Reskilling for AI: How Algorithmic Bilinguals Drive the Value of Human-Algorithm Collaboration

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Abstract

This study tests the hypothesis that the value generated from data, algorithms, and AI is amplified when the skills required to use these technologies are dispersed among the firm's domain experts. This decentralization of technical expertise stands in contrast to other business technologies for which the complementary skills are primarily embodied in IT specialists. Using two workforce data sets, I show that 1) employers have been shifting hiring towards requiring greater algorithmic expertise from domain experts, 2) algorithmic expertise in frontier firms has become more dispersed across the firm's domain experts, and 3) the market assigns higher value to firms' algorithmic investments when the relevant skills are decentralized, suggesting the presence of valuable intangible assets that can yield future productivity benefits from AI and data science investments. Finally, I show that the proliferation of no-code and LLM-based tools that make it easier for non-technical workers to interact with AI, data science, and algorithmic tools accelerates these changes. Implications for training are discussed.

Keywords: AI, workplace transformation, human capital, algorithms, AI literacy, future of work, IT complements, reskilling

1 Introduction

The impact of algorithmic decision-making on organizations is a topic of rapidly growing interest. Research in this area focuses on the labor reallocation effects of AI and automation technologies (Acemoğlu and Restrepo, 2016; Autor and Salomons, 2018; Brynjolfsson et al., 2018; Raj and Seamans, 2018; Eloundou et al., 2023), but it also demonstrates that these technologies are not simply labor displacing (Agrawal et al., 2019; Gregory et al., 2022). Instead, these technologies are also likely to generate new jobs and new types of jobs (Bessen, 2019; Autor et al., 2022), and a key

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theme of the literature in this area is how humans can be most effective when working alongside algorithms (Beane, 2019; Agrawal et al., 2019; Lebovitz et al., 2022).

This paper presents new theory and evidence that a valuable workforce complement to the effective use of algorithms by organizations is the decentralization of "algorithmic expertise" among the firm's domain experts. *Algorithmic expertise* refers to a worker's ability to use and interact with technology tools, such as machine learning and data science algorithms, predictive software, generative AI tools, and AI-powered analytics platforms, that are capable of autonomously generating decisions or content.[1] The definition of "algorithms" considered here includes AI and data science tools but excludes tools like relational databases or web technologies that do not exhibit these autonomous capabilities, and require greater human input to guide the creation of their output. *Domain expertise* refers to the knowledge required to work in a specialized field such as nursing, sales, marketing, or accounting. Prior work suggests that the effective application of algorithms may be unique in the extent to which it demands these two types of human capital to be integrated (Collins, 2004), particularly in sensitive contexts like law or medicine, where the payoff function for a decision is difficult to define or where the tolerance for machine-based prediction error is low (Kleinberg et al., 2018; Choudhury et al., 2020).

The design choice of hiring domain experts skilled with algorithms represents a departure from how technical skills are normally distributed within firms, where technical knowledge is often centralized within specialized IT workers. This shift aligns with theoretical arguments about the optimal allocation of knowledge and decision rights within firms (Garicano, 2000; Dessein and Santos, 2006). While earlier technologies may have been effectively managed through specialized departments, the general-purpose nature of AI and its deep integration into domain-specific decision-making processes suggests that technical expertise must be more widely distributed. This distribution of algorithmic capabilities across occupations generates theoretical predictions about how AI and algorithmic technologies reshape organizational boundaries and job design, particularly when the technology's effective use requires combining technical and domain-specific knowledge.

Prior work has studied the centralization versus decentralization tradeoff in IT decision-making authority (McElheran, 2012, 2014), but has focused less on how this tradeoff applies to the distribution of technical skills across workers. This gap is important because the allocation of skills, particularly algorithmic capabilities, presents unique challenges compared to traditional questions of organizational structure. While centralizing authority or information flows involves primarily organizational redesign, distributing technical skills requires significant human capital investment and careful consideration of how different types of expertise complement each other. Understanding this skills-based centralization tradeoff is especially critical as algorithmic technologies become more deeply embedded in core business processes, requiring organizations to balance the efficiency gains of concentrated technical expertise against the adaptability benefits of dispersed capabilities.

This study first develops theory that builds on the literature in job design and task allocation,

[1] This paper uses the term "expertise". The distinction between requiring deep "expertise" versus basic "literacy" with these tools has important policy implications, but making this distinction requires more detailed data than is available in our sources, so we leave this question for future work.

examining how algorithmic technologies differ from other foundational information technologies such as databases or web technologies in terms of what is required to adapt them to specialized business processes (Smith, 1776; Becker and Murphy, 1992; Teodoridis, 2017; Lindbeck and Snower, 2000). The discussion focuses on how organizations adapt jobs to technological change at the sub-occupational level - that is, how individual roles evolve (Spitz-Oener, 2006). From this theoretical foundation, I develop testable hypotheses about: i) how employers modify job roles to incorporate algorithmic expertise, ii) the optimal distribution of algorithmic expertise across an organization's decision-makers, and iii) the relationship between this workforce adaptation and measures of firm performance.

To test these hypotheses, I analyze two complementary databases that capture corporate hiring and employment patterns. The first database contains a comprehensive collection of US job listings from 2013 to 2016. This dataset, used in previous studies examining the evolution of job skill requirements (Deming and Kahn, 2018; Acemoglu et al., 2022; Goldfarb et al., 2023), provides insights into employer demand. The second database tracks the diffusion of technology skills across occupations, as reported by workers, from 2008 to 2021, focusing on a large sample of public firms.[2] I supplement this dataset with occupational knowledge content from the Bureau of Labor Statistics O*NET database and financial metrics from Compustat-Capital IQ.

The analysis produces three findings. First, from the job openings data, I show that employers have increasingly been searching for algorithmic expertise in non-technical occupations, in a pattern that more closely resembles general-purpose office software skills (e.g., word processing tools) than technical skills like database administration. By 2016, only one-third of the listings requiring algorithmic expertise were for IT occupations. In non-IT occupations, these skills were particularly likely to be embedded in listings requiring significant domain expertise.

To assess factors that influence the spread of algorithmic skills among the firm's domain experts, a second analysis utilizes workforce data from a partially overlapping seven year panel that extends through a period of greater AI adoption (2015-2021). In the large, public firms that comprise the sample, algorithmic skills spread among domain experts with decision-making responsibilities. This is consistent with the changes observed in the job openings, and is in contrast to what we observe for other information technologies. Moreover, the proliferation of software innovations that make it easier to use algorithms, such as "no-code" tools, increased the likelihood that domain experts acquired these skills.

Given that firms appear to value workers with these skills, the third analysis examines whether financial markets reflect this perceived value. It shows that investors assign greater value to firms' AI and data science investments when made in tandem with these employment choices. This interaction is observed for data science in the earlier years in the panel, and it strengthens and becomes more pronounced for AI investments in the later period of the panel. Robustness tests suggest that the higher values assigned to these assets are unique to these technologies. Similar patterns do not

[2] Details about this data source and comparisons with administrative agency data are provided in a later section and the Appendix.

emerge for other technologies or for expertise in other categories of technical skill. Taken together, the findings from these analyses of job vacancies, employment, and financial markets provide corroborating evidence that the effective use of AI, data science, and other algorithmic technologies is benefitted by decision-makers who can synthesize their domain expertise with technical capabilities.

This research contributes to two academic literatures. First, by focusing on employers' hiring practices, it advances our understanding of how employment practices complement new IT investments (Bresnahan et al., 2002; Black and Lynch, 2001; Caroli and Van Reenen, 2001; Bloom et al., 2012). While prior work has viewed IT primarily as a tool for automating routine tasks, the emergence of algorithmic technologies that handle complex, non-routine decisions has sparked new questions about how these technologies shape firms' demand for labor (Brynjolfsson et al., 2018). This paper identifies specific management practices that enable firms to effectively leverage predictive algorithms (Brynjolfsson et al., 2021; Zolas et al., 2021; Dixon et al., 2021; Xue et al., 2022).

Second, it contributes to a literature on how the adoption of algorithmic decision-making will shape the future of work, which is becoming increasingly important as new technologies subsume many of the tasks done by humans while simultaneously generating new areas of demand for human labor (Agrawal et al., 2019). Most prior work on technical skills has focused on the IT workforce (Ang et al., 2002; Mithas and Krishnan, 2008; Wiesche et al., 2019), but there has been some work on the implications of technical skills for broader workforce outcomes (Atasoy et al., 2016; Deming and Noray, 2020). Yet, the absence of more work in this area is notable given the growing demand from students and workers from all backgrounds for "coding" and other technical skills and the contemporaneous reduction in the technical skills required to use analytical and AI tools. These findings, therefore, contribute to our understanding of how the human-algorithm connection will shape the demand for skills as employers embrace these technologies.

Beyond its contributions to the academic literature, these findings have implications for managers who are implementing AI, data science, and other algorithmic technologies in their organizations. These findings suggest that managers should consider how to develop algorithmic expertise among domain experts rather than solely relying on centralized IT departments or data science teams. This is crucial in contexts requiring deep domain knowledge, such as healthcare or finance, where field-specific requirements cannot be separated from technical implementation. The evidence presented in this analysis suggests that firms integrating algorithmic capabilities with domain expertise experience higher returns on AI and data science investments, as these workers better identify opportunities and translate business needs into technical solutions.

These arguments also suggest that managers may need to ensure that decision rights are located with workers who can synthesize domain and technical knowledge effectively. This represents a departure from how many technical decisions and capabilities have historically been organized within firms. When algorithmic technologies are involved in complex, non-routine decisions, the decentralization of algorithmic expertise and associated decision rights may enable faster experimentation and learning cycles, as technically skilled domain experts can quickly iterate on algorithmic solutions without the bottleneck of coordinating with a separate technical team for each adjustment.

2 Theory and Hypothesis Development

2.1 AI, algorithms, and domain expertise

How algorithmic technologies affect job design depends on three factors: specialization, coordination, and adaptation. Specialization allows for productivity gains, as in the example of medicine where AI algorithms analyze images, freeing radiologists to concentrate on complex cases (Smith, 1776). AI can lower coordination costs by synchronizing interdependent tasks, exemplified by supply chain management where predictive models can efficiently align inventory, supply, and delivery schedules (Becker and Murphy, 1992). A third factor is adaptation, with AI excelling in tailoring tasks to local information (Dessein and Santos, 2006), such as the case of marketing professionals using AI to create personalized advertising based on consumer behavior data. These adaptive capabilities are particularly valuable where applying local knowledge is critical.[3]

Balancing specialization and coordination has been a central theme of the literature on IT and jobs because new technologies incentivize employers to adjust the mix of skills *within* occupations (Spitz-Oener, 2006). Although specialization yields greater productivity in many contexts, Lindbeck and Snower (2000) theorize that task-based complementarities in knowledge-rich jobs shift work away from specialization towards more "holistic" work in which employees handle a diversity of tasks. Multi-task work raises productivity when there are informational complementarities among tasks because productivity in one task can be interdependent with activity levels in others (Postrel, 2002).[4] Computers complement educated workers because they automate routine tasks and raise the productivity of front-line workers who can balance diverse tasks and benefit from these complementarities (Autor et al., 2003; Bresnahan et al., 2002).

While specialization and coordination tradeoffs affect many aspects of IT and job design, this study examines algorithmic decision-making specifically, where successfully combining domain and technical expertise remains an ongoing challenge. For example, consider a well-recognized and standardized process used to balance data modeling decisions with business objectives in the data-mining workflow, "CRISP-DM" (Cross Industry Standard Process for Data Mining) (Wirth and Hipp, 2000; Chapman et al., 2000).[5] This model separates the data mining process into six dis-

[3]There are parallels for these arguments in the construction of teams. Using academic publication data, Teodoridis (2017) shows that a decrease in the cost of acquiring new technical knowledge changes the optimal mix of expertise when constructing diverse teams.

[4]Relative to changes in occupational demand, sub-occupational shifts have been less widely documented because administrative data agencies do not capture it well. To fill this gap, scholars have turned towards alternative data sources. A notable example is (Spitz-Oener, 2006), who uses German data to show that within-occupational change was happening quickly in occupations that were being computerized. In that sample, within-occupational change accounted for 36% of educational upgrading.

[5]Poll results from 2014 indicate that it is the most common method used for data mining and data science projects, with about half of all respondents reporting using CRISP-DM and the other half divided over other methods. See https://www.kdnuggets.com/2014/10/crisp-dm-top-methodology-analytics-data-mining-data-science-projects.html, last visited on Jan 4, 2023.

crete steps: 1) Business Understanding, 2) Data Understanding, 3) Data Preparation, 4) Modeling, 5) Evaluation, and 6) Deployment. Domain expertise in CRISP-DM is conceptualized as residing outside of technical expertise and being drawn from other experts within the organization or from outside clients. Studies of CRISP-DM have found that coordinating between workers with different expertise is expensive and represents a major limitation of this approach (Saltz, 2021).

Data science and AI technologies present unique challenges for integrating domain expertise into data-driven decision processes, as they autonomously generate decisions and recommendations that can involve complex, non-routine cognitive tasks (Brynjolfsson et al., 2018; Agrawal et al., 2018). For non-routine decisions, there can be high costs to the separation of technical and domain expertise, as in the case of the radiologists described above working with AI-based diagnostic recommendations. If the radiologist lacks understanding of how the AI model makes predictions, they may either over-rely on its recommendations or dismiss valid insights, potentially compromising patient care. Similarly, in financial trading, separating algorithmic expertise from market knowledge can lead to costly errors when automated trading systems encounter novel market conditions that require human judgment. As such, recent qualitative work in these and related settings emphasizes that the integration of technical and domain expertise for AI and data science initiatives poses a significant challenge (Beane, 2019).

The literature on data science methods and processes has identified the challenges that arise when domain expertise needs to be effectively injected into a data-driven workflow (Mao et al., 2019; Choudhury et al., 2020; Park et al., 2021). These discussions argue that the iterative nature of data exploration, experimentation, and learning required for data science favors generalists, who have a diversity of skills, over specialists (Colson, 2019). The emphasis on decision-making and the potential for algorithmic errors, the need for iteration, and the non-routine mapping between the input data and output decisions sets these technologies apart from those where the output is an input into an employee's decision-making process rather than a decision itself (e.g., websites, cloud storage, databases).

One prominent example is the creation of the "data scientist" job title itself, which combines technical and statistical acumen with domain expertise (Davenport and Patil, 2012; Provost and Fawcett, 2013). The importance of domain expertise for effective data science has been discussed online[6], in industry panels[7], and in the press (Oostendorp, 2019). Beyond data scientists, however, workers who can couple domain expertise with technical skills are becoming important to many decision-making contexts (Jha and Topol, 2016).[8] Users of machine learning tools who operate in

[6]For example, see: Is domain knowledge necessary for a data scientist? Accessed on March 11, 2019.

[7]A video of one such industry panel is captured here: `https://youtu.be/qKcUsIqoSHE`.

[8]For instance, the notion that data-driven employers increasingly demand "bilingual" workers (i.e. individuals who have both technical skills and domain expertise) was underscored by an announcement from MIT on their investment in a new College for Artificial Intelligence. The goal of the college, said L. Rafael Reif, the president of M.I.T., is to "educate the bilinguals of the future." He defines bilinguals as people in fields like biology, chemistry, politics, history and linguistics who are also skilled in the techniques of modern computing that can be applied to them. Additionally, it is expected that the "bilingual" graduates who emerge from this new College — combining competence in computing and in other fields — will be of enormous value to employers. *New York Times*, Oct 15, 2018. MIT Plans College for Artificial Intelligence, Backed by $1 Billion.

high-stakes contexts must evaluate trade-offs when choosing which data to include in a model, how to construct model features, or how to assign costs to prediction errors (Kleinberg et al., 2018). Research situated in pharmaceutical industries has shown the importance of embedding the relevant human capital in downstream occupations (Wu et al., 2019), and Jha and Topol (2016) and Lebovitz et al. (2022) describe the challenges healthcare workers face when interpreting the accuracy of machine learning tools and output.

2.2 Hypothesis development

From a theoretical perspective, organizations face a trade-off in how they structure their technical capabilities. Centralizing IT and data science expertise into specialized departments enables economies of scale and standardization. However, this creates coordination bottlenecks as domain experts must repeatedly consult with technical teams to implement solutions. Conversely, distributing algorithmic capabilities directly to domain experts increases organizational agility and reduces coordination overhead, but requires significant investment in training and risks inconsistent practices across the organization. This tension between efficiency through centralization versus responsiveness through distribution fundamentally shapes how firms organize their technical workforce.

The first hypothesis tested in this paper is:

> ***H1****: Job listings that require algorithmic technology skills (e.g., machine learning, AI) are more likely to also require domain expertise compared to job listings that require other technology skills (e.g., spreadsheets, databases) that cannot autonomously generate decisions or content.*

This hypothesis leaves open the important question of whether technical or domain experts receive this bundle. Adaptation provides a context in which to theorize about the control of task bundles in work environments. Where domain expertise helps with localized decision-making, organizations may prefer that non-technical domain experts, like those in finance and human resources, receive these skills. An instructive example is "typing pools" which existed solely to provide typing services within the organization. Over time, the typing task became part of the knowledge worker's job because local adaptation is important for documentation.[9] This shift aligns with theories of knowledge-based hierarchies, which suggest that workers closer to the frontline often have better access to local information needed for decision-making (Garicano, 2000). Additionally, transaction cost economics suggests that when tasks are highly interdependent and require frequent adaptation, bundling them within a single role reduces costly coordination between workers (Williamson, 1979).

Conversely, the use of algorithms may substitute for domain expertise in areas such as foreign language translation which could move the bundle away from domain experts. Determining which domain experts or technical experts receive this bundle, therefore, is ultimately an empirical question.

[9] I am grateful to Anna Salomons for suggesting this instructive comparison.

***H2**: Domain experts are more likely to require algorithmic skills when their roles involve local decision-making.*

The distribution of who acquires this skill bundle could evolve over time, driven by changes in the costs of becoming proficient with algorithmic tools. This dynamic aligns with theories of skill-biased technological change, which suggest that the adoption of new technologies depends critically on the costs of acquiring the complementary skills needed to use them effectively (Acemoglu, 2002). If the costs of acquiring technical skills are high, it will be difficult and expensive to find workers who have acquired both domain and technical expertise, and employers may forgo any productivity gains associated with bundling these skills together. This reflects classic make-vs-buy decisions in organizations, where high transaction costs can lead firms to maintain separate specialized roles even when integration might otherwise be optimal (Coase, 1937).

The barriers to using many tools, however, are falling as vendors compete to speed adoption of their products in the workplace. This aligns with theories of technological diffusion that emphasize how falling adoption costs accelerate the spread of new practices across organizations. Examples include the embedding of complex machine learning logic in standardized software libraries (Rock, 2019), the proliferation of no-code tools like Tableau, and most recently, the growing conversational abilities of large language models like OpenAI's *Data Analyst GPT* that enable workers to conduct data analysis with no coding background. These developments reduce the cognitive overhead required to use algorithmic tools, making it easier for domain experts to acquire technical capabilities without extensive formal training.

***H3**: The bundling of algorithmic skills with domain expertise should increase as the barriers to acquiring algorithmic skills decrease.*

Job reconfiguration of the type proposed in the prior hypotheses is costly, but firms have strong incentives to pursue these changes. Prior work has shown that productivity-enhancing workforce adjustments are needed to realize financial returns to IT investments (Black and Lynch, 2001; Bresnahan et al., 2002; Caroli and Van Reenen, 2001; Bresnahan et al., 2002; Bloom et al., 2012). For computing technologies that perform routine tasks, the literature has shown that allocating authority to front-line decision makers yields higher productivity (Bresnahan et al., 2002), particularly in environments where the value of decisions depends on rapidly changing external conditions (Pavlou and El Sawy, 2006; Black and Lynch, 2001; Bresnahan et al., 2002).

For algorithmic technologies, investors may value firms more highly when they employ workers who can effectively leverage these tools for business objectives. While hiring workers with both technical and domain expertise requires competing in tighter labor markets at higher wages, investors recognize that building this human capital and the work structures that support them represents an intangible asset that will generate future value. The coordination challenges between technical and domain knowledge in data science and AI applications, discussed above, suggest that workers who can bridge this gap by combining both skill sets may be especially valuable for realizing productivity gains. The development of workflows that combine domain and algorithmic expertise represents a valuable intangible asset because it is challenging for competitors to replicate these workflows quickly, as the necessary human capital development requires significant investment in training and organizational learning over time.

> ***H4***: *Firms that distribute algorithmic capabilities across domain experts receive higher market valuations for their algorithmic investments.*

The next sections describe the empirical tests and databases used to test the hypotheses developed above.

3 Empirical tests

This section describes three sets of empirical tests used to evaluate whether algorithmic skills and domain expertise are unusually valuable when bundled together: (i) whether employers are searching for them together in job openings (*H1* & *H2*), (ii) factors affecting firms' incentives to make these workforce changes (*H3*), and (iii) whether financial markets reward employers who make these personnel changes (*H4*).

3.1 Tests of employer preferences

The job vacancy data allows tests of whether employers simultaneously seek domain expertise and algorithmic expertise when hiring for non-technical positions. This analysis follows a growing research stream that uses large-scale job posting data to analyze the individual skills and the combinations of skills that employers choose to list in job postings (Deming and Kahn, 2018; Braxton and Taska, 2023). In Equation 1, the dependent variable is a binary indication of whether a job vacancy requires domain expertise and i indexes the job listing.

$$DOM_i = \alpha_A ALG_i + \gamma_i + \epsilon_i \tag{1}$$

The model estimates correlations between this indicator (DOM) and algorithmic expertise (ALG), holding other factors constant. The regression includes other technical skills to contrast with the algorithmic skill measure as well as a vector of control variables (γ) that includes job title[10], four-digit industry, and the logged total skills in the listing. These estimates are compared with those from other models that substitute other job attributes in place of domain expertise: i) social skills, ii) cognitive attributes, iii) character, and iv) management skills.

To provide insight into why a combination of domain and technical expertise may be of value to these employers, a second test evaluates other tasks that co-occur with these skills in job vacancies.

$$TASK_i = \beta_D DOM_i + \beta_A ALG_i + \beta_{DA}(DOM_i \times ALG_i) + \gamma_i + \epsilon_i \tag{2}$$

[10] The data provider standardizes job title at a granular level. Exemplar job titles are "Inventory Clerk" and "UX Developer".

$TASK$ indexes a variety of tasks in the data-driven decision-making process. DOM and ALG are binary indicators of whether the job vacancy requires domain expertise or algorithmic expertise respectively, and i indexes the listing. A vector of control variables (γ) includes job title[11], four-digit industry, and the logged total skills in the listing.

3.2 Incentives for job transformation

A second set of analyses uses firm-level employment data to evaluate factors – levels of employee decision-making, ease of learning algorithmic tools, and the firm's aggregate algorithmic investment – that may affect the firm's incentives to make workforce changes (*H2* & *H3*). These analyses are conducted at (i) the firm-occupation level and (ii) the firm level. Prior work has used firm-level data to evaluate how IT investment is correlated with the adoption of specific types of work practices (Black and Lynch, 2001; Bresnahan et al., 2002; Caroli and Van Reenen, 2001) or skill distributions (Levy and Murnane, 1996; Autor et al., 2003), including how IT adoption is correlated with the skill attributes of jobs. Equation 3 takes a similar approach and tests whether algorithmic skills are more commonly found in non-technical occupations with greater decision-making responsibility:

$$Log(ALGSKL)_{ijt} = \beta_{DMK} DMK_{ijt} + Log(TOTSKL)_{ijt} + \gamma_{ijt} + \epsilon_{ijt} \tag{3}$$

In this regression, $ALGSKL$ is the count of algorithmic skills in the firm-year-occupation cell, $TOTSKL$ is the count of total skills reported by workers in that cell, i is the firm, j is SOC 6-digit occupation, t is the year, and DMK indicates levels of decision-making needed in that occupation. This specification allows varying occupation characteristics, accounting for firm differences. A variation of Equation 3 adds an indicator of whether the skill is easy to learn ($EASYLEARN$) to evaluate whether innovations that lower the cost of using these tools accelerate their spread to domain experts.

Turning to the firm level, employers are incentivized to make these workforce changes if they are at the frontier of investment in algorithmic technologies ($ALG\ IT$). This relationship is evaluated by estimating correlations between algorithmic investment and a measure of the decentralization of algorithmic skills aggregated among a firm's domain experts (ϕ^{ALG}):

$$\phi^{ALG}_{it} = ALG\ IT_{it} + \gamma_{it} + \epsilon_{it} \tag{4}$$

For this analysis, i and t are the firm and year respectively, $ALG\ IT$ is the firm's investment in algorithms, and γ includes firm-level controls for size, assets, employment, and industry. This analysis tests whether these two factors are likely to be complements in production and serves as a prelude to the financial analysis in the next section.

[11] The data provider standardizes job title at a granular level. Exemplar job titles are "Inventory Clerk" and "Ux Developer".

3.3 ϕ^{ALG} and firms' financial value

The previous section analyzes the co-occurrence of algorithms and work practices in firms, showing that firms tend to invest in these complementary assets together. To provide further validation that this combination is economically valuable, I examine how these joint investments affect firm value. Prior research has attributed value to intangible assets by examining how workplace practices that complement IT investments improve firm productivity (Black and Lynch, 2001; Bresnahan et al., 2002). Another approach uses market valuations to reveal the value of intangible assets like intellectual property and digital capital (Hall, 1999; Brynjolfsson et al., 2002), based on the premise that investors value these assets for their expected future returns. These market value regressions include the firm's tangible capital and measurable proxies for intangible assets (like patents, IT investments, or organizational practices) as explanatory variables. This hedonic approach helps estimate the value of intangible assets correlated with the measurable components, after accounting for the value of the firm's tangible assets.

This paper uses a market value based approach to study AI and data science investments. This approach could be particularly well-suited because many firms are still adapting these technologies into their workflows. Market values reflect investors' forward-looking expectations about future benefits, allowing us to detect value creation before it appears in traditional productivity measures. If the workforce transformation described above creates valuable organizational assets, investors should assign higher valuations to firms making these investments (*H4*). The following specification tests whether investors assign higher value to firms that combine algorithmic investments with decentralized algorithmic expertise:

$$\begin{aligned} Log(MV)_{it} = & Log(AT)_{it} + Log(PPE)_{it} + Log(IT)_{it} + \\ & Log(ALG\ IT)_{it} + \phi^{ALG}_{it} + (Log(ALG\ IT)_{it} \times \phi^{ALG}_{it}) + \gamma_{it} + \epsilon_{it} \end{aligned} \tag{5}$$

In Equation 5, i indexes the firm and t is year. MV is the firm's market value, and PPE and AT are capital and other assets, respectively, which account for much of the firm's value. IT measures the firm's aggregate IT investment, $ALG\ IT$ is a proxy measure of the firm's investment in algorithms, and ϕ^{ALG} is the standardized measure of the decentralization of algorithmic expertise among occupations requiring domain expertise. The control variables (γ_{it}) include year, employment, and depending on the specification, industry at the four-digit NAICS level or employer fixed-effects.

4 Data sources and key measure construction

4.1 Key data sources

The empirical tests described above are informed using data sources on a) how employers are adapting jobs to algorithms and b) how the skill composition of the workforce is changing in response. These are supplemented with financial data from public firms to assess how technological and workforce changes are connected to the value that investors assign to firms.

4.1.1 Job listings database

When employers have job vacancies, they post details on their web sites or on job boards. These listings identify employer and job title, the geography of the position, the skills and education sought from candidates, wages offered, and other fields relevant to the search process. In this analysis, listings are used to measure when skills first appear in job ads and how skills co-occur in listings with other skills.

The listings are provided by Lightcast, a labor market analytics firm that 1) uses software to crawl a "near-universe" of online job postings and 2) uses natural language processing to parse job information.[12] This provider collects and standardizes data from over 17,000 job boards and corporate web sites, and these data are processed to ensure a listing is not counted multiple times if it is posted in several places on the web. The processed data include posting date, metropolitan area, employer, job title, educational requirements, certifications required, and skill expectations for each vacancy. Several studies have used these data to study labor market dynamics including how AI related skills spread across jobs and industries (Deming and Kahn, 2018; Acemoglu et al., 2022; Goldfarb et al., 2023).

Lightcast associates each listing with a BLS O*NET code and employers are tagged with a North American Industry Classification Systems (NAICS) industry. Job openings list skills, such as *Python*, *Random Forest*, *Chemistry*, *Supply Chain*, *Accounting*, *Data Science*, *Teamwork*, or *Communication* which are standardized using a skill dictionary maintained by Lightcast. These skill data are not the same as job "requirements". Employers can omit skills from listings, some skills may be assumed but not listed, and successful candidates may not need all of the skills in a listing. Nonetheless, employers are likely to be thoughtful about the skills they place in listings because including or omitting a skill can attract or repel the wrong type of applicant.

The data collection process raises questions about industry and occupational coverage. However, prior academic work has provided information on the sampling properties of these data. See, for example, Appendix A of Deming and Kahn (2018), who conduct a detailed comparison of the Lightcast data with administrative data sources. Key findings from these comparisons are that these listings data are over-represented in computer and mathematical occupations, as well as management, health care, business, and financial occupations. They under-sample blue-collar occupations.

[12] Until June of 2022, Lightcast was known as "Burning Glass Technologies" and is referred to as such in much of the prior work that has used this data set. In this paper, for consistency, we use the name Lightcast throughout, including when referencing the use of these data in prior papers.

4.1.2 Corporate employment database

The corporate employment data were provided by Revelio Labs, a workforce intelligence company.[13] Their databases are constructed from a variety of online sources,[14] and are similar in their informational content to data posted on online professional networks such as LinkedIn. They cover a large fraction of white-collar work in the US, including both public and private US firms, but the sample used in this analysis is limited to public firms so observations can be connected with financial market data. This data source has been less widely used in the literature than the job listings, so in Appendix A, I present comparisons with administrative data from the Bureau of Labor Statistics. Like the Lightcast data, these data are over-sampled in management, business, and technology occupations and under-sampled in areas such as agriculture and manufacturing which is consistent with the greater use of online professional platforms in knowledge-intensive occupations.

This database is used to generate measures of annual firm-occupation-skill employment activity from 2008 through 2021.[15] This panel provides information on how specific technical skills, like "machine learning", diffuse across occupations and employers. The records for each employer include CUSIP identifier codes which allow them to be merged with external financial databases such as the Compustat-Capital IQ data.

4.1.3 Supplementary data sources

To identify occupations requiring domain expertise, O*NET codes in the job listing data are connected to the Occupational Information Network (O*NET) content model published by the Bureau of Labor Statistics.[16] The O*NET database has been widely used in academic research,[17] is government administered, produced by surveying occupational experts, and contains information on employment, wages, and the work content of US jobs. The O*NET taxonomy reports work requirements including the knowledge required for occupations.[18] Finally, the market value analyses use firms' financial and employment data from Compustat-Capital IQ which was collected through the WRDS data service.

[13] See https://www.reveliolabs.com/

[14] Scholars have convincingly argued that the lack of firm-level data on workforce skills is a significant constraint for understanding how firms are adjusting to technological change (Frank et al., 2019; Raj and Seamans, 2018).

[15] The provider notes potential issues with the reporting of skills in the data. The profile data is federated from multiple sources that gather publicly available profiles. However, around May 2021, user skills disappeared from the majority of public profiles. The provider imputes (predicts) skills after that date and notes whether the skill on a profile is reported or imputed. However, I do not know the imputation algorithm, and so I limit the analysis to the years through 2021.

[16] See https://www.onetonline.org.

[17] One notable example of its use for examining technical change is Autor et al. (2003).

[18] The O*NET data is periodically revised to reflect the changing structure of the US workforce. Although it was revised in 2019, I use the earlier version to match the O*NET codes in my version of the Lightcast data, which were based on the taxonomy before the revision took place.

4.2 Sample construction and key measures

4.2.1 Sample construction

For the job listings analysis, the sample includes all listings in the data set from the months ranging from January 2014 to June 2016 for a total of 30 months of job listings data. The number of listings for any given month ranges from just under 2 million listings to up to 2.5 million listings for a total sample across the 30 months of 60,769,351 listings. However, as described below, the regression-based analyses on these data restrict the sample to a single month and to job listings with a specific set of skills which significantly lowers the sample size for those analyses.

The Revelio workforce sample, which forms the core of this analysis, includes firm-occupation-year-skill counts for the years 2015 to 2021. To join these figures with financial data from Capital IQ, the sample is limited to public firms, producing a sample of 7,198 firm-years. Table 1 reports summary statistics for a single year from the mid-point of this panel (2018). The statistics are reported in logs because they are included in logs in the multi-variate regressions. Firms in this sample are large, with an average market value of over 57 billion dollars and almost 30,000 employees. The average firm in this sample has around 1,000 IT workers. Table 2 shows the distribution of these firms across NAICS 2-digit industries. Although there are firms in every major sector, the Manufacturing, Information, and Finance and Insurance industries together comprise almost 90% of the overall sample. The construction of key variables used in the analysis is described below.

4.2.2 Employee algorithmic expertise (ALG)

Skill data are used to measure whether employees have or require algorithmic expertise. A key challenge when using workforce skills for empirical analysis is the mapping of granular skills to meaningful expertise measures.[19] Recent published papers that use large quantities of archival, digitally collected workforce data have used manual mappings. For example, Abis and Veldkamp (2024) manually assign skills to "Data Management", "Analysis", "Old Technology", and "AI" categories and Goldfarb et al. (2023) select a cluster of skills related to machine learning technologies for their analysis. Deming and Kahn (2018) curate words and phrases in the Lightcast data associated with different job skills, including cognitive, social, character, and computer categories. The literature on the impact of AI technologies on labor displacement has also generated their own rubrics for measurement (Brynjolfsson et al., 2018).

This analysis takes a similar approach but it uses categorizations generated by the data providers themselves, who use clustering methods to group skill categories into different technology areas like "data science", "AI", or "Big data". Appendix B delineates the skill categories that fall into each of the technological groups used in this analysis. For algorithms, examples of these base-level categories include *machine learning*, *business analytics*, *julia*, and *natural language processing* and

[19] Because of the growing interest in the "future of work", the construction of taxonomies that make sense of emerging sources of skills data is an active and ongoing area of research among businesses and information agencies. For example, see recent efforts by Nesta in the UK or Lightcast.

each of these contain more detailed skills. For instance, *machine learning* is a skill category that includes skills like "deep learning" and "supervised learning" within it.

Skills in the AI and data science technology categories are combined to develop indicators of algorithmic expertise at the individual level. At the worker level, a record (job listing) is denoted as having (requiring) algorithmic expertise (ALG) if it has at least one skill falling into this category.

4.2.3 Domain expertise (DOM), decision-making (DMK), and other attributes

Job-level measurement of domain expertise is constructed to be consistent with the measurement of algorithmic expertise. A binary indicator (DOM) takes the value 1 if an employee reports having at least one type of domain knowledge in their skill set where the list of potential domain skills is extracted from the O*NET dictionaries, which identify all of the possible knowledge domains with which US-based jobs may require familiarity.[20] These domains are extracted from the "Knowledge" table in O*NET, which describes "organized sets of principles and facts applying in general domains."[21] From the full list, *Computers and Electronics*, *Engineering and Technology*, *Telecommunications*, and *Mathematics* were removed because they overlap with measures of algorithmic expertise.[22] Similarly, the level of *Decision-making* for an occupation (DMK) is retrieved from the O*NET database which provides this measure on a scale of 1 through 7 for each six-digit occupation.

Finally, beyond algorithmic and domain expertise, the analysis uses indicators of skills related to *cognitive*, *social*, *character*, and *management* job attributes. The construction of these attributes was based on prior work that uses the Lightcast data source to construct these measures (Deming and Kahn, 2018). As with measures of algorithmic and domain expertise, records are coded as needing these attributes if the listing contains at least one related skill.[23]

4.2.4 Organizational algorithmic expertise (ϕ^{ALG})

At the organizational level, algorithmic expertise measures are constructed as the fraction of workers with algorithmic skills ($\%ALG$) in occupation groups that satisfy the following criteria: they are i)

[20] See `https://www.onetonline.org/find/descriptor/browse/Knowledge/`.

[21] The domain categories identified in the O*NET knowledge set are *Administration and Management, Biology, Building and Construction, Chemistry, Clerical, Communications and Media, Customer and Personal Service, Design, Economics and Accounting, Education and Training, English Language, Fine Arts, Food Production, Foreign Language, Geography, History and Archeology, Law and Government, Mechanical, Medicine and Dentistry, Personnel and Human Resources, Philosophy and Theology, Physics, Production and Processing, Psychology, Public Safety and Security, Sales and Marketing, Sociology and Anthropology, Therapy and Counseling, and Transportation.*

[22] It is important to contrast this approach with one in which jobs would be identified as requiring domain expertise based solely on titles. Such an approach would impose the restriction that jobs with the same title cannot differ in their knowledge content. Relaxing this restriction is important for this analysis because it allows for an analysis of the diffusion of new skills into occupations (i.e. sub-occupational change) rather than changes to the occupational mix which is central to this analysis.

[23] Deming and Kahn (2018) construct these job attribute measures based on whether a listing has a skill related to the attribute. These skills, as reported in Table 1 of that paper, are: *cognitive* [problem solving, research, analytical, critical thinking, math, statistics], *social* [communication, teamwork, collaboration, negotiation, presentation], *character* [organized, detail oriented, multitasking, time management, meeting deadlines, energetic], and *management* [project management, supervisory, leadership, management (not project), mentoring, staff]. Deming and Kahn (2018) also include *writing*, *customer service*, *financial*, *computer*, and *software* job attributes in their analysis but those attribute families are not included in this analysis.

in the top quartile of occupations in their domain expertise requirements and ii) in the importance of decision-making for that job.[24] For organization i in year t, an aggregate measure of the dispersion of algorithmic skills across these occupational groups (ϕ^{ALG}) is computed as:

$$\phi_{it}^{ALG} = \frac{(\%ALG_{it} - MEAN(\%ALG))}{STD(\%ALG)} \tag{6}$$

Firms in which these employees have more algorithmic skills have larger ϕ^{ALG} values. For some robustness tests, parallel measures are constructed for other technological categories (e.g., ϕ^{CLOUD}).

4.2.5 Firms' investments in algorithms and other technologies

Obtaining consistent, firm-level measures of IT investment spanning multiple years has been a persistent challenge in the academic literature (Tambe and Hitt, 2012). IT investments are not consistently recorded on balance sheets, so scholars often leverage alternative sources to create proxy measures, such as hardware investment measures collected by marketing surveys, IT keywords referenced in legal filings, and IT employment or salaries (Lichtenberg, 1995; Brynjolfsson and Hitt, 1996; Tambe, 2014). The rationale behind the last approach is that human capital is the largest component of a firm's digitization investment and it has become even more important for AI and data science investment because much of that software stack is open-source, leaving no documented investment trail, and because much of the hardware is cloud-based and poorly measured by instruments that record the firm's owned servers and PCs. Conversely, most frontier software requires technical expertise to install and maintain, so quantities of complementary, technical human capital may be the most accurate available accounting of a firms' technology investments.

This approach is used to generate measures of firms' technology assets. It follows prior work where proxy investment measures are constructed as quantities or intensities of skills relevant to the technological domain (Tambe and Hitt, 2012).[25] This view of the dichotomy between technical workers and non-technical occupations is similar to work that treats the employment of technically skilled workers as the main investment into the construction of digital assets that can be subsequently deployed by an organization to achieve its business goals (Hall et al. (2000) calls this "e-capital"). Investments in aggregate IT or its sub-categories (i.e., $ALG - IT$, IT, $DS - IT$, $AI - IT$) are computed as the quantity of relevant skills in the firms' IT workforce in a given year. Because the firm-level regressions include employment measures, the "stock" of skills in a technological area can be interpreted as the intensity of investment in that domain.[26]

[24] These O*NET major occupational groups are: 11-0000 (Management), 13-0000 (Business and Financial), 17-0000 (Architecture and Engineering), 19-0000 (Life, Physical, and Social Science), 23-0000 (Legal), and 29-0000 (Healthcare Practitioners and Technical).

[25] Like most firm-level measures, this approach records investments with measurement error. See Appendix B for a brief discussion.

[26] The main findings are robust to an alternative construction of this measure based on quantities of technical workers with at least one skill in the relevant domain which has a slightly different interpretation (e.g. quantities of AI engineers, rather than the intensity of AI skills in the tech workforce). Those results are not shown due to space constraints but are available upon request.

4.2.6 Financial variables, assets, and industry classification

The Compustat-Capital IQ data are used to construct employer-year measures for total market value, employment, industry classification, the value of PPE (property, plant, and equipment), and other assets. As discussed earlier, the use of Capital IQ financial data necessitates limiting the sample to public firms. Industry variables for these firms are retrieved at the four-digit NAICS level (North American Industry Classification System). Total market value is computed as described in an existing literature relating intangible assets to firm value (e.g. see the Appendix of Brynjolfsson et al. (2002) which describes variable construction). It is computed as the value of equity at the end of the fiscal year plus the value of preferred stock plus total debt which represents the total worth of a firm as assessed by the financial markets. Assets are computed as total assets minus PP&E.

5 Results

5.1 Model-Free Evidence

5.1.1 The growth of algorithmic expertise in non-technical job vacancies

Figure 1b illustrates the growth rate of algorithmic skills in non-technical job listings from 2013 to 2016. Each x-axis tick corresponds to one month and the y-axis is the coefficient estimate (β) from the logistic regression $ALG_i = \beta_t t_i + \epsilon_i$ where i is the listing, t is a vector of dummy variables for months since January 2013 when a vacancy was posted, and ALG indicates whether an algorithmic skill appears in a job listing. The likelihood of an algorithmic skill appearing in a non-technical occupation listing rises throughout the sample.

Figure 2a shows the extent to which specific technology skills, including but not limited to algorithmic skills, are bundled with domain expertise in one month of the Lightcast data (January 2016). Algorithmic skills, shown in blue, appear more frequently alongside domain expertise (extending further rightward) and in this respect are similar to widely-used business tools like Excel and ERP systems that are prevalent in non-technical roles. Figure 2b indicates that algorithmic skills, again colored in dark blue, are more commonly found in job listings for non-technical occupations than are other technical skills. Predictive analytics, data science, and data analysis are only slightly less dispersed than skills related to the Microsoft Office Suite, which supports the claim that employers are increasingly bundling algorithmic skills with domain expertise.

5.1.2 Algorithmic expertise in the workforce data

Job listings indicate what employers want. However, they do not indicate whether these listings represent hard requirements or instead, are an employer "wish list" or whether the vacancies requiring these skills are even ultimately filled. Therefore, I turn to corporate employment data to investigate whether the changes indicated by these listings are reflected in the workforce. These analyses are shown in the four quadrants of Figure 3.

Figure 3a shows that technical skills have become more dispersed in non-technical occupations in these firms. The y-axis is the intensity with which a skill appears in non-technical occupations, with levels depicted relative to their 2008 values. There is steady growth in the rate at which AI and data science skills have penetrated non-technical occupations, consistent with the evidence from job vacancies shown in Figure 1b. By 2021, these skills appeared in 10% more non-technical occupations than in 2010. In contrast, skills corresponding to two other categories, network and cloud technologies, became increasingly specialized, and the incidence of mobile skills remained flat.

Figure 3b shows how the measure ϕ^{ALG} (Equation 6) varies across industry and time. It is highest in the Information, Professional Services, and Finance industries, which is consistent with press reports (Lohr, 2024). Retail has climbed rapidly which may reflect the growing use of consumer data for prediction. Levels are lower in Healthcare although they have been climbing, reflecting the growing use of AI and data science in healthcare.

Figure 3c depicts annual changes in ϕ^{ALG} after separating firms into quartiles according to their market values in the final year of the sample (2021). ϕ^{ALG} is greatest in higher quartiles and the differences are largest in the earlier years of the sample, consistent with a labor market where workers with these skills are a scarce resource that higher value firms can more easily attract. In the last years of the sample, however, ϕ^{ALG} converges across quartiles, suggesting that supply-side adjustments have made it easier for employers with fewer resources to attract these workers. The fourth quadrant (Figure 3d) uses data from the final year of the sample and plots firms' investments in algorithms against ϕ^{ALG} where the bubble size reflects the firm's market value. The largest circles (colored in blue) are those commonly referred to as "big-tech" firms. We can see that firms contemporaneously invest in algorithms and in business-facing workers with algorithmic skills.

5.2 Correlation tests: Domain expertise and algorithmic skills

From model-free evidence, we turn towards empirical tests of our hypotheses, beginning with Equation 1. Figure 4a depicts estimates of α_A. The sample is a single month (Jan 2016), and the unit of observation i is the job listing. In this sample, algorithmic skill is a predictor of domain expertise required in a job. The regression includes job-title fixed effects so the finding persists after removing the effects of job title differences (**Hypothesis 1**). The full set of estimates from Equation 1 can be found in Appendix C and indicates negative correlations with data management, which is consistent with database skills being more centralized within IT occupations. We observe positive correlations between the use of algorithms and social and cognitive skills and negative correlations with management-related job attributes. This negative relationship suggests that employers are not bundling people leadership (character and management) with algorithmic skills.

To provide evidence on why these skills appear together in listings, Figure 4b illustrates β_{DA} from Equation 2. Algorithmic and domain expertise most often appear together for positions that also require *Presentation* and *Decision-making*. Interpreting, communicating, and acting on data output appears to benefit from a synthesis of data and domain expertise. In contrast, this combination of skills is negatively correlated with tasks related to *Data management* and *Data* *modeling* which are tasks may not favor generalists who bring a diversity of skills to the task.

5.3 Regression tests: Incentives for job transformation

Table 3 reports the results of empirical tests from Equations 3 and 4 on the workforce data. In a reflection of Figure 4b from the job vacancy data, column (1) indicates that domain experts for whom decision-making is important are more likely to have algorithmic skills (t=3.50) (**Hypothesis 2**). The significance of this estimate remains after including firm fixed-effects (Column (2)) which eliminates the role of static firm differences in driving these relationships, such as heterogeneous demand for decision-making.

Columns (3) and (4) test the proposition that a reduction in the cost of using algorithmic tools speeds the diffusion of these skills into non-technical occupations. Columns (3) and (4) separate algorithmic skills according to whether the skill is easier to learn, using as a proxy measure whether the technology is a "no-code" tool.[27] These tools comprise a small fraction of all technical skills so the main-effect is negative (t=-28.88). Column (4), however, indicates that tools that are easy to learn see greater uptake among non-technical decision-makers (t=4.29) (**Hypothesis 3**). This finding supports a causal interpretation subject to the assumption that these tools perform the same functions as their code-based counterparts. If these two categories of tools perform substantially different functions, however, heterogeneity in usage may limit a causal interpretation of these findings.

Columns (5) and (6) aggregate the data to the firm-year level by occupation and test if algorithmic expertise is more decentralized among domain experts (ϕ^{ALG}) at employers that invest in algorithms, which would be predicted if these investments are complements in production. Investments in algorithms and ϕ^{ALG} are correlated after controlling for firm characteristics like size and industry that may otherwise influence co-investment patterns. These correlations are robust to including firm fixed-effects (t=2.34).

These findings suggest that firms should view AI and algorithmic investments as part of a broader organizational transformation that requires complementary human capital investments. The correlations between algorithmic investments and decentralized expertise (ϕ^{ALG}) suggest that successful AI adoption requires building technical capabilities throughout the organization, particularly among domain experts and decision-makers. Second, the evidence that no-code tools see greater uptake among non-technical decision-makers suggests that tools and technical advances that lower the barriers to algorithmic adoption may accelerate the development of these benefits.

5.4 Regression tests: ϕ^{ALG} and financial value

Table 4 reports estimates from the market value regression in Equation 5 on a seven-year panel of public firm investments (2015-2021). Columns (1) through (3) include year and 4-digit industry

[27] Technologies are identified as being in this category using GPT-4 based labeling. The use of Large Language Models for data annotation has been shown to be effective in domain-specific tasks and is becoming increasingly common in the literature (Møller et al., 2023).

fixed-effects. Column (1) reports results of market value on measures of IT investment, assets, capital (PPE), and employment where all of these variables are entered in logs. As prior work has also found (Brynjolfsson et al., 2002), financial markets assign economic value to investments in general IT capital (t=3.79). After adding algorithmic investment into the regression, the coefficient on general IT capital falls to zero suggesting that the market returns to IT investment are principally from frontier investments, as represented in this panel by AI and data science investments (t=3.93).

Column (3) reports estimates from the full specification shown in Equation 5 that includes the interaction term between investment in algorithms and ϕ^{ALG}. The main effect on algorithms is similar to column (2) (t=3.80) but the interpretation of the interaction is that these technical investments are valued an additional 15% higher in firms where ϕ^{ALG} is one standard deviation above the mean (t=2.67). This supports the argument that contemporaneous investment in ALG and ϕ^{ALG} builds valuable intangible assets needed to produce a future stream of AI goods and services (**Hypothesis 4**). Column (4) adds firm effects instead of industry effects. Including firm effects drives the coefficients on algorithms, ϕ^{ALG}, and the interaction term, to zero. This may reflect the limited variation in this relatively short panel, but another interpretation is that there are high adjustment costs for firms building these assets. Within the limited range of this panel, unobserved differences across firms may explain most of the heterogeneity in firms' endowments of these assets. One way to probe this argument is to separate extensive and intensive margins of investment for algorithms. Column (5) substitutes a measure indicating if ϕ^{ALG} is above or below the mean for firms in the sample. The results are similar to those in column (3) (t=3.00). By eliminating within-firm variation, they show that across-firm differences are more important for these estimates. Firms have a limited ability to change their asset mix in the years covered in this sample.

An interpretation of these findings is that firms cannot simply invest in AI and expect returns – the value of AI investments depends critically on having domain experts who can use these tools effectively. The premium for firms that combine AI investments with algorithmic-skilled domain experts indicates this is not just a technical challenge, but an organizational one. The firm fixed effects results suggest significant adjustment costs in building these capabilities. Organizations likely need sustained, multi-year investments to develop the right combination of technical infrastructure and human capital. This may explain why early movers in AI adoption currently maintain advantages, even as the underlying technologies become more widely available.

These three sets of analyses from the job vacancies, employment data, and financial markets suggest that in the last decade, (i) employers have been adjusting job search to find domain experts with expertise in algorithms, (ii) domain experts in decision-making positions increasingly have algorithmic skills, and (iii) employers that match their algorithmic investments with these workforce changes realized greater market valuations, suggesting the presence of valuable intangible assets in these firms. This evidence collectively supports the primary conclusion of the paper that a greater level of technical skill in a firm's domain experts is a valuable complement to its use of algorithms.

5.5 Effect heterogeneity and robustness tests

The average effects shown in Table 4, including the lack of a relationship indicated in column (4), could mask variation across different types of firms.

For instance, these effects may vary with firm size due to economic arguments about coordination costs and organizational complexity (Garicano and Hubbard, 2009). When technical and domain knowledge are separated, the increased organizational layers and communication channels in large firms can create bottlenecks and slow decision-making. Workers who combine both skill sets may be especially valuable in this context as they can make informed technical decisions without extensive back-and-forth consultation. Furthermore, larger firms often operate in multiple domains and markets, increasing the value of workers who can adapt algorithmic tools to different business contexts. Smaller firms, in contrast, may have simpler organizational structures with fewer coordination challenges, reducing their need for bilingual workers. This suggests that the relationship between value and distributing algorithmic capabilities across domain experts may be stronger in larger firms, which is consistent with patterns that have been observed for other digital investments (Tambe et al., 2020).

Figure 5 reports estimates of the main interaction term for Equation 5 where the sample is split by firm size (separated by tercile). The financial returns are greater for larger firms, likely due to either higher coordination costs or advantages in hiring skilled workers and deploying technologies. The first explanation would persist over time but the second may fade as market supply adjusts. Figure 3c suggests that both effects are at play.

The findings reported so far also obscure technological changes over the sample period. Until now, our analysis has combined AI and data science investments under the broad category of "algorithms", despite the fact that the technological frontier has evolved significantly from data science toward AI over our sample period. Table 5 separates these technologies and divides the panel into the years before and after 2018. The first two columns suggest a relationship between data science investment and market value during the earlier period, but there is no correlation with AI. In the later period, the estimates on AI and Data Science are both positive and significant suggesting greater market value assigned to AI investment in the later period. Columns (3) and (4) introduce interaction terms with organizational skills for these technologies (ϕ^{DS} and ϕ^{AI}). During the early period, the interaction term for data science investments shows positive returns while the AI interaction has a negative coefficient. This pattern reverses in the later period, where the AI interaction demonstrate positive and significant returns while data science returns become less precise. The differential pattern between AI and data science is informative - the complementarity between domain and algorithmic expertise may be more critical for AI technologies compared to data science due to its autonomous decision capabilities and the black-box nature of many AI models.

Figure 6 summarizes robustness tests that suggest the market value correlations reported above are likely due to the hypothesized theoretical relationships rather than omitted variable bias. These tests focus on the interaction between AI and ϕ^{AI} in the last two years of the sample which is the window in which these patterns appear to be most salient. Figure 6a retains the ϕ measure but interacts it with different technology investments (investments in data and networks, respectively). The theoretical discussion suggests we should observe the strongest correlations with investment in algorithms like AI, which is the pattern we observe. Neither of the interaction terms created using the other technologies exhibits meaningful correlations, which indicates that correlations between market value and the interaction of ϕ^{AI} and AI investment are not simply reflecting sources of unobserved heterogeneity that would be correlated with broader technology investment, such as financial resources, free cash flow, or overall digital intensity. Figure 6b performs a similar comparison but uses AI investment for all interactions and alters the decentralization measure. It includes ϕ^{AI} but it also adds measures constructed in similar ways for ϕ^{NET} and ϕ^{CLOUD}. We only observe correlations with market value when AI investment is accompanied by ϕ^{AI}.

In a final test, Figure 6c returns to the original construction of ϕ^{AI} but adds a parallel measure using occupations where decision-making is *lowest* in its importance. This comparison shows that the market value correlations are stronger for occupations where decision-making is important. In sum, Figure 6 indicates that correlations with market value only appear at the confluence of AI investment and AI skills among domain experts engaged in decision-making. Although we should be cautious before interpreting this relationship causally, these results do suggest that investments in algorithms and the workers who can apply them to meet business goals are disproportionately accumulating in high value firms. Similar patterns of resource accumulation do not exist for other technologies or skills or for employees who are not instrumental to the firm's decision-making processes.

The robustness tests presented in this section are supportive of the argument that the complementarity between AI investment and decentralized expertise is not merely a reflection of broader technological sophistication or financial resources - it represents an organizational asset that creates value. This suggests managers should focus on building AI capabilities among domain experts rather than pursuing a general "digital transformation" strategy. Second, the stronger effects found in larger firms highlight unique challenges based on organizational scale. Larger organizations may need to be more intentional about fostering AI capabilities across business units, but they also stand to gain more from successful implementation. Third, the evolution from data science to AI investments indicates that organizations need to stay attuned to technological shifts and adapt their workforce development accordingly.

6 Managerial and Theoretical Implications

Adoption of algorithmic decision-making, and particularly predictive AI applications, has been difficult and uneven (Zolas et al., 2021). The evidence from this analysis suggests that the human capital of data-driven firms differs from that of firms that lag in this domain. This implies firms face considerable adjustment costs when adopting these technologies, which in turn suggests competitive rents for firms that have successfully found the right mix of workers.

A caveat is that the costs of using AI and data science technologies are rapidly falling. Conversational interfaces driven by generative AI, for instance, represent a shift in how knowledge workers interact with information technologies, making them more accessible and user-friendly than ever. A reduction in the costs of using these tools means that employers can more easily push data analysis tasks to domain experts. The implications of this shift for managers can be significant. For managers, no-code and generative AI tools can democratize technical skill, enabling a more diverse range of employees to contribute to areas that were once the exclusive domain of technical specialists. This can lead to more innovative environments that emphasize the productive combination of human creativity and computational power. Managers, in turn, may need to adapt by focusing less on specific technical skills when hiring and more on general problem-solving abilities and adaptability.

An emerging managerial challenge is that technical skill has economic attributes that differentiate it from other types of expertise. For instance, frontier technical skills derive significant productivity benefits from geographic agglomeration. Moreover, rapid technological depreciation changes the economics of professions in which technical human capital plays an important role, which has implications for topics like gender diversity and skilled immigration that routinely attract scrutiny from legislators and managers. Given these dynamics, cultivating a learning culture within organizations becomes crucial. As algorithmic technologies evolve, firms need to continuously invest in upskilling their workforce, particularly for domain experts who must stay current with emerging tools while maintaining their core expertise. Organizations that can create effective learning environments and provide ongoing training opportunities are likely to be better positioned to capitalize on algorithmic advances. The challenge for managers is not just providing technical training, but fostering an environment where domain experts feel empowered to experiment with new tools and approaches.

From an organizational design perspective, firms need structures that facilitate collaboration between domain experts and technical specialists while carefully considering decision-making processes as domain experts become increasingly proficient with data and algorithms. This might involve creating cross-functional teams and communities of practice for knowledge sharing, while adapting traditional hierarchical processes to account for domain experts who now have both subject matter expertise and technical capabilities. The challenge is creating structures and governance mechanisms that maintain necessary specialization and oversight while enabling the productive combination of expertise. This may require new review processes for algorithmic decisions, clear guidelines for when human judgment should override algorithms, and new metrics for evaluating data-driven decisions. The goal should be to create organizational and decision-making structures that capitalize on the unique combination of domain and technical expertise while maintaining accountability.

Finally, for educators, the falling costs of technical skill acquisition associated with no-code and generative AI technologies suggest a curricular reorientation. Although technical skills will remain important for specialized workers in IT-producing industries, there may be greater emphasis from IT-using industries on understanding how to effectively interact with AI tools, interpret their outputs, and apply critical thinking to leverage AI-generated content. Educators will need to focus on educating students about how to guide and evaluate AI output. The results in this study suggest that this type of education will be required for all majors, not just technical majors. Institutions that have not traditionally been focused on providing technical skills to students, such as business schools, have observed a surge in interest in demand for courses teaching data, analytics, and AI technologies (Eisenmann, 2013; Lohr, 2017; Guetta and Griffel, 2021; Becker, 2023). These findings suggest these changes may be an appropriate response to a labor market that will increasingly demand workers with both domain expertise and algorithmic skills.

7 Conclusions

This paper provides evidence from two independent data sources that algorithmic expertise is becoming dispersed among domain experts in organizations at the algorithmic frontier and that these workforce changes, when made together with investments in algorithms, produce valuable intangible assets. It documents one early but important facet of the workforce transformation occurring to support the use of algorithms in organizations.

There are several key limitations of this analysis that should be noted. The study provides limited visibility into the precise nature of expertise required by workers and focuses on the narrow question of how specific skills are bundled together into jobs. The data does not distinguish between deep technological expertise and interactional expertise. The latter may be sufficient for engaging with developers and builders of these tools, but whether it is enough to be effective with these technologies remains an open question. Furthermore, open questions remain about how to restructure decisions around algorithms and where firms should place oversight of algorithmic decisions. Moreover, this study does not investigate the organizational structures and processes that firms may need to implement to effectively leverage these workers, which is an important area for future research. The analysis also takes a static view of technology adoption, not capturing long-term labor market consequences. Finally, more time is needed for firms to adapt to this new mode of production to gather stronger causal evidence of the impact of these workforce changes on performance.

Partly due to these limitations, there is significant scope for future work in this area. Research about the coming wave of investment in algorithmic technologies, and the work practices that will be required to accompany these changes, is in its infancy. We have much to learn about how to design organizations so that humans can effectively work with algorithms. This paper considers one facet of workforce transformation but complements to algorithmic technologies will be wide-ranging. These will likely include even more sweeping changes to workforce skills, as well as other non-labor investments to support these capabilities.

Indeed, a key limitation of this paper, like most research on technology and work, is that it takes a static view. At this early stage, there is limited evidence that the use of these technologies has had broad labor market consequences (Acemoglu et al., 2022). Stronger causal evidence of the impact of these workforce changes on performance requires allowing firms more time to adapt to this new mode of production. Additionally, new technologies for data collection, analysis, prediction, and visualization will offer improved capabilities to generate insights. As this frontier advances, it will continue to change markets for these skills, and continue to raise new questions about how employers should integrate algorithms into their processes.

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Table 1: Summary statistics for regression panel variables (2018)

Variable	Units	Mean	Std. Dev.	N
Log(Market value)	Millions (USD)	9.120	1.83	1,250
Log(Assets)	Millions (USD)	8.503	2.18	1,250
Log(PPE)	Millions (USD)	5.754	2.57	1,250
Log(Employment)	Thousands (Employees)	2.218	1.44	1,250
Log(IT)	Skill count	7.065	1.92	1,250
Log(Network IT)	Skill count	3.370	2.04	1,250
Log(Database IT)	Skill count	5.062	1.86	1,250
Log(Alg IT)	Skill count	2.949	2.21	1,250
Log(Data science)	Skill count	3.342	1.69	1,250
Log(AI)	Skill count	2.032	1.78	1,250
ϕ^{ALG}	Standardized Value	0.012	0.90	1,250

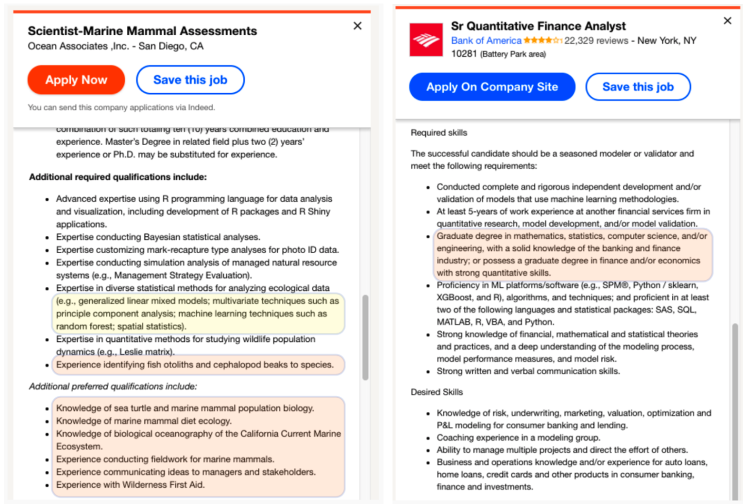
Table notes: This table reports summary statistics for firms in the 2018 cross-section of the regression panel constructed from the workforce data. The year 2018 was chosen as the midpoint in the panel window (2015-2021). The data source for the first four rows [*Market Value, Assets, PPE, Employment*] is the Capital IQ database available through Wharton Research Data Services (WRDS). The measures in the last five rows [*IT, Networks, Databases, Algorithms, Data science, AI,* ϕ^{ALG}] are constructed from the Revelio workforce database.

Table 2: Industry distribution of corporate workforce sample (2018)

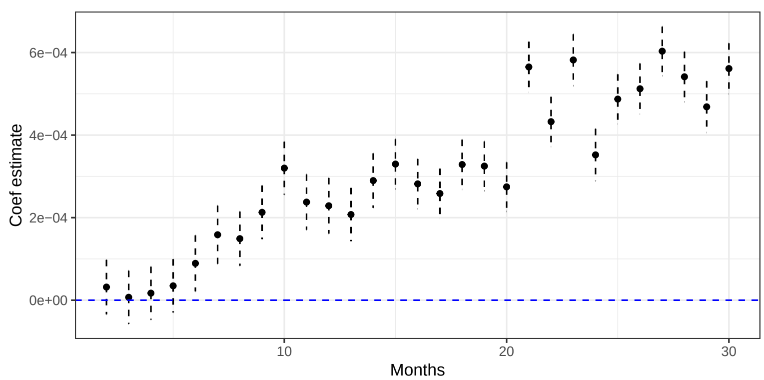
NAICS 2	Sector	N
11	Agriculture, Forestry, Fishing and Hunting	1
21	Mining, Quarrying, and Oil and Gas Extraction	29
22	Utilities	34
23	Construction	10
31-33	Manufacturing	360
42	Wholesale Trade	34
44-45	Retail Trade	42
48-49	Transportation and Warehousing	34
51	Information	268
52	Finance and Insurance	268
53	Real Estate and Rental and Leasing	26
54	Professional, Scientific, and Technical Services	60
56	Administrative and Support and Waste Management Services	25
61	Educational Services	6
62	Health Care and Social Assistance	24
71	Arts, Entertainment, and Recreation	3
72	Accommodation and Food Services	19
81	Other Services (except Public Administration)	1

Table notes: This table reports the distribution of firms across NAICS 2 digit industries in the 2018 cross-section of the regression panel. It uses the same cross-section of firms as in Table 1.

Figure 1: The growth of algorithmic skills in job listings



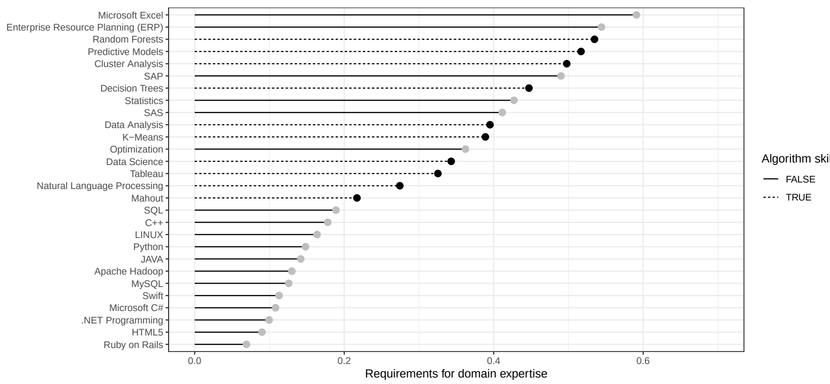
(a) Sample listings with algorithmic and domain expertise



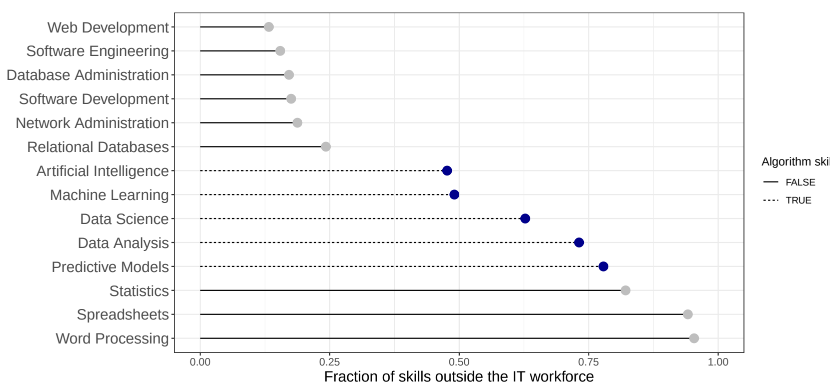
(b) Likelihood algorithmic expertise appears in a non-technical listing

Figure notes: Figure (a) shows two sample listings for jobs requiring familiarity with both algorithmic tools (highlighted in yellow) and domain expertise (highlighted in orange), related in these examples to marine biology and finance. These listings and screenshots were extracted from the website Indeed.com. Figure (b) shows coefficient estimates and standard error bars on the regression $ALG_i = \boldsymbol{\beta}\mathbf{MONTH}_i + \epsilon_i$ for the listings in the months covered by the Lightcast data a dummy variable is included for each month in the data set and where coefficients reflect differences from the Jan 2013 baseline month, i indexes job listings, and ALG takes the value 1 if a listing contains an algorithmic skill and 0 otherwise. N=60,769,351. Standard error bars show the 95% confidence interval.

Figure 2: Algorithmic skills, domain expertise, and job listings



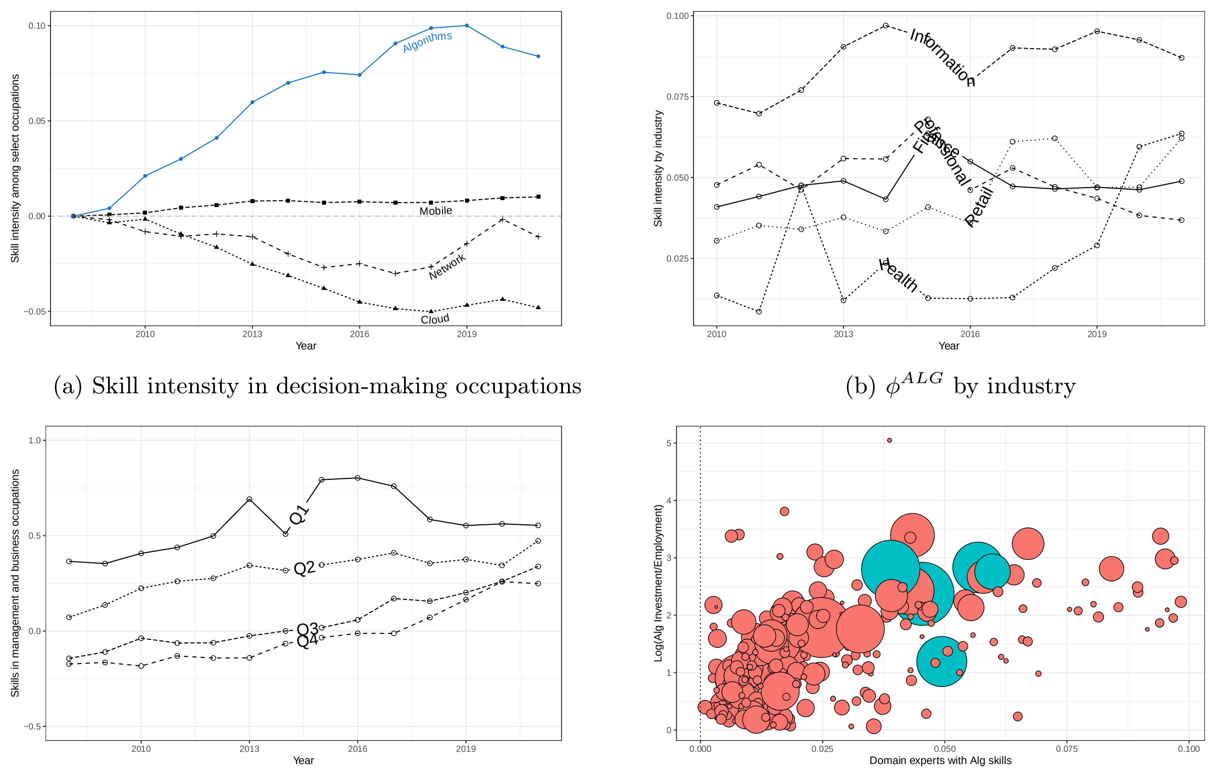
(a) Bundling of technical skills with domain expertise



(b) Fraction of skills appearing in non-technical job listings

Figure notes: Figure (a) indicates the extent to which different information technologies are bundled with domain expertise for skills appearing in a single month (January 2016) of the job listing data (N=763,986). Skills in dark blue (dashed line stems) are in the algorithms category and all other technologies are shown in gray (solid line stems). Longer bars in this figure (reaching further to the right) indicate a skill that is more likely to be bundled with domain expertise. Figure (b) indicates the fraction of occurrences where a technology appears in non-IT occupation listings. The sample is restricted to listings in one month (January 2016) of the sample data with skills in one of the areas indicated (N=263,256). Skills in dark blue (dashed lines) are those in the algorithms category. A value closer to one means that a skill is more likely to appear in non-IT occupations.

Figure 3: Changes in the locus of technical expertise in organizations from 2008-2021



(a) Skill intensity in decision-making occupations

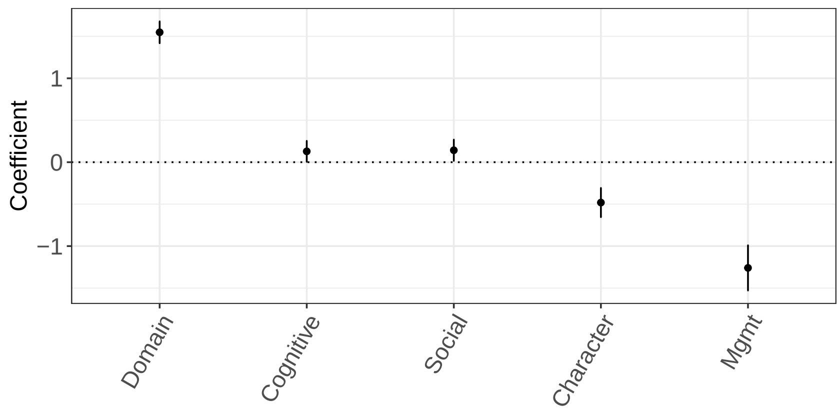
(b) ϕ^{ALG} by industry

(c) Convergence in ϕ^{ALG} across firm size quartiles

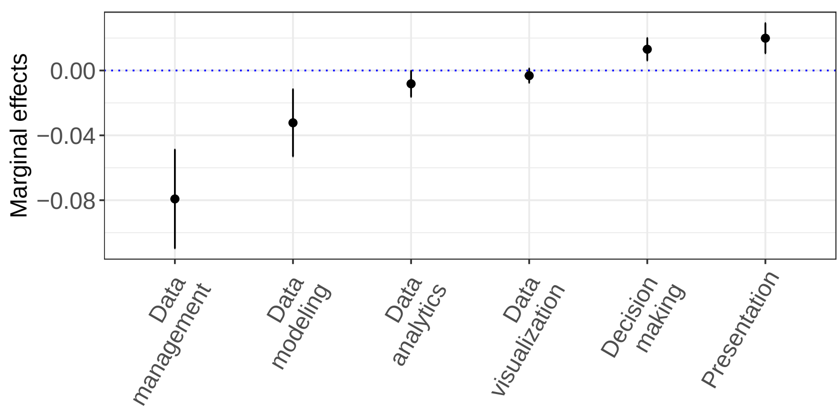
(d) Organizational accumulation of skills

Figure notes: Figure (a) illustrates changes in the intensity of different technical skills among the firm's domain experts over. time. All trend lines represent changes from their values in the base year (2008). Figure (b) illustrates changes in the ϕ^{ALG} measure in different industries over the course of the panel. Figure (c) shows changes in this measure after dividing firms into quartiles by size. Figure (d) plots ϕ^{ALG} (x-axis) against Algorithm investment levels (y-axis). The sizes of the bubbles in this figure indicate the firm's market value.

Figure 4: Skills in non-technical job listings requiring algorithmic expertise



(a) Correlations between algorithmic expertise and key job skills



(b) Marginal effects of algorithmic and domain expertise (joint) on different data tasks

Figure notes: Figure (a) depicts correlations between skills needed on-the-job and algorithmic expertise in the job listings from January 2016. Each vertical bar is a coefficient estimate from a separate regression of the form $SKILL_i = \alpha_{ALG}ALG_i + \alpha_{DATA}DATA_i + \alpha_{NET}NET_i + Log(No.\ Skills)_i + \gamma_i + \phi_i + \epsilon_i$ where for each of the five different regressions, $SKILL$ is one of $DOMAIN$, $COGNITIVE$, $SOCIAL$, $CHARACTER$, or $MANAGEMENT$, i indexes the listing, γ and ϕ are occupation and industry fixed-effects respectively, and $Log(No.\ Skills)$ is the logged number of skills in the listing. The point estimate shown is the coefficient on α_{ALG} from each regression and the vertical bars indicate 95% confidence intervals. The estimates from the full form of each of these regressions is shown in Appendix C. Figure (b) reports results from tests of which data tasks require a combination of both algorithmic and domain expertise using the January 2016 job listings. The logistic regression is $DATATASK_i = \beta_{DA}(DOM_i \times ALG_i) + \beta_D DOM_i + \beta_A ALG_i + Log(No.\ Skills)_i + \epsilon_i$ where DOM_i and ALG_i are binary variables indicating that a listing requires domain or algorithmic expertise and the data tasks can be one of either *Data management*, *Data modeling*, *Data visualization*, *Decision making*, *Data analytics*, or *Presentation*. The point estimate that is presented is the marginal effect of the β_{DA} coefficient. Standard error bars show the 95% confidence interval.

Table 3: Factors affecting the spread of algorithmic skills among the firm's domain experts

			ALG		ϕ^{ALG}	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
DMK × EASYLEARN				0.415***		
				(0.047)		
DMK	0.060**	0.091***		−0.032		
	(0.024)	(0.025)		(0.030)		
Log(Occupational count)	0.519***	0.594***	0.327***	0.332***		
	(0.013)	(0.014)	(0.009)	(0.009)		
Log(Employment)	−0.025*	0.087***	0.090***	0.090***	−0.055***	0.109
	(0.013)	(0.032)	(0.014)	(0.015)	(0.020)	(0.123)
Log(Alg IT)					0.052***	0.103***
					(0.012)	(0.031)
Log(Assets)					0.031**	0.077
					(0.015)	(0.066)
Log(PPE)					0.007	0.024
					(0.014)	(0.049)
EASYLEARN			−0.851***	−2.908***		
			(0.048)	(0.216)		
Fixed-effects						
Firm FE		Yes	Yes	Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
O*NET 2 FE	Yes	Yes	Yes	Yes		
Industry FE (NAICS 3)	Yes				Yes	
Fit statistics						
R^2	0.318	0.447	0.339	0.350	0.045	0.244
Observations	55,449	55,449	110,898	110,898	6,924	6,923

Table notes: The observations in the first four columns are at the firm-occupation-year level where occupations are at the 6-digit Standard Occupational Classification (SOC) occupation level. The model is $ALG_{ijt} = DMK_{ijt} + Log(Occ\ Count)_{ijt} + Log(Employment)_{it} + \gamma_{ijt} + \epsilon_{ijt}$ where i is the firm, j is the occupation, and t is the year and γ and ϕ are industry, firm, year, and occupational fixed-effects. *DMK* is an indicator of the importance of decision-making for the occupation as recorded in O*NET. *Occupational count* is the number of workers in that firm-occupation-year combination. *Employment* indicates firm employment levels and does not vary at the occupational level. *NOCODE* is an indicator of whether the skill is related to a "no-code" technology. Standard errors are clustered on employer. For columns (5) and (6), observations are at the firm-year level and the regression model is $\phi^{ALG}_{it} = Log(Assets)_{it} + Log(AlgIT)_{it} + Log(PPE)_{it} + Log(Employment)_{it} + \epsilon_{it}$. *Assets*, *Employment*, and *PPE* are firm level measures from the Capital IQ database. *Alg IT* is a measure of investments in algorithms. ***p<.01, **p<.05, *p<.10.

Table 4: OLS regressions of algorithms and the decentralization of expertise on market value

	Log(Market Value)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Log(Assets)	0.730***	0.725***	0.725***	0.560***	0.725***
	(0.057)	(0.057)	(0.057)	(0.036)	(0.057)
Log(PPE)	0.095**	0.094**	0.094**	0.083***	0.094**
	(0.045)	(0.044)	(0.044)	(0.026)	(0.044)
Log(IT)	0.049***	0.001	0.001	0.037***	0.001
	(0.015)	(0.018)	(0.018)	(0.012)	(0.018)
Log(Employment)	−0.010	−0.010	−0.009	0.226***	−0.009
	(0.045)	(0.044)	(0.044)	(0.046)	(0.044)
Log(Alg IT)		0.048***	0.048***	−0.007	0.042***
		(0.015)	(0.015)	(0.007)	(0.016)
ϕ^{ALG}			−0.007	−0.004	
			(0.007)	(0.007)	
Log(Alg IT) × ϕ^{ALG}			0.005**	0.002	
			(0.002)	(0.002)	
$\phi - HIGH$					−0.017
					(0.017)
Log(Alg IT) × $\phi - HIGH$					0.013***
					(0.005)
Fixed-effects					
Firm FE				Yes	
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE (NAICS 4)	Yes	Yes	Yes		Yes
Fit statistics					
R^2	0.891	0.892	0.892	0.974	0.892
Observations	7,181	7,181	7,181	7,181	7,181

Table notes: This table reports regressions of how workforce skill composition relates to firms' market value on the firm panel ranging from 2015-2021. The regression model is $Log(MV)_{it} = Log(Assets)_{it} + Log(PPE)_{it} + Log(IT)_{it} + Log(Employment)_{it} + Log(Alg)_{it} + \phi_{it}^{ALG} + (Log(Alg)_{it} \times \phi_{it}^{ALG}) + \epsilon_{it}$ where observations are at the firm-year level. Columns (1), (2), and (3) all include year and 3-digit NAICS fixed effects but add progressively more variables. Column (4) uses the same specification as (3) but substitutes firm fixed-effects instead of industry controls. Column (5) replaces ϕ^{ALG} with a binary indicator of whether ϕ^{ALG} is above or below the mean value for that variable. Standard errors are clustered on employer. ***p<.01, **p<.05, *p<.10.

Figure 5: $Alg \times \phi^{ALG}$ by employment size tercile

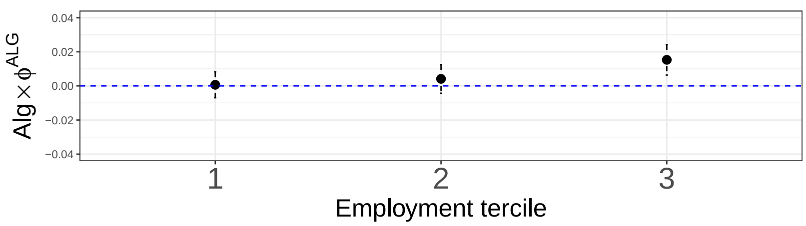


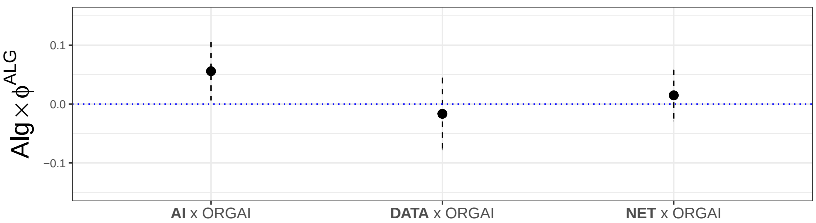
Figure notes: The y-axis indicates the coefficient on the interaction term between algorithm investment and ϕ^{ALG} from the main specification used in column (4) of Table 4 where the sample is divided into terciles by employment size. The sample size in each regression is approximately one-third the sample size used in column 4 of Table 4. On the x-axis, "1" is the smallest firms in the sample and "3" is the largest firms in the sample. Standard error bars indicate the 95% confidence interval.

Table 5: Separating AI and data science investment in market value regressions (2015-2021)

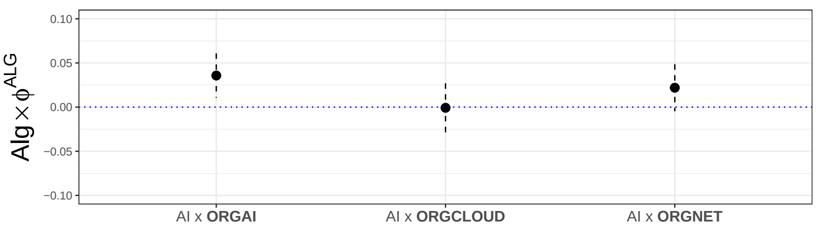
DV	Log(Market Value)			
Years	2015-2017	2018-2021	2015-2017	2018-2021
Model:	(1)	(2)	(3)	(4)
Variables				
Log(Assets)	0.717^{***}	0.697^{***}	0.717^{***}	0.695^{***}
	(0.049)	(0.046)	(0.049)	(0.046)
Log(PPE)	0.087^{**}	0.074^{*}	0.084^{**}	0.068^{*}
	(0.041)	(0.038)	(0.040)	(0.038)
Log(AI)	0.047	0.094^{***}	0.050^{*}	0.092^{***}
	(0.029)	(0.032)	(0.029)	(0.030)
Log(Data Science)	0.085^{***}	0.094^{**}	0.083^{***}	0.094^{**}
	(0.027)	(0.038)	(0.027)	(0.041)
Log(IT)	-0.078^{**}	-0.083^{*}	-0.079^{**}	-0.074
	(0.033)	(0.044)	(0.034)	(0.044)
Log(Employment)	0.004	-0.011	0.009	0.000
	(0.046)	(0.048)	(0.044)	(0.045)
ϕ^{AI}			0.030	-0.038
			(0.020)	(0.025)
ϕ^{DS}			-0.117^{***}	-0.023
			(0.040)	(0.037)
Log(AI) $\times \phi^{AI}$			-0.017^{**}	0.020^{**}
			(0.007)	(0.010)
Log(Data Science) $\times \phi^{DS}$			0.035^{***}	0.017^{*}
			(0.011)	(0.009)
Fixed-effects				
Year FE	Yes	Yes	Yes	Yes
Industry FE (NAICS 3)	Yes	Yes	Yes	Yes
Fit statistics				
R^2	0.901	0.854	0.902	0.856
Observations	1,629	2,439	1,629	2,439

Table notes: This table reports regressions of how algorithms and expertise measures relate to market value across the earlier and later parts of the panel where algorithms are separately broken into AI and data science investment and skills. Observations are at the firm-year level. The first and third columns use observations from the years 2015 to 2017 and the second and fourth columns use observations from 2018 to 2021. ϕ^{AI} and ϕ^{DS} are constructed in the same way as ϕ^{ALG} in Table 4 except on the restricted set of AI or data science skills, respectively. Standard errors are clustered on employer. ***p<.01, **p<.05, *p<.10.

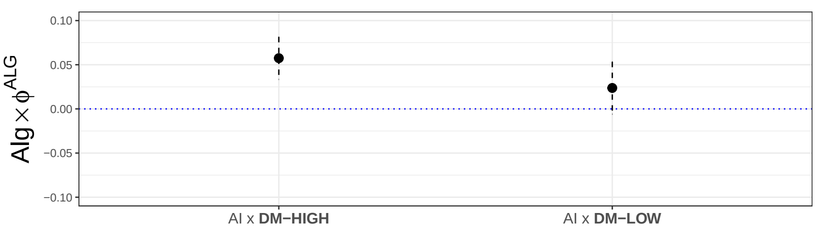
Figure 6: Placebo tests using alternative measure constructions for ϕ^{AI} and AI



(a) Comparisons with investment in other technologies



(b) Comparisons with organizational measures of other technical skills



(c) Comparisons with measures of technology and other technical skills

Figure notes: This figure illustrates placebo tests for the market value regression for AI investment in the last two years of the sample. In addition to the main interaction measure $AI \times \phi^{AI}$, it also includes interaction terms between ϕ^{AI} and investment in databases (DATA) and networks (NET) (N=1,312). In the top facet, the marker on the left is AI, the middle is databases, and the right is networks. The middle facet takes a similar approach but uses AI investment for all measures and adds interaction terms for ϕ^{CLOUD} and ϕ^{NET} in addition to ϕ^{AI} (N=2,479). The third facet separates the O*NET occupations used to construct ϕ into two separate regressions: (i) those where decision-making is important (left) and (ii) where it is unimportant (right). N=1,312 for both regressions. The standard error bars in all three facets indicate 95% confidence intervals.

A Description of corporate workforce data

This section discusses the Revelio corporate workforce data and presents comparisons with data sets with known sampling properties. This comparison is intended to discuss any limitations that sampling restrictions might impose on the main estimates. To evaluate coverage in these data, comparisons of the workforce data are presented with three different data sources: i) the distribution of US workers across occupations reported by the Bureau of Labor Statistics (BLS), ii) the distribution of employment by NAICS industry, and iii) how employment is distributed across US states.

A.1 Data generating process and sampling frame

Revelio is a workforce intelligence company that federates data across a range of Internet sources including federal databases, professional networking sites, and job posting aggregators. This analysis relies on their workforce, position, and skill databases which contain data on the movements of an extremely large sample of US-based employees across firms, the job titles they hold, and the skills they acquire. Data on employment spells, at scale, are not otherwise collected by government agencies. They are only available through resume banks so these types of data are particularly useful for studying quantities of workers in firms with different skills and the flow of workers of different types between organizations.

On the other hand, there are some potential issues when using data sources of this type. Workers participate on professional networking sites unevenly. Moreover, workers can be selective about what information they include on these sites and what information they omit. These choices generate measurement error when these data sources are being used to understand a firm's skills or occupations. Prior work discusses some of these considerations (Horton and Tambe, 2015) but the following sections calibrate specific strengths and deficiencies in terms of coverage. Measurement error in this data set is discussed later in this appendix.

A.2 BLS-SOC share comparisons

The distribution of Revelio workers across occupations is shown in Figure A.1a. Figure A.1b presents differences in shares of the major occupational groups as reported by the BLS and represented in the Revelio data, where the assignment of workers to SOC areas in the Revelio data is provided by Revelio. The blue line indicates no (zero) difference in shares such that bars to the right (left) are those occupations where the occupation accounts for a higher (lower) proportion of workers in the BLS data than the Revelio data.

From this comparison, we can see that "white-collar", knowledge-intensive occupations like management and Information Technology work tend to be over represented in the Revelio data set whereas front-line occupations in sectors like manufacturing, production, and transportation are underrepresented. This is not a surprise given that these data are gathered from professional networking sites on which white-collar workers tend to be over represented. The length of each bar is the difference in shares across these data sources. The largest imbalance in occupations in Management. The difference in the share of total workers that managers account for in the Revelio data set (15%) and the BLS (7%) is about 8% percentage points.

A.3 NAICS Industry comparisons

Employment comparisons at the North American Industry Classification System (NAICS) industry level are reported in Figures A.1c and A.1d. These industry level comparisons are conducted at the 2-digit NAICS level where the underlying allocation of workers across industries is taken from the Occupational Employment Survey data. Industry classifications in the Revelio data are generated by assigning employers to industries and like the occupational assignments, are directly reported by Revelio for each employee. The share differences we can observe in this comparison are consistent with the earlier observation that white-collar professions are over-represented in the Revelio data set. Technology, finance, professional services, and manufacturing industries account for larger shares of employees in the Revelio data than they do in the BLS data. By comparison, healthcare and construction account for smaller shares.

A.4 Geographic (state) comparison

A final comparison, shown in the bottom panel (Figures A.1e and A.1f) is state-level comparisons. This comparison evaluates the reported geographic location of workers in the Revelio data set with the distribution of workers across US states. Unsurprisingly, we can see that states with significant industry representation for finance and technology (such as New York) account for a relatively larger share of workers in the Revelio data. The largest imbalance is in North Dakota, where industries like oil extraction and agriculture play a larger role in the state economy.

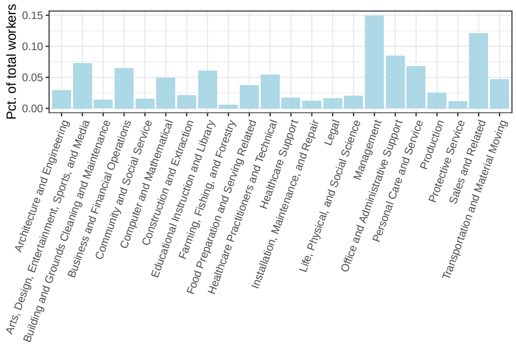
A.5 Discussion

In sum, when we consider the spread of algorithmic technologies into occupations, industries, and geographies, workers in the Revelio data set are likely to be over-representative of those information-intensive industries, occupations, and sectors that are likely to be most impacted by these technological changes.

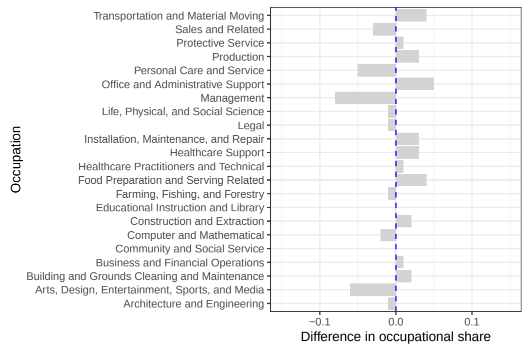
Having greater quantities of workers in this database from some sectors and occupations will affect the precision of the measurement, but this may fall into under normal, random measurement error if those workers who do report their skills are not very different from the ones who do. The number of workers in the database from each Fortune 500 firm is large though, so this type of measurement error should not be very large. Even in underrepresented occupations and industries, the database should produce a high-quality signal of the skill content of a profession.

A less innocuous issue is that the reporting of skills themselves may be inconsistent. Workers in some occupations and industries may be more inclined to report these skills on their profiles. They may consistently report skills that are likely to lead to future employment opportunities, but inconsistently report skills that the market does not deem to be particularly valuable. This can impact the interpretation of the magnitudes of the coefficients in the main regressions (e.g. market return to a marginal database engineer), although it should not impact the sign and direction of these estimates.

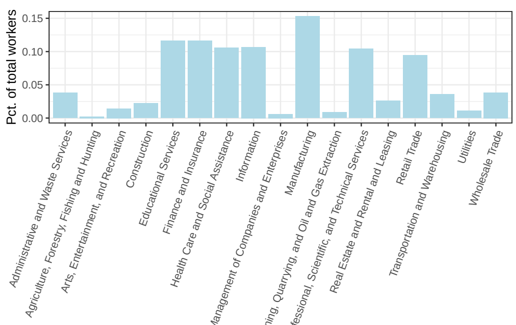
Figure A.1: Revelio data distributions



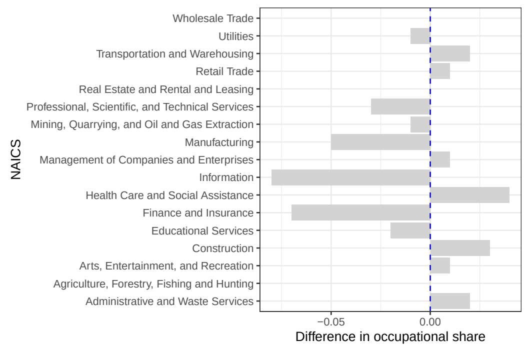
(a) Occupational code (SOC)



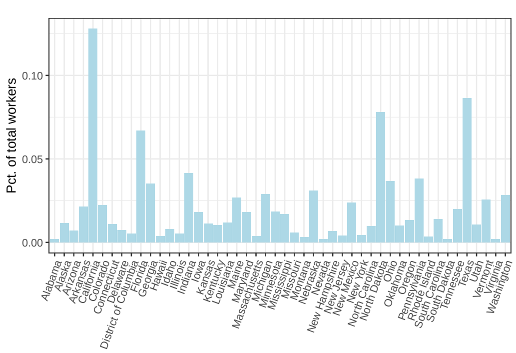
(b) Occupational code (SOC)



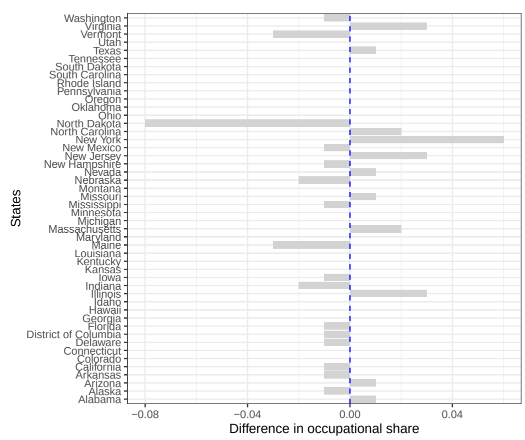
(c) Industry (NAICS)



(d) Industry (NAICS)



(e) States



(f) States

Notes: These three figures illustrate the difference in compositional shares between the Revelio and BLS data sets. The top row is comparison of occupations. The second row is comparison across NAICS industries. The third row is comparisons across states. The length of each bar for plots in the second column is computed as the difference in the share that the worker category accounts for in the Revelio data and in the administrative data. For instance, Management workers comprise 15% of the Revelio data set and 7% of the BLS data set so the length of the bar indicates an 8% difference between the two.

B Categorizing skills into technological areas

A key measurement task for this analysis is to generate a taxonomy of skills, either as embedded in job listings or reported by employees on their profiles, that enables measurement of technological expertise. This requires construction of a mapping from granular skills to the broader technological areas to which they are related. For instance, skills such as "Oracle DB" and "MySQL" both indicate expertise with relational database technologies. To construct this taxonomy in the *workforce data*, I leverage an existing structure from Revelio that categorizes skills into technological groups. This data provider uses data clustering techniques to categorize skills into a taxonomy. This approach combines skills into common groups if they inhabit a similar area of the skill landscape after clustering. The ensuing technological clusters are then assigned labels by the provider. The skills that appear in each of the key technology categories, as constructed by the data provider, are shown below. It is important to note that each of the skills shown below are one of 1,500 keyword skill categories that contain sub-skills within them. For instance, 'machine learning' may include skills within it like 'classification', 'clustering', or 'deep learning'. The skill name itself is not an indicator of a hierarchy. For instance, the 'Tableau' category also contains 'Microsoft BI' and 'Qlik', which are competitor no-code tools. Therefore, each of the technological areas shown below is a mapping of categories which themselves are a grouping of keywords.

Skills in the *job listings* data are organized under a separate taxonomy. However, to maintain consistency across the analysis, I harmonize the skills in the job listings data with the technological categories included in the workforce intelligence data. For instance, an 'Algorithms' category was created from the job listings data by identifying skills in the job listings that had a match with one of the skills in the equivalent category in the workforce data. Matches were made manually, to account for minor differences in case or how skill names were standardized by the different providers.

B.1 Technology categories created from skill categories in the workforce data

Artificial Intelligence. machine learning, natural language processing, image processing/computer vision, artificial intelligence, tensorflow, pytorch, scikit-learn

Data Science. data visualization, data mining, statistical data analysis, big data, data modeling, data analytics/-data science/big data analytics, marketing analytics, quantitative analytics, analytics, business analytics, predictive analytics/predictive modeling, pandas, tableau, nosql/redis, numpy, R, scala, spark, julia, pyspark

Big Data Technologies. distributed systems/scalability, mongodb, hive/apache pig, docker/devops, middleware, data center, centos/debian, hadoop/apache spark/mapreduce, ubuntu, server architecture, red hat linux, high performance computing, vms,socket programming, olap, soa, websphere mq, multithreading, service-oriented architecture (soa), ibm tivoli, hive/apache pig

Relational Databases. master data management, spatial databases/web mapping, data warehousing/etl, database administration, database, database security, metadata/metadata management, oracle sql developer/oracle database, data entry,data quality, data acquisition, data management, data processing, data integration/data warehouse architecture, data migration, database design,data collection, db2, sql, pl/sql, mssql/ms sql/ms sql server, sql server management studio, oracle sql, sqlite, mysql/php,performance tuning/sql tuning, oracle pl/sql development,sql server, microsoft sql server, extract/transform/load (etl),sybase, t-sql/ssis/ssrs, teradata, sap hana,jsp/jdbc, edi, sqr, rdbms, oracle rac, ibm db2

Cloud & Mobile Technologies. microsoft azure, windows azure, amazon services/aws, cloud-computing, cloud computing, amazon web services (aws), cloud applications, vmware, openstack, vmware esx/vmware infrastructure/v-sphere;; android, objective-c/ios development, mobile device management, wireless technologies, wireless communications systems, mobile application development, swift/xcode, android development/android sdk

Network Administration. lan-wan, lan, ssl, ssl certificates, wan, network operations, ip networking, computer networking, voice over ip (voip)/internet protocol (ip), network troubleshooting,network architecture, network security,network development, computer network operations, wireless networking, network administration, san/storage area networks/netapp, internet protocol suite (tcp/ip), tcp/ip, data mapping tcp/ip protocols, routing protocols/switching,switches/routers, routing/qos, wifi, dns/dhcp, ethernet, wireless, mpls, netcool, ccna/ccnp, putty, wimax, snmp

General Information Technology. software testing, software engineering/software design, software training, software documentation, software installation/laptops, software development life cycle, embedded systems/embedded software, software,software architecture, software licensing, software quality assurance, software implementation,object oriented software, software deployment, open source software, software asset management, software project management, software integration, software development life cycle (sdlc), software development, release management, unix, ftp, object oriented design, oop, c++/c, c++ language, microsoft visual studio c++, visual c++,c/c++, windows server, windows server 2008/windows server 2003, .net/asp.net, unit testing, it governance, sdlc, bash, shell, linux, object-oriented programming, it audit/cisa, assembly language, servers, user acceptance testing, it, support/server, object-oriented programming (oop), continuous integration, it infrastructure management, operating systems,visual basic for applications (vba), information technology, shell scripting/unix shell scripting, linux system administration, code review, server administration, agile testing,regular expressions, system testing/system integration testing, powershell, ldap, orm, vb.net,linux kernel, vdi, ibm rational tools, nas/enterprise storage, smtp sap, ivr, ibm iseries, asp, weblogic, dos, ibm aix,ado.net/asp.net ajax, asp.net mvc/linq/entity framework, vsam, raid, it operations

B.2 Technology categories created from skills in the job listings data

ALG. *Algorithms.*
Machine Learning, Decision Trees, Random Forests, Recommender Systems, Mahout, Support Vector Machines, Artificial Intelligence, Predictive Modeling, Predictive Analytics, Predictive Models, Data Mining, Deep Learning, Neural Networks, K-Means, Cluster Analysis, Natural Language Processing

DATA. *Relational databases & Big data.*
SQL, MySQL, Structured Query Language, database management, database administration, data cleaning, data extraction, database querying, Big Data, Apache Hadoop, NoSQL, MongoDB, Apache Hive, Splunk, MapReduce, PIG, Cassandra, SOLR, Sqoop

NET. *Web & Networks.*
Objective C, Swift, HTML5, Javascript, HTML, iOS, CSS, Cisco, Network Engineering, Network Administration, Computer Networking, Network Support, Network Concepts and Terminology, Data Communications, Network Installation, Wireless Local Area Network (LAN), Network Management System, Network Infrastructure

C Full correlation table between technologies and job skills

In this section, we present a fuller discussion for some of table results discussed in an abbreviated manner in the main text. Table C.1 presents results corresponding to the coefficient estimates depicted in Figure 4. The table reports results from the full form of the regression which is:

$$ATTR_i = \beta_A ALG_i + \beta_D DAT_i + \beta_N NET_i + \gamma_i + \epsilon_i$$

Figure 4 in the main text shows that algorithmic skill is correlated with domain expertise and cognitive skill. There are negative correlations with *Character* and *Management*, after conditioning on job title and industry. The regression also includes measures of skills related to databases (DATA) and network administration (NET). Database management is negatively correlated with all dependent variables which is probably a by-product of the skill-intensive nature of that position. Network administration exhibits relatively weak correlations with all of these job attributes.

Table C.1: Logistic regression of algorithmic tools on domain expertise and other job attributes

	Dependent variable:				
	Domain	Social	Character	Cognitive	Management
	(1)	(2)	(3)	(4)	(5)
ALG	1.548^{***}	0.142^{**}	-0.481^{***}	0.129^{**}	-1.260^{***}
	(0.066)	(0.064)	(0.088)	(0.063)	(0.137)
$DATA$	-0.833^{***}	-0.194^{***}	-0.173^{**}	-0.209^{***}	-0.646^{***}
	(0.070)	(0.055)	(0.072)	(0.056)	(0.084)
NET	-0.423^{***}	0.033	0.079	-0.036	-0.009
	(0.055)	(0.041)	(0.057)	(0.042)	(0.066)
Log(No. of Skills)	1.680^{***}	1.540^{***}	1.885^{***}	1.800^{***}	2.247^{***}
	(0.047)	(0.035)	(0.053)	(0.038)	(0.064)
Constant	-6.461^{***}	-4.779^{***}	-7.233^{***}	-5.890^{***}	-7.965^{***}
	(0.162)	(0.111)	(0.174)	(0.120)	(0.203)
Job Title FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	24,888	24,888	24,888	24,888	24,888
Log Likelihood	-8,951.652	-13,366.200	-7,837.757	-12,908.540	-6,061.045
Akaike Inf. Crit.	18,315.300	27,144.390	16,087.510	26,229.070	12,534.090

Table notes: This table reports results from the logit regression $ATTR_i = \beta_A ALG_i + \beta_D DAT_i + \beta_N NET_i + \gamma_i + \epsilon_i$. It estimates conditional correlations between algorithmic expertise and other job attributes. $Log(No.of skills)$ is the log of the total number of skills in the job ad. The dependent variable indicates whether or not a job listing requires knowledge of an application domain, social skills, character, cognitive skills, and people management skills, respectively. All regressions include job title and industry fixed-effects (NAICS 4). Standard errors are shown in parentheses. ***p<.01, **p<.05, *p<.10.