AI Adoption and Firm Performance: Management versus IT *

Preliminary.

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Abstract

We examine the impact of AI adoption on firm growth, productivity, and investment decisions and explore whether the impact on firm size and policies stems from AI adoption among management ranks or IT specialists. We measure the firm-level AI adoption using the demand for AI-related skills in online job postings. First, we document a positive association between the firm-level AI adoption and the firm's size, Capex, R&D, and total investments. We do not find robust relationships with productivity measures. Second, we find that the adoption of AI skills among managers drives the positive association with growth in sales and market capitalization, as well as with R&D and Capex. AI adoption among IT specialists does not show any robust association with firm outcomes.

Keywords: artificial intelligence; machine learning; productivity; technology adoption

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1 Introduction

The rise in Artificial Intelligence (AI) adoption has the potential to transform how firms operate and perform. Two main conjectures regarding the effect of AI on firms, as a technology that reduces the costs of predictions (Agrawal, Gans and Goldfarb, 2018), have been outlined in the literature. First, as a data-based technology, AI adoption is likely to benefit from the economies of scale resulting from a larger data available at larger or older firms; and therefore, firms adopting AI have strong incentives to grow. Second, AI's ability to improve forecasting can help firms to target customers better and to optimize costs; and thus, firms adopting AI can be expected to improve their productivity.

However, before reaping benefits from AI, the firm faces a challenge to identify the key areas in the organization where an improved prediction fuelled by AI will generate positive outcomes. Someone has to determine what problem AI will be solving, what data will be required to train the algorithm, what expertise is required to complement the AI, and how the algorithm's output will be used to make decisions. These are some of the essential questions for a successful AI implementation and they are usually addressed by employees with a management rank. However, the role of management in AI adoption and in ensuring the benefit of AI deployment for the firm performance has not yet been examined by the empirical literature.

Our goal in this paper is twofold. First we examine the impact of a firm-level AI adoption on three aspects of firm performance: growth, productivity, and investment decisions. In particular, we expect that AI adoption will facilitate firm growth and investments in order to benefit from the economies of scale (e.g., Brynjolfsson and McElheran, 2016). AI also offers opportunities for productivity growth: it can replace humans with cheaper and faster algorithms in some roles (Acemoglu and Restrepo, 2018) thus increasing processes' efficiency and reliability, it allows a better targeting of clients thus attracting more customers and allowing to set higher prices on products, and it also can increase the precision of forecasts and thus facilitate a better decision-making and costs optimization, such as the reduction in the cost of handling customer orders and in the inventory management costs. Therefore, we expect AI to improve firms' productivity in terms of sales per employee and TFP as well as to generate higher profit margins.

Second, we explore whether the impact on firm outcomes and policies stems from the AI adoption among management ranks or from the IT teams with AI expertise. In this, we build on the prior literature analysing the value of IT investments and their complementarity with organizational processes and skills (e.g., Brynjolfsson and Hitt, 1996; Bresnahan, Brynjolfsson and Hitt, 2002; Brynjolfsson, Hitt and Yang, 2002). In particular, we are interested in whether managers with AI knowledge is a necessary element for the impact of AI on the firm performance to materialize.

There are two main challenges we need to address to answer this broad question. The first one is to find an accurate measure of a firm-level AI adoption without knowing the specific technology used in the firm's production function. Our approach is to proxy the firm-level adoption of AI through the demand of AI-related skills in firms' job postings. Application of AI technology, in contrast with other types of information technologies, requires a high degree of customization to a particular firm's needs and data and therefore requires highly specialized human capital. Thus, focusing on skills and abilities demanded by firms may allow us to proxy for the level of AI technology adoption in the firm.

We track the firm-level demand for AI skills using online job vacancies database collected by Burning Glass Technologies (BGT) which contains nearly a universe of online job postings in the United States. Due to the detailed nature, BGT data allow us to follow the hiring of specialists with AI skills across various occupations within the firm. This is a unique feature that allows us estimate the demand for AI skills across organizational roles, such as in Management, IT, Business and Finance, and Sales jobs among others. The intensity of AI specialists hiring across firm occupations may provide insights about how AI is used in the organization and through which channels it may impact firms' growth and policies.

The second important challenge in the analysis of the AI impact on firm performance is on the causal estimation of the effect of AI adoption vis-à-vis other firm dynamics such as prior R&D and sales growth paths. As shown in Alekseeva et al. (2020), firms that are larger, that hold more cash in their balance sheet and have higher R&D investments are more likely to demand AI-related skills.

Our sample includes all listed Compustat firms that we were able to match with the BGT vacancies data in 2010-2018 period, but excluding firms from Information and Professional Services industry sectors which mostly produce and implement AI solutions for other firms. Thus, we are primarily interested in organizations that purchase AI solutions or produce them for own use. We first document that the average share of vacancies requiring AI skills in our sample is steadily rising over the whole observation period. 17% of firms in our sample demanded AI skills in their vacancies in 2010 and 45% - in 2018. The average percentage of vacancies demanding AI increased 4 times over the analysed period. When we observe the demand for AI skills across various occupations, we also see that AI skills are demanded beyond IT occupations - over 2010-2018 period, the proportion of firms that were hiring managers with AI skills increased from 4% to 22% of the sample and the average share of managers with AI skills increased by the factor of 20 over the observation period.

We first explore how overall firm-level AI adoption affects firm outcomes, mainly size, productivity, and investments. We start our regression analysis using a long differences specification since the timing between AI adoption and the firm outcome changes may be hard to pin down. We document a positive association between the changes in AI adoption and the firm's growth in terms of sales. Also, our long differences results show positive and strong associations with the changes in Capex and total investments. There is also a positive association with changes in sales per employee and EBITDA margin, but no association with the TFP. Panel regressions with firm and year fixed effects offer similar results on the association of AI adoption with size and investments, but no support of the association with sales per employee or profit margin.

Next, we build on prior literature that suggests that the benefits from IT investments cannot be realized without substantial investments in other organizational capabilities, such as organizational structure or skills (e.g., Bresnahan, Brynjolfsson and Hitt, 2002; Brynjolfsson, Hitt and Yang, 2002). In our case, the proliferation of AI skills among managers can allow them to make better choices about AI applications due to a better understanding of the AI's potential benefits and a possible decrease in the lags or adjustment costs of AI implementation, since managers can facilitate a necessary reorganization of the firm's activities.

We explore this hypothesis and find that when we account for AI adoption among management positions vis-à-vis IT specialists, the association between AI adoption and firm outcomes is mostly driven by the adoption of AI skills among managers. AI adoption among managers drives the association with size (both in terms of sales and market capitalization) and the association with investments(both in terms of R&D and Capex). It is worth noting that AI adoption among IT specialist is not robustly associated with any of the firm outcomes, while AI adoption among "other" occupations (i.e. mostly engineering, business and financial, science, and sales jobs) is positively associated with the increase in R&D. The results are consistent using both a long differences specification and a panel regression specification with firm and year fixed effects.

We aim to contribute to the research analysing the impact of IT and data analytics technologies on firm performance. This line of research suggests that technologies facilitating data-driven decision-making have a substantial effects on firm performance results (e.g., Brynjolfsson, Hitt and Kim, 2011; Tambe, 2014; Müller, Fay and vom Brocke, 2018; Wu, Hitt and Lou, 2020). The role of AI in driving firm outcomes has been much less explored, mostly due to the lack of data allowing to measure firm-level AI adoption. Our paper is related to a few recent empirical studies analysing the effect of AI on firm performance: Rock (2019) looking at the market value effect of AI labor, Alderucci and Zolas (2020) analysing the effect of AI-related patenting on firm productivity and growth, and a simultaneous to ours work of Babina et al. (2020) showing the effect of AI adoption on firm growth and industry concentration. With our skill-based measure of AI adoption, we provide a complementary evidence on the impact of AI on firm performance and investment decisions.

We also aim to contribute to the literature that highlights the role of organizational changes in the realization of gains from technological investments. It has long been recognized that IT investments generate higher productivity gains when accompanied by complementary organizational changes (e.g., Zammuto and O'Connor, 1992; Brynjolfsson and Hitt, 1996; Bresnahan, Brynjolfsson and Hitt, 2002; Brynjolfsson, Hitt and Yang, 2002). Prior literature have found several kinds of such organizational changes that drive the productivity premium: for example, incentive systems and analytics processes (Aral, Brynjolfsson and Wu, 2012), firm's ability to identify and respond to changes in external operating environment (Tambe, Hitt and Brynjolfsson, 2012).

The effect of specific technical skills adoption in various organizational roles, especially management roles, as a kind of such complementary organizational change is less explored, however. Literature provides evidence on the tight relationship between management practices and IT (Bloom, Sadun and Van Reenen, 2012) and management practices and firm performance (Bloom et al., 2013). But in contrast with these studies, we focus on the role of managers with the knowledge of AI technology rather than on the role of general management practices such as performance monitoring and incentives. Thus, our results may suggest the importance of managerial expertise in a specific technology for unleashing its potential. AI is expected to become a "general purpose technology" (Bresnahan and Trajtenberg, 1995), a class of technologies with applications across industries and functions that are key drivers of innovation and economic growth. Therefore, the exploration of mechanisms generating value from the adoption of AI is a question of relevance that can help firms accelerate the pace of their growth and reap all the benefits from this technology.

This paper proceeds as follows. Section 2 describes our data, measurements, and the procedures we use to estimate AI adoption through skills. It also shows which firms adopt AI more intensively overall and in specific occupations. Section 3 presents the results on the effect of AI adoption on firm size, productivity and investments both for the long differences and the panel specifications. Section 4 concludes.

2 Estimating AI Adoption through skills

2.1 Data

In this paper, we propose a skilled-based definition of AI using the data from Burning Glass Technologies' (BGT) job postings as a proxy for AI adoption. BGT is one of the leading vendors of labor market data. BGT constantly track more than 3 million unique and active vacancies by scanning over 40,000 different online sources, including job boards and corporate websites. The BGT dataset contains details on almost 200 million vacancies in the United States from January 2010 to July 2019, offering a great granularity of skill description within each job posting.

BGT job postings data includes details such as job title, name and industry of the employer, job location, and wage offered. It also offers details on the profile of the desired job candidates, such as education and work experience, but most importantly, it includes a list of skills required from a potential employee. This level of granularity provided on each individual job vacancy represents one of the main strengths of the BGT data, allowing for a thorough examination of skill requirements in a specific job or occupation as well as for conducting a firm-level analysis of skill demand (e.g., Hershbein and Kahn, 2018). Importantly, the BGT data allow us to track the demand for AI skills across occupations such as Management, Business and Financial, and others, as presented in Alekseeva et al. (2020).

The fact that BGT compiles its data from a broad number of different sources provides a clear advantage over other data vendors such as CareerBuilder.com, where the data is gathered from one unique source. It is worth mentioning that BGT data covers only online job vacancies, which may raise the question of how good a representation of the overall labour market it might be. Still, we have seen an increasing trend in job vacancies appearing online rather than in traditional sources, with between 60% and 70% of all jobs being posted online, according to a study by Carnevale, Jayasundera and Repnikov (2014) which conducted a comprehensive analysis of the BGT data accuracy and representativeness compared to the overall job market. The report concludes that BGT online job ads correlate strongly with the job openings data in JOLTS and provides a detailed employment demand in a timely manner. The authors warn though that BGT may over-represent job openings for college graduates and for industries that demand high-skilled workers. As well, based on the analysis by Hershbein and Kahn (2018), the aggregate and industry trends of the number of vacancies in the BGT data are consistent with other sources of job vacancies data, in particular CPS, OES and JOLTS. Indeed, we should be cautious about interpreting results in occupations and industries employing less skilled workers, since the BGT data can under-represent such vacancies. Finally, BGT data is based on job postings and, therefore, may not represent the exact profile of the actual employment. In a recent paper, Babina et al. (2020) explore the similarity between the demand for AI-skilled employees in BGT vacancies and the actual employment of workers with AI skills based on the resume data from Cognism. They find that the two measures of the AI hiring intensity - based on BGT and based on Cognism - have a strong correlation and generate qualitatively similar results in the analysis of the AI impact on firm performance. Overall, given the detailed information and dynamic nature of the online job postings data, it provides a unique source of information which allows us to trace the demand for AI talent across firms and occupations.

2.2 Estimating AI Adoption

Estimating a firm-level AI adoption is a hard endeavor. How can we grasp weather firms are adopting AI without knowing much about their underlying production processes nor the specific technology in use? AI technology, in contrast with other type of technologies, requires highly-specialized human capital (e.g., Tambe (2014) discusses the importance of highly skilled labor to extract value from big data technologies). Therefore, focusing on the demand for employees' skills and abilities may allow us to proxy for the level of AI technology adoption within the firm. That is, we propose a skilled-based measure of AI adoption at the firm level[1].

To identify skills required in each job vacancy, BGT uses the natural-language processing technology to read each job description[2]. In particular, for AI-related skills, BGT identifies words and phrases commonly associated with the knowledge of AI. The most clear candidates are "artificial intelligence","machine learning", "machine vision", "deep learning", "image processing", "speech recognition", as well AI skills related to AI-specific software and systems such as "IBM Watson", and programming libraries, such as "TensorFlow", "Pybrain", and "ND4J". This bag of words approach allows us to define AI skills in the most straightforward manner. Indeed, AI skills are highly correlated with other software skills (Alekseeva et al., 2020). However, if the job posting does not specify a skill directly linked to AI technology, it is not labeled as an AI posting in our approach. This may entail that our measure is relatively conservative and may represent a lower bound in AI adoption. Using this approach, we are in line with Goldfarb, Taska and Teodoridis (2019) who use a bag-of-words approach to measure several general-purpose technologies adoption. They argue that this approach allows to capture early technology diffusion because firms are likely to be specific about the needed technology skills in their job postings. Appendix Table A1 provides a complete list of skills that we use to identify vacancies demanding AI[3].

We build our main measure of AI adoption in firm i and time t as the ratio of job postings requesting AI skills over the total number of job postings:

$$\text{AI Share}_{it} = \frac{\text{Number of Job Postings requesting AI skills}_{it}}{\text{Total Number of Job Postings}_{it}} \tag{1}$$

In a similar manner, we calculate AI Share within management, computer and mathematical (IT), and "other" occupations as a ratio of job postings requesting AI skills in management occupations (2-digit SOC code 11), IT occupations (2-digit SOC code 15), or the rest of occupations (2-digit SOC code not equal to 11 or 15) over the total number of management, IT, or "other" job postings respectively. To

[1]The number of IT workers as a measure of the firm's IT investments has been widely used in the literature (e.g., Tambe and Hitt, 2012; Tambe, Hitt and Brynjolfsson, 2012; Tambe et al., 2019)

[2]BGT's skill taxonomy development process is described in Burning Glass Technologies (2019)

[3]In the construction of our measure of AI adoption we differ from a recent study by Babina et al. (2020), which is also based on the BGT data, in that our measure can be considered more conservative since it is based only on skills directly associated with AI and does not include skills that may go hand-in-hand with AI but be primarily used for tasks not involving the specific AI application. However, our measure can also be considered less flexible when skills previously not associated with AI start being used for AI purposes.

clarify, positions in Management occupation primarily require coordinating the work of others, supervising, directing, developing people, and performing other work activities related to the "management" of employees or processes. IT jobs in turn are primarily focused on performing analysis, design, coding, monitoring of processes and less frequently on supervising or coaching other employees [4]. "Other" occupations in our sample primarily consist of vacancies in Architecture and Engineering (2-digit SOC 17), Business and Financial Operations (2-digit SOC 13), Life, Physical, and Social Science (2-digit SOC 19), and Sales (2-digit SOC 41) occupations.

Our sample consists of all job vacancies excluding internships from January 2010 until July 2019 which encompasses a total of approximately 190.2 million vacancies. Figure A1 in Appendix shows the evolution of the demand for AI skills in the overall BGT data. We match our vacancies data to Compustat based on the employer's name. BGT provided an initial linking table which we have extended by manually verifying name matches not included in the initial link due to an imprecise name match. In particular, we checked all name matches to which the algorithm assigned the likelihood of a correct name match above 50% and all BGT names that matched with the firm's website URL provided in Compustat[5]. From the main analysis we exclude firms that come from industries producing or implementing AI solutions for other firms (2-digit NAICS equal 51 and 54) as in Acemoglu et al. (2020). We drop observations with missing or negative Total Assets and Sales resulting in 1,302 unique Compustat's GVKEYs included in the long differences analysis which requires that the firm exists in the beginning and in the end of the observation period and 4,868 unique GVKEYs in the panel data analysis that does not impose restrictions on the period that firm has to be present in the sample.

Panel A of Table 1 shows financial and operational characteristics of the firms in the BGT-Compustat-matched sample for the long differences sample. All monetary variables in Compustat are adjusted for inflation and ratios are winzorised at 1 and 99 percent levels. Panel B of Table 1 shows the number of observations per year and the proportion of firms requesting AI skills in their vacancies. On average, 17% of firms demanded some level of AI-related skills at the beginning of the sample period, while 45% of firms demanded AI in 2018. When we focus on firms that demanded AI among their management po-

[4]Descriptions of jobs in various occupations on O*NET website: https://www.onetonline.org/find/. We use 2010 Standard Occupational Classification.

[5]For example, we are able to add cases when Compustat uses a full name and BGT uses an abbreviation of this name, when a firm changed its name but kept the website address, or when in vacancies' text a firm uses its "brand name" instead of a legal name as in Compustat.

sitions, we observe that the percentage of such firms increased from a mere 4% to 22%. Figure 1 displays the share of vacancies demanding AI skills over time. Panel A shows how AI share for Management positions grows steadily through the time series, but in 2016 it takes off and mimics the overall AI Share growth. Panel B displays AI Share for Management positions relative to IT positions. The intensity of AI skills demand among IT specialists is significantly larger than for Management positions.

2.3 Firm Characteristics and AI Adoption

AI skills are increasingly demanded across a wide array of occupations and industries, it is becoming a sought after skill beyond Computer occupations or Information industry sector. However, the intensity of the demand for AI seems to vary substantially across firms. Given the fast-growing pace of AI skills demand across occupations and industries, we want to understand what type of firms are demanding AI skills.

We explore the relationship between AI Share and firm characteristics using the following specification:

$$\text{AI Share}_{i,t+1} = \beta_1 \text{Firm Char}_{i,t} + \gamma_s + \zeta_t + \varepsilon_{i,t}, \tag{2}$$

where AI Share is the percentage of job posting demanding AI skills over the total number of job postings in year $t+1$, as defined in equation (1), Firm $\text{Char}_{i,t}$ is the vector of Compustat-based financial and operational characteristics of firm i in year t and U.S. Census-based characteristics of the firm i's location (constant as at 2010), γ_s and ζ_t are 2-digit NAICS industry and year fixed effects, and $\epsilon_{i,t}$ is an error term. We also run the same specification for AI Share of management, IT, and other jobs as the dependent variables.

Table 2 shows the results of the regression analysis weighted by firm employment, with overall firm-level AI Share as the dependent variable. All independent variables in the regression are lagged by one year, except for the commuting zone's (CZ) population density, percent of population with a college degree, and log average wages which are measured as of 2010. Column (1) is the log market capitalization, column (2) the log of employment, column (3) the log sales, column (4) the market-to-book ratio, column (5) the return on assets, column (6) the cash holdings ratio, column (7) the book leverage, column (8) the R&D expenses over sales, column (9) the capital expenditures over assets, column (10) the PP&E over assets, column (11) the log of total vacancies, column (12) the log of population density in the CZ of firm location, column (13) the percent of population with a college degree in the CZ, and column (14) log average wages in the CZ[6]. Columns (15) and (16) present the multivariate specifications.

The results show that, in the cross section, there is a positive association between firms' market capitalization, employment, sales, liquidity, R&D expenditures over sales, and total vacancies and the firm-level demand for AI skills. There is also a negative association with PP&E over assets and AI Share. These results are in line with Alekseeva et al. (2020) who show that larger firms with higher liquidity and R&D intensity are more likely to demand AI skills and with Babina et al. (2020) who show that AI adoption is positively related to the initial firm's sales, cash holdings ratio, and R&D intensity. The log of market capitalization is highly significant both in the individual and multivariate specifications. However, when controlling for other characteristics in a multivariate specification, the significance of the liquidity ratio coefficient becomes weaker and the coefficient of the R&D intensity loses its significance. AI adoption is also positively correlated with the location characteristics: percent of college graduates and log average wage in the CZ of the firm location have a positive association with AI Share both, when included separately and jointly with other characteristics; at the same time, density is positively correlated when included separately, but reverses the sign in a multivariate specification in column (16). Overall, Table 2 gives some evidence that larger firms, firms that have higher liquidity and higher R&D investments but lower fixed capital ratio, and that are located in areas characterised by a higher concentration of a valuable human capital tend to demand more AI skills. For example, a one standard deviation increase in the logarithm of market capitalization is associated with a 0.33 percentage points increase in the AI share of vacancies, or nearly a 100 percent increase in the sample mean of AI Share (based on the summary statistics for an unbalanced sample, not reported).

Table 3 shows the regression results for the AI adoption in management. As for the overall AI Share, the intensity of the demand for AI skills in management jobs is predicted by the firm's size measured by all, the log market capitalization in column (1), the log employment in column (2), and the log sales in column (3), log total vacancies in column (11). AI Share of management jobs, however, has only a weak positive association with liquidity and R&D over sales. Again, similar to the overall AI Share, it has a strong positive association with the location characteristics (columns (12)-(14)). In a multivariate specification in column (16), after including various characteristics together, AI Share of managers only

[6] If the firm posts vacancies in several CZ, we calculate weighted averages of the CZ's characteristics using shares of the firm's vacancies in each CZ as weights.

preserves its positive association with log market capitalization, log total vacancies, and log average CZ wages; log population density switches the sign after controlling for other variables. Therefore, larger firms located in areas with higher average salaries, but lower density are more likely to search for managers with AI skills. In contrast with the results for the overall AI Share, AI Share (Management) is not significantly associated with other financial characteristics of the firm in a multivariate setting. Controlling for the AI Share in IT and other jobs (column (17)) does not affect the results.

Table 4 shows the results for the regressions with AI Share of IT jobs as the dependent variable. The most interesting result is that this measure of AI adoption is not associated with any financial characteristics besides size when the characteristics are included one-by-one. However, it does positively correlate with the location characteristics. In a multivariate specification in column (16), however, cash holdings ratio and leverage become weakly statistically significant, while ROA gets a negative weak association. Location characteristics cease to have a significant association. Statistical significance of ROA and leverage disappears if we also control for the AI Share of managers and other occupations (column (17)), but the positive coefficient of PP&E over assets becomes weakly significant. Overall, firms with larger market capitalization and cash holdings are expected to have a higher AI Share of IT specialists; at the same time, other financial and location characteristics do not robustly predict the adoption of AI among IT.

Finally, Table 5 shows the analysis of predictors of AI adoption in other occupations. This AI Share has a strong positive association with all size variables and also with liquidity and R&D over sales. In contrast with the results for AI Share of managers and IT, which do not show a robust statistically significant association with PP&E over assets, AI Share of other jobs is negatively correlated with PP&E over assets, the significance of the coefficient is robust across specifications. Again, location characteristics have a positive significant association when included one-by-one. Multivariate specification (column (16)) shows that log market capitalization, liquidity, and the percentage of college graduates in the firm location have a strong positive association, while PP&E over assets still shows a significant negative association. Thus, AI adoption among other employees (mostly represented by engineers, scientists, sales, business and financial) are strongly predicted by the firm's size, liquidity, fixed capital intensity, and the education level of human capital in the area. Interestingly, when we control for the AI share of managers and IT, only liquidity and fixed capital ratio remain as significant predictors of AI adoption among "other" jobs, and R&D over sales becomes weakly significant.

Overall, this analysis shows that, although AI adoption in all three considered occupation groups is predicted by the firm's size, there are unique predictors for AI adoption in various roles (based on the multivariate specification in column (16)). First, firms located in areas with higher average salaries, but lower density, are more likely to search for managers with AI skills. Second, location characteristics do not predict the adoption of AI skills among IT and AI Share (IT) has only weak associations with financial characteristics (ROA, liquidity, and leverage). Third, AI adoption among "other" jobs is higher in firms with a higher liquidity but a lower fixed capital intensity and among firms located in areas with a higher education level.

3 AI Adoption and Firm Size, Productivity and Investments

How does the adoption of AI technology affect firm outcomes? We start examining this question using a long differences specification since the adoption of AI may have some timing effects that are hard to pin down ex-ante. We want to explore if corporations that increased their AI share through time experienced as well changes in other major corporate outcomes such as size and productivity on the one hand, and investments in R&D, Capex, and acquisitions on the other.

We analyse the change in firm outcomes using the following long differences specification:

$$\Delta \text{Outcome}_{i,[t,t+d]} = \beta \cdot \Delta \text{AI Share}_{i,[t,t+d]} + \gamma_1 \cdot \Delta \text{Firm Char}_{i,[t,t+d]} + \gamma_2 \cdot \text{X}_{i,[t]} + \delta_s + \varepsilon_i. \tag{3}$$

$\Delta \text{Outcome}_{i,[t,t+d]}$ is the change in the outcome variable measured as a difference between the average value in 2017-2018 and the average value in 2010-2011, $\Delta \text{AI Share}_{i,[t,t+d]}$ is the change in the firm-level AI Share and $\Delta \text{Firm Char}_{i,[t,t+d]}$ is the change in financial and operational controls over the same period. $\text{X}_{i,[t]}$ is a vector of initial conditions for firm characteristics, δ_s denotes 2-digit industry fixed effects. We use averages in the beginning and in the end of the observation period to minimize the effect of year-to-year fluctuations.

The long differences specification has a few strengths as an initial analysis. First, it helps to avoid a problem of unobserved firms' heterogeneity driving the results (Caroli and Van Reenen, 2001). Second, it allows for substantial lags between AI adoption and the corresponding change in the outcome variables. Adopting AI may not deliver immediate results in some cases. Does it take one, two or three years from an investment in AI to display any correlation with the growth in sales, employment, or market capitalization? In some instances the impact may be immediate: for example the local newspaper in Barcelona, La Vanguardia, adopted AI technology to better estimate the number of newspapers per stand and minimize obsolete unread newspapers that increase costs. The impact was immediate, within a quarter they were able to improve operations, mostly reducing costs and improving margins. Sales increased as well now that they could service each newspaper stand better. In contrast, another local firm, FC Barcelona (aka Barça), as well adopted AI to better predict the demand for each soccer game. However, in this case the implementation of an AI-driven demand model required additional operational adjustments such as the creation of a centralized secondary market of tickets between the club members and outsiders looking for a ticket. The Barça example shows that AI implementation in many instances may force a material reorganization of operations and the revision of the legal framework that not only takes time but, most importantly, requires the leadership of the top management.

3.1 Firm Growth and Investment decisions

Table 6 presents the result of the cross-sectional long differences regressions. In Panel A, we analyze the effects of the change in the firm-level AI share over outcome variables related to firm growth, particularly the change in the log of employment in column (1), the change in log of sales in column (2), the change in log of market capitalization in column (3). As well, we present the changes in productivity measures, such as the log of Sales per worker in column (4), the change in the log of TFP estimated based on a two-factor translog Cobb-Douglas production function in column (5) and the change in the ratio of EBITDA over sales in column (6). The leading independent variable is the change in AI Share from 2010-2011 to 2017-2018, showing the change in the intensity of the firm's demand for AI skills over the period.

Control variables include the change in Software Share (the share of vacancies requesting specialised software skills), the change in the log of employment, the change in the log of assets, the change in cash-to-assets, the change in R&D-to-sales[7], the change in PP&E over assets, the change in log of total vacancies[8]. Controlling for changes in firm characteristics allows to avoid attributing the changes in

[7]We replace missing R&D data in Compustat with zero and include a dummy for the missing R&D data.

[8]We exclude Δlog employment as a control from column (1) and column (4) of Panel A and exclude ΔR&D-to-sales as a

outcomes occurring due to firm transformations not related to AI (e.g., due to the increase in software and data intensity of the firm, M&A activity, the intensification of R&D) to the change in AI Share. However, we also include in Appendix some results where we exclude controls in changes to check the robustness of the results. We also control for several initial firm characteristics (log total assets, R&D-to-sales ratio, cash-to-assets ratio, PP&E-to-assets ratio) and the characteristics of the firm location (log population density, share of college graduates, log average CZ wage, share of employment in finance sector, share of employment in manufacturing sector, share of female workers, share of workers of color, share of workers in computer and mathematical occupations) and industry (log average 3-digit NAICS industry wage) as of 2010 to account for differences in the growth rates stemming from the initial firm heterogeneity.

The results in Panel A show that there is a positive association between the change in AI Share and changes in firms' size in terms of sales. As well, we observe a positive association with the changes in sales per employee and EBITDA margin.

Panel B focuses on outcome variables related to investment, where column (1) is the change in the log of R&D expenses, column (2) the change in log of capital expenditures, column (3) the change in log of total investment (includes R&D, Capex, and acquisition expenses), column (4) the change in R&D over sales, column (5) the change in capital expenditures over assets, and column (6) the change in total investments over assets. The main independent variable is again the change in AI Share, and control variables are the same as in Panel A. Results show that there is a positive and highly significant association between the change in AI Share and the changes in the firm's investments in Capex and total investments that include acquisition expenses along with Capex and R&D. The association is still positive, but insignificant, for the change in R&D alone.

3.2 AI Adoption and Firm Outcomes: Management vs IT Specialists

Next we explore whether this positive association between an increase in AI Share and size and productivity are driven by specific occupations within the firm. Is it the case that the results are driven by teams of IT specialists or is it driven by managers that have a better understanding of AI? Organizational changes literature suggests that productivity increases from IT investments cannot realize without

control from columns (1), (3), (4), and (6) of Panel B since these variables are included in the calculation of the corresponding dependent variables.

the corresponding investments in other organizational capabilities, such as organizational structure or skills (e.g., Brynjolfsson and Hitt, 1996; Bresnahan, Brynjolfsson and Hitt, 2002). Demand for AI skills in management jobs might reflect such organizational transformations of firms.

The following specification considers the share of AI-related postings that correspond to management positions: that is, management positions that require AI over total management positions.

$$\Delta \text{Outcome}_{i,[t,t+d]} = \beta_1 \Delta \text{AI Share(Management)}_{i,[t,t+d]} + \beta_2 \Delta \text{Firm Char}_{i,[t,t+d]} + \delta_s + \varepsilon_i. \tag{4}$$

Both Panels of Table 7 display that changes in AI Share of managers are strongly correlated with the firm growth and investments. Using the same control variables as in Table 6, we observe that firms that increase AI Share of managers see increases in sales, market capitalization, and sales per worker. In panel B as well we observe that change in AI Share of managers is associated with the increase in investments in R&D and Capex.

Our next step is to include the changes in AI Share for IT positions and the remaining types of occupations (i.e., Sales, Business and Finance, Engineers, and Scientists) in the regression. Table 8 follows the same specifications as in Tables 6 and 7, but this time we consider not only the share of postings related to management that require AI but also the share of AI related to IT positions and the remaining occupations, which we categorize as "Other". Once again, Panel A analyses outcome variables related to growth while Panel B points to outcome variables in terms of firm investment. Interestingly, the change in AI Share in management jobs is highly significant to explain growth in terms of market capitalization and slightly less strong with respect to growth of sales. Changes in AI share for IT positions are not significant to explain changes in size nor, to our surprise, productivity.

Panel B shows a positive association as well between the change in AI Share of managers and the firm's investment decisions being significant at the 10% level to explain the changes in the log of R&D and the log of CAPEX. It is worth noting the relevance of AI Share (Other) for R&D investments which is capturing the effect from Engineering positions (untabulated results). Somehow surprisingly, the change in AI Share of IT jobs has a negative association with the change in log R&D expenses, but it is related positively to the change in the ratio of total investments over assets.

So overall, our results point to the relevance of incorporating AI skills among management positions to deliver size effects.

3.3 AI Adoption and Firm Outcomes: A Panel Data View

So far we have established a correlation between changes in AI adoption and changes in outcome variables. This long difference approach requires that firms are present both in 2010-2011 and in 2017-2018 and restricts our sample substantially to a subset of firms. We now proceed to examine a similar specification but now in levels, which increases the sample of unique firms nearly fourfold - from 1,302 to 4,868 firms. Our panel specification includes firm and year fixed effects and the main independent variable is the level of AI Share instead of the change in AI Share.

Panel A in Table 9 shows that AI Share is again positively associated with firm size in terms of sales and market capitalization. Panel B shows as well a strong association with the levels of R&D and total investments; the association with the level of Capex is weaker (at 10%) but the association with Capex over assets is rather strong (5%).

Table 10 parallels Table 7 but presents the results of the specification in levels and considers the share of management positions that require AI over the total management positions opened. Panel A shows that the AI share (Management) is strongly correlated to firm growth as measured by the log of market capitalization. AI Share (Management) is also significant at the 5% level when we measure growth by employment (was insignificant in long differences specification). Regarding the firm's investment, as seen in Panel B, AI Share (Management) appear to explain a firm's investment decisions in terms of R&D, Capex, total investments and CAPEX/Assets.

Finally, we explore the role of AI Share across different occupations: AI Share (Management), AI Share (IT), and AI Share (Other). Once more, AI Share (IT) proved to be not significant in most specifications, as seen in Table 11 Panel A and Panel B, which was not what we expected ex-ante. AI Share (IT) only has a negative association, although significant at the 10% level, with employment, suggesting a labor substitution effect. Panel A shows that, instead, AI Share in management is highly significant to explain market capitalization, as was seen in the long differences specification of Table 8. AI share (Management) has a significant, but at the 5% level, association with the log of employment. When we look at the firm's investments, Panel B shows a positive association between the level of AI Share (Management) and the levels of R&D, CAPEX, and total investments, as well as with Capex over assets (all at a 5% level).

4 Conclusion

Given the increasing importance of artificial intelligence (AI) for economic activity and the lack of knowledge about its effects, we have examined the adoption of AI by looking at the demand for AI-related skills at the firm level. We measure this demand through online job postings provided by Burning Glass Technologies (BGT), whose database consists nearly of the universe of online job postings in the United States. Specifically, we explore the impact of AI adoption on firm growth, productivity and investment decisions.

First, we used a long differences specification to be able to analyse the effect of an increased AI Share through time. We observed a positive association between the growth in AI adoption and the changes in size in terms of sales, as well as with some productivity measures and investments.

Next, we explored the question of whether any specific occupation within the firm were driving these positive associations between AI Share changes and firm outcomes. Particularly, we asked ourselves whether results were driven by IT specialists acquiring more AI skills or by management positions with AI knowledge. Although a large proportion of the demand for AI skills is focused in information technology professionals, we find that the growth in the demand for AI skills among management positions is driving the positive associations we found. Our results are consistent both using a long differences specification and a panel regression specification with firm and year fixed effects.

Overall, our findings suggest a general positive association between the adoption of AI at the firm level and changes in firms size and investments. These associations are mostly driven by the adoption of AI skills among managers rather than among IT specialists.

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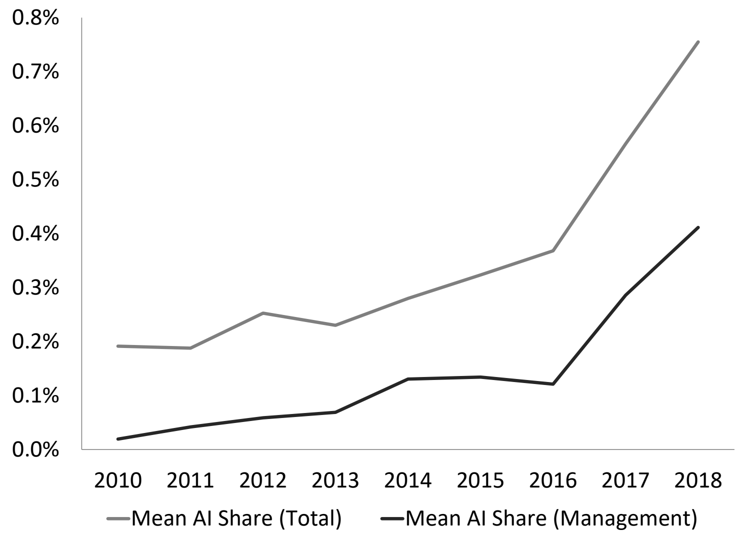
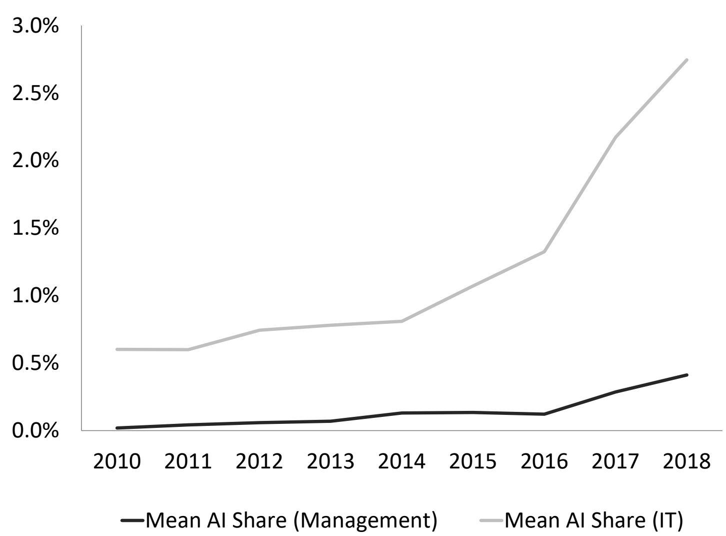


(a) Overall AI Share and AI Share within Management occupation over time.



(b) AI Share within Management and Computer and Mathematical (IT) occupations over time.

Figure 1. Share of vacancies demanding AI skills over time, overall and within occupations. The figure shows the average percentage of overall firms' vacancies requiring AI skills, and the average percentage of firms' vacancies in Management and Computer and Mathematical (IT) occupations requiring AI skills.

Table 1. Summary statistics.

(a) Panel A: Sample characteristics.

Sample only includes firms that have Compustat and BGT data available in 2010, 2011, 2017, and 2018. Here and further in the analysis, ratios are winsorized at 1% and 99% and all monetary variables are deflated by the CPI and log-transformed.

Variable	Obs.	Mean	Std.	Min	Max
BGT-based Characteristics:					
AI Share	11,531	0.35%	1.19%	0%	13.19%
AI Share (Management)	10,599	0.15%	0.73%	0%	8.51%
AI Share (IT)	9,900	1.24%	3.57%	0%	30.00%
AI Share (Other)	11,398	0.17%	0.68%	0%	7.27%
Software Share	11,531	28.96%	22.38%	0%	100.00%
Log(Vacancies)	11,531	5.270	2.272	0	12.000
Compustat-based Characteristics:					
Log(Employment)	11,531	1.514	1.872	-4.510	7.741
Log(Sales)	11,527	7.415	1.928	-3.335	13.076
Log(MCap)	11,372	7.714	1.914	-0.496	13.812
Log(Assets)	11,531	7.969	2.047	1.611	14.880
Log(Sales/Worker)	11,527	5.908	0.923	-1.950	11.333
Log(TFP)	10,134	0.055	0.448	-9.140	3.777
EBITDA/Sales	11,202	0.151	0.341	-3.328	0.678
Log(R&D)	11,531	1.744	2.438	-4.091	10.195
R&D/Sales	11,531	0.058	0.207	0	2.395
Log(CAPEX)	11,061	4.069	2.335	-5.036	10.546
CAPEX/Assets	11,489	0.041	0.044	0	0.299
Log(Tot Inv)	10,963	4.854	2.221	-4.723	11.149
Tot Inv/Assets	11,489	0.092	0.098	-0.010	0.552
Cash/Assets	11,531	0.144	0.160	0.000	0.802
PPE/Assets	10,167	0.544	0.409	0.005	2.065
ROA	11,206	0.103	0.115	-0.551	0.419
Book Leverage	11,484	0.240	0.203	0	1.118
Tobin's Q	11,275	1.837	1.242	0.617	9.049
Non-transformed Firm Characteristics:					
Total Vacancies	11,531	1,698	5,862	1	162,817
Sales	11,531	9,067	27,152	0	496,785
Employment	11,531	24	81	0	2,300
Total Assets	11,531	31,769	170,392	5	2,807,491
Market Capitalization	11,372	12,028	35,613	1	1,073,391
Sales/Worker	11,531	626	1,666	0	83,515

(b) Panel B: Number of observations per year and percentage of firms demanding AI skills in their vacancies.

Sample only includes firms that have Compustat and BGT data available in 2010, 2011, 2017, and 2018. Column (1) shows the total number of observations per year, columns (2) and (3) show the number and the percentage of observations in which the firm posted at least one vacancy demanding AI skills, columns (4) and (5) show the number and the percentage of observations in which the firm posted at least one vacancy demanding AI skills in Management occupation (SOC 11), columns (6) and (7) show the number and the percentage of observations in which the firm posted at least one vacancy demanding AI skills in Computer and Mathematical occupation (SOC 15), columns (8) and (9) show the number and the percentage of observations in which the firm posted at least one vacancy demanding AI skills in all other occupations (jobs in SOC not equal 11 or 15).

		Firms with AI >0		Firms with Mgt AI >0		Firms with IT AI >0		Firms with Other AI >0	
Year	Total N obs	N obs	%	N obs	%	N obs	%	N obs	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2010	1,302	217	17%	53	4%	151	12%	144	11%
2011	1,302	258	20%	85	7%	179	14%	174	13%
2012	1,253	281	22%	90	7%	189	15%	201	16%
2013	1,273	311	24%	91	7%	224	18%	195	15%
2014	1,266	355	28%	120	9%	253	20%	253	20%
2015	1,265	364	29%	131	10%	284	22%	238	19%
2016	1,266	398	31%	138	11%	326	26%	256	20%
2017	1,302	502	39%	178	14%	403	31%	324	25%
2018	1,302	592	45%	283	22%	490	38%	395	30%
Total	11,531	3,278	28%	1,169	10%	2,499	22%	2,180	19%

Table 2. Which Firms Adopt AI? AI Adoption and Firm Characteristics - Regressions Weighted by Employment.

Sample includes firms that have Compustat and BGT data available. Independent variables: column (1) is the log market capitalization, column (2) the log of employment, column (3) the log sales, column (4) the market-to-book ratio, column (5) the return on assets, column (6) the cash holdings to assets ratio, column (7) the book leverage, column (8) the R&D expenses over sales, column (9) the capital expenditures over assets, column (10) the PP&E over assets, column (11) the log of total vacancies, column (12) the log of population density, column (13) is the percentage of population with college degree, and column (14) is the log of average wages in the commuting zone (CZ) of the firm's location as of 2010 (if the firm posts vacancies in several commuting zones, we calculate weighted averages of the commuting zone characteristics using shares of the firm's vacancies in each commuting zone as weights). Columns (15) and (16) present the multivariate specifications. Independent variables are lagged by one period, except for commuting zone characteristics measured as at 2010. Standard errors in parentheses are clustered by Firm. Significance levels are denoted as: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	Dependent Variable: AI $Share_{t+1}$															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$Log(MCap)_t$	0.00158***														0.00166***	0.00151***
	(0.000430)														(0.000495)	(0.000433)
$Log(Employment)_t$		0.000705**														
		(0.000290)														
$Log(Sales)_t$			0.00116***													
			(0.000288)													
Tobin's Q_t				0.00234												
				(0.00164)												
ROA_t					0.000521										-0.0131	-0.0128
					(0.00689)										(0.0102)	(0.0105)
$Cash/Assets_t$						0.0261**									0.0286**	0.0211*
						(0.0123)									(0.0128)	(0.0116)
Book $Leverage_t$							0.000426								0.00443	0.00575*
							(0.00199)								(0.00292)	(0.00326)
$R\&D/Sales_t$								0.00137**							4.48e-05	0.000556
								(0.000690)							(0.000347)	(0.000638)
$CAPEX/Assets_t$									0.0138						0.0487	0.0540
									(0.0183)						(0.0337)	(0.0361)
$PPE/Assets_t$										-0.00462**					-0.00396	-0.00426
										(0.00225)					(0.00242)	(0.00274)
$Log(Vacancies)_t$											0.000647***				0.000205	1.58e-05
											(0.000139)				(0.000137)	(0.000184)
$Log(PDensity)_{2010}$												0.00157***				-0.00361***
												(0.000460)				(0.00135)
College $Share_{2010}$													0.0766***			0.0410**
													(0.0230)			(0.0183)
$Log(CZ Wage)_{2010}$														0.0299***		0.0264**
														(0.00904)		(0.0104)
Observations	17,717	18,295	18,028	17,561	17,682	18,295	18,212	18,295	18,243	16,064	18,295	15,411	15,411	15,411	15,377	13,052
R-squared	0.183	0.148	0.162	0.174	0.138	0.179	0.142	0.146	0.143	0.151	0.158	0.157	0.201	0.208	0.241	0.294
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 3. AI Adoption in Management Occupations and Firm Characteristics - Regressions Weighted by Employment.

Sample includes firms that have Compustat and BGT data available. Independent variables: column (1) is the log market capitalization, column (2) the log of employment, column (3) the log sales, column (4) the market-to-book ratio, column (5) the return on assets, column (6) the cash holdings to assets ratio, column (7) the book leverage, column (8) the R&D expenses over sales, column (9) the capital expenditures over assets, column (10) the PP&E over assets, column (11) the log of total vacancies, column (12) the log of population density, column (13) is the percentage of population with college degree, and column (14) is the log of average wages in the commuting zone (CZ) of the firm's location as of 2010 (if the firm posts vacancies in several commuting zones, we calculate weighted averages of the commuting zone characteristics using shares of the firm's vacancies in each commuting zone as weights). Columns (15), (16), and (17) present the multivariate specifications. Independent variables are lagged by one period, except for commuting zone characteristics measured as at 2010. Standard errors in parentheses are clustered by Firm. Significance levels are denoted as: *** p<0.01, ** p<0.05, * p<0.1.

	Dependent Variable: AI Share (Management)$_{t+1}$																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Log(MCap)$_t$	0.00120*** (0.000248)														0.00112*** (0.000283)	0.000993*** (0.000250)	0.000463*** (0.000140)
Log(Employment)$_t$		0.000808*** (0.000187)															
Log(Sales)$_t$			0.00102*** (0.000165)														
Tobin's Q$_t$				0.00121 (0.000955)													
ROA$_t$					-0.000162 (0.00423)										-0.00903 (0.00599)	-0.00851 (0.00592)	-0.00532 (0.00357)
Cash/Assets$_t$						0.0123* (0.00720)									0.0134* (0.00745)	0.00800 (0.00681)	0.00278 (0.00419)
Book Leverage$_t$							0.000289 (0.00110)								0.00195 (0.00163)	0.00261 (0.00170)	0.000761 (0.00124)
R&D/Sales$_t$								0.000704* (0.000413)							6.02e-05 (0.000221)	0.000302 (0.000432)	0.000152 (0.000342)
CAPEX/Assets$_t$									0.0121 (0.0116)						0.0301 (0.0203)	0.0307 (0.0207)	0.0170 (0.0125)
PPE/Assets$_t$										-0.00200 (0.00134)					-0.00143 (0.00144)	-0.00151 (0.00159)	-0.000848 (0.00104)
Log(Vacancies)$_t$											0.000607*** (9.65e-05)				0.000308*** (9.45e-05)	0.000237** (0.000114)	0.000248** (0.000122)
Log(PDensity)$_{2010}$												0.000813*** (0.000306)				-0.00235*** (0.000857)	-0.00203*** (0.000681)
College Share$_{2010}$													0.0407*** (0.0149)			0.0114 (0.0108)	-0.00597 (0.00978)
Log(CZ Wage)$_{2010}$														0.0177*** (0.00598)		0.0221*** (0.00784)	0.0212*** (0.00778)
AI Share (IT)$_t$																	0.0525*** (0.0184)
AI Share (Other)$_t$																	0.563*** (0.139)
Observations	15,581	16,077	15,858	15,440	15,534	16,077	16,007	16,077	16,027	14,202	16,077	13,746	13,746	13,746	13,612	11,716	9,929
R-squared	0.186	0.155	0.168	0.159	0.139	0.156	0.141	0.143	0.141	0.140	0.163	0.157	0.180	0.191	0.210	0.261	0.409
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 4. AI Adoption in IT Occupations and Firm Characteristics - Regressions Weighted by Employment.

Sample includes firms that have Compustat and BGT data available. Independent variables: column (1) is the log market capitalization, column (2) the log of employment, column (3) the log sales, column (4) the market-to-book ratio, column (5) the return on assets, column (6) the cash holdings to assets ratio, column (7) the book leverage, column (8) the R&D expenses over sales, column (9) the capital expenditures over assets, column (10) the PP&E over assets, column (11) the log of total vacancies, column (12) the log of population density, column (13) is the percentage of population with college degree, and column (14) is the log of average wages in the commuting zone (CZ) of the firm's location as of 2010 (if the firm posts vacancies in several commuting zones, we calculate weighted averages of the commuting zone characteristics using shares of the firm's vacancies in each commuting zone as weights). Columns (15), (16), and (17) present the multivariate specifications. Independent variables are lagged by one period, except for commuting zone characteristics measured as at 2010. Standard errors in parentheses are clustered by Firm. Significance levels are denoted as: *** p<0.01, ** p<0.05, * p<0.1.

	Dependent Variable: AI Share (IT)$_{t+1}$																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Log(MCap)$_t$	0.00609***														0.00671***	0.00654***	0.00512***
	(0.00121)														(0.00161)	(0.00173)	(0.00181)
Log(Employment)$_t$		0.00526***															
		(0.00161)															
Log(Sales)$_t$			0.00609***														
			(0.00149)														
Tobin's Q$_t$				0.00252													
				(0.00302)													
ROA$_t$					-0.00900										-0.0516**	-0.0484*	-0.0391
					(0.0219)										(0.0257)	(0.0280)	(0.0254)
Cash/Assets$_t$						0.0283									0.0443**	0.0324*	0.0167*
						(0.0232)									(0.0211)	(0.0193)	(0.00880)
Book Leverage$_t$							0.00801								0.0119	0.0154*	0.00844
							(0.00814)								(0.00743)	(0.00824)	(0.00734)
R&D/Sales$_t$								0.00191							-0.000498	0.000280	-0.000793
								(0.00126)							(0.000694)	(0.00135)	(0.000956)
CAPEX/Assets$_t$									0.0151						0.0564	0.0611	-0.00798
									(0.0384)						(0.0585)	(0.0622)	(0.0305)
PPE/Assets$_t$										-0.00444					0.00143	0.00162	0.00775*
										(0.00444)					(0.00501)	(0.00593)	(0.00432)
Log(Vacancies)$_t$											0.00236***				0.000577	0.000229	-0.000419
											(0.000430)				(0.000704)	(0.000848)	(0.000935)
Log(PDensity)$_{2010}$												0.00345**				-0.00279	0.00225
												(0.00158)				(0.00344)	(0.00276)
College Share$_{2010}$													0.122***			0.0705	0.0380
													(0.0440)			(0.0673)	(0.0658)
Log(CZ Wage)$_{2010}$														0.0494***		0.0250	-0.0138
														(0.0166)		(0.0323)	(0.0301)
AI Share (Management)$_t$																	1.525***
																	(0.222)
AI Share (Other)$_t$																	1.174***
																	(0.232)
Observations	14,090	14,555	14,414	13,959	14,192	14,555	14,489	14,555	14,511	13,055	14,555	12,599	12,599	12,599	12,512	10,877	10,022
R-squared	0.268	0.242	0.262	0.215	0.206	0.213	0.210	0.214	0.210	0.209	0.225	0.230	0.240	0.243	0.292	0.315	0.427
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 5. AI Adoption in Other Occupations and Firm Characteristics - Regressions Weighted by Employment.

Sample includes firms that have Compustat and BGT data available. Independent variables: column (1) is the log market capitalization, column (2) the log of employment, column (3) the log sales, column (4) the market-to-book ratio, column (5) the return on assets, column (6) the cash holdings to assets ratio, column (7) the book leverage, column (8) the R&D expenses over sales, column (9) the capital expenditures over assets, column (10) the PP&E over assets, column (11) the log of total vacancies, column (12) the log of population density, column (13) is the percentage of population with college degree, and column (14) is the log of average wages in the commuting zone (CZ) of the firm's location as of 2010 (if the firm posts vacancies in several commuting zones, we calculate weighted averages of the commuting zone characteristics using shares of the firm's vacancies in each commuting zone as weights). Columns (15), (16), and (17) present the multivariate specifications. Independent variables are lagged by one period, except for commuting zone characteristics measured as at 2010. Standard errors in parentheses are clustered by Firm. Significance levels are denoted as: *** p<0.01, ** p<0.05, * p<0.1.

	Dependent Variable: AI Share (Other)$_{t+1}$																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Log(MCap)$_t$	0.000699***														0.000648***	0.000593***	0.000171
	(0.000181)														(0.000194)	(0.000177)	(0.000119)
Log(Employment)$_t$		0.000310**															
		(0.000139)															
Log(Sales)$_t$			0.000504***														
			(0.000162)														
Tobin's Q$_t$				0.000927													
				(0.000583)													
ROA$_t$					0.00146										-0.00347	-0.00311	0.000261
					(0.00320)										(0.00412)	(0.00440)	(0.00320)
Cash/Assets$_t$						0.0120***									0.0125***	0.00944**	0.00789***
						(0.00442)									(0.00463)	(0.00438)	(0.00270)
Book Leverage$_t$							0.000823								0.00269	0.00329*	0.00240
							(0.00150)								(0.00177)	(0.00195)	(0.00192)
R&D/Sales$_t$								0.000648**							0.000116	0.000506	0.000541*
								(0.000279)							(0.000171)	(0.000342)	(0.000308)
CAPEX/Assets$_t$									0.00492						0.0211	0.0243*	0.0147
									(0.00793)						(0.0131)	(0.0143)	(0.00961)
PPE/Assets$_t$										-0.00226**					-0.00207**	-0.00227**	-0.00176**
										(0.000887)					(0.000961)	(0.00109)	(0.000763)
Log(Vacancies)$_t$											0.000341***				0.000153**	8.57e-05	5.97e-05
											(6.92e-05)				(6.25e-05)	(8.60e-05)	(9.60e-05)
Log(PDensity)$_{2010}$												0.000834***				-0.000938	-0.000309
												(0.000203)				(0.000579)	(0.000435)
College Share$_{2010}$													0.0322***			0.0208**	0.00898
													(0.00909)			(0.0104)	(0.00786)
Log(CZ Wage)$_{2010}$														0.0117***		0.00615	0.00297
														(0.00360)		(0.00508)	(0.00427)
AI Share (Management)$_t$																	0.342***
																	(0.0711)
AI Share (IT)$_t$																	0.0316***
																	(0.00955)
Observations	17,312	17,874	17,639	17,158	17,284	17,874	17,794	17,874	17,824	15,694	17,874	15,128	15,128	15,128	15,030	12,814	9,965
R-squared	0.141	0.114	0.124	0.128	0.108	0.140	0.109	0.112	0.109	0.116	0.127	0.122	0.151	0.151	0.188	0.218	0.384
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 6. Changes in AI Intensity and Firm Outcomes. Long Differences Regressions.

Sample only includes firms that have Compustat and BGT data available in 2010, 2011, 2017, and 2018. For each variable, the change (denoted by Δ) is calculated as the difference between the variable's average value in 2017-2018 and its average value in 2010-2011, to minimize the effect of year-to-year fluctuations. The main independent variable, Δ AI Share, is a change in the ratio of job postings requesting AI skills over the total number of job postings. Controls included in the regression are: changes in the firm's financial characteristics (share of vacancies requesting specialised software skills, log employment, log total assets, cash-to-assets ratio, R&D-to-sales ratio, PP&E-to-assets ratio, and log total vacancies); firm characteristics as at the beginning of the period (log total assets, R&D-to-sales ratio, cash-to-assets ratio, PP&E-to-assets ratio); characteristics of the commuting zone (CZ) where the firm is located (log population density, share of college graduates, log average CZ wage, share of employment in finance sector, share of employment in manufacturing sector, share of female workers, share of workers of color, share of workers in computer and mathematical occupations) and of the firm's industry (log average 3-digit NAICS industry wage) as at 2010. When the firm posts vacancies in several CZ, we calculate a weighted average of CZ characteristics, using the shares of the firm's vacancies in CZ as weights. We replace missing R&D data in Compustat with zero and include a dummy for the missing R&D data. We exclude Δ log employment as a control from column (1) and column (4) of Panel A and exclude Δ R&D-to-sales as a control from columns (1), (3), (4), and (6) of Panel B since these variables are included in the calculation of the corresponding dependent variables. Standard errors are clustered by 2-digit NAICS industry. Significance levels are denoted as: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

(a) Panel A: Firm Growth.

	ΔLog(Empl)	ΔLog(Sales)	ΔLog(MCap)	ΔLog(Sales/Worker)	ΔLog(TFP)	Δ(EBITDA/Sales)
	(1)	(2)	(3)	(4)	(5)	(6)
Δ AI Share	0.0506	0.849***	2.325	0.822**	0.563	0.736***
	(0.468)	(0.268)	(1.357)	(0.381)	(0.356)	(0.106)
Δ Software Share	0.0118	0.0581	-0.0998	0.0519	0.157	0.0528
	(0.0482)	(0.0371)	(0.129)	(0.0431)	(0.0952)	(0.0306)
Δ Log(Employment)		0.471***	0.187***		0.00784	-0.0290
		(0.0530)	(0.0536)		(0.0292)	(0.0522)
Δ Log(Assets)	0.668***	0.390***	0.692***	0.0366	-0.0387**	0.0520
	(0.0293)	(0.0341)	(0.0611)	(0.0285)	(0.0173)	(0.0459)
Δ Cash/Assets	-0.460***	0.167	1.245***	0.410***	0.215*	-0.0668
	(0.121)	(0.116)	(0.173)	(0.0836)	(0.112)	(0.0838)
Δ R&D/Sales	-0.622***	-1.729***	-0.480**	-1.400***	-1.459***	-1.572***
	(0.129)	(0.0387)	(0.168)	(0.0771)	(0.192)	(0.0443)
Δ PPE/Assets	0.352***	0.0124	-0.587***	-0.174***	-0.285***	-0.0237
	(0.0840)	(0.0670)	(0.125)	(0.0572)	(0.0474)	(0.0229)
Δ Log(Vacancies)	0.0433***	0.00313	0.0118	-0.0198***	0.00552	0.000924
	(0.0145)	(0.00751)	(0.0142)	(0.00634)	(0.00705)	(0.00244)
$\text{Log(Assets)}_{2010/2011}$	-0.00868	-0.00723	0.0242*	-0.00264	0.00670	0.00932***
	(0.00630)	(0.00667)	(0.0138)	(0.00699)	(0.00412)	(0.00304)
$\text{R\&D/Sales}_{2010/2011}$	-0.232**	0.153***	-0.197***	0.276***	0.353***	-0.181*
	(0.101)	(0.0438)	(0.0648)	(0.0421)	(0.0985)	(0.103)
$\text{Cash/Assets}_{2010/2011}$	0.0189	-0.0560	0.191	-0.0660	-0.0606	0.00651
	(0.112)	(0.114)	(0.140)	(0.141)	(0.0702)	(0.0298)
$\text{PPE/Assets}_{2010/2011}$	-0.0890*	0.0179	0.0282	0.0650	0.0470	0.0226
	(0.0426)	(0.0230)	(0.0948)	(0.0378)	(0.0333)	(0.0248)
Observations	1,135	1,135	1,111	1,135	1,131	1,134
R-squared	0.664	0.738	0.516	0.256	0.340	0.440
CZ and Industry Controls	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓

(b) Panel B: Investment.

	ΔLog(R&D) (1)	ΔLog(CAPEX) (2)	ΔLog(Tot Inv) (3)	ΔR&D/Sales (4)	ΔCAPEX/Assets (5)	ΔTot Inv/Assets (6)
Δ AI Share	0.984	2.289***	2.279**	0.147	0.0880**	0.255***
	(1.201)	(0.782)	(0.933)	(0.255)	(0.0351)	(0.0499)
Δ Software Share	0.0993	0.00468	-0.0521	0.00579	0.00434	-0.000207
	(0.0619)	(0.101)	(0.133)	(0.0151)	(0.00345)	(0.0101)
Δ Log(Employment)	0.104	0.450***	0.223***	-0.0482	0.00765***	0.0112*
	(0.0770)	(0.0804)	(0.0719)	(0.0407)	(0.00227)	(0.00601)
Δ Log(Assets)	0.381***	0.668***	0.845***	0.0270	-0.00758**	-0.0154*
	(0.120)	(0.0700)	(0.0518)	(0.0270)	(0.00315)	(0.00858)
Δ Cash/Assets	-0.126	-0.199	-0.739***	0.0923	-0.0123	-0.0850***
	(0.106)	(0.316)	(0.210)	(0.0558)	(0.00960)	(0.0155)
Δ R&D/Sales		0.0992			0.0191**	
		(0.142)			(0.00716)	
Δ PPE/Assets	0.124	0.331**	-0.0360	-0.0205**	0.0140	-0.0263*
	(0.147)	(0.141)	(0.117)	(0.00968)	(0.00812)	(0.0131)
Δ Log(Vacancies)	0.00775	0.0445***	0.0105	0.00270	0.00141**	-1.09e-05
	(0.00784)	(0.0134)	(0.0175)	(0.00517)	(0.000624)	(0.00138)
$\text{Log(Assets)}_{2010/2011}$	0.00299	0.00611	0.0124	-0.000158	6.09e-05	-0.000175
	(0.00666)	(0.00836)	(0.0142)	(0.00141)	(0.000477)	(0.00100)
$\text{R\&D/Sales}_{2010/2011}$	-0.0978*	-0.455***	-0.155	-0.342***	0.00149	-0.0385***
	(0.0562)	(0.154)	(0.109)	(0.0257)	(0.00350)	(0.0113)
$\text{Cash/Assets}_{2010/2011}$	0.228	0.138	-0.150	0.139	0.00187	-0.00665
	(0.167)	(0.211)	(0.184)	(0.0916)	(0.00600)	(0.0124)
$\text{PPE/Assets}_{2010/2011}$	-0.00671	0.0212	0.126**	-0.0223**	-0.00244	0.00147
	(0.0668)	(0.0666)	(0.0595)	(0.00847)	(0.00386)	(0.00660)
Observations	1,135	1,126	1,128	1,135	1,134	1,134
R-squared	0.377	0.532	0.494	0.335	0.221	0.108
CZ and Industry Controls	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓

Table 7. AI Intensity in Management Occupation and Firm Outcomes. Long Differences Regressions.

Sample only includes firms that have Compustat and BGT data available in 2010, 2011, 2017, and 2018. For each variable, the change (denoted by Δ) is calculated as the difference between the variable's average value in 2017-2018 and its average value in 2010-2011, to minimize the effect of year-to-year fluctuations. The main independent variable, Δ AI Share (Management), is a change in the ratio of job postings in the management occupation (2-digit SOC code 11) requesting AI skills over the total number of job postings in the management occupation. Controls included in the regression are: changes in the firm's financial characteristics (share of vacancies requesting specialised software skills, log employment, log total assets, cash-to-assets ratio, R&D-to-sales ratio, PP&E-to-assets ratio, and log total vacancies); firm characteristics as at the beginning of the period (log total assets, R&D-to-sales ratio, cash-to-assets ratio, PP&E-to-assets ratio); characteristics of the commuting zone (CZ) where the firm is located (log population density, share of college graduates, log average CZ wage, share of employment in finance sector, share of employment in manufacturing sector, share of female workers, share of workers of color, share of workers in computer and mathematical occupations) and of the firm's industry (log average 3-digit NAICS industry wage) as at 2010. When the firm posts vacancies in several CZ, we calculate a weighted average of CZ characteristics, using the shares of the firm's vacancies in CZ as weights. We replace missing R&D data in Compustat with zero and include a dummy for the missing R&D data. We exclude Δ log employment as a control from column (1) and column (4) of Panel A and exclude Δ R&D-to-sales as a control from columns (1), (3), (4), and (6) of Panel B since these variables are included in the calculation of the corresponding dependent variables. Standard errors are clustered by 2-digit NAICS industry. Significance levels are denoted as: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

(a) Panel A: Firm Growth.

	ΔLog(Empl)	ΔLog(Sales)	ΔLog(MCap)	ΔLog(Sales/Worker)	ΔLog(TFP)	Δ(EBITDA/Sales)
	(1)	(2)	(3)	(4)	(5)	(6)
Δ AI Share (Management)	0.275	1.532***	4.127***	1.385*	-0.123	0.444
	(0.698)	(0.503)	(0.846)	(0.719)	(0.790)	(0.388)
Observations	1,046	1,046	1,024	1,046	1,043	1,045
R-squared	0.680	0.768	0.537	0.326	0.466	0.498
Δ Firm Characteristics	✓	✓	✓	✓	✓	✓
Initial Firm Characteristics	✓	✓	✓	✓	✓	✓
CZ and Industry Controls	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓

(b) Panel B: Investment.

	ΔLog(R&D)	ΔLog(CAPEX)	ΔLog(Tot Inv)	ΔR&D/Sales	ΔCAPEX/Assets	ΔTot Inv/Assets
	(1)	(2)	(3)	(4)	(5)	(6)
Δ AI Share (Management)	2.839***	3.757*	2.344	0.253**	0.108**	0.0837
	(0.975)	(1.900)	(1.994)	(0.116)	(0.0426)	(0.154)
Observations	1,046	1,039	1,040	1,046	1,045	1,045
R-squared	0.390	0.569	0.527	0.301	0.238	0.109
Δ Firm Characteristics	✓	✓	✓	✓	✓	✓
Initial Firm Characteristics	✓	✓	✓	✓	✓	✓
CZ and Industry Controls	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓

Table 8. AI Intensity in Management Occupation vs. AI Intensity in IT and Other Jobs. Long Differences Regressions.

Sample only includes firms that have Compustat and BGT data available in 2010, 2011, 2017, and 2018. For each variable, the change (denoted by Δ) is calculated as the difference between the variable's average value in 2017-2018 and its average value in 2010-2011, to minimize the effect of year-to-year fluctuations. The main independent variables are: Δ AI Share (Management) is a change in the ratio of job postings in the management occupation (2-digit SOC code 11) requesting AI skills over the total number of job postings in the management occupation; ΔAI Share (IT) is a change in the ratio of job postings in the computer and mathematical (IT) occupation (2-digit SOC code 15) requesting AI skills over the total number of job postings in the IT occupation; and ΔAI Share (Other) is a change in the ratio of job postings in occupations other than management or IT (2-digit SOC code not equal to 11 or 15) requesting AI skills over the total number of job postings in these occupations. Controls included in the regression are: changes in the firm's financial characteristics (share of vacancies requesting specialised software skills, log employment, log total assets, cash-to-assets ratio, R&D-to-sales ratio, PP&E-to-assets ratio, and log total vacancies); firm characteristics as at the beginning of the period (log total assets, R&D-to-sales ratio, cash-to-assets ratio, PP&E-to-assets ratio); characteristics of the commuting zone (CZ) where the firm is located (log population density, share of college graduates, log average CZ wage, share of employment in finance sector, share of employment in manufacturing sector, share of female workers, share of workers of color, share of workers in computer and mathematical occupations) and of the firm's industry (log average 3-digit NAICS industry wage) as at 2010. When the firm posts vacancies in several CZ, we calculate a weighted average of CZ characteristics, using the shares of the firm's vacancies in CZ as weights. We replace missing R&D data in Compustat with zero and include a dummy for the missing R&D data. We exclude Δ log employment as a control from column (1) and column (4) of Panel A and exclude Δ R&D-to-sales as a control from columns (1), (3), (4), and (6) of Panel B since these variables are included in the calculation of the corresponding dependent variables. Standard errors are clustered by 2-digit NAICS industry. Significance levels are denoted as: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

(a) Panel A: Firm Growth.

	ΔLog(Empl)	ΔLog(Sales)	ΔLog(MCap)	ΔLog(Sales/Worker)	ΔLog(TFP)	Δ(EBITDA/Sales)
	(1)	(2)	(3)	(4)	(5)	(6)
Δ AI Share (Management)	0.393	1.203*	4.163***	0.987	-0.859	-0.0460
	(0.748)	(0.610)	(1.127)	(0.693)	(1.025)	(0.268)
Δ AI Share (IT)	-0.126	-0.128	0.240	-0.0581	-0.164	0.00667
	(0.147)	(0.220)	(0.555)	(0.249)	(0.215)	(0.0582)
Δ AI Share (Other)	0.185	0.815	-1.093	0.713	2.196	1.476
	(1.241)	(0.579)	(1.095)	(1.010)	(1.277)	(1.109)
Observations	928	928	908	928	925	927
R-squared	0.675	0.783	0.543	0.279	0.416	0.556
Δ Firm Characteristics	✓	✓	✓	✓	✓	✓
Initial Firm Characteristics	✓	✓	✓	✓	✓	✓
CZ and Industry Controls	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓

(b) Panel B: Investment.

	ΔLog(R&D)	ΔLog(CAPEX)	ΔLog(Tot Inv)	ΔR&D/Sales	ΔCAPEX/Assets	ΔTot Inv/Assets
	(1)	(2)	(3)	(4)	(5)	(6)
Δ AI Share (Management)	2.309*	3.418*	1.221	0.125	0.0937	-0.105
	(1.237)	(1.827)	(1.805)	(0.181)	(0.0604)	(0.170)
Δ AI Share (IT)	-0.699**	0.193	0.605	0.0112	0.00342	0.0653*
	(0.323)	(0.272)	(0.451)	(0.156)	(0.0176)	(0.0336)
Δ AI Share (Other)	3.975**	-0.726	0.269	0.124	0.0236	0.272
	(1.577)	(2.377)	(1.939)	(0.0800)	(0.0679)	(0.202)
Observations	928	921	922	928	927	927
R-squared	0.409	0.552	0.547	0.282	0.223	0.110
Δ Firm Characteristics	✓	✓	✓	✓	✓	✓
Initial Firm Characteristics	✓	✓	✓	✓	✓	✓
CZ and Industry Controls	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓

Table 9. AI Intensity and Firm Outcomes: A Panel regression.

Sample only includes firms that have Compustat and BGT data available. All variables are in levels. The main independent variable, AI Share, is the ratio of job postings requesting AI skills over the total number of job postings. Controls included in the regression are the firm's financial characteristics (share of vacancies requesting specialised software skills, log employment, log total assets, cash-to-assets ratio, R&D-to-sales ratio, PP&E-to-assets ratio, and log total vacancies). We also include year and firm fixed effects. We replace missing R&D data in Compustat with zero and include a dummy for the missing R&D data. We exclude log employment as a control from column (1) and column (4) of Panel A and exclude R&D-to-sales as a control from columns (1), (3), (4), and (6) of Panel B since these variables are included in the calculation of the corresponding dependent variables. Standard errors are clustered by firm. Significance levels are denoted as: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

(a) Panel A: Firm Growth.

	Log(Empl) (1)	Log(Sales) (2)	Log(MCap) (3)	Log(Sales/Worker) (4)	Log(TFP) (5)	EBITDA/Sales (6)
AI Share	0.228	0.466*	1.781***	0.319	0.192	0.597
	(0.224)	(0.244)	(0.481)	(0.254)	(0.276)	(1.182)
Observations	20,371	19,960	19,654	19,960	19,873	19,886
R-squared	0.990	0.988	0.963	0.934	0.849	0.962
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

(b) Panel B: Investment.

	Log(R&D) (1)	Log(CAPEX) (2)	Log(Tot Inv) (3)	R&D/Sales (4)	CAPEX/Assets (5)	Tot Inv/Assets (6)
AI Share	1.128***	1.024*	1.069**	1.618	0.0448**	0.105
	(0.317)	(0.536)	(0.452)	(1.935)	(0.0227)	(0.0766)
Observations	20,371	20,075	20,079	20,371	20,346	20,346
R-squared	0.985	0.963	0.937	0.619	0.780	0.744
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

Table 10. AI Intensity in Management Occupations and Firm Outcomes: A Panel Regression.

Sample only includes firms that have Compustat and BGT data available. All variables are in levels. The main independent variable, AI Share (Management), the ratio of job postings in the management occupation (2-digit SOC code 11) requesting AI skills over the total number of job postings in the management occupation. Controls included in the regression are the firm's financial characteristics (share of vacancies requesting specialised software skills, log employment, log total assets, cash-to-assets ratio, R&D-to-sales ratio, PP&E-to-assets ratio, and log total vacancies). We also include year and firm fixed effects. We replace missing R&D data in Compustat with zero and include a dummy for the missing R&D data. We exclude log employment as a control from column (1) and column (4) of Panel A and exclude R&D-to-sales as a control from columns (1), (3), (4), and (6) of Panel B since these variables are included in the calculation of the corresponding dependent variables. Standard errors are clustered by firm. Significance levels are denoted as: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

(a) Panel A: Firm Growth.

	Log(Empl)	Log(Sales)	Log(MCap)	Log(Sales/Worker)	Log(TFP)	EBITDA/Sales
	(1)	(2)	(3)	(4)	(5)	(6)
AI Share (Management)	0.779**	0.301	3.555***	-0.107	0.204	-2.017
	(0.374)	(0.296)	(0.765)	(0.356)	(0.277)	(2.398)
Observations	16,724	16,454	16,167	16,454	16,386	16,398
R-squared	0.990	0.988	0.962	0.938	0.857	0.962
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

(b) Panel B: Investment.

	Log(R&D)	Log(CAPEX)	Log(Tot Inv)	R&D/Sales	CAPEX/Assets	Tot Inv/Assets
	(1)	(2)	(3)	(4)	(5)	(6)
AI Share (Management)	1.481***	2.109***	1.852***	-0.163	0.0890***	0.141
	(0.471)	(0.713)	(0.663)	(1.745)	(0.0284)	(0.0918)
Observations	16,724	16,533	16,526	16,724	16,705	16,705
R-squared	0.987	0.965	0.934	0.626	0.799	0.742
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

Table 11. AI Intensity in Management Occupation vs. AI Intensity in IT and Other Jobs: A Panel Regression.
Sample only includes firms that have Compustat and BGT data available. All variables are in levels. The main independent variables are: AI Share (Management) is the ratio of job postings in the management occupation (2-digit SOC code 11) requesting AI skills over the total number of job postings in the management occupation; AI Share (IT) is the ratio of job postings in the computer and mathematical (IT) occupation (2-digit SOC code 15) requesting AI skills over the total number of job postings in the IT occupation; and AI Share (Other) is the ratio of job postings in occupations other than management or IT (2-digit SOC code not equal to 11 or 15) requesting AI skills over the total number of job postings in these occupations. Controls included in the regression are the firm's financial characteristics (share of vacancies requesting specialised software skills, log employment, log total assets, cash-to-assets ratio, R&D-to-sales ratio, PP&E-to-assets ratio, and log total vacancies). We also include year and firm fixed effects. We replace missing R&D data in Compustat with zero and include a dummy for the missing R&D data. We exclude log employment as a control from column (1) and column (4) of Panel A and exclude R&D-to-sales as a control from columns (1), (3), (4), and (6) of Panel B since these variables are included in the calculation of the corresponding dependent variables. Standard errors are clustered by firm. Significance levels are denoted as: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

(a) Panel A: Firm Growth.

	Log(Empl) (1)	Log(Sales) (2)	Log(MCap) (3)	Log(Sales/Worker) (4)	Log(TFP) (5)	EBITDA/Sales (6)
AI Share (Management)	0.810**	0.283	2.595***	-0.172	0.114	-0.737
	(0.363)	(0.296)	(0.752)	(0.350)	(0.283)	(1.752)
AI Share (IT)	-0.152*	0.0261	0.195	0.0930	0.0614	-0.196
	(0.0783)	(0.103)	(0.155)	(0.107)	(0.0989)	(0.181)
AI Share (Other)	0.629	0.666	0.940	0.388	-0.0355	1.516*
	(0.397)	(0.518)	(0.875)	(0.540)	(0.558)	(0.897)
Observations	13,857	13,741	13,417	13,741	13,688	13,707
R-squared	0.990	0.990	0.961	0.949	0.872	0.977
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

(b) Panel B: Investment.

	Log(R&D) (1)	Log(CAPEX) (2)	Log(Tot Inv) (3)	R&D/Sales (4)	CAPEX/Assets (5)	Tot Inv/Assets (6)
AI Share (Management)	1.008**	1.517**	1.507**	1.788	0.0772**	0.0981
	(0.498)	(0.752)	(0.727)	(1.522)	(0.0307)	(0.102)
AI Share (IT)	0.0370	0.213	0.256	0.235	0.00964	0.0326
	(0.101)	(0.172)	(0.169)	(0.311)	(0.00927)	(0.0286)
AI Share (Other)	1.447**	1.058	0.606	-6.470*	0.0241	0.0917
	(0.568)	(0.893)	(0.902)	(3.716)	(0.0352)	(0.151)
Observations	13,857	13,732	13,718	13,857	13,845	13,845
R-squared	0.989	0.968	0.932	0.642	0.818	0.739
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓

A Appendix

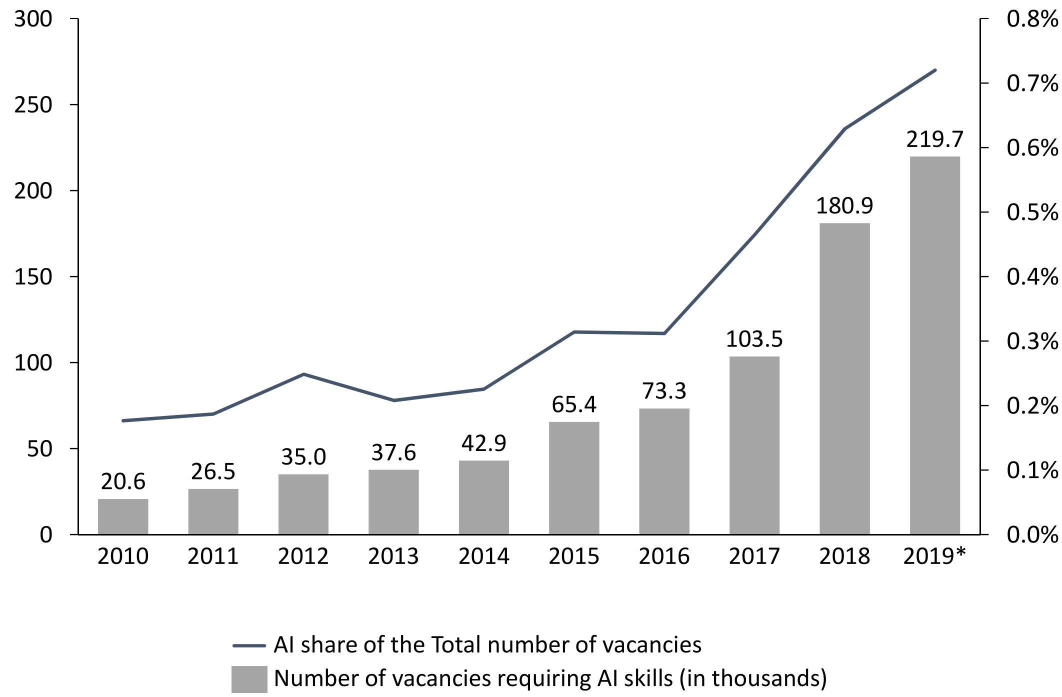


Figure A1. AI share of total BGT vacancies over time. The figure shows the number of vacancies requiring AI skills over time (bars) and the ratio of the number of vacancies requiring AI skills to the total number of vacancies (line). The total number of vacancies requiring AI in 2019 is a projection based on the annualized number of vacancies posted in January-July, 2019. Data source: Burning Glass Technologies full data.

Table A1. List of skills in the Burning Glass Technologies job vacancies dataset used to identify AI vacancies.

N	Skill	N	Skill
1	AI ChatBot	31	Machine Translation (MT)
2	AI KIBIT	32	Machine Vision
3	ANTLR	33	Madlib
4	Apertium	34	Mahout
5	Artificial Intelligence	35	Microsoft Cognitive Toolkit
6	Automatic Speech Recognition (ASR)	36	MLPACK (C++ library)
7	Caffe Deep Learning Framework	37	Mlpy
8	Chatbot	38	Modular Audio Recognition Framework (MARF)
9	Computational Linguistics	39	MoSes
10	Computer Vision	40	MXNet
11	Decision Trees	41	Natural Language Processing
12	Deep Learning	42	Natural Language Toolkit (NLTK)
13	Deeplearning4j	43	ND4J (software)
14	Distinguo	44	Nearest Neighbor Algorithm
15	Google Cloud Machine Learning Platform	45	Neural Networks
16	Gradient boosting	46	Object Recognition
17	H2O (software)	47	Object Tracking
18	IBM Watson	48	OpenCV
19	Image Processing	49	OpenNLP
20	Image Recognition	50	Pattern Recognition
21	IPSoft Amelia	51	Pybrain
22	Ithink	52	Random Forests
23	Keras	53	Recommender Systems
24	Latent Dirichlet Allocation	54	Semantic Driven Subtractive Clustering Method (SDSCM)
25	Latent Semantic Analysis	55	Semi-Supervised Learning
26	Lexalytics	56	Sentiment Analysis / Opinion Mining
27	Lexical Acquisition	57	Sentiment Classification
28	Lexical Semantics	58	Speech Recognition
29	Libsvm	59	Supervised Learning (Machine Learning)
30	Machine Learning	60	Support Vector Machines (SVM)

Continued on next page

Table A1 – *Continued from previous page*

N	Skill	N	Skill
61	TensorFlow	67	Virtual Agents
62	Text Mining	68	Vowpal
63	Text to Speech (TTS)	69	Wabbit
64	Tokenization	70	Word2Vec
65	Torch (Machine Learning)	71	Xgboost
66	Unsupervised Learning		

Table A2. AI Intensity in Management Occupation and Firm Outcomes. Long Differences Regressions.

Sample only includes firms that have Compustat and BGT data available in 2010, 2011, 2017, and 2018. For each variable, the change (denoted by Δ) is calculated as the difference between the variable's average value in 2017-2018 and its average value in 2010-2011, to minimize the effect of year-to-year fluctuations. The main independent variable, Δ AI Share (Management), is a change in the ratio of job postings in the management occupation (2-digit SOC code 11) requesting AI skills over the total number of job postings in the management occupation. Controls included in the regression are: firm characteristics as at the beginning of the period (share of vacancies requesting specialised software skills, log employment, log total assets, cash-to-assets ratio, R&D-to-sales ratio, PP&E-to-assets ratio, and log total vacancies); characteristics of the commuting zone (CZ) where the firm is located (log population density, share of college graduates, log average CZ wage, share of employment in finance sector, share of employment in manufacturing sector, share of female workers, share of workers of color, share of workers in computer and mathematical occupations) and of the firm's industry (log average 3-digit NAICS industry wage) as at 2010. When the firm posts vacancies in several CZ, we calculate a weighted average of CZ characteristics, using the shares of the firm's vacancies in CZ as weights. We replace missing R&D data in Compustat with zero and include a dummy for the missing R&D data. Standard errors are clustered by 2-digit NAICS industry. Significance levels are denoted as: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

(a) Panel A: Firm Growth.

	ΔLog(Empl)	ΔLog(Sales)	ΔLog(MCap)	ΔLog(Sales/Worker)	ΔLog(TFP)	Δ(EBITDA/Sales)
	(1)	(2)	(3)	(4)	(5)	(6)
Δ AI Share (Management)	2.029	3.094*	6.522***	1.065	-0.724	-0.475
	(1.806)	(1.649)	(2.124)	(1.028)	(0.863)	(0.544)
Observations	1,053	1,053	1,031	1,053	1,043	1,048
R-squared	0.165	0.197	0.190	0.207	0.283	0.091
Initial Firm Characteristics	✓	✓	✓	✓	✓	✓
CZ and Industry Controls	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓

(b) Panel B: Investment.

	ΔLog(R&D)	ΔLog(CAPEX)	ΔLog(Tot Inv)	ΔR&D/Sales	ΔCAPEX/Assets	ΔTot Inv/Assets
	(1)	(2)	(3)	(4)	(5)	(6)
Δ AI Share (Management)	4.515***	6.451***	3.911	0.458***	0.112**	-0.0332
	(1.050)	(1.660)	(2.996)	(0.155)	(0.0442)	(0.226)
Observations	1,053	1,042	1,044	1,053	1,052	1,052
R-squared	0.106	0.128	0.110	0.267	0.207	0.094
Initial Firm Characteristics	✓	✓	✓	✓	✓	✓
CZ and Industry Controls	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓

Table A3. AI Intensity in Management Occupation vs. AI Intensity in IT and Other Jobs. Long Differences Regressions.

Sample only includes firms that have Compustat and BGT data available in 2010, 2011, 2017, and 2018. For each variable, the change (denoted by Δ) is calculated as the difference between the variable's average value in 2017-2018 and its average value in 2010-2011, to minimize the effect of year-to-year fluctuations. The main independent variables are: Δ AI Share (Management) is a change in the ratio of job postings in the management occupation (2-digit SOC code 11) requesting AI skills over the total number of job postings in the management occupation; ΔAI Share (IT) is a change in the ratio of job postings in the computer and mathematical (IT) occupation (2-digit SOC code 15) requesting AI skills over the total number of job postings in the IT occupation; and ΔAI Share (Other) is a change in the ratio of job postings in occupations other than management or IT (2-digit SOC code not equal to 11 or 15) requesting AI skills over the total number of job postings in these occupations. Controls included in the regression are:firm characteristics as at the beginning of the period (share of vacancies requesting specialised software skills, log employment, log total assets, cash-to-assets ratio, R&D-to-sales ratio, PP&E-to-assets ratio, and log total vacancies); characteristics of the commuting zone (CZ) where the firm is located (log population density, share of college graduates, log average CZ wage, share of employment in finance sector, share of employment in manufacturing sector, share of female workers, share of workers of color, share of workers in computer and mathematical occupations) and of the firm's industry (log average 3-digit NAICS industry wage) as at 2010. When the firm posts vacancies in several CZ, we calculate a weighted average of CZ characteristics, using the shares of the firm's vacancies in CZ as weights. We replace missing R&D data in Compustat with zero and include a dummy for the missing R&D data. Standard errors are clustered by 2-digit NAICS industry. Significance levels are denoted as: *** p<0.01, ** p<0.05, * p<0.1.

(a) Panel A: Firm Growth.

	ΔLog(Empl) (1)	ΔLog(Sales) (2)	ΔLog(MCap) (3)	ΔLog(Sales/Worker) (4)	ΔLog(TFP) (5)	Δ(EBITDA/Sales) (6)
Δ AI Share (Management)	1.888	2.627	5.972***	0.739	-1.449	-0.894
	(2.064)	(1.547)	(2.034)	(1.278)	(1.387)	(0.887)
Δ AI Share (IT)	-0.395	-0.445	0.259	-0.0501	-0.152	-0.0636
	(0.333)	(0.527)	(0.860)	(0.366)	(0.390)	(0.264)
Δ AI Share (Other)	1.277	2.290	0.650	1.013	2.004*	1.190
	(3.277)	(3.275)	(4.176)	(0.897)	(1.097)	(1.069)
Observations	935	935	915	935	925	930
R-squared	0.185	0.212	0.209	0.185	0.230	0.116
Initial Firm Characteristics	✓	✓	✓	✓	✓	✓
CZ and Industry Controls	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓

(b) Panel B: Investment.

	ΔLog(R&D) (1)	ΔLog(CAPEX) (2)	ΔLog(Tot Inv) (3)	ΔR&D/Sales (4)	ΔCAPEX/Assets (5)	ΔTot Inv/Assets (6)
Δ AI Share (Management)	3.567**	5.714	2.713	0.333	0.0927	-0.194
	(1.684)	(3.324)	(3.630)	(0.347)	(0.0612)	(0.222)
Δ AI Share (IT)	-0.577**	-0.145	0.271	0.0395	0.000992	0.0568*
	(0.218)	(0.447)	(0.627)	(0.133)	(0.0203)	(0.0323)
Δ AI Share (Other)	5.384	1.830	2.022	0.0940	0.0445	0.201
	(3.692)	(5.990)	(5.624)	(0.0563)	(0.0669)	(0.188)
Observations	935	924	926	935	934	934
R-squared	0.132	0.134	0.140	0.253	0.193	0.096
Initial Firm Characteristics	✓	✓	✓	✓	✓	✓
CZ and Industry Controls	✓	✓	✓	✓	✓	✓
2-digit NAICS FE	✓	✓	✓	✓	✓	✓