The t-statistic on the regression slope is 23.6 in the top figure and 23.9 in the bottom figure.

(a) AI Investments and Local Average Wage



(b) AI Investments and Local Share of College-educated Workers

Figure 6. Distribution of AI Investments across US Geographies

This figure plots the heat map of changes in the job-posting-based measure of AI investments across geographies in the US. The figure plots the change in the average AI-relatedness measure ($w_j^{NarrowAI}$) of job postings of public firms in each commuting zone from 2010 to 2018.

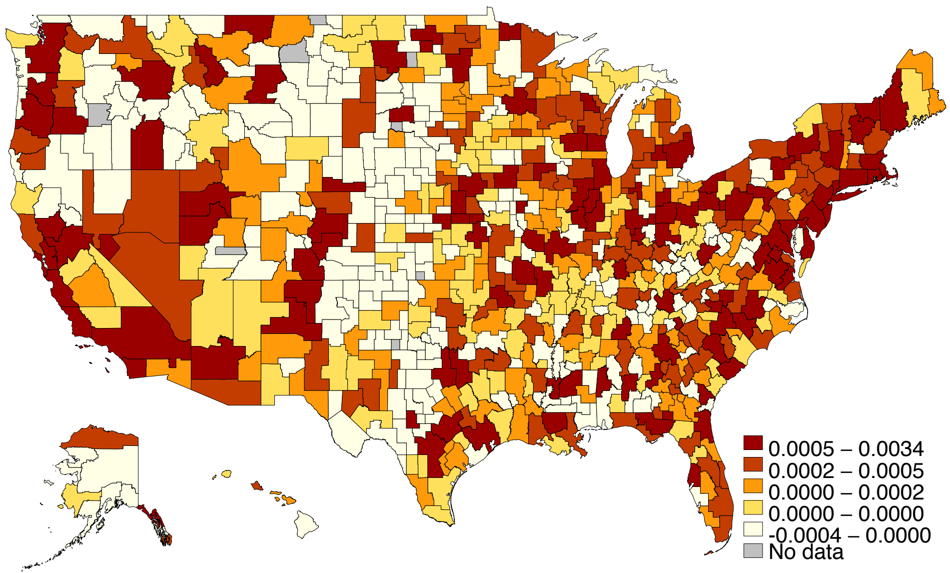
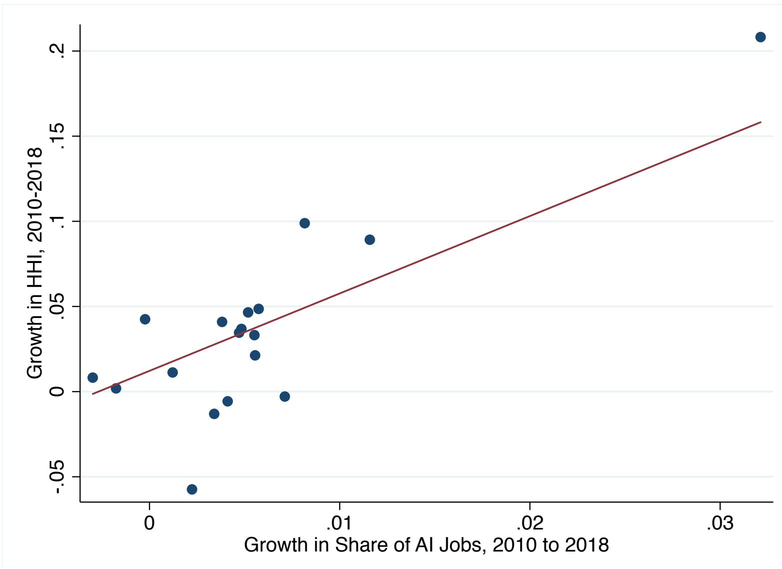
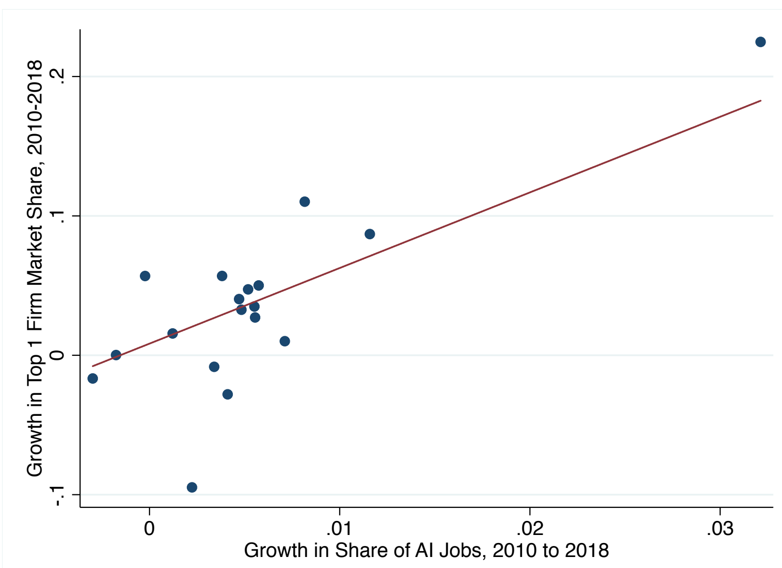


Figure 7. AI Investments and Increase in Industry Concentration

This figure shows the correlation between industry-level growth in the share of AI workers (on the X-axis) and the changes in industry concentration (on the Y-axis) controlling for NAICS-2 fixed effects. AI growth is calculated using the job-posting-based share of AI workers from Burning Glass data (based on the sample of public firms). For each NAICS–5 industry, we compute the growth in the fraction of all job postings that are classified as AI-related from 2010 to 2018. We measure industry-level changes in market concentration from 2010 to 2018 using: (a) the Herfindahl-Hirschman Index (HHI) in the top figure, and (b) the market share of the top firm in an industry using firm sales data from Compustat in the bottom figure. The t-statistic on the regression slope is 4.9 in the top figure and 5.9 in the bottom figure.



(a) Herfindahl-Hirschman Index (HHI)



(b) Market Share of Top 1 Firm

Table 1. Correlations Between Job-posting-based and Resume-based AI Measures

This table reports correlations between three pairs of variables: (i) the absolute number of AI job postings in Burning Glass against the absolute number of AI employees in resume-based data from Cognism; (ii) the fraction of employees classified as AI-related in the two datasets; and (iii) the fraction of AI employees in Cognism against the continuous $share_{f,t}^{NarrowAI}$ measure in Burning Glass. Panel 1 shows the Pearson correlation, and Panel 2 displays the Spearman rank correlation, with both correlations computed over the cross-section of firms with at least 50 total employees in the Cognism resume data in each year of the sample.

Panel 1: Pearson correlation

	Correlations between:		
Year	Numbers of AI jobs	Fractions	Cognism frac & BG $share^{NarrowAI}$
2007	0.652	0.210	0.280
2010	0.892	0.290	0.372
2011	0.783	0.211	0.311
2012	0.831	0.253	0.467
2013	0.807	0.271	0.431
2014	0.777	0.419	0.566
2015	0.804	0.481	0.602
2016	0.670	0.495	0.562
2017	0.719	0.582	0.629
2018	0.830	0.608	0.658

Panel 2: Spearman correlation

	Correlations between:		
Year	Numbers of AI jobs	Fractions	Cognism frac & BG $share^{NarrowAI}$
2007	0.396	0.348	0.303
2010	0.431	0.397	0.371
2011	0.433	0.390	0.353
2012	0.383	0.346	0.367
2013	0.479	0.422	0.416
2014	0.522	0.474	0.475
2015	0.533	0.462	0.491
2016	0.582	0.511	0.524
2017	0.636	0.552	0.566
2018	0.618	0.532	0.553

Table 2. Determinants of AI Investments

This table reports the coefficients from regressions of cross-sectional changes in AI investments by US public firms from 2010 to 2018 on ex-ante firm characteristic measured in 2010: log firm employment in column 1, market share in column 2, log sales in column 3, Cash/Assets in column 4, R&D/Sales in column 5, return on sales in column 6, log markup measured following De Loecker et al. (2020) in column 7, and log markup measured following Traina (2018) in column 8. In Panel 1, the dependent variable is the growth in the share of AI jobs from 2010 to 2018 using the resume-based measure of AI adoption generated from Cognism data. In Panel 2, the dependent variable is the growth in the share of AI jobs from 2010 to 2018 using the job-posting-based measure of AI investments generated from Burning Glass data. The dependent variable is normalized to have a mean of zero and a standard deviation of one.

Panel 1: AI measure from resume data

	Δ Share of AI Workers, 2010–2018								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Employment 2010	0.026								
	(0.018)								
Market Share 2010		0.454***							
		(0.174)							
Log Sales 2010			0.044***						0.071***
			(0.017)						(0.017)
Cash/Assets 2010				1.107***					1.199***
				(0.264)					(0.292)
R&D/Sales 2010					0.682**				0.598
					(0.287)				(0.470)
ROS 2010						0.028			0.000
						(0.138)			(0.247)
Log Markup (COGS) 2010							0.240**		0.271*
							(0.101)		(0.140)
Log Markup (Total Exp) 2010								0.179	-0.034
								(0.157)	(0.283)
4-digit NAICS FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj R-Sq	0.045	0.046	0.050	0.067	0.049	0.044	0.052	0.045	0.090
Obs	1,524	1,585	1,582	1,585	1,582	1,546	1,581	1,582	1,545

Panel 2: AI measure from job postings data

	Δ Share of AI Workers, 2010–2018								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Employment 2010	0.096***								
	(0.023)								
Market Share 2010		1.335***							
		(0.316)							
Log Sales 2010			0.112***						0.150***
			(0.022)						(0.022)
Cash/Assets 2010				0.193					0.523*
				(0.242)					(0.272)
R&D/Sales 2010					0.133				0.763***
					(0.182)				(0.262)
ROS 2010						0.061			0.010
						(0.116)			(0.111)
Log Markup (COGS) 2010							0.137		0.240**
							(0.087)		(0.099)
Log Markup (Total Exp) 2010								0.176	0.212
								(0.165)	(0.207)
4-digit NAICS FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj R-Sq	0.081	0.072	0.094	0.057	0.057	0.051	0.060	0.059	0.132
Obs	1,207	1,244	1,242	1,244	1,242	1,222	1,242	1,242	1,222

Table 3. Effect of AI Investments on Firm Growth: OLS results

This table reports the coefficients from long-differences regressions of changes in firm size of US public firms from 2010 to 2018 on the contemporaneous firm-level changes in AI investments. We consider three measures of firm size: log sales (columns 1 and 2), log employment (columns 3 and 4), and market share in the NAICS 4-digit industry (columns 5 and 6). The dependent variables are measured as growth from 2010 to 2018. For the main independent variable, Panel 1 considers the resume-based measure of the share of AI workers, while Panel 2 looks at the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. The main independent variable is the growth in the share of AI jobs from 2010 to 2018, standardized to mean zero and standard deviation of one. All specifications control for sector fixed effects. Columns 2, 4 and 6 also control for log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (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 6–digit NAICS industry level.

Panel 1: AI measure from resume data

	Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.106**	0.146***	0.114*	0.133**	0.012	0.013
	(0.052)	(0.045)	(0.064)	(0.053)	(0.012)	(0.009)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Sq	0.149	0.362	0.102	0.243	0.212	0.277
Obs	827	827	827	827	827	827

Panel 2: AI measure from job postings data

	Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.133***	0.121***	0.148**	0.100*	0.013	0.015*
	(0.050)	(0.038)	(0.066)	(0.052)	(0.009)	(0.008)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Sq	0.208	0.394	0.311	0.410	0.179	0.259
Obs	909	909	909	909	909	909

Table 4. Effect of AI Investments on Firm Growth: Foreign Industry IV

This table estimates the relationship between AI investments and changes in firm size from 2010 to 2018 for US public firms, using the change in the share of AI workers in European public firms in the same NAICS 5-digit industry as an instrument for the two firm-level AI measures. Panel 1 presents the results for the resume-based measure of the share of AI workers, while Panel 2 focuses on the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. The first stage is tabulated in columns 1 and 2, and the second stage results are displayed in columns 3-8. The independent variable is the growth in the share of AI jobs from 2010 to 2018. AI growth and the IV are standardized to mean zero and standard deviation of one. We consider changes in log sales in columns 3 and 4, in log employment in columns 5 and 6, and in market share in columns 7 and 8. All specifications control for sector fixed effects. Columns 2, 4, 6 and 8 also control for log employment, cash/assets, log sales, log industry wages, log commuting zone wages, and the share of college graduates, as well as characteristics of the commuting zones the firms are located in (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 6–digit NAICS industry level.

Panel 1: IV results using AI measure from resume data

	First Stage		Second Stage					
	Δ Share of AI Workers		Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument	0.391***	0.247***						
	(0.076)	(0.041)						
Δ Share AI Workers			0.173	0.274**	0.217	0.327*	0.024**	0.053**
			(0.185)	(0.123)	(0.177)	(0.173)	(0.011)	(0.026)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
F Statistic	26.8	35.8	26.8	35.8	26.8	35.8	26.8	35.8
Adj R-Sq	702	702	702	702	702	702	702	702

Panel 2: IV results using AI measure from job postings data

	First Stage		Second Stage					
	Δ Share of AI Workers		Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument	0.555***	0.477***						
	(0.140)	(0.091)						
Δ Share AI Workers			0.217***	0.197***	0.244**	0.225**	0.024***	0.043***
			(0.068)	(0.061)	(0.099)	(0.101)	(0.007)	(0.012)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
F Statistic	15.7	27.6	15.7	27.6	15.7	27.6	15.7	27.6
Adj R-Sq	771	771	771	771	771	771	771	771

Table 5. Effect of AI Investments on Industry-level Employment and Sales

This table reports the coefficients from industry-level long-differences regressions of the changes in sales and employment on contemporaneous changes in AI investments. Each observation is a 5-digit NAICS industry. The independent variable is the change in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. For the main independent variable, Panel 1 considers the resume-based measure of the share of AI workers, while Panel 2 looks at the job-posting-based measure. Regressions are weighted by the total industry number of Cognism resumes in 2010 in Panel 1 and the total industry number of Burning Glass job postings in 2010 in Panel 2. Columns 1 to 4 are estimated by OLS, and in columns 5 to 8 the independent variable is instrumented by the contemporaneous growth in the share of AI workers in European firms in each industry. The dependent variables are changes in log total sales (columns 1, 2, 5 and 6) and log total employment (columns 3, 4, 7 and 8) at the industry level from 2010 to 2018. All specifications control for sector fixed effects. Regressions in columns 2, 4, 6 and 8 also control for log total employment and log total sales in 2010, as well as growth in log total sales and log total employment from 2000 to 2008. Reported standard errors are robust against heteroskedasticity.

Panel 1: AI measure from resume data

	OLS				IV			
	Δ Log Sales		Δ Log Employment		Δ Log Sales		Δ Log Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	0.125***	0.151***	0.130**	0.158***	0.210***	0.248***	0.177*	0.218***
	(0.039)	(0.029)	(0.063)	(0.056)	(0.047)	(0.038)	(0.106)	(0.074)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
F Statistic					15.0	13.9	15.0	13.9
Obs	213	213	213	213	142	142	142	142

Panel 2: AI measure from job postings data

	OLS				IV			
	Δ Log Sales		Δ Log Employment		Δ Log Sales		Δ Log Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	0.132***	0.097**	0.135	0.091	0.201***	0.250***	0.228*	0.291***
	(0.050)	(0.048)	(0.087)	(0.069)	(0.072)	(0.060)	(0.134)	(0.099)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
F Statistic					7.0	9.8	7.0	9.8
Obs	223	223	223	223	146	146	146	146

Table 6. Heterogeneous Effects on Firm Growth by Initial Firm Size

This table reports the coefficients from long-differences regressions of changes in firm size from 2010 to 2018 on contemporaneous changes in AI investments among US public firms, separately for each tercile of starting employment in 2010. We consider three measures of firm size for the dependent variable: log sales (columns 1 and 2), log employment (columns 3 and 4), and market share (columns 5 and 6). For the main independent variable, Panel 1 considers the resume-based measure of AI investments, while Panel 2 looks at the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. The main independent variable is the growth in the share of AI jobs from 2010 to 2018, standardized to mean zero and standard deviation of one. All specifications control for sector fixed effects and initial firm size tercile fixed effects. Columns 2, 4 and 6 also control for log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (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 6–digit NAICS industry level.

Panel 1: AI measure from resume data

	Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers*Size Tercile 1	0.025	0.008	0.058**	0.039	0.001	-0.000
	(0.032)	(0.029)	(0.027)	(0.030)	(0.002)	(0.003)
Δ Share AI Workers*Size Tercile 2	0.108*	0.073	0.077*	0.035	0.007	0.006
	(0.056)	(0.063)	(0.042)	(0.045)	(0.009)	(0.011)
Δ Share AI Workers*Size Tercile 3	0.124**	0.164***	0.134*	0.151**	0.013	0.015
	(0.058)	(0.050)	(0.072)	(0.060)	(0.014)	(0.010)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Size tercile FE	Y	Y	Y	Y	Y	Y
Adj R-Sq	0.181	0.365	0.127	0.246	0.209	0.276
Obs	827	827	827	827	827	827
T-test statistic	3.2	10.8	1.2	4.2	0.8	1.9
T-test p value	0.077	0.001	0.265	0.042	0.372	0.170

Panel 2: AI measure from job postings data

	Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers*Size Tercile 1	-0.076	-0.075	-0.039	-0.082	-0.005**	-0.002
	(0.058)	(0.049)	(0.037)	(0.053)	(0.003)	(0.005)
Δ Share AI Workers*Size Tercile 2	0.006	-0.021	-0.007	-0.026	0.003	0.002
	(0.043)	(0.039)	(0.038)	(0.040)	(0.003)	(0.004)
Δ Share AI Workers*Size Tercile 3	0.143***	0.128***	0.158**	0.106*	0.013	0.016*
	(0.051)	(0.039)	(0.067)	(0.054)	(0.009)	(0.008)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Size tercile FE	Y	Y	Y	Y	Y	Y
Adj R-Sq	0.227	0.397	0.319	0.411	0.176	0.256
Obs	909	909	909	909	909	909
T-test statistic	8.0	11.4	7.1	8.3	3.4	3.4
T-test p value	0.005	0.001	0.008	0.004	0.068	0.067

Table 7. Effect of AI Investments on Productivity

This table reports the coefficients from long-differences regressions of changes in firm productivity from 2010 to 2018 on contemporaneous changes in AI investments by US public firms. We consider two measures of productivity: log sales per worker (columns 1–2) and revenue TFP (columns 3–4). Revenue TFP is the residual from regressing log revenue on log employment and log capital (constructed using perpetual inventory method), with separate regressions for each industry sector. We also look at two measures of costs: log COGS in columns 5 and 6 and log operating expenses in columns 7 and 8. The main independent variable is the growth in the share of AI workers from 2010 to 2018. The share of AI workers is calculated based on resumes in Panel 1 and job postings in Panel 2. All independent variables are standardized to mean zero and standardized deviation of one. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. All specifications control for sector fixed effects. Columns 2, 4, 6 and 8 also control for log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (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 6–digit NAICS industry level.

Panel 1: AI measure from resume data

	Δ Log Sales per Worker		Δ Revenue TFP		Δ Log COGS		Δ Log Operating Expense	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	-0.028	-0.006	-0.015	0.004	0.112***	0.124***	0.110**	0.140***
	(0.038)	(0.035)	(0.033)	(0.035)	(0.041)	(0.046)	(0.049)	(0.043)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Adj R-Sq	0.158	0.277	0.159	0.289	0.171	0.344	0.176	0.376
Obs	827	827	779	779	827	827	827	827

Panel 2: AI measure from job postings data

	Δ Log Sales per Worker		Δ Revenue TFP		Δ Log COGS		Δ Log Operating Expense	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	-0.044	-0.018	-0.018	-0.014	0.156***	0.121***	0.141***	0.119***
	(0.042)	(0.037)	(0.037)	(0.035)	(0.035)	(0.025)	(0.044)	(0.032)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
Adj R-Sq	0.414	0.488	0.228	0.279	0.213	0.336	0.212	0.380
Obs	909	909	845	845	909	909	909	909

Table 8. Effect of AI Investments on Markups

This table reports the coefficients from long-differences changes in markups from 2010 to 2018 on the contemporaneous changes in AI investments by US public firms. We consider three measures of mark-ups: sales divided by cost of goods sold (COGS) in columns 1 and 2, sales over total operating expenses in columns 3 and 4, and the Lerner Index in columns 5 and 6. For the main independent variable, Panel 1 considers the resume-based measure of the growth in the share of AI workers from 2010 to 2018, while Panel 2 looks at the job-posting-based measure. Both measures are standardized to mean zero and standardized deviation of one. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. All specifications control for sector fixed effects. Columns 2, 4, 6 and 8 also control for log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (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 6–digit NAICS industry level.

Panel 1: AI measure from resume data

	Δ Log Markup (COGS)		Δ Log Markup (Total Exp)		Δ Lerner Index	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.001	0.031	-0.001	0.010	-0.005	0.004
	(0.016)	(0.028)	(0.006)	(0.011)	(0.003)	(0.006)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Sq	0.279	0.360	0.234	0.317	0.179	0.277
Obs	827	827	827	827	827	827

Panel 2: AI measure from job postings data

	Δ Log Markup (COGS)		Δ Log Markup (Total Exp)		Δ Lerner Index	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	-0.022	-0.000	-0.008	0.002	-0.007	0.003
	(0.028)	(0.028)	(0.009)	(0.011)	(0.006)	(0.007)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Sq	0.256	0.324	0.300	0.372	0.137	0.223
Obs	909	909	909	909	909	909

Table 9. Heterogeneous Effects by Initial Firm Productivity (TFP)

This table reports the coefficients from long-differences regressions of changes in firm size and productivity from 2010 to 2018 on the contemporaneous changes in AI investments among US public firms, separately for each tercile of starting firm productivity (measured by revenue TFP) in 2010. We consider three measures of firm size: log sales (columns 1 and 2), log employment (columns 3 and 4), and market share (columns 5 and 6). The independent variables are changes in the share of AI jobs interacted with indicator variables for the productivity tercile in 2010. Panel 1 considers the resume-based measure of the growth in the share of AI jobs from 2010 to 2018, while Panel 2 looks at the job-posting-based measure. Both measures are standardized to mean zero and standardized deviation of one. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. All specifications control for sector fixed effects and productivity tercile fixed effects. Regressions in even columns also control for log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (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 6–digit NAICS industry level.

Panel 1: AI measure from resume data

	Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers*TFP Tercile 1	0.020	0.059	0.129	0.152*	-0.005	-0.011
	(0.103)	(0.093)	(0.079)	(0.079)	(0.008)	(0.013)
Δ Share AI Workers*TFP Tercile 2	-0.005	0.061	-0.004	0.050	-0.005	0.000
	(0.072)	(0.052)	(0.042)	(0.037)	(0.011)	(0.008)
Δ Share AI Workers*TFP Tercile 3	0.362***	0.364***	0.283***	0.281***	0.048	0.047*
	(0.070)	(0.065)	(0.076)	(0.074)	(0.038)	(0.029)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
TFP tercile FE	Y	Y	Y	Y	Y	Y
Adj R-Sq	0.230	0.398	0.228	0.334	0.287	0.345
Obs	783	783	783	783	783	783
T-test statistic	7.8	8.3	2.1	1.6	1.9	2.8
T-test p value	0.006	0.004	0.152	0.201	0.166	0.095

Panel 2: AI measure from job postings data

	Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers*TFP Tercile 1	0.041	0.054	0.219***	0.188***	0.002	0.002
	(0.046)	(0.048)	(0.084)	(0.054)	(0.010)	(0.010)
Δ Share AI Workers*TFP Tercile 2	0.039	0.038	0.026	0.006	-0.002	0.005
	(0.026)	(0.024)	(0.031)	(0.030)	(0.006)	(0.006)
Δ Share AI Workers*TFP Tercile 3	0.257***	0.243***	0.223***	0.168***	0.030	0.032*
	(0.045)	(0.033)	(0.078)	(0.060)	(0.018)	(0.017)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
TFP tercile FE	Y	Y	Y	Y	Y	Y
Adj R-Sq	0.274	0.432	0.434	0.541	0.212	0.285
Obs	850	850	850	850	850	850
T-test statistic	12.8	13.5	0.0	0.1	1.7	2.2
T-test p value	0.000	0.000	0.971	0.819	0.196	0.142

Table 10. AI Investments and Expansion into New Markets

This table reports the coefficients from long-differences regressions of the changes in the number of markets spanned by US public firms from 2010 to 2018 on the contemporaneous changes in AI investments. In columns 1 and 2, the dependent variable is the change in the log number of counties with at least 1% of the firm's job postings in Burning Glass; in columns 3 and 4, the dependent variable is the change in the log number of NAICS 6-digit industries associated with at least 1% of the firm's job postings in Burning Glass; in columns 5 and 6, the dependent variable is the change in the log number of job postings of product managers; in columns 7 and 8, the dependent variable is the change in log R&D investment; in columns 7 and 8, the dependent variable is the change in R&D expenditure as a fraction of sales. For the main independent variable, Panel 1 considers the resume-based measure of the growth in the share of AI jobs from 2010 to 2018, while Panel 2 looks at the job-posting-based measure. Both measures are standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. All specifications control for sector fixed effects. Columns 2, 4, 6, 8 and 10 also control for log employment, cash/assets, log sales, log industry wages, log commuting zone wages, and the share of college graduates, as well as characteristics of the commuting zones where the firms are headquartered (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 6–digit NAICS industry level.

Panel 1: AI measure from resume data

	Δ Log Number of Counties		Δ Log Number of Industries		Δ Log Number of Product Managers		Δ Log R&D		Δ R&D/Sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.067***	0.078***	-0.001	0.022	0.165***	0.134**	0.207**	0.210**	0.009***	0.008***
	(0.020)	(0.024)	(0.015)	(0.020)	(0.046)	(0.067)	(0.090)	(0.086)	(0.002)	(0.003)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Sq	0.152	0.260	0.094	0.137	0.069	0.140	0.147	0.251	0.074	0.150
Obs	817	817	819	819	816	816	827	827	827	827

Panel 2: AI measure from job postings data

	Δ Log Number of Counties		Δ Log Number of Industries		Δ Log Number of Product Managers		Δ Log R&D		Δ R&D/Sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Share AI Workers	0.036	0.070***	0.005	0.017	0.172***	0.129*	0.190**	0.174**	0.006***	0.004
	(0.022)	(0.023)	(0.009)	(0.016)	(0.037)	(0.068)	(0.078)	(0.081)	(0.002)	(0.003)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Adj R-Sq	0.412	0.588	0.061	0.094	0.118	0.180	0.213	0.320	0.005	0.086
Obs	907	907	909	909	909	909	909	909	909	909

A Appendix

Figure A.1. Matching Rate to Compustat in Job Posting Data

This figure shows the time series of the share of all jobs and the share of AI jobs (jobs with continuous measure $\omega^{NarrowAI}$ above 0.1) that are matched to Compustat in the Burning Glass data in each year from 2007 to 2018.

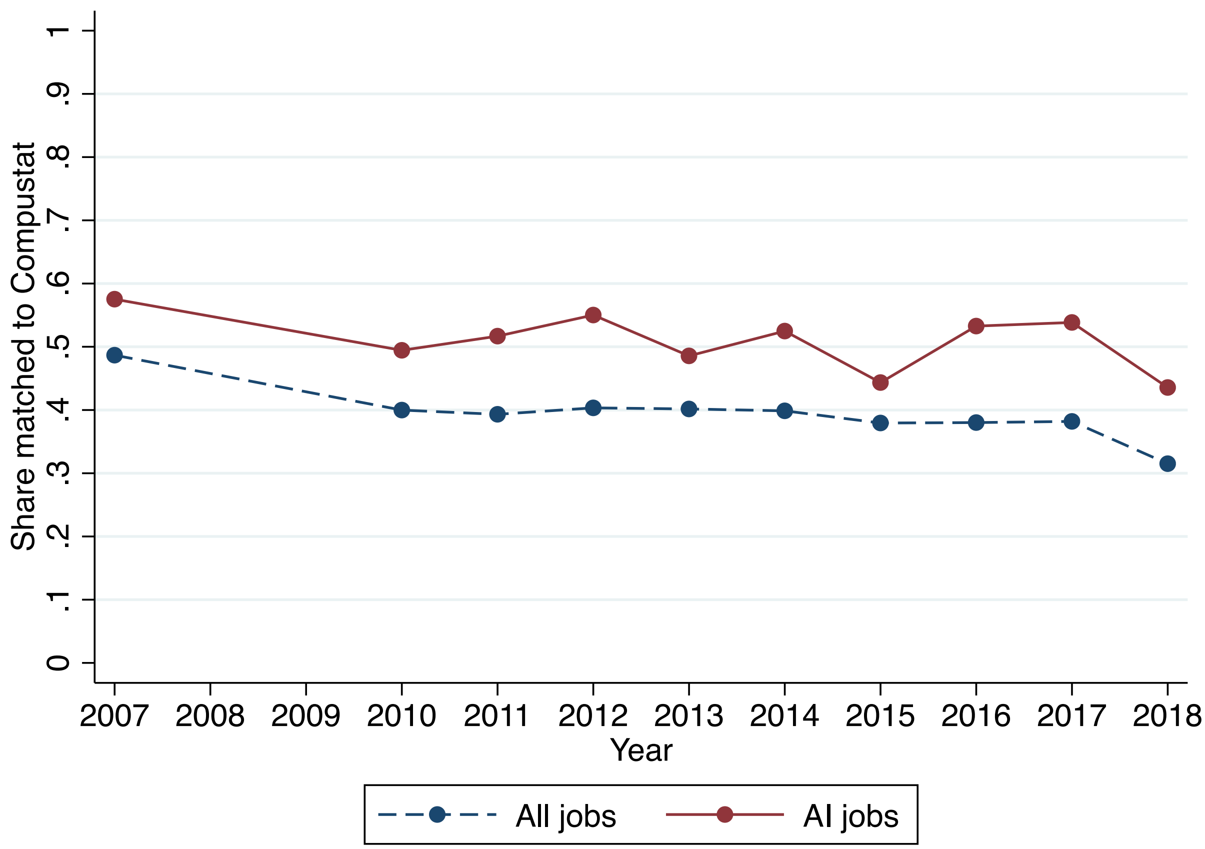


Table A.1. Job Titles with the Highest Average AI-relatedness Measure

This table reports the job titles in Burning Glass with the highest average AI measure $\omega^{NarrowAI}$. We only include job titles that have at least 50 job postings and include job postings that are matched to Compustat firms.

	cleantitle	share narrowai
1	Artificial Intelligence Engineer	0.476
2	Senior Data Scientist - Machine Learning Engineer	0.367
3	Ai Consultant	0.365
4	Ai Senior Analyst	0.354
5	Lead Machine Learning Scientist - Enterprise Products	0.313
6	Technician Architecture Delivery Senior Analyst Ai	0.294
7	Artificial Intelligence Analyst	0.291
8	Artificial Intelligence Architect	0.288
9	Software Engineer, Machine Learning	0.283
10	Machine Learning Engineer	0.283
11	Computer Vision Engineer	0.272
12	Machine Learning Researcher	0.261
13	Senior Machine Learning Engineer	0.260
14	Senior Software Engineer - Machine Learning	0.252
15	Senior Machine Learning Scientist	0.250
16	Artificial Intelligence Consultant	0.245
17	Computer Vision Scientist	0.233
18	Senior Ai Engineer	0.229
19	Senior Engineer II - Data Scientist	0.227
20	Senior Machine Learning Researcher	0.226
21	Artificial Intelligence Manager	0.216
22	Senior Applied Scientist	0.215
23	Lead Machine Learning Researcher	0.215
24	Vice President- Data Analytics	0.202
25	Big Data Hadoop Consultant	0.198
26	Machine Learning Scientist	0.195
27	Software Engineer - Data Mining/Data Analysis/Machine Learning	0.193
28	Applied Scientist	0.189
29	Senior Engineer - Machine Learning	0.187
30	Senior Associate, Data Scientist	0.183
31	Data Scientist - Engineer	0.181
32	Architect - Relevance Infrastructure	0.177
33	Data Scientist Specialist	0.175
34	Director, Data Scientist	0.175
35	Senior Staff Data Scientist	0.171
36	Data Scientist, Junior	0.169
37	Engineering Manager - Feed Personalization Platform	0.167
38	Manager, Data Scientist	0.162
39	Principal Data Scientist	0.161
40	Director, Data Science	0.161
41	Senior Risk Modeler	0.160
42	Data Science Specialist	0.160
43	Manager/Senior Manager Small Business Open Digital Acquisition	0.159
44	Chief Data Scientist	0.159
45	Manager, Data Science	0.157
46	Research And Development Engineer - Data Mining/Data Analysis/Machine Learning	0.157
47	Senior Manager, Data Science	0.157
48	Big Data Scientist	0.153
49	Data Scientist II	0.152
50	Senior Data Science Engineer	0.151

Table A.2. Job Titles with the Largest Number of AI Jobs

This table reports the job titles in Burning Glass with the highest number of AI jobs. AI jobs are defined as jobs with continuous measure $\omega^{NarrowAI}$ above 0.1. We only include job postings that are matched to Compustat firms.

	cleantitle	**number of AI jobs**
1	Data Scientist	3,529
2	Senior Data Scientist	1,547
3	Software Engineer	665
4	Principal Data Scientist	434
5	Data Engineer	409
6	Senior Software Engineer	399
7	Research Scientist	398
8	Lead Data Scientist	358
9	Machine Learning Engineer	305
10	Big Data Engineer	239
11	Senior Data Engineer	230
12	Big Data Architect	197
13	Big Data Consultant	191
14	Data Analyst	176
15	Data Scientist, Senior	168
16	Data Scientist II	153
17	Hadoop Developer	153
18	Software Development Engineer	151
19	Data Science Engineer	147
20	Machine Learning Scientist	144
21	Big Data Developer	144
22	Software Engineer - Data Mining/Data Analysis/Machine Learning	140
23	Data Scientist, Mid	132
24	Senior Research Scientist	128
25	Research Engineer	128
26	Artificial Intelligence Consultant	126
27	Machine Learning Researcher	125
28	Research And Development Engineer - Data Mining/Data Analysis/Machine Learning	116
29	Applied Scientist	113
30	Lead Machine Learning Scientist - Enterprise Products	113
31	Software Engineer Ads & Data Mining	112
32	Software Engineer - Entry Level	111
33	Business Process Analyst	110
34	Artificial Intelligence Manager	109
35	Big Data Scientist	109
36	Big Data Engineer Consultant	108
37	Principal Software Engineer	106
38	Big Data Manager	105
39	Senior Applied Scientist	103
40	Software Developer	103
41	Principal Digital Product Manager	103
42	Senior Engineer II - Data Scientist	102
43	Artificial Intelligence Analyst	102
44	Senior Engineer I	102
45	F - Program Intel Threat Analyst	101
46	Staff Data Scientist	97
47	Engineering Manager - Feed Personalization Platform	96
48	Architect - Relevance Infrastructure	93
49	Software Engineer, Machine Learning	93
50	Computer Vision Engineer	91

Table A.3. Occupations with the Largest Number of AI Jobs

This table reports the names of the BLS occupations with the highest number of AI jobs in Burning Glass. AI jobs are defined as jobs with continuous measure $\omega^{NarrowAI}$ above 0.1. We only include job postings that are matched to Compustat firms.

	BLS Occupation Name	**number of AI jobs**
1	Computer and Information Research Scientists	21,273
2	Software Developers, Applications	20,977
3	Computer Occupations, All Other	12,692
4	Operations Research Analysts	6,980
5	Database Administrators	3,451
6	Marketing Managers	2,760
7	Managers, All Other	2,592
8	Architectural and Engineering Managers	1,559
9	Engineers, All Other	1,391
10	Computer Systems Analysts	1,212
11	General and Operations Managers	1,070
12	Management Analysts	1,047
13	Information Security Analysts	811
14	Mechanical Engineers	761
15	Detectives and Criminal Investigators	741
16	Statisticians	736
17	Web Developers	658
18	Computer Hardware Engineers	648
19	Electrical Engineers	628
20	Computer Network Architects	625
21	Financial Specialists, All Other	599
22	Sales Managers	594
23	Medical and Health Services Managers	539
24	Engineering Technicians, Except Drafters, All Other	524
25	Natural Sciences Managers	460
26	Market Research Analysts and Marketing Specialists	454
27	Computer Programmers	425
28	Medical Scientists, Except Epidemiologists	408
29	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	398
30	Computer and Information Systems Managers	357

Table A.4. Robustness: Continuous Narrow AI Measure

This table reports the coefficients from long-differences regressions of the changes in firm size of US public firms from 2010 to 2018 on the contemporaneous changes in AI investments. The firm-level measure of AI investments is the average job-level continuous AI measure based on narrow AI skills ($\omega_j^{NarrowAI}$) across all job postings in a given year. Panel 1 presents OLS results, while Panel 2 shows IV results. In the IV analysis, the independent variable is instrumented using the change in the share of AI workers in European public firms in the same NAICS 5-digit industry. We consider three measures of firm size: log sales (Panel 1: columns 1 and 2; Panel 2: columns 3 and 4), log employment (Panel 1: columns 3 and 4; Panel 2: columns 5 and 6), and market share (Panel 1: columns 5 and 6; Panel 2: columns 7 and 8). The main dependent variables are measured as growth from 2010 to 2018. The key independent variable is the growth in the continuous firm-level measure of AI-relatedness from 2010 to 2018. The growth in the AI measure and the IV are standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Burning Glass job postings in 2010. All specifications control for sector fixed effects. Even-numbered columns also control for log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (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 6–digit NAICS industry level.

Panel 1: OLS

	Δ Log Sales		Δ Log Employment		Δ Log Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.135***	0.125***	0.151**	0.103*	0.012	0.014*
	(0.050)	(0.040)	(0.066)	(0.054)	(0.009)	(0.008)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Sq	0.209	0.395	0.312	0.411	0.176	0.255
Obs	909	909	909	909	909	909

Panel 2: IV

	First Stage		Second Stage					
	Δ Share of AI Workers		Δ Log Sales		Δ Log Employment		Δ Log Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument	0.535***	0.585***						
	(0.164)	(0.192)						
Δ Share AI Workers			0.214***	0.322***	0.270**	0.166	0.001	0.021
			(0.052)	(0.108)	(0.114)	(0.201)	(0.018)	(0.031)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
F Statistic	10.6	9.3	18.0	9.3	18.0	9.3	18.0	9.3
Adj R-Sq	909	909	909	909	909	909	909	909

Table A.5. Robustness: Continuous All-skill AI measure

This table reports the coefficients from long-differences regressions of the changes in firm size of US public firms from 2010 to 2018 on the contemporaneous changes in AI investments. The firm-level measure of AI investments is the average job-level continuous AI measure based on all skills (ω_j^{AllAI}) across all job postings in a given year. Panel 1 presents OLS results, while Panel 2 shows IV results. In the IV analysis, the independent variable is instrumented using the change in the share of AI workers in European public firms in the same NAICS 5-digit industry. We consider three measures of firm size: log sales (Panel 1: columns 1 and 2; Panel 2: columns 3 and 4), log employment (Panel 1: columns 3 and 4; Panel 2: columns 5 and 6), and market share (Panel 1: columns 5 and 6; Panel 2: columns 7 and 8). The main dependent variables are measured as growth from 2010 to 2018. The key independent variable is the growth in the continuous firm-level measure of AI-relatedness from 2010 to 2018. The growth in the AI measure and the IV are standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Burning Glass job postings in 2010. All specifications control for sector fixed effects. Even-numbered columns also control for log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (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 6–digit NAICS industry level.

Panel 1: OLS

	Δ Log Sales		Δ Log Employment		Δ Log Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers	0.135***	0.125***	0.151**	0.103*	0.012	0.014*
	(0.050)	(0.040)	(0.066)	(0.054)	(0.009)	(0.008)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Adj R-Sq	0.209	0.395	0.312	0.411	0.176	0.255
Obs	909	909	909	909	909	909

Panel 2: IV

	First Stage		Second Stage					
	Δ Share of AI Workers		Δ Log Sales		Δ Log Employment		Δ Log Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument	0.535***	0.585***						
	(0.164)	(0.192)						
Δ Share AI Workers			0.214***	0.322***	0.270**	0.166	0.001	0.021
			(0.052)	(0.108)	(0.114)	(0.201)	(0.018)	(0.031)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
F Statistic	10.6	9.3	18.0	9.3	18.0	9.3	18.0	9.3
Adj R-Sq	909	909	909	909	909	909	909	909

Table A.6. Robustness: Pre-trend of Foreign Industry IV

This table investigates pre-trends in firm size variables of US public firms, measured over 2000-2008, before the AI investments during 2010-2018. We estimate an IV regression of each pre-trend variable against the two AI measures (based on resume data in Panel 1 and based on job posting data in Panel 2). The independent variable is the growth in the share of AI jobs from 2010 to 2018, standardized to mean zero and standard deviation of one. The independent variable is instrumented using the change in the share of AI workers for European public firms in the NAICS 5-digit industry. Column 1 looks at pre-trends in log sales; Column 2 considers pre-trends in log employment, and Column 3 reports pre-trends in market share. All specifications control for sector fixed effects and log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industry, 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 6–digit NAICS industry level.

Panel 1: Testing for pre-trends using AI measure from resume data

	Δ Log Sales, 2000–2008	Δ Log Employment, 2000–2008	Δ Market Share, 2000–2008
	(1)	(2)	(3)
Δ Share AI Workers	-0.246	-0.199	0.001
	(0.443)	(0.399)	(0.049)
NAICS2 FE	Y	Y	Y
Controls	Y	Y	Y
F Statistic	8.7	7.7	8.8
Adj R-Sq	597	567	600

Panel 2: Testing for pre-trends using AI measure from job postings data

	Δ Log Sales, 2000–2008	Δ Log Employment, 2000–2008	Δ Market Share, 2000–2008
	(1)	(2)	(3)
Δ Share AI Workers	0.180	0.016	0.009
	(0.117)	(0.093)	(0.021)
NAICS2 FE	Y	Y	Y
Controls	Y	Y	Y
F Statistic	18.8	19.5	18.7
Adj R-Sq	524	502	527

Table A.7. Effect of AI Investments on Firm Growth: Bartik IV

This table estimates the relationship between AI investments and changes in firm size from 2010 to 2018 for US public firms, using a weighted average of national industry-level changes in the share of AI workers as an instrument for the two firm-level AI measures. Panel 1 presents the results for the resume-based measure of AI investments, while Panel 2 focuses on the job-posting-based measure. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. The first stage is provided in columns 1 and 2, and the second stage results are displayed in columns 3-8. The independent variable is the growth in the share of AI jobs from 2010 to 2018. AI growth and the IV are standardized to mean zero and standard deviation of one. We consider changes in log sales in columns 3 and 4, in log employment in columns 5 and 6, and in market share in columns 7 and 8. All specifications control for sector fixed effects. Columns 2, 4, 6 and 8 also control for log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industry, 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 6–digit NAICS industry level.

Panel 1: IV results using AI measure from resume data

	First Stage		Second Stage					
	Δ Share of AI Workers		Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument	0.558***	0.642***						
	(0.082)	(0.162)						
Δ Share AI Workers			0.325***	0.246***	0.282***	0.230**	0.029	0.021
			(0.075)	(0.074)	(0.083)	(0.089)	(0.039)	(0.016)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
F Statistic	46.6	15.8	46.6	15.8	46.6	15.8	46.6	15.8
Obs	827	827	827	827	827	827	827	827

Panel 2: IV results using AI measure from job postings data

	First Stage		Second Stage					
	Δ Share of AI Workers		Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument	0.766***	0.539***						
	(0.205)	(0.192)						
Δ Share AI Workers			0.214***	0.325***	0.274**	0.147	-0.001	0.024
			(0.052)	(0.125)	(0.120)	(0.222)	(0.019)	(0.033)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
F Statistic	13.9	7.9	13.9	7.9	13.9	7.9	13.9	7.9
Obs	909	909	909	909	909	909	909	909

Table A.8. Robustness: Pre-trend of Bartik IV

This table investigates pre-trends in firm size variables of US public firms, measured over 2000-2008, before the AI investments during 2010-2018 . We estimate an IV regression of each pre-trend variable against the two AI measures (based on resume data in Panel 1 and based on job posting data in Panel 2). The independent variable is the growth in the share of AI jobs from 2010 to 2018, standardized to mean zero and standard deviation of one. The independent variable is instrumented using a weighted average of national industry-level changes in the share of AI workers. Column 1 looks at pre-trends in log sales; Column 2 considers pre-trends in log employment, and Column 3 reports pre-trends in market share. All specifications control for sector fixed effects and log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (average log wage, the share of college graduates, the share of routine workers, the share of workers in finance and manufacturing industry, 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 6–digit NAICS industry level.

Panel 1: Testing for pre-trends using AI measure from resume data

	Δ Log Sales, 2000–2008	Δ Log Employment, 2000–2008	Δ Market Share, 2000–2008
	(1)	(2)	(3)
Δ Share AI Workers	0.031	0.095	0.004
	(0.182)	(0.153)	(0.023)
NAICS2 FE	Y	Y	Y
Controls	Y	Y	Y
F Statistic	12.9	12.0	13.0
Adj R-Sq	703	666	706

Panel 2: Testing for pre-trends using AI measure from job postings data

	Δ Log Sales, 2000–2008	Δ Log Employment, 2000–2008	Δ Market Share, 2000–2008
	(1)	(2)	(3)
Δ Share AI Workers	-0.270	-0.345	-0.028
	(0.282)	(0.364)	(0.033)
NAICS2 FE	Y	Y	Y
Controls	Y	Y	Y
F Statistic	6.6	4.8	6.7
Adj R-Sq	758	724	762

Table A.9. Effect of AI Investments on Industry-level Employment and Sales Including Entry and Exit

This table reports the coefficients from industry-level regressions of the changes in total sales and employment for all firms in Compustat (including entrants and exits between 2010 and 2018) on contemporaneous changes in AI investments. Each observation is a 5-digit NAICS industry. The independent variable is the change in the share of AI workers from 2010 to 2018, standardized to mean zero and standard deviation of one. For the main independent variable, Panel 1 considers the resume-based measure of AI investments, while Panel 2 looks at the job-posting-based measure. Regressions are weighted by the total industry number of Cognism resumes in 2010 in Panel 1 and the total industry number of Burning Glass job postings in 2010 in Panel 2. Columns 1 to 4 are estimated by OLS, and in columns 5 to 8 the independent variable is instrumented by the contemporaneous growth in the share of AI workers in European firms in each industry. The dependent variables are changes in log total sales (columns 1, 2, 5 and 6) and log total employment (columns 3, 4, 7 and 8) at the industry level from 2010 to 2018. All specifications control for sector fixed effects. Regressions in columns 2, 4, 6 and 8 also control for log total employment and log total sales in 2010, as well as growth in log total sales and log total employment from 2000 to 2008.

Panel 1: AI measure from resume data

	OLS				IV			
	Δ Log Sales		Δ Log Employment		Δ Log Sales		Δ Log Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	0.109**	0.142***	0.104	0.134**	0.155***	0.181***	0.167*	0.203***
	(0.051)	(0.035)	(0.070)	(0.061)	(0.056)	(0.038)	(0.090)	(0.073)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
F Statistic					15.0	13.9	15.0	13.9
Obs	213	213	213	213	142	142	142	142

Panel 2: AI measure from job postings data

	OLS				IV			
	Δ Log Sales		Δ Log Employment		Δ Log Sales		Δ Log Employment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Share AI Workers	0.152***	0.119***	0.141	0.106	0.137*	0.180***	0.260**	0.321***
	(0.057)	(0.044)	(0.092)	(0.073)	(0.076)	(0.057)	(0.100)	(0.100)
NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
F Statistic					7.0	9.8	7.0	9.8
Obs	223	223	223	223	146	146	146	146

Table A.10. Effect of AI Investments on Productivity for Early Adopters

This table reports the coefficients from long-differences regressions of changes in firm productivity from 2010 to 2018 on the changes in AI investments by US public firms from 2010 to 2014. We consider two measures of productivity: log sales per worker and revenue TFP. Revenue TFP is the residual from regressing log revenue on log employment and log capital (constructed using perpetual inventory method), with separate regressions for each industry sector. The main independent variable is growth in the share of AI workers from 2010 to 2014. The share of AI workers is calculated based on resumes in Panel 1 and job postings in Panel 2. All independent variables are standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. All specifications control for sector fixed effects. Columns 2 and 4 also control for log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (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 6–digit NAICS industry level.

Panel 1: AI measure from resume data

	Δ Log Sales per Worker		Δ Revenue TFP	
	(1)	(2)	(3)	(4)
Δ Share AI Workers 2010-2014	-0.062	-0.034	-0.034	-0.011
	(0.060)	(0.055)	(0.053)	(0.054)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Sq	0.163	0.279	0.161	0.289
Obs	827	827	779	779

Panel 2: AI measure from job postings data

	Δ Log Sales per Worker		Δ Revenue TFP	
	(1)	(2)	(3)	(4)
Δ Share AI Workers 2010-2014	-0.062	-0.034	-0.034	-0.011
	(0.060)	(0.055)	(0.053)	(0.054)
NAICS2 FE	Y	Y	Y	Y
Controls	N	Y	N	Y
Adj R-Sq	0.163	0.279	0.161	0.289
Obs	827	827	779	779

Table A.11. Heterogeneous Effects by Initial Labor Productivity

This table reports the coefficients from long-differences regressions of changes in firm size and productivity from 2010 to 2018 on the contemporaneous changes in AI investments among US public firms, separately for each tercile of starting firm productivity (measured by sales per worker) in 2010. We consider three measures of firm size: log sales (columns 1 and 2), log employment (columns 3 and 4), and market share (columns 5 and 6). The independent variables are changes in the share of AI jobs interacted with indicator variables for productivity terciles in 2010. Panel 1 considers the resume-based measure of the growth in the share of AI jobs from 2010 to 2018, while Panel 2 looks at the job-posting-based measure. Both measures are standardized to mean zero and standard deviation of one. Regressions are weighted by the number of Cognism resumes in 2010 in Panel 1 and the number of Burning Glass job postings in 2010 in Panel 2. All specifications control for sector fixed effects and productivity tercile fixed effects. Regressions in even columns also control for log employment, cash/assets, log sales, log industry wages, as well as characteristics of the commuting zones where the firms are located in (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 6–digit NAICS industry level.

Panel 1: AI measure from resume data

	Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers*Productivity Tercile 1	0.023	0.011	0.096	0.092	-0.006	-0.009
	(0.076)	(0.102)	(0.095)	(0.113)	(0.016)	(0.019)
Δ Share AI Workers*Productivity Tercile 2	-0.249*	-0.153	-0.193	-0.145	-0.040***	-0.035***
	(0.148)	(0.109)	(0.118)	(0.099)	(0.011)	(0.013)
Δ Share AI Workers*Productivity Tercile 3	0.152**	0.155***	0.114	0.123**	0.017	0.018
	(0.075)	(0.053)	(0.073)	(0.058)	(0.016)	(0.012)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Productivity tercile FE	Y	Y	Y	Y	Y	Y
Adj R-Sq	0.188	0.393	0.132	0.280	0.252	0.319
Obs	827	827	827	827	827	827
T-test statistic	1.4	1.8	0.0	0.1	1.1	1.3
T-test p value	0.232	0.175	0.874	0.783	0.304	0.256

Panel 2: AI measure from job postings data

	Δ Log Sales		Δ Log Employment		Δ Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Share AI Workers*Productivity Tercile 1	0.115	0.115	-0.017	-0.303	0.018	0.018
	(0.276)	(0.219)	(0.474)	(0.299)	(0.023)	(0.024)
Δ Share AI Workers*Productivity Tercile 2	0.055	0.039	0.054	-0.006	-0.029**	-0.023*
	(0.074)	(0.073)	(0.070)	(0.079)	(0.014)	(0.014)
Δ Share AI Workers*Productivity Tercile 3	0.145**	0.113***	0.145*	0.103*	0.016	0.019**
	(0.060)	(0.043)	(0.075)	(0.058)	(0.011)	(0.010)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Productivity tercile FE	Y	Y	Y	Y	Y	Y
Adj R-Sq	0.209	0.400	0.313	0.423	0.194	0.280
Obs	909	909	909	909	909	909
T-test statistic	0.0	0.0	0.1	1.7	0.0	0.0
T-test p value	0.915	0.993	0.732	0.194	0.945	0.963