# Artificial Intelligence and Jobs: Evidence from Online Vacancies

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We study the impact of artificial intelligence (AI) on labor markets using establishment-level data on the near universe of online vacancies in the United States from 2010 onward. There is rapid growth in AI-related vacancies over 2010–18 that is driven by establishments whose workers engage in tasks compatible with AI's current capabilities. As these AI-exposed establishments adopt AI, they simultaneously reduce hiring in non-AI positions and change the skill requirements of remaining postings. While visible at the establishment level, the aggregate impacts of AI-labor substitution on employment and wage growth in more exposed occupations and industries is currently too small to be detectable.

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## I. Introduction

The past decade has witnessed rapid advances in artificial intelligence (AI) based on new machine learning techniques and the availability of massive data sets.[1] This change is expected to accelerate in the years to come (e.g., Neapolitan and Jiang 2018; Russell 2019), and AI applications have already started to impact businesses (e.g., Agarwal, Gans, and Goldfarb 2018). Some commentators see this as a harbinger of a jobless future (e.g., Ford 2015; West 2018; Susskind 2020), while others consider the oncoming AI revolution as enriching human productivity and work experience (e.g., McKinsey Global Institute 2017). The persistence of these contrasting visions is unsurprising given the limited evidence to date on the labor market consequences of AI. Data collection efforts have only recently commenced to determine the prevalence of commercial AI use, and we lack systematic evidence even on whether there has been a major increase in AI adoption—as opposed to just extensive media coverage.

This paper studies AI adoption in the United States and its implications. Our starting point is that AI adoption can be partially identified from the footprints it leaves at adopting establishments as they hire workers specializing in AI-related activities, such as supervised and unsupervised learning, natural language processing, machine translation, or image recognition. To put this idea into practice, we build an establishment-level data set of AI activity based on the near universe of US online job vacancy postings and their detailed skill requirements from Burning Glass Technologies (hereafter, Burning Glass or BG) for the years 2007 and 2010 through 2018.[2]

We start with a task-based perspective, linking the adoption of AI and its possible implications to the task structure of an establishment. This perspective emphasizes that current applications of AI are capable of performing specific tasks and predicts that firms engaged in those tasks will be the ones

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[1] AI is a collection of algorithms that act intelligently by recognizing and responding to the environment to achieve specified goals. AI algorithms process, identify, and act on patterns in unstructured data (e.g., speech data, text, or images) to achieve specified goals.

[2] The BG data have been used in several recent papers. Alekseeva et al. (2021) and Babina et al. (2020), discussed below, use BG data to study AI use and its consequences. Papers using BG data to explore other questions include Hershbein and Kahn (2018), Azar et al. (2020), Modestino, Shoag, and Ballance (2020), Hazell and Taska (2019), and Deming and Noray (2020).

that adopt AI technologies.[3] To identify the tasks compatible with current AI technologies, we use three different but complementary measures: Felten, Raj, and Seamans's (2018, 2019) AI occupational impact measure; Brynjolfsson, Mitchell and Rock's (2018, 2019) suitability for machine learning (SML) index; and Webb's (2020) AI exposure score. These indices all identify sets of tasks and occupations that are most impacted by AI technologies, but each is computed on the basis of different assumptions about AI capabilities. We construct an establishment's AI exposure from its baseline (2010–12) occupational structure according to each one of these indices and use these baseline measures as proxies for AI exposure throughout our analysis.[4] Since our goal is to study the impact of AI on AI-using firms rather than AI-producing firms, we exclude firms in the professional and business services and information technology sectors (North American Industry Classification System [NAICS] 51 and 54), both of which are primary suppliers of AI services.

Our first result is that there is a rapid takeoff in AI vacancy postings starting in 2010 and significantly accelerating around 2015–16. Consistent with a task-based view of AI, this activity is driven by establishments with task structures that are compatible with current AI capabilities. For instance, a 1 standard deviation increase in our baseline measure of AI exposure based on Felten et al.—approximately the difference in the average AI exposure between finance and mining and oil extraction—is associated with 15% more AI vacancy posting. The strong association between AI exposure and subsequent AI activity is robust to numerous controls and specification checks when using the Felten et al. and the Webb measures, but this is less apparent with the SML index. This leads us to place greater emphasis on the Felten et al. and Webb measures when exploring the effects of AI exposure on the demand for different types of skills and non-AI hiring.

Our second result establishes a strong association between AI exposure and changes in the types of skills demanded by establishments. With the Felten et al. and Webb measures (and, to a lesser extent, with SML), we find that AI exposure is associated with both a significant decline in some of the skills previously sought in posted vacancies and the emergence of new skills. This evidence bolsters the case that AI is altering the task structure of jobs,

[3] See Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018, 2019). This is not the only possible approach to AI. One could also think of AI as complementing some business models (rather than performing specific tasks within those models) or as allowing firms to generate and commercialize new products (see Agarwal, Gans, and Goldfarb 2018; Bresnahan 2019). We explain below why the task-based approach is particularly well suited to our empirical approach and how it receives support from our findings.

[4] Figure 4 below shows that the relationship between the mean wage of an occupation and the three AI exposure measures is distinct, which is the basis of our claim that each one of these indices captures a different aspect of AI exposure.

replacing some human-performed tasks while simultaneously generating new tasks accompanied by new skill demands.

The finding that establishments with AI-suitable tasks hire workers into AI positions and change their demand for certain types of skills does not, of course, tell us whether AI is increasing or reducing overall non-AI hiring in exposed establishments. In principle, AI-exposed establishments may see an increase in (non-AI) hiring if either AI directly complements workers in some tasks, increasing their productivity and encouraging more hiring, or AI substitutes for workers in some tasks but increases total factor productivity sufficiently to raise demand in nonautomated tasks via a productivity effect (Acemoglu and Restrepo 2019). Alternatively, AI adoption may reduce hiring if AI technologies are replacing many tasks previously performed by workers and the additional hiring they spur in nonautomated tasks does not make up for this displacement.

Our third main result shows that AI exposure is associated with lower (non-AI and overall) hiring. These results are robust in all of our specifications using the Felten et al. measure and in most specifications with the Webb measure but, as anticipated, not with SML. The timing of these relationships is also plausible: substantial declines in hiring take place in the time window during which AI activity surged—between 2014 and 2018. This pattern of results, combined with the concentration of AI activity in more AI-exposed tasks, suggests that the recent AI surge is driven in part by the automation of some of the tasks formerly performed by labor. We find no evidence for either the view that there are major human-AI complementarities in these establishments or the expectation that AI will increase hiring because of its large productivity effects—although we cannot rule out that other applications of AI that are not captured here could have such effects.

In contrast to the establishment-level patterns, we do not detect any relationship between AI exposure and overall employment or wages at the industry or occupation level. There are no significant employment impacts on industries with greater exposure to AI, and there are also no employment or wages effects for occupations that are more exposed to AI. We conclude that despite the notable surge in AI adoption, the impact of this new technology is still too small relative to the scale of the US labor market to have had first-order impacts on employment patterns outside of AI hiring itself. Nevertheless, our main findings—that AI adoption is driven by establishments that have a task structure that is suitable for AI use and that this has been associated with significant declines in establishment hiring—imply that any positive productivity and complementarity effects from AI are at present small compared with its displacement consequences.

Our paper builds on Alan Krueger's seminal work on the effects of new digital technologies on workers and wages (Krueger 1993; Autor, Katz, and Krueger 1998). Subsequent literature has investigated the implications of automation technologies, focusing on wages, employment polarization, and wage inequality (e.g., Autor, Levy, and Murnane 2003; Goos and Manning 2007; Autor and Dorn 2013; Goos, Manning, and Salomons 2014; Michaels, Natraj, and Van Reenen 2014; Gregory, Salomons, and Zierahn, forthcoming). Recent work has studied the impact of specific automation technologies, especially industrial robots, on employment and wages, focusing on industry-level variation (Graetz and Michaels 2018), local labor market effects (Acemoglu and Restrepo 2020), or firm-level variation (Dinlersoz and Wolf 2018; Bessen et al. 2019; Bonfiglioli et al. 2019; Humlum 2019; Acemoglu, Lelarge, and Restrepo 2020; Dixon, Hong, and Wu 2021; Koch, Manuylov, and Smolka 2021).

There are fewer studies of the effects of AI specifically, although this body of work is growing rapidly. Bessen et al. (2018) conduct a survey of AI startups and find that about 75% of AI startups report that their products help clients make better predictions, manage data better, or provide higher quality. Only 50% of startups report that their products help customers automate routine tasks and reduce labor costs. Grennan and Michaely (2019) study how AI algorithms have affected security analysts and find evidence of task substitution: analysts are more likely to leave the profession when they cover stocks for which there are abundant data available. Differently from these papers' focus on AI-producing sectors and specific applications of AI, such as finance, we study this technology's effects on AI-using establishments and non-AI workers throughout the economy.

Most closely related to our paper are a few recent works also investigating the effects of AI on firm-level outcomes. Babina et al. (2020) study the relationship between AI adoption and employment and sales at both the firm and the industry level. They document that, consistent with Alekseeva et al. (2021), AI investment is stronger among firms with higher cash reserves, higher markups, and higher R&D intensity and, moreover, that these firms grow more than nonadopters. A contrast between our approach and Babina et al.'s is that we focus on AI suitability based on establishments' occupational structures rather than observed AI adoption, and this may explain why we arrive at different results for hiring. Also related is Deming and Noray (2020), who use Burning Glass data to study the relationship between wages, technical skills, and skills obsolescence. Although their focus is not AI, their work demonstrates that Burning Glass data are suitable for detecting changes in job skill requirements, an angle of inquiry we pursue below.

As noted above, our work exploits measures of AI suitability developed by Felten, Raj, and Seamans (2018, 2019), Brynjolfsson, Mitchell, and Rock (2018, 2019), and Webb (2020). Our results are consistent with Felten, Raj, and Seamans (2019), who find a positive relationship between AI suitability and AI vacancy posting, but no relationship with employment growth, at the occupational level. We confirm that AI suitability is not at present associated with greater hiring in more highly exposed occupations or industries, but we find robust effects on skill demand and a negative impact on establishment hiring.

The rest of the paper is organized as follows. Section II presents a model motivating our empirical strategy and interpretation. Section III describes the data, and section IV presents our empirical strategy. Section V presents our main results on AI exposure and AI hiring, while section VI looks at changes in the types of skills AI-exposed establishments are looking for. Section VII explores the effects of AI on hiring at the establishment, industry, and occupation levels. Section VIII concludes. Appendix A contains additional material on our model, and additional robustness checks and empirical results are presented in appendix B (appendixes are available online).

## II. Theory

In this section, we provide a model that motivates our empirical approach and interpretation.

### A. Tasks, Algorithms, and Production

Establishment $e$'s output, $y_e$, is produced by combining the services, $y_e(x)$, of tasks $x \in \mathcal{T}_e \subset \mathcal{T}$ with unit elasticity (i.e., a Cobb-Douglas aggregator):

$$\ln y_e = \ln A_e + \int_{\mathcal{T}_e} \alpha(x) \ln y_e(x)\, dx, \tag{1}$$

where $\mathcal{T}$ is the set of feasible tasks, a subset $\mathcal{T}_e$ of which is used in the production process of establishment $e$, and $\alpha(x) \geq 0$ designates the importance or quality of task $x$ in the production process, which is common across establishments. We impose $\int_{\mathcal{T}_e} \alpha(x)\, dx = 1$ for all feasible $\mathcal{T}_e$, which ensures that all establishments have constant returns to scale.

Establishments differ in their productivity term $A_e$ and, more importantly, in the set of tasks they perform (e.g., because they produce different goods and services or use distinct production processes). We also assume that each establishment faces a downward-sloping demand curve for its product and will set its price $p_e$ to maximize profits (and its problem is separable from the profit-maximization problem of the firm's other establishments in case of multiestablishment firms). In this profit-maximization problem, we assume that each establishment is small in the labor market and takes other prices and aggregate output as given.

Tasks are produced by human labor, $\ell_e(x)$, or by services from AI-powered algorithms, $a_e(x)$:

$$y_e(x) = \left[(\gamma_\ell(x)\ell_e(x))^{(\sigma-1)/\sigma} + (\gamma_a(x)a_e(x))^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)}, \tag{2}$$

where $\sigma$ is the elasticity of substitution between labor and algorithms and $\gamma_\ell(x)$ and $\gamma_a(x)$ are assumed to be common across establishments. We assume that AI services are provided by combining AI capital (machinery or algorithms) purchased from the outside, $k_e(x)$, and in-house workers operating, programming, or maintaining this capital, $\ell_e^{\mathrm{AI}}(x)$, with the following technology:

$$a_e(x) = \min\{k_e(x), \ell_e^{\mathrm{AI}}(x)\}, \tag{3}$$

which implies that in-house AI workers need to be combined with capital in fixed proportions.[5] We assume throughout that all establishments are price takers for production workers, AI workers, and AI capital, whose respective prices are $w$, $w^{\mathrm{AI}}$, and $R$.

We view recent advances in AI as increasing the ability of algorithms to perform certain tasks—corresponding to an increase $\gamma_a(x)$ for some $x$. In what follows, we denote by $\mathcal{T}^A$ the subset of tasks that, due to these advances, can now be profitably performed by algorithms/AI. These advances in AI technology will have heterogeneous impacts on establishments depending on their task structure. For example, an increase in $\gamma_a(x)$ for text recognition will impact establishments in which workers perform significant text recognition tasks and will change the factor demands of these "exposed establishments."

To make these ideas precise, we define establishment $e$'s exposure to AI as

$$\text{exposure to AI}_e = \frac{\int_{x\in\mathcal{T}_e\cap\mathcal{T}^A}\ell_e(x)\,dx}{\int_{x\in\mathcal{T}_e}\ell_e(x)\,dx}, \tag{4}$$

where the employment shares are measured before the advances in AI take place. This measure represents the share of tasks performed in an establishment that can now be performed by AI-powered algorithms.[6]

We next explore how advances in AI impact AI activity and the demand for (non-AI) workers.

[5] This assumption can be relaxed in various ways. First, the technology can be more general than Leontief, so that factor prices affect how intensively AI workers are used. Second, establishments may be allowed to substitute outsourced AI workers for in-house services. The first modification would not have any major effect on our results, while the second would imply that our proxy for AI activity at the establishment level may understate the extent of AI, potentially leading to attenuation of our estimates. The common technology assumption in eqq. (2) and (3) can also be relaxed but is useful for simplifying the exposition by ensuring that differences in factor demands across establishments are driven entirely by task structures, making the link between the model and our empirical approach more transparent.

[6] When $\sigma = \infty$, as in propositions 1 and 2 below and the share of AI algorithms in cost is initially small, exposure to AI is $\int_{x\in\mathcal{T}_e\cap\mathcal{T}^A}\alpha(x)\,dx$, which gives the share of tasks that can now be completed with AI in total costs.

### B. Task Structure and AI Adoption

To illustrate how the task structure determines AI adoption, we follow Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018, 2019) and assume that $\sigma = \infty$, so that algorithms and labor are perfectly substitutable within a task. We also focus on the realistic case in which the initial cost share of AI, denoted by $s_e^A$ $(= (Rk_e(x) + w^{\mathrm{AI}}\ell_e^{\mathrm{AI}}(x))/\text{total costs})$, is small. Additionally, we consider the problem of a single establishment, holding the prices of other establishments in the market as given.

Proposition 1. Suppose that $\sigma = \infty$ and the initial cost share of AI, $s_e^A$, is small. Consider an improvement in AI technologies that increases $\gamma_a(x)$ in $\mathcal{T}^A$ and leads to the use of AI algorithms in these tasks. Then the effects on the cost share of AI and in-house AI employment are given by

$$ds_e^A = \text{exposure to AI}_e \geq 0$$

and

$$d\ln \ell_e^{\mathrm{AI}} = \left(\frac{1 - s_e^A}{s_e^A} + (\varepsilon_e \cdot \rho_e - 1) \cdot (1 - s_e^A) \cdot \pi_e\right) \cdot \text{exposure to AI}_e \geq 0,$$

where $\varepsilon_e > 1$ is the demand elasticity faced by the establishment, $\rho_e > 0$ is the establishment's pass-through rate, and $\pi_e \geq 0$ is the average percentage cost reduction in tasks performed by AI.

The proof of this proposition is provided in appendix A, where we also provide the expressions for the pass-through rate, $\rho_e$, and average cost savings from the use of AI algorithms, $\pi_e$.

The proposition shows that changes in AI activity and hiring of AI workers are both proportional to exposure to AI. Motivated by these results, in our empirical work we use exposure to AI as the key right-hand side variable and identify greater use of AI with the posting of more vacancies for in-house AI workers.

Although in this proposition we focused on the case where $\sigma = \infty$, a similar logic applies when $\sigma > 1$ and AI does not fully replace workers in the tasks it is used. In this case, AI advances still increase the cost share of AI and the hiring of AI workers in exposed establishments. When $\sigma < 1$, however, technological advances will not raise the cost share of AI because of strong complementarities between tasks produced by algorithms and humans.

### C. AI, Task Displacement, and Hiring

The next proposition characterizes the effects of AI advances on hiring of (non-AI) workers. Its proof is also in appendix A.

PROPOSITION 2. Suppose that $\sigma = \infty$ and the initial AI share of costs, $s_e^A$, is small. Consider an improvement in AI technologies that increases $\gamma_a(x)$ in $\mathcal{T}^A$ and leads to the use of AI algorithms in these tasks. The effects on non-AI employment, $\ell_e$, are

$$d \ln \ell_e = (-1 + (\varepsilon_e \cdot \rho_e - 1) \cdot \pi_e) \cdot \text{exposure to AI}_e, \tag{5}$$

where $\varepsilon_e > 1$ is the demand elasticity faced by the establishment, $\rho_e > 0$ is the establishment's pass-through rate, and $\pi_e \geq 0$ is the average percentage cost reduction in tasks performed by AI.

Proposition 2 shows that the effects of AI advances on labor demand are proportional to our exposure measure. More centrally, it clarifies the effects of AI advances on labor demand. The direct consequence of such advances is to expand the set of tasks performed by algorithms, $\mathcal{T}^A$, and to shrink the set of tasks allocated to workers in exposed establishments. Because $\sigma = \infty$, this technological improvement displaces workers from tasks in $\mathcal{T}^A$. This displacement effect is captured by the "$-1$" in the parentheses on the right-hand side of equation (5). In addition, as emphasized in Acemoglu and Restrepo (2018), the reallocation of tasks from workers to algorithms reduces costs and expands establishment output, $y_e$ (and this output response depends on the demand elasticity and the pass-through rate). This " productivity effect," the magnitude of which is proportional to the cost reductions due to AI, $\pi_e \geq 0$, increases hiring in nonautomated tasks. If the second term on the right-hand side of equation (5), $(\varepsilon_e \cdot \rho_e - 1) \cdot \pi_e$, exceeds $-1$, the productivity effect dominates and AI technologies increase hiring.[7] Otherwise, AI advances will reduce (non-AI) hiring in exposed establishments.

We make two additional remarks. First, as with the results on AI activity, the main conclusions of proposition 2 can be generalized to the case in which $\sigma > 1$. In this case, not all workers previously employed in AI ex post tasks would be displaced, but the substitution away from them to algorithms would create a negative displacement and a positive productivity effect, similar to those in the proposition.

Second, if different tasks require different skills, then the adoption of AI technologies may also change the set of skills that exposed establishments demand (and list in their vacancies). Skills relevant for tasks now performed by algorithms will be demanded less frequently, and new skills necessary for working alongside AI algorithms may also start being included in vacancies.

Our empirical work will be based on equation (5). We will explore the relationship between AI exposure, as defined in equation (4), and changes

[7] This expression also clarifies that when the pass-through rate is less than $1/\varepsilon_e$, the establishment's price increases sufficiently that output does not expand and thus employment always declines.

in the number and skill content of the vacancies an establishment posts. Specifically, we will look at whether exposed establishments hire more AI workers, demand different sets of skills, and increase or reduce their hiring of non-AI workers.

## D. Human-Complementary AI

We have so far not considered human-complementary effects of AI. The possibility that AI will complement workers engaged in exposed tasks can be captured by assuming that $\alpha(x)$ increases for exposed tasks (see eq. [1]) or, alternatively, that $\sigma < 1$, so that algorithms and human labor are complementary within a task (or both). This type of human-complementary AI may increase labor demand because algorithms raise human productivity in exactly the tasks in which AI is being adopted.

Evidence that AI is associated with greater establishment-level employment would be consistent with the human-complementary view but could also be consistent with task substitution associated with large productivity gains that nonetheless increase hiring at exposed establishments. Conversely, evidence of negative, or even zero, effects would weigh against both the human-complementary view and the possibility of large productivity gains from AI—since both AI-human complementarity and large productivity effects boosting employment in nonautomated tasks could generate a positive relationship between AI exposure and establishments hiring. Our evidence below finds negative effects of AI exposure on (non-AI) hiring and thus suggests that the current generation of AI technologies is predominantly task replacing and generates only modest productivity gains.[8] It remains possible that other AI technologies than the ones we are proxying here could have different effects.

## E. Measuring Exposure to AI

Propositions 1 and 2 show that we should see the effects of advances in AI in establishments with task structures that make them highly exposed to AI. Differences in exposure are, in turn, driven by the different task structures across establishments. In our empirical exercise, we will use the occupational mix of an establishment prior to the major advances in AI to infer its task structure and compute its exposure to AI. Formally, we assume that the set of tasks in the economy, $\mathcal{T}$, is partitioned into tasks performed by a set of distinct occupations and denote the set of tasks performed in occupation $o \in O$ by $\mathcal{T}^o$. Each establishment $e$'s task structure is thus represented by the set of occupations that the establishment employs, denoted by $O_e \subset O$, and

[8] Or that productivity gains, if present, have little effect on demand, potentially because of low pass-through rates.

so $\mathcal{T}_e = \cup_{o \in O_e} \mathcal{T}^o$. For example, some establishments will employ accountants and their production will use the set of tasks accountants perform, while others require the tasks performed by security analysts or retail clerks and thus hire workers into these occupations. In our empirical work, we will use the occupational indices provided by Felten, Raj, and Seamans (2018, 2019), Webb (2020) and Brynjolfsson, Mitchell, and Rock (2018, 2019) to identify the set of occupations involving tasks where AI can (or could) be deployed. We will then compute measures of AI exposure based on the occupational structure of an establishment.[9]

## III. Data

We next describe the BG data, document that it is broadly representative of employment and hiring trends across occupations and industries, present our AI exposure indices, and document their distribution across occupations and their evolution over time.

### A. Burning Glass Data

Burning Glass collects data from roughly 40,000 company websites and online job boards, with no more than 5% of vacancies from any one source. BG applies a deduplication algorithm and converts the vacancies into a form amenable to data analysis. The coverage is the near universe of online vacancies from 2010 onward in the United States, with somewhat more limited coverage in 2007. Our primary sample comprises data from the start of 2010 until October 2018, although we also make use of the 2007 data. The vacancy data enumerate occupation, industry, and region information; firm identifiers; and detailed information on occupations and skills required by vacancies, garnered from the text of job postings.

A key question concerns the representativeness of BG data given that the source of the vacancies is online job postings. Figure 1 shows that BG data

[9] Formally, these AI indices are the empirical analog of our theoretical exposure to AI measure in eq. (4). To see this, note that

$$\text{AI index}^o = \frac{\int_{x \in \mathcal{T}^o \cap \mathcal{T}^A} \ell(x)\, dx}{\int_{x \in \mathcal{T}^o} \ell(x)\, dx},$$

where $\ell(x)$ is average employment in task $x$ and we denote average employment in occupation $o$ by $\ell^o = \int_{x \in \mathcal{T}^o} \ell(x)\, dx$. When $\ell(x) = \ell_e(x)$, which follows from our common technology assumption, the exposure to AI measure is equal to the employment weighted average of the occupation AI exposure measure:

$$\frac{\sum_{o \in O_e} \text{AI index}^o \ell^o}{\sum_{o \in O_e} \ell^o} = \frac{\sum_{o \in O_e} \frac{\int_{x \in \mathcal{T}^o \cap \mathcal{T}^A} \ell(x)\, dx}{\int_{x \in \mathcal{T}^o} \ell(x)\, dx} \ell^o}{\sum_{o \in O_e} \ell^o} = \frac{\int_{x \in \mathcal{T}_e \cap \mathcal{T}^A} \ell(x)\, dx}{\int_{x \in \mathcal{T}_e} \ell(x)\, dx} = \text{exposure to AI}_e.$$

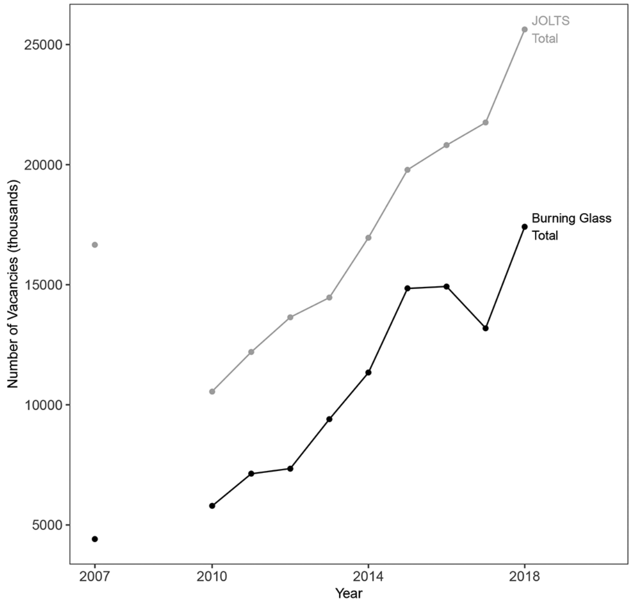


FIG. 1.—Vacancies in Burning Glass and JOLTS. This figure plots the total number of vacancies in JOLTS and the total number of vacancies in Burning Glass by year. We multiply the number of job openings in JOLTS by a constant factor of 0.65 to arrive at a number of vacancies that matches the concept of a vacancy in Burning Glass. This method follows Carnevale, Jayasundera, and Repnikov (2014). A color version of this figure is available online.

closely track the evolution of overall vacancies in the US economy as recorded by the nationally representative Bureau of Labor Statistics (BLS) Job Openings and Labor Turnover Survey (JOLTS). The exception is the downturn in BG postings data between 2015 and 2017.[10] Figure A1 (available online) shows that over the 2010–18 period, the occupational and industry composition in BG is closely aligned with both overall occupation employment shares from Occupational Employment Statistics (OES) and with industry vacancy shares from JOLTS.[11]

[10] While JOLTS measures a snapshot of open vacancies posted by establishments during the last business day of the month, BG counts new vacancies posted by the establishment during the entire month. We adjust the numbers of job openings in JOLTS to match BG's concept of vacancies, using the approach developed by Carnevale, Jayasundera, and Repnikov (2014). The difference in concept between JOLTS and Burning Glass vacancies likely accounts for the downturn in BG postings data between 2015 and 2017.

[11] We note that BG data represent vacancy flows while the OES reports employment stocks; thus, we do not expect the two data sources to align perfectly. Moreover, online vacancy postings tend to overrepresent technical and professional jobs

We make use of Burning Glass's detailed industry and establishment data. When this information is available from the text of postings, vacancies are assigned a firm name and a location, typically at the city level, as well as an industry code. We classify each firm as belonging to the industry in which it posts the most vacancies over our sample period. We define an establishment of a firm as the collection of vacancies pertaining to a firm and commuting zone (CZ). CZs are groups of counties that, because of their strong commuting ties, approximate a local labor market (Tolbert and Sizer 1996).

Of particular importance for our paper are BG's detailed skill and occupation coding. Vacancies in BG data contain information on skill requirements, scraped from the text of the vacancy. The skills are organized according to several thousand standardized fields. Groups of related skills are collected together into "skill clusters." More than 95% of vacancies are assigned a six-digit (Standard Occupational Classification [SOC]) occupation code.[12]

We use these skill data to construct two measures of AI vacancies, narrow and broad. The narrow category includes a selection of skills relating to AI.[13] The broad measure of AI includes skills belonging to the broader skill clusters of machine learning, AI, natural language processing, and data science. A concern with our broad AI measure is that it may include various IT functions that are separate from core AI activities. For this reason, we focus on the narrow AI measure in the text and show the robustness of our main results with the broad occupation measure in appendix B. Figure 2 shows the evolution of postings of narrow and broad AI vacancies in the BG data, highlighting the rapid takeoff of AI vacancies after 2015, as noted in the introduction. While a sharp uptick is visible in all industries, the right panel of figure 2 shows that the takeoff is particularly pronounced in the information, professional and business services, finance, and manufacturing sectors.

In what follows, our primary focus is on AI-using sectors, and we drop establishments belonging to sectors that are likely to be producing AI-related products, namely, the information sector (NAICS sector 51) and

relative to blue collar and personal service jobs (Carnevale, Jayasundera, and Repnikov 2014).

12 Six-digit occupation codes are highly granular, including occupations such as pest control worker, college professor in physics, and home health aide.

13 The skills are machine learning, computer vision, machine vision, deep learning, virtual agents, image recognition, natural language processing, speech recognition, pattern recognition, object recognition, neural networks, AI chatbot, supervised learning, text mining, unsupervised learning, image processing, Mahout, recommender systems, support vector machines, random forests, latent semantic analysis, sentiment analysis/opinion mining, latent Dirichlet allocation, predictive models, kernel methods, Keras, gradient boosting, OpenCV, XGBoost, Libsvm, Word2vec, machine translation, and sentiment classification.

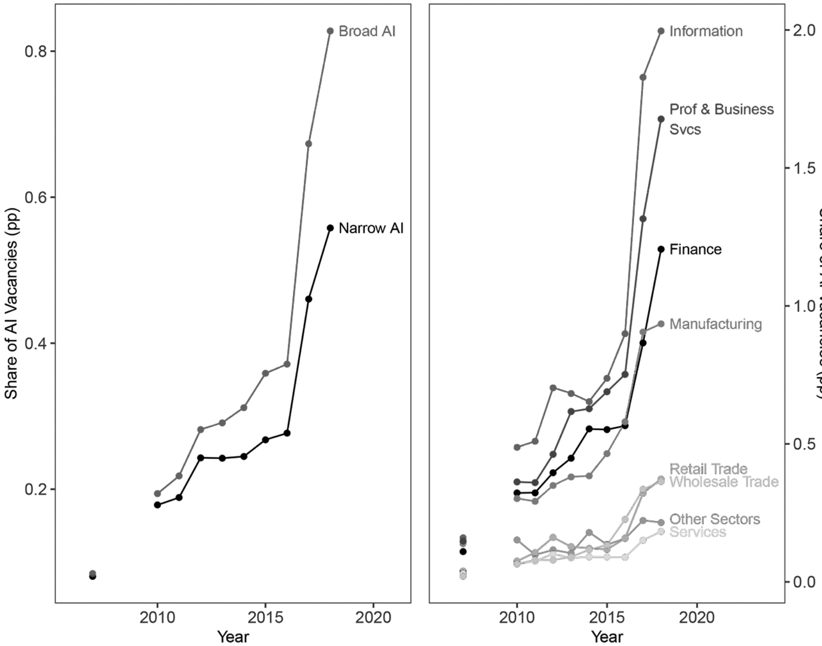


FIG. 2.—Share of AI vacancies in Burning Glass. The left panel plots the share of vacancies in Burning Glass that post a skill in the broad or narrow AI categories, as defined in the main text. The right panel plots the share of narrow AI vacancies in Burning Glass, by year, in each industry sector. pp = percentage point. A color version of this figure is available online.

the professional and business services sector (NAICS sector 54). The former includes various information technology industries, likely to be selling AI products, while the latter contains industries such as management consultancy, likely to be integrating AI into other industries' production processes.

## B. AI Indices

We study three measures of AI exposure. Each is assigned at the six-digit SOC occupation level, and each is designed to capture occupations concentrating in tasks that are compatible with the current capabilities of AI technologies.

The first measure is from Felten, Raj, and Seamans (2019). It is based on data from the AI Progress Measurement project, from the Electronic Frontier Foundation. The Electronic Frontier data identify a set of nine application areas in which AI has made progress since 2010, such as image recognition or language modeling. Felten et al. use Amazon MTurk to collect crowdsourced assessments of the relevance of each of these application areas to the 52 O*NET ability scales (e.g., depth perception, number facility, and written comprehension). The authors then construct the AI occupational impact for each O*NET occupation as the weighted sum of the 52 AI application-ability scores, where weights are equal to the O*NET-reported prevalence and importance of each ability in the occupation.

The second measure is from Webb (2020). Webb's analysis seeks to measure what tasks AI can perform by identifying overlaps between claims about capabilities in AI patents and job descriptions in O*NET. Occupations that have a larger fraction of such overlapping tasks are classified as more exposed.

The third measure is SML from Brynjolfsson, Mitchell, and Rock (2019). To build this measure, Brynjolfsson, Mitchell, and Rock (2019) develop a 23-item rubric that enables the scoring of the suitability of any task for machine learning. They derive the SML scores by applying this rubric to the textual description of the full set of O*NET occupations using CrowdFlower, a crowdsourcing platform.

The three measures introduced above identify occupations that involve tasks in which AI algorithms have made (or could make) significant advances. The measures differ in the way they capture the applicability of AI to a task. Felten et al. and Webb focus on identifying tasks that fall within existing capabilities, either by relying on the reports from the AI Progress Measurement project or based on the text of patents. The Brynjolfsson et al. SML index is more forward looking and identifies tasks that could be performed by machine learning/AI in the near term, even if outside the reach of existing capabilities. Given the short period of time covered by the BG data, we expect, and in fact find, that Felten et al.'s AI occupational impact and Webb's measure should have greater explanatory power for current adoption dynamics and establishment outcomes.

Figure 3 shows the distribution of our three indices by broad occupation categories and by one-digit industry.[14] Figure 4 relates this same information to wages by plotting average AI exposure by occupational wage percentile for each index. The figures confirm that these three measures capture different aspects of AI. The Felten et al. measure, for example, is particularly high for managers, professionals, and office and administrative staff and is very low for service, production, and construction workers, capturing the fact that these occupations involve various manual tasks that cannot currently be performed by algorithms. The Webb measure is not particularly high in sales occupations and shows a strong positive relationship with occupational wage percentiles. In contrast, the SML measure is high for office and administrative occupations and for sales occupations and is (perhaps surprisingly) above average for personal services, but it is

[14] The broad occupational categories are those utilized by Autor (2019) and aggregate six-digit occupations into 12 roughly one-digit categories.

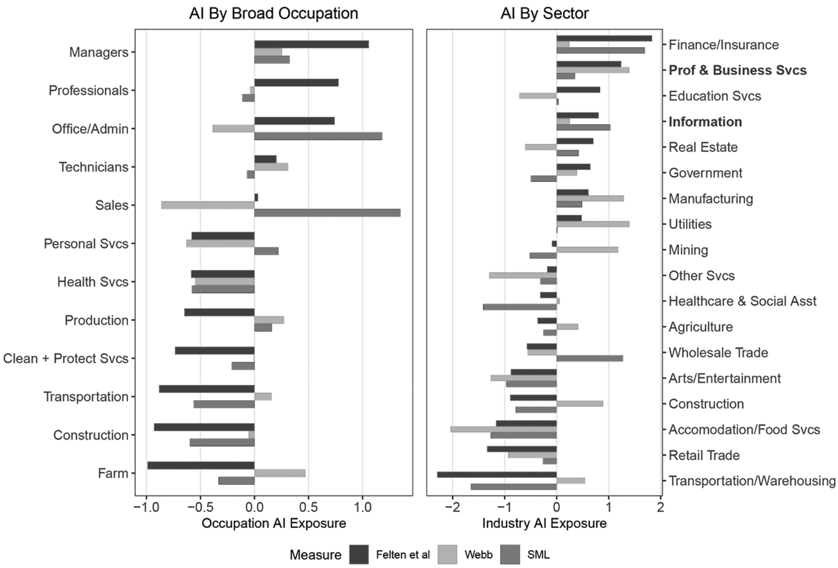


FIG. 3.—AI exposure by broad occupation and sector. The left panel plots the average of the standardized measures of AI exposure across broad occupations. The right panel plots the average of the standardized measures of AI exposure across two-digit NAICS sectors by taking the mean across the six-digit SOC occupations posted in each two-digit NAICS sector weighted by the number of vacancies posted by each sector in each occupation. A color version of this figure is available online.

low for professional occupations and most blue-collar and service occupations. Consequently, SML has no systematic relationship with occupational wage percentiles.[15]

## IV. Empirical Strategy

Our empirical strategy links measures of AI activity and job-posting outcomes to AI exposure, where both outcome and exposure variables are measured at the establishment level.

We estimate the following regression model:

$$\Delta y_{e,t-t_0} = \beta \mathrm{AI}_{e,t_0} + \mathbf{x}'_{e,t_0}\boldsymbol{\gamma} + \varepsilon_{e,t-t_0}, \tag{6}$$

[15] Another notable difference is that the Webb index finds very little AI suitability in either office or sales occupations. Alongside his AI index, Webb (2020) creates a separate software exposure index, pertaining to traditional non-AI software, that detects substantial software suitability in office, administrative, and sales occupations. We use this index as a control in our robustness checks.

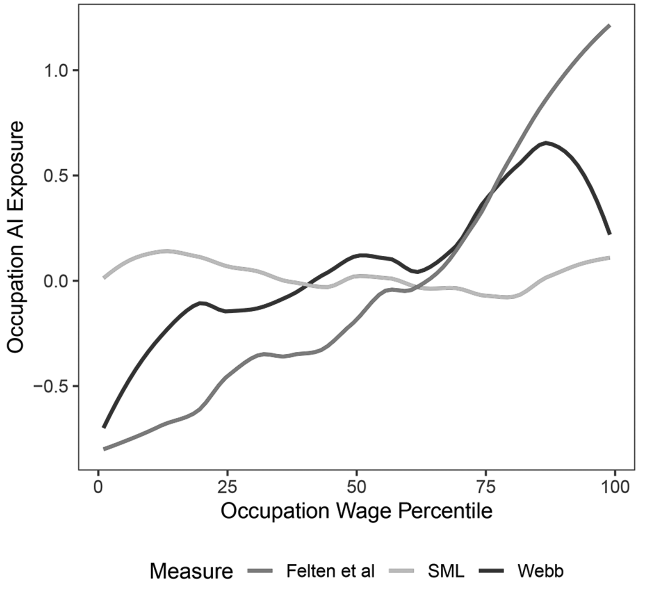


FIG. 4.—AI exposure by occupation wages. This figure plots a smoothed polynomial regression of the (standardized) measures of AI exposure in each six-digit SOC occupation against its rank in the wage distribution. We rank occupations according to their mean hourly wage for 2010–18, obtained from the OES. A color version of this figure is available online.

where $e$ denotes establishment, $\Delta y_{e,t-t_0}$ denotes the change in one of our establishment-level outcomes between 2010–12 and 2016–18, $\mathrm{AI}_{e,t_0} = \Sigma_o \text{share postings}_{oe,t_0} \cdot \text{AI score}_o$ is one of our three measures of establishment AI exposure calculated using establishment data for 2010–12, and $\mathbf{x}_{e,t_0}$ is a vector of baseline controls including industry dummies, firm size decile dummies, a dummy for the CZ in which the establishment is located, and, in some specifications, a set of firm fixed effects.[16] Finally, $\varepsilon_{e,t-t_0}$ is an error term representing all omitted factors.

Our primary interest is in the coefficient $\beta$, which captures the relationship between AI exposure and the outcome variable. We standardize the establishment AI exposure measure by dividing it by its weighted standard deviation, with weights given by vacancies in 2010–12. Hence, $\beta$ is the change in the outcome variable associated with a standard deviation difference in AI exposure.

The three main outcome measures we focus on for $\Delta y_{e,t-t_0}$ are AI vacancies, changes in job skill requirements of posted vacancies, and overall non-AI hiring, all measured at the establishment level.

[16] We pool 2010–12 data and, separately, 2016–18 data to improve precision.

## V. AI Exposure and AI Vacancies

We first document that AI exposure predicts establishment-level AI activity, as proxied by our measure of narrow AI vacancies. Table 1 presents the main estimates. Panel A of this table shows the relationship between AI exposure based on Felten et al.'s index and growth in AI vacancies, while the subsequent two panels present results for our other measures of AI exposure. We estimate regression models based on equation (6), with the left-hand side variable defined as the change in the inverse hyperbolic sine of AI vacancies between 2010–12 and 2016–18.[17] We focus on weighted specifications, using baseline establishment vacancies as weights. In the text, we report heteroscedasticity-robust standard errors that allow for arbitrary cross-sectional correlation across the establishments of each firm and consider alternative standard errors in appendix B.

Column 1 is our most parsimonious specification and includes no covariates, thus depicting the unconditional bivariate relationship. The coefficient estimate in panel A of $\beta = 15.96$ is precisely estimated (SE = 1.73) and shows a sizable association between AI exposure and AI vacancies. This estimate implies that a 1 standard deviation increase in AI exposure—which corresponds to the difference between finance and mining and all extraction—is associated with approximately a 16% increase in AI vacancies.

The remaining columns explore the robustness of this relationship. Column 2 controls for firm size decile and CZ fixed effects. The coefficient estimate of AI exposure declines slightly to 13.82 but is now more precisely estimated. Column 3 additionally adds three-digit (NAICS) industry fixed effects. Reflecting the sizable variation in AI exposure across industries shown in figure 3, these controls are more important for our regressions, and they reduce the magnitude of our estimate by about a third, to 9.19, but the standard error of the estimate also declines (to 1.21).

Column 4 goes one step further and includes a full set of firm fixed effects, so that now the comparison is among establishments of the same firm that differ in their AI exposure. The estimate of $\beta$ is similar to the bivariate relationship reported in column 1, 16.53, albeit slightly less precise, since all of the cross-firm variation is now purged.

Figure 3 documented significant differences in AI exposure across occupations. This raises the concern that our results may be confounded by secular trends across broad occupational categories. Columns 5 and 6 additionally

[17] The inverse hyperbolic sine transformation is given by

$$\ln\left(x + \sqrt{(x^2 + 1)}\right).$$

For small values of $x$, this approximates a proportional change but is well defined when $x = 0$, which is a frequent occurrence in our sample of establishments.

**Table 1**
**Effects of AI Exposure on Establishment AI Vacancy Growth, 2010–18**

| | Growth of Establishment AI Vacancies, 2010–18 | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | A. Felten et al. Measure of AI Exposure | | | | | |
| Establishment AI | 15.96 | 13.82 | 9.19 | 16.53 | 9.75 | 16.87 |
| Exposure, 2010 | (1.73) | (1.43) | (1.21) | (1.89) | (1.20) | (1.86) |
| Observations | 1,075,474 | 1,075,474 | 954,519 | 1,075,474 | 954,518 | 762,672 |
| | B. Webb Measure of AI Exposure | | | | | |
| Establishment AI | 6.59 | 5.08 | 3.21 | 5.91 | .42 | 1.14 |
| Exposure, 2010 | (1.13) | (.96) | (.81) | (1.27) | (.82) | (1.08) |
| Observations | 1,159,789 | 1,159,789 | 1,021,673 | 1,159,789 | 1,021,673 | 824,803 |
| | C. SML Measure of AI Exposure | | | | | |
| Establishment AI | 3.76 | 2.30 | −2.21 | −3.04 | 1.95 | 4.47 |
| Exposure, 2010 | (1.19) | (1.04) | (.96) | (1.38) | (.89) | (1.34) |
| Observations | 1,159,789 | 1,159,789 | 1,021,673 | 1,159,789 | 1,021,673 | 824,803 |
| Covariates: | | | | | | |
| Share of vacancies in sales and administration, 2010 | | | | | ✓ | ✓ |
| Fixed effects: | | | | | | |
| Firm size decile | | ✓ | ✓ | | ✓ | |
| CZ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Three-digit industry | | | ✓ | | ✓ | |
| Firm | | | | ✓ | | ✓ |

Note.—This table presents estimates of the effects of establishment AI exposure on establishment AI vacancy growth. The sample is establishments posting vacancies in 2010–12 or 2016–18 outside NAICS sectors 51 (information) and 54 (business services). The outcome variable, constructed from Burning Glass data, is the growth rate of AI vacancies between 2010 and 2018, multiplied by 100. We approximate this growth rate with the change in the inverse hyperbolic sine of the number of vacancies posted by the establishment in 2010–12 and 2016–18. The regressor, establishment AI exposure in 2010, is the standardized mean of occupation AI exposure over the six-digit SOC occupations for which the establishment posts vacancies in 2010–12 weighted by the number of vacancies posted per occupation. In panel A, the measure of occupation AI exposure is from Felten, Raj, and Seamans (2019). In panel B, the measure of occupation AI exposure is SML, from Brynjolfsson, Mitchell, and Rock (2019). In panel C, the measure of occupation AI exposure is from Webb (2020). The covariates included in each model are reported at the bottom of the table. Column 1 contains only establishment AI exposure. Columns 2, 3, and 5 include fixed effects for the decile of firm size (defined as the total vacancies posted by an establishment's firm in 2010–12). Columns 2–6 include CZ fixed effects. Columns 3 and 5 include three-digit NAICS industry fixed effects. Columns 4 and 6 include firm fixed effects. Columns 5 and 6 control for the share of 2010–12 vacancies in each establishment belonging to the broad occupations of either sales or administration. In each regression, observations are weighted by total establishment vacancies in 2010–12. Standard errors are clustered by firm.

control for the baseline shares of vacancies that are in sales and administration, two of the broad occupational categories that have been in decline for other reasons (e.g., Autor and Dorn 2013). These controls do not substantially change the estimate in either column, which remain, respectively, at 9.75 (SE = 1.20) and 16.87 (SE = 1.86).[18]

Figure 5*A* shows the specification from column 3 in the form of a bin scatterplot, where each bin represents about 50,000 establishments. The relationship between AI exposure and AI vacancy postings is fairly close to linear across the distribution and does not appear to be driven by outliers. The left panel of figure 6 provides a complementary visualization, depicting the evolution of AI vacancies for the four quartiles of the establishment AI exposure measure. It shows that the top two quartiles post significantly more AI vacancies and drive the surge in AI vacancies after 2015.[19]

Our simple measure of exposure to AI explains a significant fraction of the increase in AI vacancy posting. To document this point, we calculate the adjusted $R^2$ associated with the specifications in table 1. For comparison, in table A3 we also compute the share of the increase in AI activity associated with initial occupation composition by estimating a version of our main regression equation (6), with the share of establishment vacancies in each detailed occupation in 2010–12 as regressors. The adjusted $R^2$ of the Felten et al. measure of AI exposure is 0.0256. The adjusted $R^2$ when initial occupation shares are used as regressors is 0.10.[20] Hence, our AI exposure measure accounts for more than one-quarter of the AI adoption associated with baseline occupation structures.

Panels B and C of table 1 repeat the panel A regressions using the Webb and SML indices of AI exposure. Estimates using the Webb measure, reported in panel B, are similar to those in panel A in the first four specifications, although they are not fully robust to controls for the baseline shares of sales and administration vacancies in columns 5 and 6. Figure 5*B* shows

[18] Table A1 (tables A1–A15 are available online) shows that the results in panel A are also robust if we include the baseline shares of 10 broad occupational categories. For example, the coefficients in the specifications that parallel cols. 5 and 6 are, respectively, 7.24 (SE = 1.44) and 13.70 (SE = 2.12). However, some of the results for the Webb and SML AI exposure measures are sensitive to these controls.

[19] Our exposure measure is a "shift-share" instrument, and the heteroscedasticity-robust standard errors are not the most conservative ones because they do not recognize the additional correlation coming from the covariation of these shares (Adao, Kolesár, and Morales 2019; Borusyak, Hull, and Jaravel 2022). Table A2 repeats table 1 with standard errors from Borusyak, Hull, and Jaravel (2022), with similar results.

[20] We estimate the regressions in table A3 on a 10% sample, since there are many regressors in the model with initial occupation shares. We have verified that the adjusted $R^2$ is similar in the sample and the full data when the regressors are our measures of AI exposure.

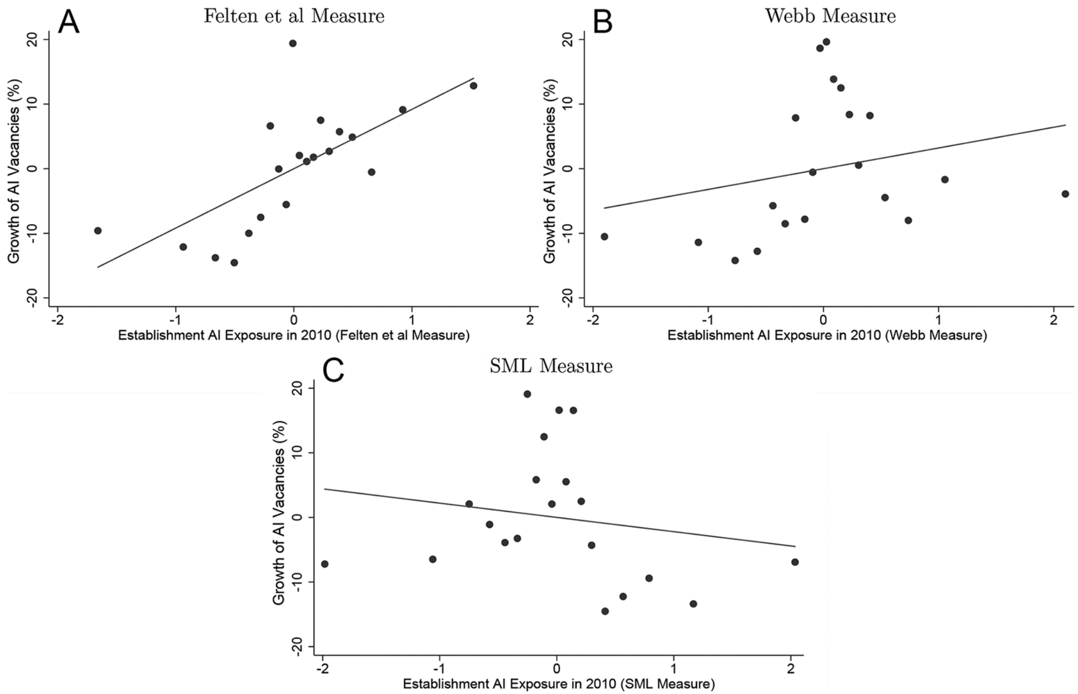


Fig. 5.—Bin scatterplot of AI growth and establishment AI exposure. This figure presents binned scatterplots that summarize the relationship between establishment AI exposure in 2010 and the growth of AI establishment vacancies between 2010 and 2018. *A* uses the measure of AI exposure from Felten, Raj, and Seamans (2019). *B* uses the Webb (2020) measure. *C* uses the SML measure, from Brynjolfsson, Mitchell, and Rock (2019). In all panels, the covariates from column 3 of table 1 are partialed out. The solid line corresponds to a regression with 2010 establishment vacancies as the weight. The corresponding point estimates and standard errors are reported at the bottom of each panel. We exclude vacancies in industry sectors 51 (information) and 54 (business services). A color version of this figure is available online.

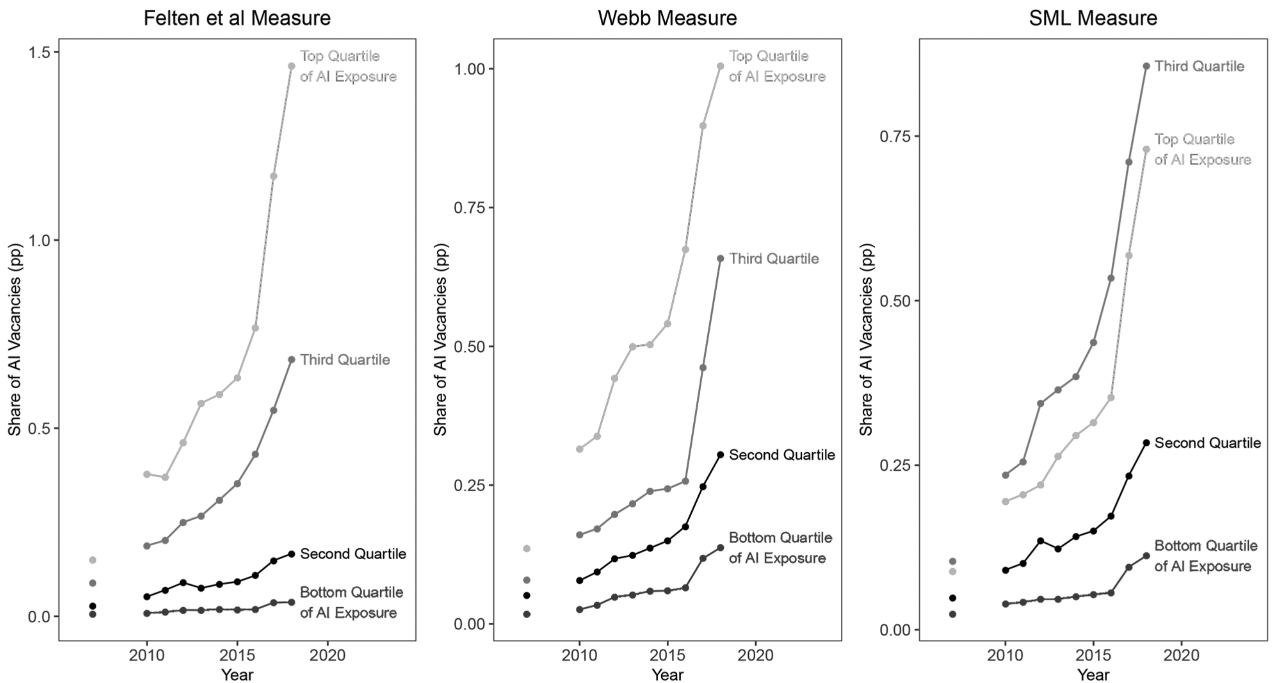


FIG. 6.—Establishment share of AI vacancies by quartile of AI exposure. This figure plots establishments' share of AI vacancies in Burning Glass, for each quartile of the distribution of 2010 establishment AI exposure, after partialing out their 2010–12 share of vacancies in sales and administration. In the left panel, the measure of occupation AI exposure is from Felten, Raj, and Seamans (2019). In the middle panel, the measure is SML, from Brynjolfsson, Mitchell, and Rock (2019). In the right panel, the measure is from Webb (2020). We exclude vacancies in industry sectors 51 (information) and 54 (business services). A color version of this figure is available online.

that the bin scatterplot with the Webb measure looks similar to—although noisier than—the one in figure 5*A* with the Felten et al. measure, and figure 6 confirms that the surge in AI vacancies is again driven by the top two quartiles. Given that the Felten et al. and Webb indices capture different components of AI exposure (recall fig. 3), the broadly similar picture they depict is reassuring. However, from table A3, the partial $R^2$ associated with the Webb measure is 0.0074, roughly one-quarter of the corresponding $R^2$ for the Felten et al. measure.

Results with the SML index in panel C are broadly similar but significantly weaker. There is a positive association between the SML-based measure of AI exposure and AI vacancy growth without any covariates, but when three-digit industry fixed effects are included, this relationship becomes negative. The proximate explanation for this pattern is that the sales and administration occupations have a high SML score, as noted above, and are negatively associated with AI adoption. When we control for the baseline shares of these occupations in columns 5 and 6, the positive relationship in column 1 is restored. Figure 5*C* and the right panel of figure 6 show a less clear pattern relative to the Felten et al. and Webb measures as well. The bin scatterplot confirms the lack of a robust relationship between exposure to AI based on the SML measure and AI vacancies (from the specification in col. 3), and the evolution of AI vacancy growth by exposure quartiles in figure 6 no longer shows a monotone pattern. These weaker results with SML motivate our greater emphasis on the results using the Felten et al. and Webb measures in the remainder of the paper.

A concern with the estimates in table 1 is that the AI measures may be proxying for exposure to non-AI digital technologies. If so, this would cloud the interpretation of our estimates as primarily capturing the impacts of AI exposure on establishment outcomes. We check for this possibility in table 2 by additionally controlling for Webb's measure of exposure to "software," which is calculated analogously to his AI exposure measure but focusing on occupations and tasks suitable for traditional software and digital technologies. The inclusion of the software exposure measure has little impact on the coefficients of interest, particularly in the case of the Felten et al. index. For example, in the most loaded specification (col. 6), the point estimate is now 17.47 with a standard error of 1.90, compared with 16.87 and a standard error of 1.86 in table 1. The software exposure measure itself does not have a consistent association with AI vacancy growth: it is positive and statistically significant in some specifications, small and insignificant in others, and negative and significant in yet others. This set of estimates bolsters our confidence that the AI exposure variable identifies meaningful variation in the suitability of establishment task structure for AI and that this variation is distinct from exposure to traditional software and digital technologies.

We provide several robustness checks on these basic patterns in appendix B. In table A4, we report estimates for AI vacancy growth using AI exposure

**Table 2**
**Effects of AI Exposure on Establishment AI Vacancy Growth, Controlling for Software Exposure**

| | Growth of Establishment AI Vacancies, 2010–18 | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | A. Felten et al. Measure of AI Exposure | | | | | |
| Establishment AI | 16.28 | 14.10 | 9.63 | 17.43 | 9.96 | 17.47 |
| Exposure, 2010 | (1.74) | (1.44) | (1.23) | (1.95) | (1.24) | (1.90) |
| Establishment software | 2.36 | 2.24 | 2.62 | 4.83 | .66 | 1.83 |
| Exposure | (.76) | (.71) | (.76) | (1.23) | (.82) | (1.19) |
| Observations | 1,059,620 | 1,059,620 | 941,046 | 1,059,620 | 941,046 | 1,059,620 |
| | B. Webb Measure of AI Exposure | | | | | |
| Establishment AI | 10.64 | 7.88 | 3.85 | 6.81 | 1.50 | 2.57 |
| Exposure, 2010 | (1.83) | (1.50) | (1.10) | (1.52) | (1.07) | (1.41) |
| Establishment software | −6.28 | −4.27 | −.96 | −1.44 | −1.81 | −2.54 |
| Exposure | (1.51) | (1.26) | (.96) | (1.34) | (1.00) | (1.49) |
| Observations | 1,159,789 | 1,159,789 | 1,021,673 | 1,159,789 | 1,021,673 | 1,159,789 |
| | C. SML Measure of AI Exposure | | | | | |
| Establishment AI | 4.14 | 2.64 | −1.96 | −2.42 | 1.90 | 4.37 |
| Exposure, 2010 | (1.18) | (1.04) | (.96) | (1.28) | (.88) | (1.28) |
| Establishment software | 1.56 | 1.44 | 1.09 | 2.40 | −.90 | −.76 |
| Exposure | (.80) | (.77) | (.69) | (1.04) | (.78) | (1.11) |
| Observations | 1,159,789 | 1,159,789 | 1,021,673 | 1,159,789 | 1,021,673 | 1,159,789 |
| Covariates: | | | | | | |
| Share of vacancies in sales and administration, 2010 | | | | | ✓ | ✓ |
| Fixed effects: | | | | | | |
| Firm size decile | | ✓ | ✓ | | ✓ | |
| CZ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Three-digit industry | | | ✓ | | ✓ | |
| Firm | | | | ✓ | | ✓ |

NOTE.—This table presents estimates of the effects of establishment AI exposure on establishment AI vacancy growth, controlling for establishment software exposure. Our measure of software exposure is from Webb (2020). Establishment software exposure is the standardized mean of occupation software exposure over the six-digit SOC occupations for which the establishment posts vacancies in 2010–12 weighted by the number of vacancies posted per occupation. The sample is establishments posting vacancies in 2010–12 and 2016–18 outside NAICS sectors 51 (information) and 54 (business services). The outcome variable, constructed from Burning Glass data, is the growth rate of AI vacancies between 2010 and 2018, multiplied by 100. We approximate this growth rate with the change in the inverse hyperbolic sine of the number of vacancies posted by the establishment in 2010–12 and 2016–18. The regressor, establishment AI exposure in 2010, is the standardized mean of occupation AI exposure over the six-digit SOC occupations for which the establishment posts vacancies in 2010–12 weighted by the number of vacancies posted per occupation. In panel A, the measure of occupation AI exposure is from Felten, Raj, and Seamans (2019). In panel B, the measure of occupation AI exposure is SML, from Brynjolfsson, Mitchell, and Rock (2019). In panel C, the measure of occupation AI exposure is from Webb (2020). The covariates included in each model are reported at the bottom of the table. Column 1 contains only establishment AI exposure. Columns 2, 3, and 5 include fixed effects for the decile of firm size (defined as the total vacancies posted by an establishment's firm in 2010–12). Columns 2–6 include CZ fixed effects. Columns 3 and 5 include three-digit NAICS industry fixed effects. Columns 4 and 6 include firm fixed effects. Columns 5 and 6 control for the share of 2010–12 vacancies in each establishment belonging to the broad occupations of either sales or administration. In each regression, observations are weighted by total establishment vacancies in 2010–12. Standard errors are clustered by firm.

calculated using establishments' occupational structures in 2007 rather than 2010. Although this greatly reduces the sample size, as many establishments operating in both 2010 and 2018 are not present in the 2007 data, we obtain results that are qualitatively similar to those in table 1.

In table A5, we replace the narrow AI vacancy measures used in table 1 with the broad AI vacancy indices discussed above (see fig. 2), and in table A6 we use the change in the share of AI vacancies among all vacancy postings as the dependent variable. The results in both tables corroborate our main findings in table 1 and, if anything, are stronger and more stable, especially with the Webb measure. The quantitative magnitudes implied by the estimates in these tables are comparable to our baseline estimates. For example, with the Felten et al. measure and the specification in column 6, an additional standard deviation of AI exposure is associated with a 19 percentage point increase (SE = 0.02) in the share of AI vacancies between 2010 and 2018.

We also explored firm-level variants of the establishment-level models described above. Because of the many zeros in the data, the establishment-level estimates do not aggregate cleanly to firm-level estimates. As shown in columns 1 and 2 of table A7, these estimates are generally imprecise and inconsistently signed. However, when we estimate models for the firm-level mean of establishment AI vacancy growth (cols. 3, 4) or models with share of AI vacancies (cols. 5, 6), the estimates are very similar to our main results in table 1.

In summary, the data point to a recent surge in AI-related hiring, and our regression evidence reveals that establishments whose task structures enable the use of AI technologies have substantially increased their AI-related postings. This evidence suggests that an important component of AI activity is linked to the types of tasks performed in an establishment—although it does not preclude the possibility that AI activity has other drivers, such as the development of new products or business models.

## VI. AI and New Skills

Having established the link between AI suitability and AI activity/hiring at the level of establishments, we now turn to the broader labor market implications of growing AI adoption. AI is intended to supplement, replicate, and in some cases exceed human-level intelligence in a variety of tasks. We therefore anticipate that establishments with task structures that are suitable for AI will tend to change the types of worker skills they demand.

To investigate whether AI exposure predicts skill demands in non-AI jobs, we build on work by Deming and Noray (2020), who document such changes associated with broader IT-related activity. We adapt their measure of change in skill demands to establishments and separate their gross skill change measure into negative and positive changes, capturing the disappearance of existing skills and the emergence of new skills:

$$\text{negative skill change}_{e,t_2,t_1} = -\min\left\{\sum_{s=1}^{S}\left[\left(\frac{\text{skill}^s_{e,t_2}}{\text{vacancies}_{e,t_2}}\right) - \left(\frac{\text{skill}^s_{e,t_1}}{\text{vacancies}_{e,t_1}}\right)\right], 0\right\},$$

$$\text{positive skill change}_{e,t_2,t_1} = \max\left\{\sum_{s=1}^{S}\left[\left(\frac{\text{skill}^s_{e,t_2}}{\text{vacancies}_{e,t_2}}\right) - \left(\frac{\text{skill}^s_{e,t_1}}{\text{vacancies}_{e,t_1}}\right)\right], 0\right\},$$

Here, $\text{skill}^s_{e,t}$ is the number of times skill $s$ is posted by establishment $e$ in year $t$, which we normalize by dividing it by the total number of vacancies posted by that establishment. The negative skill change measure therefore represents a decline in the frequency with which some of the skills that were formerly posted appear in vacancies, while the positive skill change measure captures increases in the frequency with which other skills are posted in vacancies—which may include the addition of skills that were not previously posted. We calculate these measures for non-AI vacancies and, as before, for all establishments except those in the professional and business services and information technology sectors (51 and 54).

Tables 3 and 4 show that establishment AI exposure is robustly associated with negative and positive skill changes. For example, in panel A of table 3, which focuses on negative skill changes, column 1 shows an estimate of 0.83, which indicates that a 1 standard deviation increase in the Felten et al. exposure measure is associated with a 0.83 absolute decline in the per-vacancy frequency with which skills previously demanded are posted (SE = 0.09). This is a large change compared with the mean negative skill change in our sample, 4.70, and suggests that the deployment of AI technologies goes hand in hand with significant skill redundancies. Equally interesting is the pattern in table 4, which shows that AI exposure is associated with demand for new skills. Column 1 of this table shows that a 1 standard deviation increase in the Felten et al. AI exposure measure is associated with a 0.95 absolute increase (SE = 0.08) in the per-vacancy frequency of skills that were either demanded less frequently previously or were not previously demanded. This too is a sizable impact compared with the mean positive skill change in our sample of 6.30.

These patterns are quite robust, as is shown in the remaining columns and panels of tables 3 and 4. Each of the three AI exposure measures—Felten et al., Webb, and SML—predict both negative and positive establishment-level skill changes between 2010 and 2018. Paralleling our findings at many points in the paper, the Felten et al. measure proves to have the most stable and largest quantitative relationship to the outcome variable, followed by Webb and SML. In particular, all measures prove robust to the inclusion of firm size deciles, CZ dummies, and controls for initial establishment vacancy structures in sales and administrative occupations. All three are also robust to the inclusion of firm fixed effects when we look at negative skill changes. The association between AI exposure and positive skill changes is no longer present when we include firm fixed effects, however, suggesting that the

**Table 3**
**Effects of AI Exposure on Establishment Negative Skill Change, 2010–18**

| | Establishment Negative Skill Change, 2010–18 | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | A. Felten et al. Measure of AI Exposure | | | | | |
| Establishment AI | .83 | .83 | .97 | .50 | 1.00 | .54 |
| Exposure, 2010 | (.09) | (.09) | (.07) | (.05) | (.07) | (.05) |
| Observations | 339,282 | 339,282 | 322,901 | 339,282 | 322,901 | 339,282 |
| | B. Webb Measure of AI Exposure | | | | | |
| Establishment AI | .62 | .60 | .45 | .20 | .68 | .34 |
| Exposure, 2010 | (.11) | (.11) | (.06) | (.04) | (.11) | (.04) |
| Observations | 353,107 | 353,107 | 335,589 | 353,107 | 335,589 | 353,107 |
| | C. SML Measure of AI Exposure | | | | | |
| Establishment AI | .53 | .52 | .32 | .26 | .46 | .36 |
| Exposure, 2010 | (.08) | (.07) | (.07) | (.04) | (.09) | (.04) |
| Observations | 353,107 | 353,107 | 335,589 | 353,107 | 335,589 | 353,107 |
| Covariates: | | | | | | |
| Share of vacancies in sales and administration, 2010 | | | | | ✓ | ✓ |
| Fixed effects: | | | | | | |
| Firm size decile | | ✓ | ✓ | | ✓ | |
| CZ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Three-digit industry | | | ✓ | | ✓ | |
| Firm | | | | ✓ | | ✓ |

NOTE.—This table presents estimates of the effects of establishment AI exposure on establishment negative skill change. The sample is establishments posting in both 2010 and 2018 outside NAICS sectors 51 (information) and 54 (business services). The outcome variable, constructed from Burning Glass data, is establishment negative skill change for 2010–18, as defined in the main text. The regressor, establishment AI exposure in 2010, is the standardized mean of occupation AI exposure over the six-digit SOC occupations for which the establishment posts vacancies in 2010–12 weighted by the number of vacancies posted per occupation. In panel A, the measure of occupation AI exposure is from Felten, Raj, and Seamans (2019). In panel B, the measure of occupation AI exposure is SML, from Brynjolfsson, Mitchell, and Rock (2019). In panel C, the measure of occupation AI exposure is from Webb (2020). The covariates included in each model are reported at the bottom of the table. Column 1 contains only establishment AI exposure. Columns 2, 3, and 5 include fixed effects for the decile of firm size (defined as the total vacancies posted by an establishment's firm in 2010–12). Columns 2–6 include CZ fixed effects. Columns 3 and 5 include three-digit NAICS industry fixed effects. Columns 4 and 6 include firm fixed effects. Columns 5 and 6 control for the share of 2010–12 vacancies in each establishment belonging to the broad occupations of either sales or administration. In each regression, observations are weighted by total establishment vacancies in 2010–12. Standard errors are clustered by firm.

addition of new skills may not be localized to highly exposed establishments but rather occur throughout the firm or at the headquarters. Finally, tables A8 and A9 additionally confirm that controlling for Webb's measure of exposure to software, as we did in table 2, has little effect on the relationship between AI exposure and changes in skill demands. Akin to the table 2 results, this pattern underscores that the predictive relationship between AI exposure and establishment outcomes is distinct from that for exposure to traditional software.

To provide insight into what types of skills are affected by AI, we estimate the same models as in tables 3 and 4 within 28 skill families created

**Table 4**
**Effects of AI Exposure on Establishment Positive Skill Change, 2010–18**

| | Establishment Positive Skill Change, 2010–18 | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | A. Felten et al. Measure of AI Exposure | | | | | |
| Establishment AI | .95 | .94 | .58 | .02 | .62 | .05 |
| Exposure, 2010 | (.08) | (.09) | (.09) | (.04) | (.09) | (.04) |
| Observations | 339,282 | 339,282 | 322,901 | 339,282 | 322,901 | 339,282 |
| | B. Webb Measure of AI Exposure | | | | | |
| Establishment AI | .69 | .66 | .26 | −.01 | .43 | .13 |
| Exposure, 2010 | (.09) | (.09) | (.08) | (.03) | (.08) | (.04) |
| Observations | 353,107 | 353,107 | 335,589 | 353,107 | 335,589 | 353,107 |
| | C. SML Measure of AI Exposure | | | | | |
| Establishment AI | .62 | .59 | .19 | .10 | .26 | .03 |
| Exposure, 2010 | (.09) | (.09) | (.09) | (.04) | (.09) | (.04) |
| Observations | 353,107 | 353,107 | 335,589 | 353,107 | 335,589 | 353,107 |
| Covariates: | | | | | | |
| Share of vacancies in sales and administration | | | | | ✓ | ✓ |
| Fixed effects: | | | | | | |
| Firm size decile | | ✓ | ✓ | | ✓ | |
| CZ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Three-digit industry | | | ✓ | | ✓ | |
| Firm | | | | ✓ | | ✓ |

Note.—This table presents estimates of the effects of establishment AI exposure on establishment positive skill change. The sample is establishments posting vacancies in 2010–12 and 2016–18 outside NAICS sectors 51 (information) and 54 (business services). The outcome variable, constructed from Burning Glass data, is establishment positive skill change for 2010–18, as defined in the main text. The sample is establishments posting in both 2010 and 2019. The regressor, establishment AI exposure in 2010, is the standardized mean of occupation AI exposure over the six-digit SOC occupations for which the establishment posts vacancies in 2010–12 weighted by the number of vacancies posted per occupation. In panel A, the measure of occupation AI exposure is from Felten, Raj, and Seamans (2019). In panel B, the measure of occupation AI exposure is SML, from Brynjolfsson, Mitchell, and Rock (2019). In panel C, the measure of occupation AI exposure is from Webb (2020). The covariates included in each model are reported at the bottom of the table. Column 1 contains only establishment AI exposure. Columns 2, 3, and 5 include fixed effects for the decile of firm size (defined as the total vacancies posted by an establishment's firm in 2010–12). Columns 2–6 include CZ fixed effects. Columns 3 and 5 include three-digit NAICS industry fixed effects. Columns 4 and 6 include firm fixed effects. Columns 5 and 6 control for the share of 2010–12 vacancies in each establishment belonging to the broad occupations of either sales or administration. In each regression, observations are weighted by total establishment vacancies in 2010–12. Standard errors are clustered by firm.

by Burning Glass. These families, which are enumerated in figures 7 and 8, cover major job activities and skill sets within white-collar, blue-collar, and service occupations. We find that both positive and negative skill changes concentrate in the same, relatively small subset of skills. This is shown in figure 7, which reports point estimates and 95% confidence intervals for a regression of establishment negative skill change separately for each skill family on establishment AI exposure using each of our three measures. Using both the Felten et al. measure and the Webb measure, AI exposure predicts increasing demands for skills relating to engineering, analysis, marketing,

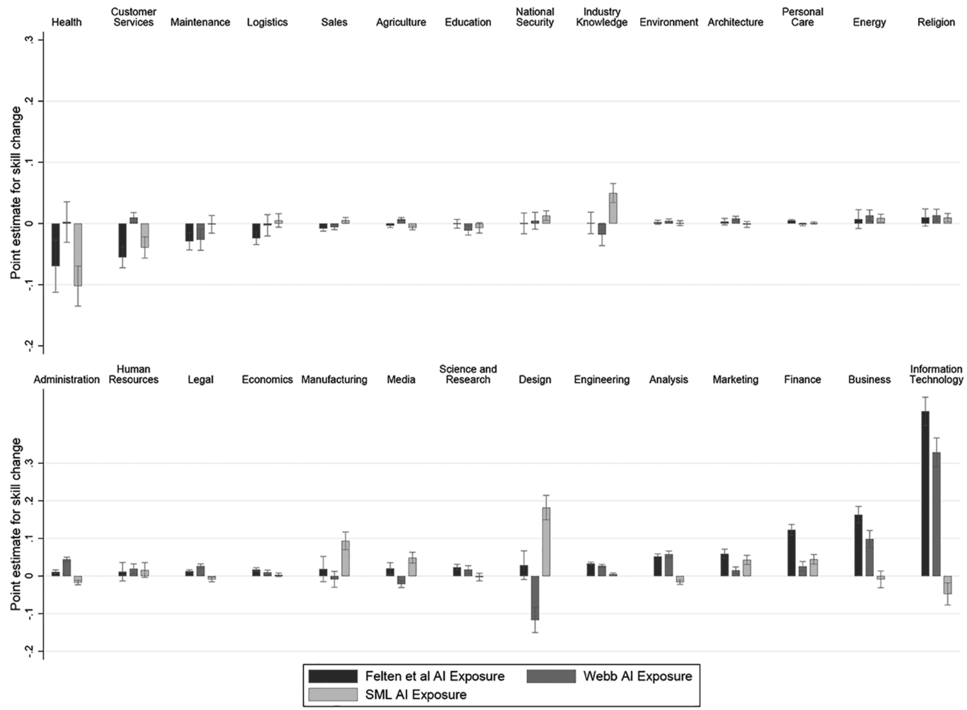


FIG. 7.—Effect of establishment AI exposure on negative skill change, by skill family. This figure plots the effect of establishment AI exposure on negative skill change by skill family. We construct measures of negative skill change at the establishment level as defined in the main text, separately for each skill family in Burning Glass. Then we regress establishment negative skill change on establishment AI exposure, using the specification of column 3, table 3, separately for each skill family. We plot the resulting point estimates and 95% confidence intervals for our three measures of AI exposure. We list the results separately for each skill family, as described at the top of the graph. We report estimates using our AI exposure measures based on Felten et al., Webb, and SML with bars of different shades. A color version of this figure is available online.

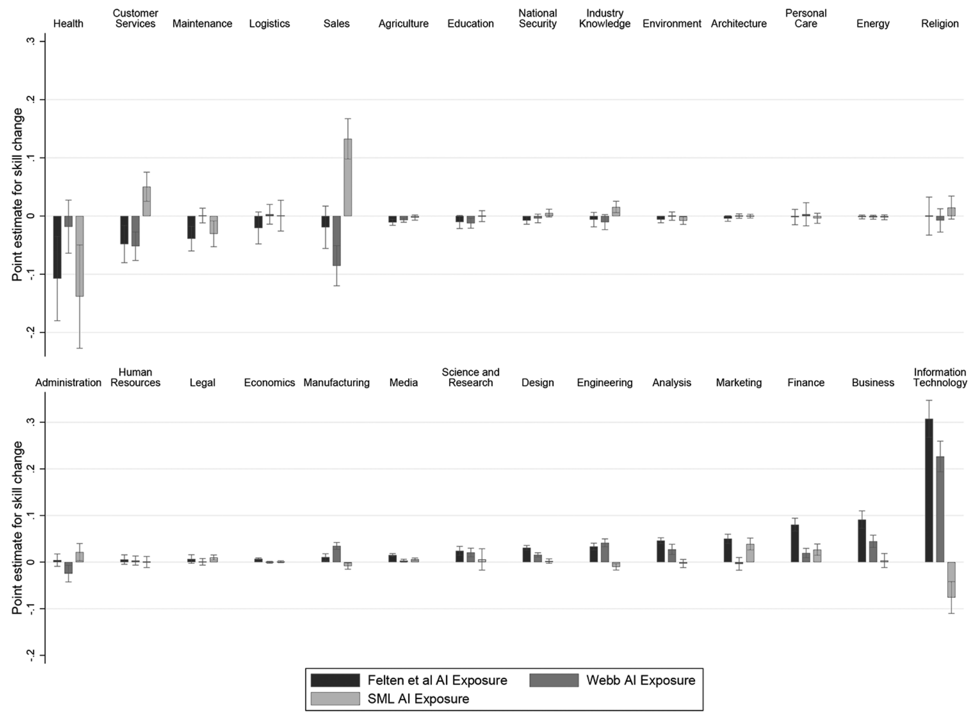


Fig. 8.—Effect of establishment AI exposure on positive skill change, by skill family. This figure plots the effect of establishment AI exposure on positive skill change by skill family. We construct measures of positive skill change at the establishment level as defined in the main text, separately for each skill family in Burning Glass. Then we regress establishment positive skill change on establishment AI exposure, using the specification of column 3, table 3, separately for each skill family. We plot the resulting point estimates and 95% confidence intervals for our three measures of AI exposure. We list the results separately for each skill family, as described at the top of the graph. We report estimates using our AI exposure measures based on Felten et al., Webb, and SML with bars of different shades. A color version of this figure is available online.

finance, and information technology. Conversely, figure 8 presents estimates for the relationship between AI exposure and positive skill change by skill family. For the Felten et al. and Webb measures, AI-exposed establishments have lower demands for skills in the same families in which negative skill change is greatest.

The finding that AI exposure is associated with significant changes in the skills listed in vacancies bolsters our confidence that AI adoption has real effects on the task content of non-AI jobs—enabling firms to replace some of the tasks previously performed by workers, making certain skills redundant while simultaneously generating demand for new skills. These results are also consonant with our theoretical model in section II, which suggests that AI adoption will induce churn of tasks performed by workers, as some tasks previously performed by humans are taken over by algorithms.

## VII. AI and Jobs

Our theory leaves open the possibility that AI may increase or reduce overall (and non-AI) hiring. We next investigate the effects of AI exposure on vacancies for non-AI positions.

### A. AI Exposure and Establishment Hiring

Table 5 turns to the relationship between AI exposure and hiring. The structure of the table is identical to that of table 1 except that the left-hand side variable is now the change in the inverse hyperbolic sine of total non-AI vacancies (and there are two extra columns, which we describe below). The non-AI vacancy measure is chosen so as to focus on the effects of AI activity on establishment hiring exclusive of already-reported impact on AI hiring itself. As before, we drop professional and business services and information technology sectors (NAICS 51 and 54).

In panel A, where we focus on Felten et al.'s measure, we see a robust negative association between AI exposure and subsequent non-AI hiring. The estimate in column 1 is $-13.80$ (SE $= 4.22$), indicating that a 1 standard deviation increase in AI exposure is associated with a roughly 14% decline in overall non-AI vacancies. (We interpret the economic magnitudes of these point estimates below.) This coefficient estimate remains stable when we control for firm size decile, CZ, and three-digit industry fixed effects in columns 2 and 3.

In column 4, we replace firm-level covariates with firm fixed effects while retaining the CZ dummies from the prior column. This is a stringent specification, since we are now comparing across establishments of the same firm that differ in their AI exposure. In this specification, the point estimate for AI exposure is $-4.81$, which is about half of the magnitude in the preceding column. Simultaneously, the estimates become more precise as the standard error falls from 4.08 to 1.44. The relationship between AI exposure and

**Table 5**
**Effects of AI Exposure on Establishment Non-AI Vacancy Growth, 2010–18**

| | Growth of Establishment Non-AI Vacancies, 2010–18 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Full Sample | | | | | | Establishments Posting in 2018 | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | A. Felten et al. Measure of AI Exposure | | | | | | | |
| Establishment AI Exposure, 2010 | −13.80 | −16.36 | −11.90 | −4.81 | −12.42 | −4.04 | −8.38 | −3.56 |
| | (4.22) | (4.11) | (4.08) | (1.44) | (4.01) | (1.47) | (3.46) | (1.86) |
| Observations | 1,075,474 | 1,075,474 | 954,519 | 1,075,474 | 954,519 | 1,075,474 | 324,901 | 341,525 |
| | B. Webb Measure of AI Exposure | | | | | | | |
| Establishment AI Exposure, 2010 | −17.24 | −18.21 | −6.73 | −2.22 | −8.30 | 1.51 | −4.70 | −1.44 |
| | (3.72) | (3.63) | (3.01) | (.93) | (3.70) | (.98) | (2.66) | (1.36) |
| Observations | 1,159,789 | 1,159,789 | 1,021,673 | 1,159,789 | 1,021,673 | 1,159,789 | 337,758 | 355,529 |
| | C. SML Measure of AI Exposure | | | | | | | |
| Establishment AI Exposure, 2010 | 7.02 | 5.74 | 2.05 | .95 | 2.21 | −3.01 | .01 | −.91 |
| | (3.13) | (3.01) | (2.92) | (1.16) | (3.61) | (1.22) | (2.94) | (1.38) |
| Observations | 1,159,789 | 1,159,789 | 1,021,673 | 1,159,789 | 1,021,673 | 1,159,789 | 337,758 | 355,529 |

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Covariates: | | | | | | | | |
| Share of vacancies in sales and administration, 2010 | | | | | ✓ | ✓ | | |
| Fixed effects: | | | | | | | | |
| Firm size decile | | ✓ | ✓ | | ✓ | | ✓ | |
| CZ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Three-digit industry | | | ✓ | | ✓ | | ✓ | |
| Firm | | | | ✓ | | ✓ | | ✓ |

NOTE.—This table presents estimates of the effects of establishment AI exposure on establishment non-AI vacancy growth. The sample is establishments posting vacancies in 2010–12 and 2016–18 outside NAICS sectors 51 (information) and 54 (business services). The outcome variable, constructed from Burning Glass data, is the growth rate of non-AI vacancies between 2010 and 2018, multiplied by 100. We approximate this growth rate with the change in the inverse hyperbolic sine of the number of vacancies posted by the establishment in 2010–12 and 2016–18. The regressor, establishment AI exposure in 2010, is the standardized mean of occupation AI exposure over the six-digit SOC occupations for which the establishment posts vacancies in 2010–12 weighted by the number of vacancies posted per occupation. In panel A, the measure of occupation AI exposure is from Felten, Raj, and Seamans (2019). In panel B, the measure of occupation AI exposure is SML, from Brynjolfsson, Mitchell, and Rock (2019). In panel C, the measure of occupation AI exposure is from Webb (2020). The final two columns exclude establishments that do not post positive vacancies in 2018. The covariates included in each model are reported at the bottom of the table. Column 1 contains only establishment AI exposure. Columns 2, 3, 5, and 7 include fixed effects for the decile of firm size (defined as the total vacancies posted by an establishment's firm in 2010–12). Columns 2–8 include CZ fixed effects. Columns 3, 5, and 7 include three-digit NAICS industry fixed effects. Columns 4, 6, and 8 include firm fixed effects. Columns 5 and 6 control for the share of 2010–12 vacancies in each establishment belonging to the broad occupations of either sales or administration. In each regression, observations are weighted by total vacancies in 2010–12. Standard errors are clustered by firm.

non-AI vacancies remains comparable when we include the baseline shares of sales and administration occupations in columns 5 and 6: −12.42 (SE = 4.01) and −4.04 (SE = 1.47), respectively.[21]

We also investigated whether these estimates are driven by establishments that posted jobs in 2010–12 and then stopped posting in 2016–18 (which may reflect either true zero vacancy postings or establishment exits, perhaps for sampling reasons). Columns 7 and 8 limit the sample to establishments that posted in 2016–18. The estimates are now somewhat smaller but still negative and statistically significant at 5%: −8.38 (SE = 3.46) in column 7, with three-digit industry fixed effects, and −3.56 (SE = 1.86) in column 8, with firm fixed effects.[22]

How large are the effects reported in panel A? The interpretation of the regression coefficients is not straightforward because our outcome variable is vacancy flows, which differ from the stock of employment. To estimate the implied impact on employment, we cumulate vacancies between 2010 and 2018 to create a measure of 2018 employment for each establishment. Then we regress our measure of cumulative hiring between 2010 and 2018 on AI exposure in 2010 exactly as in table 5.[23] Table A11 reports the results of this exercise. In panel A, with Felten et al.'s measure of AI exposure, the regression coefficient in column 1 of −7.24 (SE = 4.66) implies that a 1 standard deviation increase in AI exposure is associated with a 7.2% decline in non-AI employment between 2010 and 2018. Since a 1 standard deviation increase in AI exposure is quite large, this is a sizable but not implausible relationship. We also note that because this coefficient estimates the relative change in non-AI hiring at more versus less AI-exposed establishments, it does not imply an aggregate reduction in total hiring.[24]

[21] Since AI exposure predicts an increase in AI vacancies, it is not self-evident whether the implied impact on total vacancies (inclusive of AI hiring) is also negative. We show in table A10 that the answer is yes, as expected, since AI vacancies are a tiny share of total vacancies.

[22] In table A12, we calculate the standard errors from Borusyak, Hull, and Jaravel (2022) for the specifications in table 5 to account for the shift-share structure of our AI exposure measure. The standard errors change little.

[23] More specifically, we assume that establishment employment, $\ell_{e,t}$, follows the law of motion $\ell_{e,t+1} = fv_{e,t} + (1 - s)\ell_{e,t}$, where $v_{e,t}$ denotes the establishment's vacancies, $f$ is the vacancy fill rate, and $s$ is the separation rate. We calculate employment in 2010 by assuming that the establishment is in steady state initially, and we compute employment in 2018 by iteratively solving the law of motion forward. We set $s = 0.4$ to match the 2018 annual separation rate from JOLTS. We thank Andreas Mueller for suggesting this exercise.

[24] One can combine the reduced-form estimates in tables 1 and 5 to obtain a Wald estimate of how AI activity driven by differences in tasks structures across establishments affects non-AI hiring. For example, the estimates in col. 4 of tables 1 and 5, using Felten et al.'s measure, yield an elasticity of −0.3—i.e., a 10% increase in AI adoption is associated with a 10% × 4.81/16.53 = 3% decline in non-AI hiring. Between 2010 and 2018, the increase in AI vacancies ranged from 218 log points in

Panel B of table 5 turns to Webb's measure of AI exposure. The pattern is broadly similar to the one we see in panel A but less stable. The coefficient estimate without any covariates in column 1 is −17.24 (SE = 3.72). It is comparable in column 2 when we control for CZ and three-digit industry fixed effects. However, the estimate declines substantially to −2.22 (SE = 0.93) in column 4 when we control for firm fixed effects and is inconsistent in sign and magnitude in columns 5–8. Finally, when we use SML in panel C, there is no consistent evidence for a negative association between AI exposure and non-AI vacancy postings (negative and statistically significant in col. 6, but positive in six of eight columns and significantly so in two cases).

As in table 2, we next control for Webb's measure of exposure to software in order to distinguish the effects of other (traditional) software applications from AI. The results reported in table 6 document that the software exposure measure itself has no consistent association with non-AI hiring, while the effects of AI exposure remain very similar to our baseline estimates in table 5. For example, the estimate using Felten et al.'s measure in column 1 is −14.62, compared with −13.80 for the same specification in table 5.[25]

We showed in figure 2 that AI adoption sharply accelerated around 2015 after having grown comparatively slowly in the prior 5 years. This discontinuous growth provides an opportunity to test whether any potential association between AI exposure and non-AI hiring fits this timing. We perform this exercise in table 7, where we break the outcome period of 2010–18 into two subperiods, 2010–14 and 2014–18, and estimate a subset of the specifications in table 5 for these subintervals.

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finance to 198 log points in manufacturing. Assuming that 1.6% of these increases—the partial $R^2$ of our AI exposure measure in table 1—were driven by task-level substitution of algorithms for labor, one may infer that this type of AI adoption led to a decline of 1% in non-AI hiring in finance and 0.92% in manufacturing. These estimates should be interpreted with caution, since they ignore general equilibrium effects and spillovers and the partial $R^2$ may over- or understate the role of task substitution in AI activity. Indeed, the OLS relationship between AI adoption and hiring, reported in table A13, is positive. This underscores that other sources of variation, including possible links between an establishment's growth potential and its AI activity, matter more for AI adoption than the baseline task structure captured by our AI exposure measure.

[25] Another prediction of our conceptual framework is that hiring should decline particularly in occupations that are themselves highly exposed to AI. Consistent with this prediction, all of our three AI exposure measures predict a decline in "at-risk" vacancies. We are nevertheless cautious in interpreting these specifications and do not report them because they suffer from potential mean reversion. In particular, because the exposure measure is equal to the share of establishment postings that are at-risk in 2010–12, any mean reversion in this measure will induce a spurious negative relationship between an establishment's at-risk vacancy share in 2010–12 and its subsequent change.

**Table 6**
**Effects of AI Exposure on Establishment Non-AI Vacancy Growth, Controlling for Software Exposure**

| | Growth of Establishment Non-AI Vacancies, 2010–18 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Full Sample | | | | | | Establishments Posting in 2018 | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | A. Felten et al. Measure of AI Exposure | | | | | | | |
| Establishment AI | −14.62 | −17.21 | −12.02 | −5.43 | −12.47 | −3.93 | −8.68 | −3.73 |
| Exposure, 2010 | (4.28) | (4.17) | (4.00) | (1.49) | (3.94) | (1.54) | (3.36) | (1.90) |
| Establishment software | −7.50 | −7.35 | .66 | −1.77 | 1.07 | 2.03 | −1.67 | −.41 |
| Exposure | (3.68) | (3.60) | (3.09) | (1.08) | (3.28) | (1.17) | (3.41) | (1.40) |
| Observations | 1,059,620 | 1,059,620 | 941,046 | 1,059,620 | 941,046 | 1,059,620 | 322,187 | 338,645 |
| | B. Webb Measure of AI Exposure | | | | | | | |
| Establishment AI | −23.04 | −25.36 | −14.04 | −3.06 | −14.95 | −.29 | −7.30 | −2.56 |
| Exposure, 2010 | (4.61) | (4.47) | (4.68) | (1.05) | (5.59) | (1.09) | (4.51) | (1.56) |
| Establishment software | 9.01 | 10.88 | 10.98 | 1.36 | 11.16 | 3.19 | 3.80 | 1.74 |
| Exposure | (4.32) | (4.22) | (4.79) | (1.14) | (5.11) | (1.18) | (5.26) | (1.54) |
| Observations | 1,159,789 | 1,159,789 | 1,021,673 | 1,159,789 | 1,021,673 | 1,159,789 | 337,758 | 355,529 |

| | C. SML Measure of AI Exposure | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Establishment AI | 5.97 | 4.70 | 2.62 | .84 | 2.40 | −2.67 | −.17 | −.94 |
| Exposure, 2010 | (3.15) | (3.03) | (2.93) | (1.12) | (3.63) | (1.20) | (2.89) | (1.39) |
| Establishment software | −4.41 | −4.37 | 2.46 | −.43 | 3.04 | 2.80 | −.85 | −.13 |
| Exposure | (3.66) | (3.60) | (3.10) | (.95) | (3.30) | (1.03) | (3.36) | (1.34) |
| Observations | 1,159,789 | 1,159,789 | 1,021,673 | 1,159,789 | 1,021,673 | 1,159,789 | 337,758 | 355,529 |
| Covariates: | | | | | | | | |
| Share of vacancies in sales and administration, 2010 | | | | | ✓ | ✓ | | |
| Fixed effects: | | | | | | | | |
| Firm size decile | | ✓ | ✓ | | ✓ | | ✓ | |
| CZ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Three-digit industry | | | ✓ | | ✓ | | ✓ | |
| Firm | | | | ✓ | | ✓ | | ✓ |

Note.—This table presents estimates of the effects of establishment AI exposure on establishment non-AI vacancy growth, controlling for establishment software exposure. Our measure of software exposure is from Webb (2020). Establishment software exposure is the standardized mean of occupation software exposure over the six-digit SOC occupations for which the establishment posts vacancies in 2010–12 weighted by the number of vacancies posted per occupation. The sample is establishments posting vacancies in 2010–12 and 2016–18 outside NAICS sectors 51 (information) and 54 (business services). The outcome variable, constructed from Burning Glass data, is the growth rate of non-AI vacancies between 2010 and 2018, multiplied by 100. We approximate this growth rate with the change in the inverse hyperbolic sine of the number of vacancies posted by the establishment in 2010–12 and 2016–18. The regressor, establishment AI exposure in 2010, is the standardized mean of occupation AI exposure over the six-digit SOC occupations for which the establishment posts vacancies in 2010–12 weighted by the number of vacancies posted per occupation. In panel A, the measure of occupation AI exposure is from Felten, Raj, and Seamans (2019). In panel B, the measure of occupation AI exposure is SML, from Brynjolfsson, Mitchell, and Rock (2019). In panel C, the measure of occupation AI exposure is from Webb (2020). The final two columns exclude establishments that do not post positive vacancies in 2018. The covariates included in each model are reported at the bottom of the table. Column 1 contains only establishment AI exposure. Columns 2, 3, 5, and 7 include fixed effects for the decile of firm size (defined as the total vacancies posted by an establishment's firm in 2010–12). Columns 2–8 include CZ fixed effects. Columns 3, 5, and 7 include three-digit NAICS industry fixed effects. Columns 4, 6, and 8 include firm fixed effects. Columns 5 and 6 control for the share of 2010–12 vacancies in each establishment belonging to the broad occupations of either sales or administration. In each regression, observations are weighted by total vacancies in 2010–12. Standard errors are clustered by firm.

**Table 7**
**Effects of AI Exposure on Establishment Non-AI Vacancy Growth, 2010–14 and 2014–18**

| | Growth of Establishment Non-AI Vacancies | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2010–14 Growth | | | | 2014–18 Growth | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | A. Felten et al. Measure of AI Exposure | | | | | | | |
| Establishment AI Exposure, 2010 | −1.86 | −.59 | −1.82 | .39 | −11.94 | −11.32 | −10.60 | −5.21 |
| | (4.77) | (3.52) | (3.46) | (1.11) | (3.80) | (2.93) | (2.82) | (1.02) |
| Observations | 1,075,474 | 954,519 | 954,519 | 1,075,474 | 1,075,474 | 954,519 | 954,519 | 1,075,474 |
| | B. Webb Measure of AI Exposure | | | | | | | |
| Establishment AI Exposure, 2010 | −7.51 | −2.57 | −6.04 | −.35 | −9.73 | −4.16 | −2.26 | −1.86 |
| | (3.38) | (2.17) | (2.66) | (.64) | (2.42) | (1.83) | (2.16) | (.71) |
| Observations | 1,159,789 | 1,021,673 | 1,021,673 | 1,159,789 | 1,159,789 | 1,021,673 | 1,021,673 | 1,159,789 |
| | C. SML Measure of AI Exposure | | | | | | | |
| Establishment AI Exposure, 2010 | 3.73 | 1.17 | 2.79 | 1.90 | 3.30 | .88 | −.58 | −.95 |
| | (2.66) | (2.46) | (3.08) | (.73) | (2.09) | (2.30) | (2.75) | (.91) |
| Observations | 1,159,789 | 1,021,673 | 1,021,673 | 1,159,789 | 1,159,789 | 1,021,673 | 1,021,673 | 1,159,789 |

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Covariates: | | | | | | | | |
| Share of vacancies in sales and administration, 2010 | | | ✓ | | | | ✓ | |
| Fixed effects: | | | | | | | | |
| Firm size decile | | ✓ | ✓ | | | ✓ | ✓ | |
| CZ | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ |
| Three-digit industry | | ✓ | ✓ | | | ✓ | ✓ | |
| Firm | | | | ✓ | | | | ✓ |

NOTE.—This table presents estimates of the effects of establishment AI exposure on establishment non-AI vacancy growth, separately for 2010–14 and 2014–18. The sample is establishments posting vacancies in 2010–12 and 2016–18 outside NAICS sectors 51 (information) and 54 (business services). In columns 1–4, the outcome variable, constructed from Burning Glass data, is the growth rate of non-AI vacancies between 2010 and 2014, multiplied by 100. We approximate this growth rate with the change in the inverse hyperbolic sine of the number of vacancies posted by the establishment in 2010–12 and 2013–15. In cols. 5–8, the outcome variable is the change in the inverse hyperbolic sine of the number of vacancies posted by the establishment in 2013–15 and 2016–18. The regressor, establishment AI exposure in 2010, is the standardized mean of occupation AI exposure over the six-digit SOC occupations for which the establishment posts vacancies in 2010–12 weighted by the number of vacancies posted per occupation. In panel A, the measure of occupation AI exposure is from Felten, Raj, and Seamans (2019). In panel B, the measure of occupation AI exposure is SML, from Brynjolfsson, Mitchell, and Rock (2019). In panel C, the measure of occupation AI exposure is from Webb (2020). The covariates included in each model are reported at the bottom of the table. Columns 1 and 5 contain only establishment AI exposure. Columns 2, 3, 6, and 7 include fixed effects for the decile of firm size (defined as the total vacancies posted by an establishment's firm in 2010–12) as well as three-digit NAICS industry fixed effects. All columns other than 1 and 5 include CZ fixed effects. Columns 4 and 8 include firm fixed effects. Columns 3 and 7 control for the share of 2010–12 vacancies in each establishment belonging to the broad occupations of either sales or administration. In each regression, observations are weighted by total vacancies in 2010–12. Standard errors are clustered by firm.

Focusing on Felten et al.'s AI exposure measure in panel A, we see no economically or statistically significant relationship between AI exposure in 2010 and non-AI hiring during the years 2010–14, while there is a strong negative association for 2014–18, during the period of rapid AI takeoff. In the baseline regression for 2014–18 (col. 5), the point estimate is −11.94 (SE = 3.80), indicating that a 1 standard deviation increase in AI exposure is associated with approximately a 12% decline in overall non-AI vacancies. This estimate remains stable and becomes more precise when we control for firm size deciles, CZ controls, and three-digit industry fixed effects in column 6. The relationship also remains comparable when we include the baseline shares of sales and administration occupations in column 7—a coefficient of −10.60 with a standard error of 2.82. This result is robust to firm fixed effects, added in column 8, although as before their inclusions reduces the magnitude of the relationship. Panels B and C report the same specifications for the Webb and SML measures, respectively. As in table 5, the relationships between non-AI hiring and AI exposure are less consistent and robust for these indexes.

Table A14 presents results at the firm level, which are, on the whole, similar to the establishment-level results. Table A15, on the other hand, depicts similar if slightly smaller estimates with average establishment size weights (rather than baseline establishment size weights as in table 5).

In sum, the evidence using the Felten et al. and Webb measures of AI exposure shows statistically significant and economically meaningful negative effects, especially between 2015 and 2018, the period during which AI activity surged.

### B. AI and Industry Employment

Associated with the surge in AI activity, there may also be industry-level changes that potentially offset or amplify the establishment-level consequences. To investigate whether more exposed industries are contracting (or expanding), we aggregate our AI exposure measure to the CZ-by-industry level and merge it with employment data. We proxy industry-level AI activity using the mean occupation AI exposure across the six-digit occupations posted in each sector-by-CZ cell during 2010–12, weighted by the number of vacancies posted in each occupation. We measure the change in (the log of) industry-by-CZ employment using County Business Patterns (CBP) data for 2000–2016. Because of increased suppression of industry-by-location data in the CBP starting in 2017, our analysis of CBP data ends in 2016, thus (unfortunately) excluding the last several years of rapid AI expansion.[26]

[26] In processing the CBP data, we use the harmonization and imputation procedures developed by Fabian Eckert, Teresa Fort, Peter Schott, and Natalie Yang, available at http://fpeckert.me/cbp/.

The results are reported in the first three columns of table 8, which again contains one panel for each AI exposure measure. The outcome variable in these regressions is industry-by-CZ employment. All models include industry fixed effects, CZ fixed effects, and baseline occupational shares in sales and administration. The standard errors are robust to heteroscedasticity and correlation within CZs.

Columns 1 and 2 examine trends in industry employment during 2003–7 and 2007–10, before the major AI advances that followed. These columns show that industry AI exposure in 2010 does not predict differential employment behavior before 2010; thus, three-digit industries with different AI exposure were on roughly parallel trends before the pickup in AI activity in the late 2010s. This pattern is essentially unchanged after 2010. We do not see consistent positive or negative effects associated with AI exposure between 2010 and 2016. For example, the estimate in column 3 is −0.05 (SE = 0.08). The point estimate implies very small effects associated with industry AI exposure: a 1 standard deviation increase in industry AI predicts an economically small and statistically insignificant 0.049% decline in industry employment. Panels B and C of the table show similar results using the Webb and SML measures in place of the Felten et al. index.

This set of null results may indicate that it is premature to detect AI's impact on industry reorganization or growth. Indeed, our calculations in footnote 24 suggest that the present effects of AI adoption on even some highly impacted sectors, such as finance, might still be small. These results might also indicate that much of the effect of AI on employment, if eventually present, will occur within industries.

### C. Employment and Wages in AI-Exposed Occupations

As a second approach to measuring impacts that extend beyond firms, columns 4–9 of table 8 assess whether occupations with greater AI exposure exhibit differential employment or wage trends after the onset of rapid AI hiring. For this analysis, we use occupational employment and wage information from the US BLS OES data. This establishment-based data series provides more accurate estimates of employment and wages in occupations than is available from household surveys.

The observations in this table are at the six-digit occupation level, and the dependent variable is the sum of employment in a six-digit occupation across all industries (excluding sectors 51 and 54). In all columns, we control for three-digit occupation fixed effects and use baseline employment as weights. The standard errors are robust against heteroscedasticity. In columns 4–6, the dependent variable is change in employment, while in columns 7–9 it is change in the (log) average wage in the occupation.

The results for employment and wage growth using each of the AI exposure measures are similar to the industry-level findings in earlier columns:

**Table 8**
**Effects of AI Exposure on Market Employment and Wage Growth**

| | Industry by CZ Employment Growth (CBP) | | | Occupation Employment Growth (OES) | | | Occupation Wage Growth (OES) | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2003–7 (1) | 2007–10 (2) | 2010–16 (3) | 2004–7 (4) | 2007–10 (5) | 2010–18 (6) | 2004–7 (7) | 2007–10 (8) | 2010–18 (9) |
| | A. Felten et al. Measure of AI Exposure | | | | | | | | |
| Market AI exposure, 2010 | .03 | .10 | −.05 | .34 | .86 | .51 | −.00 | .02 | −.17 |
| | (.17) | (.20) | (.08) | (.34) | (.32) | (.35) | (.17) | (.20) | (.06) |
| Observations | 10,937 | 10,926 | 10,929 | 736 | 700 | 680 | 680 | 648 | 629 |
| | B. Webb Measure of AI Exposure | | | | | | | | |
| Market AI exposure, 2010 | .10 | .18 | .11 | .00 | .11 | −.17 | .11 | −.05 | −.02 |
| | (.15) | (.17) | (.09) | (.17) | (.21) | (.29) | (.08) | (.10) | (.04) |
| Observations | 10,981 | 10,968 | 10,968 | 713 | 704 | 717 | 660 | 653 | 663 |
| | C. SML Measure of AI Exposure | | | | | | | | |
| Market AI exposure, 2010 | −.14 | .37 | −.01 | .00 | −.17 | −.37 | −.03 | .18 | .04 |
| | (.17) | (.18) | (.08) | (.25) | (.29) | (.25) | (.08) | (.12) | (.05) |
| Observations | 10,981 | 10,968 | 10,968 | 713 | 704 | 717 | 660 | 653 | 663 |

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Covariates: | | | | | | | | | |
| Share of vacancies in sales and administration, 2010 | ✓ | ✓ | ✓ | | | | | | |
| Fixed effects: | | | | | | | | | |
| CZ | ✓ | ✓ | ✓ | | | | | | |
| Sector | ✓ | ✓ | ✓ | | | | | | |
| Three-digit occupation | | | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

NOTE.—This table presents estimates of the effects of market AI exposure on market employment and wage growth. In cols. 1–3, the outcome is the growth rate of sector (i.e., two-digit NAICS industry) by CZ employment, measured in percentage points per year (i.e., 100 times the log change divided by number of years), from the CBP for 2003–7, 2007–10, and 2010–16, respectively. The sample excludes industry sectors 51 (information) and 54 (business services). In cols. 4–6, the outcome is the growth rate of six-digit SOC occupation employment outside sectors 51 and 54, measured in percentage points per year, from the OES for 2004–7, 2007–10, and 2010–18, respectively. In cols. 7–9, the outcome is the growth of six-digit SOC median hourly wages outside sectors 51 and 54, measured in percentage points per year, also from the OES. In cols. 1–3, the regressor is the standardized mean occupation AI exposure across the six-digit occupations posted in each sector by CZ cell, based on the distribution of vacancies by detailed occupation in each zone and industry in 2010–12. The regressions are weighted by baseline employment in each sector by CZ. In cols. 4–9, the regressor is standardized occupation AI exposure by six-digit SOC occupation. In panel A, the measure of occupation AI exposure is from Felten, Raj, and Seamans (2019). In panel B, the measure of occupation AI exposure is SML, from Brynjolfsson, Mitchell, and Rock (2019). In panel C, the measure of occupation AI exposure is from Webb (2020). All regressions are weighted by baseline employment. The covariates included in each model are reported at the bottom of the table. Columns 1–3 contain sector and CZ fixed effects as well as controls for the share of 2010–12 vacancies in either sales or administration in each sector by CZ, measured from Burning Glass. Columns 4–9 control for three-digit SOC occupation fixed effects. Standard errors are clustered by CZ in cols. 1–3 and are robust against heteroskedasticity in cols. 4–9.

we detect no differential employment or wage behavior in more AI-exposed occupations after 2010.[27]

Our evidence is fairly clear that there is no systematic aggregate relationship between AI exposure and industry and occupation-level outcomes. Our overall interpretation is that while AI technologies appear to be changing task and skill composition at exposed establishments and firms, any aggregate effects of AI are too small to detect.[28]

## VIII. Conclusion

There is much excitement and quite a bit of apprehension about AI and its labor market effects. In this paper, we explored the nature of AI activity in the US labor market and its consequences for skill change, hiring, and industry- and occupation-level changes in employment and earnings. We have three main findings.

1. We see a surge in AI activity, particularly after 2015, proxied by vacancies seeking workers with AI skills, and this surge is driven by establishments with high exposure to AI—meaning that their task structure in 2010 was suitable for the AI technologies that are subsequently introduced. This pattern is highly robust with two of our three AI-exposure measures—those based on the indices constructed by Felten et al. and Webb—and still present but less robust with our third measure, SML, based on Brynjolfsson, Mitchell, and Rock's work.
2. We estimate consistent and robust changes in the skills demanded by high-exposure establishments. In particular, establishments with task structures suitable for AI cease to post vacancies that list a range of previously sought skills and start posting additional skill requirements. This evidence suggests that some of the tasks that workers used to perform in these establishments are no longer required, while new skills are simultaneously being introduced.
3. With two of our three measures, we find that AI-exposed establishments reduce their non-AI and overall hiring. These results are statistically significant, economically sizable, and robust with the Felten

[27] Differently from our industry results, we detect a significantly faster increase in the employment of more exposed occupations between 2007 and 2010 when using the Felten et al. AI measure. This may reflect fast expansion in some IT-related occupations that have high Felten et al. scores, or it may be a chance finding given the large number of point estimates reported in this table.

[28] One alternative reading of these results is that AI is displacing and reinstating tasks at approximately the same rate, yielding no net effect on labor demand. Our main results do not support this interpretation, however, since we find significant declines in non-AI vacancies at exposed establishments.

et al. measure and robust in most specifications with the Webb measure. We do not detect such negative employment effects with SML, which is as expected, since the relationship between AI exposure and AI hiring is much less robust and stable with SML as well.

In contrast to these three findings, we do not detect any relationship between AI exposure and employment or wages at the occupation or industry level.

The totality of the results reported above on the labor market effects of AI convince us that AI is having real effects on establishments that are exposed to this new technology: there is a significant surge in vacancies for AI workers in establishments with task structures that are more suitable for AI; skill churn increases differentially at AI-exposed establishments, with both greater retirement of previously posted skills and greater introduction of new skills; and finally, AI-exposed establishments appear to be reducing their non-AI hiring. These patterns are consistent with the hypothesis that AI-powered algorithms are substituting for human skills. However, while AI technologies appear to be changing task and skill composition at exposed establishments, any aggregate effects of AI, if present, are not yet detectable—plausibly because AI technologies are still in their infancy and have spread to only a limited part of the US economy.

Our results leave open important questions and have evident shortcomings. First, it will be valuable to further explore and understand the juxtaposition of negative establishment-level impacts and zero aggregate effects. Second, our focus on AI adoption driven by the task structure of establishments may exclude other types of AI impacts that are less related to task structures, such as the use of AI to launch new products and services. These applications could have different and possibly more positive effects on jobs. Naturally, our estimates are not informative about AI applications that are missed by our AI exposure measures. Finally, because the next generation of AI-enabled technologies will likely have different capabilities from the current generation, our results do not foretell whether future AI technologies will prove more complementary or more substitutable with human capabilities.

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