Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey*

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Abstract

This paper describes the adoption of automation technologies by US firms across all economic sectors by leveraging a new module introduced in the 2019 Annual Business Survey, conducted by the US Census Bureau in partnership with the National Center for Science and Engineering Statistics (NCSES). The module collects data from over 300,000 firms on the use of five advanced technologies: AI, robotics, dedicated equipment, specialized software, and cloud computing. The adoption of these technologies remains low (especially for AI and robotics), varies substantially across industries, and concentrates on large and young firms. However, because larger firms are much more likely to adopt them, 12-64% of US workers and 22-72% of manufacturing workers are exposed to these technologies. Firms report a variety of motivations for adoption, including automating tasks previously performed by labor. Consistent with the use of these technologies for automation, adopters have higher labor productivity and lower labor shares. In particular, the use of these technologies is associated with a 11.4% higher labor productivity, which accounts for 20–30% of the difference in labor productivity between large firms and the median firm in an industry. Adopters report that these technologies raised skill requirements and led to greater demand for skilled labor, but brought limited or ambiguous effects to their employment levels.

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1 Introduction

Advanced technologies, including robotics, artificial intelligence (AI), and software systems, are thought to be spreading rapidly in industrialized economies.[1] These technologies are argued to increase productivity, automate tasks performed by labor, and raise the demand for skills, contributing to rising inequality and declining labor shares. There is little direct evidence, however, on how widespread these technologies are and which firms are adopting them, especially in the US.

This paper leverages a new module introduced in the 2019 Annual Business Survey (ABS) conducted by the US Census Bureau in partnership with the National Center for Science and Engineering Statistics (NCSES) to shed light on these questions. The module focuses on the adoption of five advanced technologies: artificial intelligence (AI), robotics, dedicated equipment, specialized software, and cloud computing. The 2019 ABS module sampled over 300,000 employer businesses and collected information on firms' adoption and use of these technologies for the 2016–2018 reference period. The module also asked questions on firms' motivation for adoption, allowing us to measure the extent to which these technologies are being used for automating tasks, and on firms' assessments of the impact of technology on their employment level and skill requirements. Using the ABS module, we describe the adoption of advanced technologies by US firms in all economic sectors, documenting for the first time the extent to which these technologies are being used for automation and how they affect firms' production processes and demand for skills.

We first document that adoption remains limited when measured by the share of firms using these technologies in their processes and methods. This is especially the case for AI and robotics: only 3.2% of firms used AI and 2% used robotics during 2016–2018. There is wider adoption of the remaining technologies, with 19.6% of firms using dedicated equipment, 40.2% using specialized software, and 34% using cloud computing. Still, half of US firms did not use any of these technologies during 2016–2018. Firms identify the lack of applicability and high costs of deploying and integrating these technologies as the main factors limiting wider adoption.

Despite the low shares of user firms, adopters account for a sizable share of employment and economic activity. This is because adoption concentrates in large firms. 12.6% of US workers were employed at firms using AI during 2016-2018 (even though these are only 3.2% of firms). The shares of employment at adopting firms are 15.7% for robotics, 36.4% for dedicated equipment, 64.4% for specialized software, and 61.8% for cloud computing. These high shares indicate that advanced technologies have been an important force affecting US labor and product markets, despite their limited adoption by small firms.

After presenting these aggregate facts, we document differences in adoption rates between and within industries. Adoption rates vary substantially across industries, which is in line with firms' reports that these technologies have highly specific applicability. Detailed industry differences account for 10-30% of the employment-weighted variation in adoption rates across firms. Within

[1] See Brynjolfsson and McAfee (2014), Ford (2015), Susskind and Susskind (2015) and Schwab (2017).

industries, adoption concentrates in larger and younger firms, presumably reflecting large fixed costs and organizational barriers involved in adopting these technologies.

The ABS module allows us to document for the first time the extent to which US firms use advanced technologies for automation. Firms report a number of motivations for their investments in advanced technologies, including most commonly improving process quality, upgrading existing processes, and automating tasks performed by labor. The use of AI and robotics is closely related to automation. In terms of employment shares, 55% of AI users and 65% of robotics users report adopting these technologies for automation. Dedicated equipment and specialized software have more diverse uses, with 30–35% of users (in employment shares) adopting these technologies for automation. Other uses of these technologies, such as expanding product offerings or meeting industry standards, are less common.

The fraction of the US workforce exposed to automation-related uses of advanced technologies is sizable, with 30.4% of US workers employed at firms using advanced technologies for automation. Worker exposure to automation is particularly high in (though not exclusive to) manufacturing, where 52% of workers are employed at firms using these technologies for automation.[2] Although AI and robotics stand out as the two technologies that are more closely related to automation, most of workers' exposure to automation comes from dedicated equipment and specialized software due to their wider adoption.

Consistent with the importance of automation as a major application of these technologies, adopters have higher labor productivity and lower labor shares than other firms in their industry, size class, and cohort.[3] Also, consistent with higher incentives for automation when wages are higher, we find that high-wage firms are more likely to adopt these technologies.[4]

We estimate that the use of advanced technologies is associated with a 11.4% higher labor productivity (and a 21.2% higher labor productivity for firms using all five technologies surveyed in the ABS). From a pure descriptive viewpoint, the adoption of advanced technologies accounts for 16–30% of the labor productivity differences between small and large firms in each industry—the so-called *superstar firm* phenomenon (see Autor et al., 2020).[5]

[2] When interpreting these measures, one should keep in mind that not all workers currently employed at firms using these technologies are subject to the effects of automation. Our numbers do not imply that 30% of US workers are or will be at risk of having their jobs automated. Nevertheless, these high shares suggest that past and future changes in the demand for skills at automating firms associated with automation will have sizable effects on labor markets (see Acemoglu and Restrepo, 2022, for evidence on the aggregate effect of automation on inequality).

[3] This is in line with recent papers that emphasize the role of automation as a key driver behind the labor share decline in some sectors, most notably in manufacturing (see Acemoglu, Lelarge and Restrepo, 2020; Acemoglu and Restrepo, 2022; Dauth et al., 2021; Cheng et al., 2021; Kogan et al., 2021).

[4] See Acemoglu and Restrepo (2021) and Dechezleprêtre et al. (2021) for evidence on how high wages drive the adoption of automation technologies across countries and firms, respectively.

[5] This is consistent with the results of Acemoglu, Lelarge and Restrepo (2020) from French manufacturing, which indicate that a sizable portion of the covariance between labor share changes and size is related to robotics investments. It also aligns with the conclusions in Hubmer and Restrepo (2021), who use a calibrated model of firm dynamics with differences in fixed costs of technology adoption to show that automation technologies adopted by large firms contributed to the rise of superstar firms.

Finally, we explore firms' self-assessments of the implications of advanced technologies for their demand for labor and skills. Most firms report that advanced technology adoption did not change their employment level, and among firms that report a change, the reported direction of change is split. These findings point to limited and ambiguous effects of advanced technologies on firm employment.[6] Instead, a significant share of firms (between 30–40% depending on the technology surveyed) assess that advanced technologies increased their skill demands, while almost no firms report a reduction in their demand for skills. These self-reports are consistent with theories in which advanced technologies increase the demand for skills.

Our paper contributes to a growing literature on measuring the adoption of advanced technologies across firms and industries and understanding their implications for firms and workers. Our first contribution is on data collection and the measurement of technology use and adoption. In this we build and expand on the work using the 2018 ABS, summarized in Zolas et al. (2020). Due to data limitations, prior research on the effects of modern automation technologies on firms and workers has relied on indirect proxies of technology, or on datasets with limited and coarse coverage. Earlier work focused on industry-level robot adoption measures, from the International Federation of Robotics.[7] A more recent series of papers uses data on robot imports and in some cases detailed surveys of manufacturing firms in order to explore firm-level outcomes for robot adopters in manufacturing.[8] Our paper extends these efforts by collecting comprehensive data for the entire economy, not just manufacturing, and including AI, dedicated equipment, specialized software, cloud computing, and robotics. In doing so, we confirm and extend four findings that several papers have documented for robotics and extend it to the other technologies in the ABS: (i) larger firms are more likely to adopt these advanced technologies; (ii) adoption is associated with higher labor productivity; (iii) adoption is associated with lower labor shares; and (iv) advanced technology adoption is associated with an increasing demand for skills (for example, in the form of reductions in the share of production workers for robotics).

There is also a nascent literature using various proxies for firm-level adoption of AI and new technologies obtained from the text in job postings, conference calls, and patent data. For example, Alekseeva et al. (2021); Babina et al. (forthcoming) and Acemoglu et al. (2022) use data from online vacancies, specifically from postings including AI-related skills, to estimate establishment-level AI activity. Bloom et al. (2021) combine job-postings data with the text data from patents and

[6] We also caution that, as documented in Koch, Manuylov and Smolka (2021) and Acemoglu, Lelarge and Restrepo (2020), the expansion of firms adopting automation technologies might come at the expense of competing firms that do not automate. Hence the increases in employment and the lack of negative employment effects reported by adopters is consistent with potentially negative industry or market-level effects as found in a number of studies, such as Acemoglu and Restrepo (2020), Dauth et al. (2021), Acemoglu, Lelarge and Restrepo (2020), or no positive aggregate effects, as in Graetz and Michaels (2018).

[7] See, for example, Graetz and Michaels (2018) and Acemoglu and Restrepo (2020).

[8] See for example Humlum (2020); Bonfiglioli et al. (2020); Rodrigo (2023); Dixon, Hong and Wu (2021); de Souza and Li (2023) for papers using data on robot imports to measure firm-level adoption of robotics in various countries. Acemoglu, Lelarge and Restrepo (2020) combine imports data and detailed accounting information to construct a somewhat more complete picture of robot adoption in French manufacturing. Aghion et al. (2020) also complement these data with accounting information on the use of motor equipment.

conference calls to measure the diffusion of AI and other novel technologies across US firms. Mann and Püttmann (2019), Dechezleprêtre et al. (2021), and Martinez and Moen-Vorum (2022) use patent texts to identify and measure the diffusion of automation technologies. The ABS module contributes to these efforts as it is more representative and offers a more direct measurement of technology use at the firm level. The ABS also distinguishes between users and providers of technology—a distinction that approaches based on patent data and job postings miss.

The ABS technology module complements new surveys that have been recently used to measure technology adoption in other countries. For example, there are similar surveys measuring firms' investments in advanced technologies and automation for Germany (Genz et al., 2021), Italy (Calvino et al., 2022), South Korea (Cho et al., 2023), the Netherlands (Bessen et al., 2019) and manufacturing in Spain (Koch, Manuylov and Smolka, 2021).

Finally, we expand on work using previous Census surveys devoted to measuring technology use in specific sectors. These include earlier work using the Survey of Manufacturing Technology, conducted in 1988, 1991, and 1993, which collected data on robots, automated storage and retrieval systems, automated guided vehicle systems, and automated testing equipment for a subset of manufacturing industries (Doms, Dunne and Troske, 1997; Dinlersoz and Wolf, 2024); work on computer use in manufacturing using the Annual Survey of Manufacturers (Dunne et al., 2004); work on telecommunication technologies using the Information and Communication and Technology Survey (ICTS) (Eckert, Ganapati and Walsh, 2022); work on e-business practices using the Computer Network Use Supplement (CNUS) (McElheran, 2015); work on self-service gas stations using the Census of Retail Trade (Basker, Foster and Klimek, 2017); and work using the Management and Organizational Practices Survey (MOPS), which collects detailed information on firm organization and management practices (Brynjolfsson, Jin and McElheran, 2021).

The rest of the paper is organized as follows. Section 2 describes the ABS module. Section 3 outlines the conceptual framework that motivates our empirical work and interpretation. Sections 4, 5, 6, and 7 provide our analysis of the ABS data. Section 8 concludes, while the Appendix includes additional details on the design of the ABS module and empirical results.

2 The Technology Module in the 2019 ABS

The 2019 technology module is the second module on technology collected as part of the ABS. The first technology module featured in the 2018 ABS focused on questions regarding firms' digitization of information along with the adoption of some specific business technologies (see Zolas et al., 2020, for an analysis of the data collected by the 2018 ABS technology module). The 2019 technology module features questions related to the use of five advanced technologies that are relevant for automation. In addition, the module collects data on firms' motivations for adoption, asking firms to report whether they are using these advanced technologies for automation, and their assessment of the effect of these technologies on the size and composition of their workforce. Finally, the module asks firms about the bottlenecks limiting their adoption of advanced technologies.[9]

The five technologies surveyed in the 2019 ABS were defined as follows:

- **Artificial Intelligence:** Artificial intelligence is a branch of computer science and engineering devoted to making machines intelligent. Intelligence is that quality that enables an entity to perceive, analyze, determine response and act appropriately in its environment.
- **Robotics:** Robotic equipment (or robots) are automatically controlled, reprogrammable, and multipurpose machines used in automated operations in industrial and service environments.
- **Specialized Software (excluding Artificial Intelligence):** Software dedicated to performing a particular business function.
- **Dedicated Equipment (excluding Robotics):** Equipment capable of automatically carrying out a pre-specified task.
- **Cloud-based Computing Systems and Applications:** Computing resources available on-demand via the internet.

According to these definitions, AI algorithms powering a chatbot would count as **artificial intelligence**. Industrial robots used in manufacturing would be considered **robotics**. A software system for document discovery or handling appointments would be **specialized software**. And an automatic retrieval system for warehouses would be **dedicated equipment**. On the other hand, **cloud computing** is typically used together with the other technologies to satisfy their demand for computing power. For example, a firm using a software system for trading would host the algorithms and data on the cloud.

The 2019 ABS data were collected from June through December 2019. The module starts by asking firms about their use of these technologies during the reference period of 2016–2018.[10] For each technology, a firm may respond that it did not use the technology; tested the technology, but did not use it; used the technology with a specified degree of intensity (low use, moderate use, or high use); or do not know whether the technology was used during the three years 2016–2018. Conditional on responding with some degree of technology use (low, moderate, or high), firms are then asked about the motivations for adopting or using the technology. Respondents may choose from the following list of motivations: "automate tasks performed by labor," "upgrade outdated processes or methods," "improve quality or reliability of processes or methods," "expand the range of goods or services," "adopt standards and accreditation," and "some other reason." In addition, the module asks firms whether they are using the technologies as part of their production processes

[9] Appendix A provides an overview of the development of the 2019 ABS module.

[10] The exact wording and organization of the questions is available in the official survey instrument for 2019 ABS on the ABS website: https://www.census.gov/programs-surveys/abs/technical-documentation/surveys-instructions.2019.html.

and methods, or whether they are providers of these technologies (or goods and services that embed these technologies).

The module then dives into the workforce effects of technology. First, respondents reporting some degree of technology use are asked about the effects of the technology on overall employment, overall skill level, and STEM skills of their workers. Firms may respond with "increased," "decreased," or "did not change" ("not applicable" is also an option for STEM skills in the case that the firm did not employ any workers with STEM skills). Next, firms are asked about how technology use affected four types of workers—production, non-production, supervisory, and non-supervisory. Firms can respond that technology use either increased, decreased, did not change the number of each of these types of workers (again, with the additional option "not applicable"). These questions, while qualitative in nature, provide a broad assessment of various effects of the technology on a firm's workforce size and composition.

Finally, all firms—regardless of reporting technology use or not—were asked to assess all factors adversely affecting adoption and utilization of each technology. The factors included represent a wide variety of considerations and concerns, including applicability ("technology not applicable to this business"), the cost and maturity of technology ("this technology was too expensive," "lacked access to capital," "this technology was not mature"), inputs needed to deploy the technology ("lacked access to required data," "required data not reliable," "lacked access to required human capital and talent"), regulatory environment ("laws and regulations"), and security considerations ("concerns regarding safety and security—physical and cyber"). A response option of unhindered adoption and utilization was also included ("no factors adversely affected the adoption of this technology").

The set of firms sampled in the technology module was determined by the general sampling scheme for the 2019 ABS, a primary goal of which is to provide tabulations of collected data by various ownership characteristics. [11] The ABS sampling universe was created using Census Bureau's Business Register administrative data from 2018, which provides the information on industry classification, receipts, payroll and employment for the construction of the ABS universe. The ABS universe was stratified by state, frame, and industry, where *frame* refers to categories of ownership characteristics for businesses. The Census Bureau used several sources of information to estimate the probability that a business is minority or women-owned. These probabilities were then used to place each firm in the ABS universe to one of nine frames that span key race and ethnicity categories, plus gender and public ownership status. Large companies were selected with certainty based on volume of sales, payroll, or number of paid employees.[12] The remaining universe was subjected to stratified systematic random sampling.

[11] For details on the sampling methodology, see https://www.census.gov/programs-surveys/abs/technical-documentation/methodology.2019.html.

[12] More specifically, certainty cases satisfy the following criteria: firms with more than 500 employees; firms responding to the 2016 Business R&D and Innovation Survey for Micro-businesses (BRDI-M) survey with R&D costs of $1 million or higher; and firms larger than stratum-specific payroll and receipt cut-off. The certainty cutoffs vary by stratum, depending on the number and the size distribution of firms in the stratum.

Because of these sampling procedures and selective survey completion, the set of firms that responded to the technology module does not constitute a nationally representative sample of firms, when compared to the full set of employer businesses in the Longitudinal Business Database (LBD).[13] We therefore construct firm weights based on the 2018 LBD to make the sample representative of the universe of employer businesses. These weights are calculated using a methodology similar to the one used in Zolas et al. (2020).[14]

The response rate for the portion of the survey used in this paper was 68.7%, which is comparable to the 2018 ABS technology module response rate, and similar to the response rate for other modules of the 2019 ABS. Still, about 5% of respondents claimed not knowing whether they used some of the technologies in the survey and 9% of respondents missed answering some of the items in the questionnaire. We remove firms that responded "Don't Know"or missed an item when tabulating the responses to a specific question in our analysis.

3 Conceptual Framework

This section sketches a partial-equilibrium version of the model in Acemoglu and Restrepo (2022), expanded to include firm competition within an industry, in order to frame our interpretation of the results from the ABS technology module. In our framework, firms complete tasks to produce output, and their key decision is the assignment of these tasks across workers with different skills and specialized capital equipment or algorithms (e.g., AI, robotics, specialized software, etc.). Automation is the use of specialized capital in order to perform tasks previously assigned to labor. The results presented in this section follow from those in Acemoglu and Restrepo (2022) and their proofs are omitted.

3.1 Production, Tasks and Demand

We consider a partial equilibrium model of a single industry. To save on notation, we omit industry subscripts, with the understanding that all objects and technologies might vary by industry. Firms are indexed by f and engage in monopolistic competition, facing a demand curve for their products given by

$$y_f = y \cdot \left(\frac{p_f}{p}\right)^{-\sigma}, \quad \text{with } \sigma > 1 \tag{1}$$

and charge a constant markup of $\mu = \sigma/(\sigma - 1)$. Here, y is industry output and p the industry price index.

[13] The LBD contains the universe of non-farm employer businesses (or firms) in the US (see Chow et al., 2021, for details).

[14] We first stratify firms in the 2018 LBD and 2019 ABS by the same size, age, and industry categories (12 size categories, 12 age groups and 19 two-digit NAICS sectors). Each firm in a stratum in the ABS is then assigned the same weight calculated by dividing the firm count in the corresponding 2018 LBD stratum by the firm count in the 2019 ABS stratum.

Output is produced by completing a mass M of tasks indexed by x and belonging to some set $\mathcal{T}$. The production function for firm f is

$$y_f = z_f \cdot \left(\frac{1}{M} \int_{\mathcal{T}} (M \cdot y_f(x))^{\frac{\lambda-1}{\lambda}} \cdot dx \right)^{\frac{\lambda}{\lambda-1}},$$

where z_f denotes the (factor-neutral) productivity of the firm, $y_f(x)$ denotes the quantity of task x completed, and $\lambda > 0$ is the elasticity of substitution between tasks.

All firms in the industry complete the same set of tasks, $\mathcal{T}$, but differ in their productivity z_f, the factor prices they face, and how they assign tasks to different factors. Specifically, task x can be performed using workers from different skill groups, indexed by g,

$$y_f(x) = \sum_g A_g \cdot \psi_g(x) \cdot \ell_{g,f}(x).$$

Here, $\ell_{g,f}(x)$ is the quantity of labor of type g employed by the firm at task x, A_g denotes the productivity level of these workers across all tasks, and $\psi_g(x)$ denotes their productivity at task x. Task-specific productivities $\psi_g(x)$ capture the comparative advantages of groups of workers across tasks (e.g., less educated workers might have a comparative advantage in manual tasks).

Firm f can pay a fixed cost $\kappa_f(x)$ to adopt and integrate the technology required to automate the production of task x. Depending on the task, this may involve the use of AI, robotics, dedicated equipment or specialized software to complete the task. We denote the specialized capital used for this purpose by $k_f(x)$, which yields the automated production of task x for firms that pay the fixed cost as

$$y_f(x) = A_k \cdot \psi_k(x) \cdot k_f(x),$$

where A_k gives capital productivity across all tasks and $\psi_k(x)$ is the productivity of specialized capital at task x. The fact that automation takes place at the task level, using task-specific specialized equipment or algorithms, aligns with the way in which industrial robots, narrow AI algorithms, dedicated equipment and specialized software are used in practice. This also underscores that automation technologies are not "general-purpose", but highly customized for certain applications and tasks.

We close the model by assuming that firms pay exogenous wages given by $w_{f,g} = \tau_f \cdot w_g$, where w_g is the common component of the wage for workers in skill group g, faced by all firms in the industry, while τ_f is a firm-specific component, reflecting differences in the labor supplied faced by firms or the way they share rents with workers. On the other hand, we take the user cost of capital, w_k, to be common across firms and tasks.

3.2 Costs of Automation and Differences in Technology Across Firms

In the benchmark case in which wages are identical across firms and there are no fixed costs of automation, all firms would make the same cost-minimizing automation decisions. Differences in the factor-neutral productivity term z_f do not impact automation decisions and simply translate into differences in firm scale. In this benchmark, despite having different scales, all firms in an industry would employ the same bundle of workers, machines, and software to produce, and would have the exact same labor productivity and labor share.

As described in the Introduction, however, there are sizable differences in adoption rates across firms, both between and within industries. We view these differences as being due to three factors:

- The nature of tasks required in an industry and firm determines the applicability of automation technologies. For example, industrial robots are not useful in most non-manufacturing industries, and within manufacturing, they are most suitable for various manual tasks involved in heavy industry, such as welding, painting, sorting and assembly, while certain fine-motor tasks, such as stitching of shoes, are harder for robots. Yet, other manual tasks involved in spinning, weaving and stitching in textile industries can be automated using dedicated equipment. Likewise, a range of white-collar tasks in services can be automated using specialized software and increasingly AI.
- Firms that compete in the same industry may face different wages, contributing to differences in adoption decisions.
- The fixed costs of adopting and integrating automation technologies will preclude some firms from using them. These fixed costs depend on industry (e.g., because it determines the engineering complexity of the tasks to automate), firm age (e.g., because they might face less organizational barriers), and other firm-level characteristics (e.g., how digitally savvy or informed the management may be and whether the firm needs to customize its products). For this reason, younger firms might have lower fixed costs, while the same fixed cost will make automation technologies less profitable for smaller firms in industries with limited applications for advanced technologies. Integration costs can be sizable. For example, in manufacturing, integration costs associated with the use of industrial robots can add up to four times the cost of the actual equipment (see, for example, Leigh and Kraft, 2018).

3.3 Automation, Factor Shares, and Labor Productivity

Let $\mathcal{T}_{f,k}$ denote the set of tasks that firm f has automated, while $\mathcal{T}_g$ denotes the set of tasks for which production by worker of type g would minimize costs in the absence of automation. Following

Acemoglu and Restrepo (2022), define the *task share* of workers of type g and capital at firm f as

$$\Gamma_{f,g} = \frac{1}{M}\int_{\mathcal{T}_g - \mathcal{T}_{f,k}} \psi_g(x)^{\lambda-1}\cdot dx, \qquad \Gamma_{f,k} = \frac{1}{M}\int_{\mathcal{T}_{f,k}} \psi_k(x)^{\lambda-1}\cdot dx.$$

The unit cost of production for firm f is then

$$c_f = \frac{1}{z_f}\cdot\left(\sum_g \Gamma_{f,g}\cdot w_{f,g}^{1-\lambda} + \Gamma_{f,k}\cdot w_k^{1-\lambda}\right)^{\frac{1}{1-\lambda}}.$$

Although this unit cost resembles the standard constant elasticity of substitution price index (which would result when firms have CES production functions), the shares are now endogenous and depend on $\mathcal{T}_{f,k}$ —the set of tasks that the firm has automated. Input shares are also related to $\mathcal{T}_{f,k}$. As a result, the share of labor in costs, which is proportional to the share of labor in value added, is

$$s_{\ell,f} = \frac{\sum_g \Gamma_{f,g}\cdot w_g^{1-\lambda}}{\sum_g \Gamma_{f,g}\cdot w_g^{1-\lambda} + \Gamma_{f,k}\cdot w_k^{1-\lambda}}.$$

Likewise, the share of labor of type g in the wage bill can be computed as

$$s_{g,f} = \frac{\Gamma_{f,g}\cdot w_g^{1-\lambda}}{\sum_{g'} \Gamma_{f,g'}\cdot w_{g'}^{1-\lambda}},$$

and labor productivity (defined as sales per worker) as:

$$\text{labor productivity}_f = \mu\cdot\bar{w}_f\cdot\frac{\sum_g \Gamma_{f,g}\cdot w_g^{1-\lambda} + \Gamma_{f,k}\cdot w_k^{1-\lambda}}{\sum_g \Gamma_{f,g}\cdot w_g^{1-\lambda}},$$

where $\bar{w}_f$ denotes the average wage paid by the firm. These expressions show that the labor share, the share of each skill in costs, and labor productivity are shaped by task shares and which tasks are automated.

In summary, labor shares and labor productivity will differ across firms because of variation in task shares. In particular, firms' automation decisions, summarized by the set of tasks they have automated $\{\mathcal{T}_{k,f}\}$, determine their factor shares and labor productivity. In turn, firms will automate different sets of tasks depending on the fixed costs $\kappa_f(x)$, firm-specific wages, and industry differences in the nature of tasks.

3.4 Implications

The framework delivers the following implications:

- The adoption rate of automation technologies could be low because of the high specificity of the tasks that can be effectively automated, high integration costs, or organizational barriers to new technology.

- There are large differences in adoption across industries driven by the applicability of advanced technologies to production tasks.

- Because of the fixed cost of adoption, large firms are more likely to adopt automation technologies. If the fixed costs of adoption, κ_f, are lower for younger firms, then we expect younger firms to also adopt these technologies at a higher rate, conditional on their size.

- All else equal, higher-wage firms—those with larger τ_f —are more likely to adopt automation technologies as well.

- Adopters of automation technologies will have lower labor shares and higher labor productivity.

- Automation, by reducing production costs, always expands firm sales but has an ambiguous effect on firm employment. The overall employment effect depends on whether the productivity effect (the higher sales induced by the cost reduction generated by automation) dominates the displacement effect (the fact that the firm becomes less labor intensive). Independently of which effect dominates, firm employment effects of automation overstate the industry-level implications, since automating firms expand in part at the expense of their competitors.

- If automated tasks used to be performed by lower-skill groups (which is what we would expect to the extent that routine tasks are more likely to be automated), then advanced technologies will also increase (average) skill requirements directly.

- The implications of each technology (AI, robotics, etc...) for labor productivity and the demand for skills depend on the types of tasks that it automates. Technologies automating tasks performed by workers with lower skill levels will lead to a greater increase in labor productivity and demand for skills.

Our framework also underscores a key distinction between automation and other forms of technological progress. For example, a technology that simply raises productivity in a factor-neutral way—z_f in our model— would also raise firm sales and employment by the same amount, but would have no impact on the labor share, skill requirements or labor productivity (measured as sales per worker).[15] Hence, automation technologies have very distinct effects than factor-neutral technologies on firms' demand for skills, factor shares, and labor productivity. As we will see, the correlations in the data are consistent with the implications we expect from advanced technologies being used for automation, and not simply to increase TFP in a factor neutral way.

[15]It might at first be counter intuitive that higher z_f has no effect on labor productivity. To understand this result, first note that higher z_f increases TFP, but labor productivity, defined as (dollar value of) sales divided by labor, is invariant to it. To see this, take the simple example in which there is only one type of labor, no capital, and the firm's production function is simply $z_f \ell_f$, and the firm still faces the demand curve given by (1). In this case, an increase in z_f increases real output per worker, but reduces price by exactly as much, so labor productivity remains constant. As this example clarifies, this holds so long as firms face a demand curve with constant demand elasticity.

4 The Adoption of Advanced Technologies

This section documents the aggregate patterns of adoption by technology, differences in adoption between and within industries, and the main bottlenecks limiting wider adoption.

4.1 Adoption Rates by Technology

Table 1 reports the share of firms using each of the technologies as part of their processes and methods. Column 1 shows that the share of firms using these advanced technologies is low for AI and robotics (with 3.2% of US firms using AI and 2% using robotics), and moderate for the remaining technologies (19.6% for dedicated equipment, 40.2% for specialized software, and 34% for cloud computing).[16] In total, 47.6% of US firms had adopted at least one of these technologies by 2018.[17]

Table 1: Technology adoption rates for processes and methods and as part of goods and services, ABS data for 2016–2018.

	Technology users		Technology providers	
	Share of firms using technology (1)	Share of workers employed at firms using technology (2)	Share of firms selling technology (3)	Share of workers employed at firms selling technology (4)
Artificial Intelligence	3.2%	12.6%	0.5%	2.2%
Robotics	2.0%	15.7%	0.3%	1.8%
Dedicated Equipment	19.6%	36.4%	2.5%	4.8%
Specialized software	40.2%	64.4%	4.3%	7.8%
Cloud computing	34.0%	61.8%	3.5%	7.1%
Any technology	47.6%	69.9%	6.3%	11.1%

Notes: Data from the 2019 ABS technology module and authors' calculations. Technology use rates are based on firms' answers to questions E3 of the ABS: "During the three years 2016 to 2018, to what extent did this business use the following technologies in production processes for goods or services?" The table provides the share of firms that report using the technology in any capacity (low, moderate, or high use). Technology provision rates are based on firms' answers to questions E20 of the ABS: "During the three years 2016 to 2018, did this business sell the following technologies or goods or services that included the following technologies?" We exclude firms who either responded "do not know" or did not respond to these questions from our calculations.

[16] The adoption rates of robotics and AI are close to the rates obtained in the 2018 ABS technology module: 1.4% and 5.8%, respectively (see Zolas et al., 2020), even though there are some differences across the two modules in the way technologies are defined and the survey reference periods for measurement (2017 in the 2018 ABS versus 2016-18 in the 2019 ABS).

[17] The 2019 ABS also queries firms on the intensity of use (low, moderate, or high use). The most heavily adopted technologies turn out to be also the most intensively used. Specialized software has the highest intensity of use with 44% of users reporting high and 35% reporting moderate use, followed by cloud and specialized equipment, each with 32%–33% high use and 36%–39% moderate use. AI and robotics have the lowest intensity of use with only 15%–18% of users reporting high use and 33%–35% moderate use.

Even though a moderate share of firms use these technologies, these firms are among the largest in the US and account for a sizable share of employment. As a result, the share of workers *exposed* to advanced technologies is significantly higher than the share of firms using these technologies. Even though only 2% of US firms use robotics, 15.7% of US workers are employed at firms using robots. As shown in column 2, the employment share of users is 12.6% for AI, 36.4% for dedicated equipment, 64.4% for specialized software, and 61.8% for cloud computing. These employment shares are informative of the aggregate importance of these technologies for labor and product markets.

A key advantage of the ABS module is that it distinguishes between *users* and *producers* of technology. Columns 1 and 2 reported the share of firms and workers at firms *using* these technologies as part of their production processes. But the ABS also asks firms whether they sold goods or provided services that embedded these technologies (e.g., whether the firm produces and sells robots or provides cloud-based solutions to customers). Column 3 shows that the supply side of these technologies is more concentrated than their use, with only 0.3% of firms selling robots, 0.5% providing goods and services embedding AI algorithms, and 3.5% of firms selling cloud-based solutions. Column 4 shows that suppliers account for a small share of US employment too, so that more workers are employed at firms using these technologies than at firms producing them. In the rest of this paper we will focus on users of advanced technologies.

Table 2: Conditional adoption rates of multiple technologies, ABS data for 2016–2018.

	Share of firms using technology Y (column) conditional on using X (row)				
	Y =Artificial Intelligence (1)	Y =Robotics (2)	Y =Dedicated Equipment (3)	Y =Specialized Software (4)	Y =Cloud Computing (5)
X =Artificial Intelligence	100%	19.3%	54.4%	90.0%	85.8%
X =Robotics	30.2%	100%	87.7%	89.6%	73.1%
X =Dedicated Equipment	8.7%	9.0%	100%	82.9%	59.8%
X =Specialized Software	7.1%	4.5%	40.7%	100%	68.2%
X =Cloud Computing	7.9%	4.3%	34.4%	79.9%	100%
Unconditional rates	3.2%	2.0%	19.6%	40.2%	34.0%

Notes: Data from the 2019 ABS technology module and authors' calculations. The table reports the conditional probability of a firm using technology Y (reported across columns) given that it uses technology X (reported across rows). Technology use rates are based on firms' answer to questions E3 of the ABS: "During the three years 2016 to 2018, to what extent did this business use the following technologies in production processes for goods or services?" These conditional probabilities exclude firms who either responded "do not know" or did not respond from our calculations.

Firms adopt multiple technologies at the same time, which points to complementarities between technologies. Table 2 shows that 86% of the firms that use AI also use cloud, and 90% of the firms that use robotics also use specialized software. Columns 4 and 5 of Table 2 show that this is particularly the case for cloud computing and specialized software, which are typically used to control and handle the computing needs of robotic systems and dedicated equipment.[18]

4.2 Differences in Adoption by Sector and Industry

Figure 1 summarizes the differences in adoption rates both in terms of the share of firms using the technology (Panel A) and the share of workers at using firms (Panel B) across sectors.

figures/Figure_sectors_unw.png

(a) Panel A: Share of firms using technologies

figures/Figure_sectors_wtd.png

(b) Panel B: Share workers at firms using technologies

Figure 1: Technology use across US economic sectors, ABS data for 2016–2018. Technology use rates are based on firms' answers to questions E3 of the ABS, "During the three years 2016 to 2018, to what extent did this business use the following technologies in production processes for goods or services?" excluding firms who responded "do not know" or did not respond.

The adoption of advanced technologies is particularly high in manufacturing, the information sector, professional services, healthcare, retail, and wholesale. The exception to this pattern is robotics, which remains highly concentrated in manufacturing, with 8.7% of manufacturing firms using robotics and 45.1% of all manufacturing workers being exposed to this technology, while firms in other sectors exhibit much lower adoption rates.

[18]Likewise, some specialized software products such as Customer Relationship Management (CRM) or Enterprise Resource Planning (ERP) systems as well as some cloud services (e.g., AWS) have (or are planning to incorporate) some built-in AI capabilities. 59% of early AI adopters report using such tools to implement or test AI applications, according to a survey conducted by Deloitte (Loucks, Davenport and Schatsky, 2018).

figures/Figure_histogram_industries.png

Figure 2: Technology use across 4-digit NAICS industries, ABS data for 2016–2018. Adoption rates based on firms' answers to questions E3 of the ABS, "During the three years 2016 to 2018, to what extent did this business use the following technologies in production processes for goods or services?" excluding firms who responded "do not know" or did not respond. The figure plots histograms with the number of industries by adoption rate in bins 0-10%, 10-20%, ..., and 90-100%.

Table 3: Coefficients of variation for technology adoption rates across 4-digit industries

	Coefficient of variation	
	Adoption rates by industry	Employment-weighted adoption rates by industry
	Panel A. All sectors	
AI	0.83	1.26
Robotics	1.25	1.13
Equipment	0.57	0.55
Software	0.33	0.25
Cloud	0.39	0.29
	Panel B. Manufacturing	
AI	0.64	1.10
Robotics	0.54	0.56
Equipment	0.22	0.22
Software	0.25	0.21
Cloud	0.25	0.27
	Panel C. Non-manufacturing	
AI	0.91	1.30
Robotics	1.73	1.45
Equipment	0.57	0.58
Software	0.37	0.26
Cloud	0.42	0.30

Notes: Data from the 2019 ABS technology module based on authors' calculations. Column 1 reports the coefficient of variation (standard deviation divided by mean) for adoption rates across 4-digit industries. Column 2 reports the CV for employment-weighted adoption rates.

The ABS data reveals large variation across detailed industries in the same broad sectors. Figure 2 and Table 3 illustrate this variation. The figure plots a histogram of the number of 4-digit industries by mean adoption rate for all industries, manufacturing, and non-manufacturing. The table complements this information with coefficients of variation for the adoption rate of each technology across 4-digit industries. It shows that there is sizable dispersion in adoption of AI and robotics across industries, and considerable (but less) dispersion in the adoption of dedicated equipment, specialized software, and cloud computing.[19] One explanation for the importance of detailed industry in determining adoption patterns is that the nature of products and tasks varies across detailed industries, and this determines the applicability of advanced technologies to specific tasks in those industries.

[19] For example, in manufacturing, 87.4% of the workers in hardware manufacturing (NAICS code 3325), 81.8% of the workers in forging (NAICS 3321), 67.2% of the workers in motor vehicle manufacturing (NAICS 3363), and 75.4% of workers in dairy product manufacturing (NAICS 3115) are employed at firms using robotics, which are much higher than the manufacturing sector mean of 45.1%.

4.3 Adoption Rates by Firm Size and Age

Even though industries play an important role in determining adoption, there is sizable variation in adoption across firms within detailed industries. Figure 3 explores the role of size and age, which our framework identifies as important dimensions that mediate adoption decisions. For each technology, we report adoption rates in 36 size–age categories, defined in terms of employment and age percentiles within detailed 6-digit industries.[20] The figure also reports the average adoption rate for firms by size.

Adoption rises significantly with size across all technologies. For example, 5.5% of firms in the top percentile of industries' employment distribution use AI, 5.1% use robots, 31.4% use dedicated equipment, 67.4% use specialized software, and 63.5% use cloud computing. In contrast, the adoption rate among firms in the 50th to 75th percentile of industries' employment distribution is much lower: 3.1% for AI, 1.7% for robots, 18.6% for dedicated equipment, 39.6% for specialized software, and 33.4% for cloud computing. These facts support the idea that automating tasks, or adopting advanced technologies more generally, involves large integration costs, which imply that large and growing firms will select into adopting these technologies.[21]

Although not as strong as the pattern for size, we see that among firms of a given size, adoption tends to decrease with age. For most size classes, younger firms are more likely to adopt advanced technologies than older ones.[22] The declining adoption rates by age is in line with the idea that younger firms face fewer organizational barriers or do not have to pay a cost to reallocate workers as they automate tasks. The patterns in Figure 3 also suggest that new entrants play an important role in the diffusion of advanced technologies, as is commonly assumed in models of technology diffusion (see, for example, Perla, Tonetti and Waugh, 2021; Hubmer and Restrepo, 2021). Likewise, these patterns point to the slowdown in entry as potentially contributing to the low adoption rates observed at the aggregate level, especially for smaller firms (see Decker et al., 2020, for evidence on the decline of entry and dynamism).

[20] We assign firms to their predominant 6-digit NAICS industry in terms of payroll across all its establishments. In this and all subsequent exercises, the employment percentiles are defined based on the employment distribution from the LBD in each industry.

[21] In a companion paper Acemoglu et al. (2023), we provide additional evidence in support of this interpretation. In particular, we document that adopters have had larger establishments than non-adopters from their same cohort at every age and that, for many cohorts, these differences preceded the arrival of advanced technologies. Moreover, these size differences between adopters and non-adopters have become smaller for more recent cohorts, presumably as these technologies become standardized and the costs of integration falls.

[22] One exception to this pattern is that technology adoption rates for firms in the 95+ age percentile group are higher than that of the 90–95 group. One difficulty in interpreting the results for the oldest firms is that the LBD only extends back to 1976, meaning that we cannot identify precise age values for firms born before 1977. Thus, the age distribution of firms in our ABS sample is truncated from above at 42 years, with all firms of age 42+ being assigned to the highest age percentile group.

figures/Figure_adoption_AI.png

Panel A: Artificial intelligence

figures/Figure_adoption_Robotics.png

Panel B: Robotics

figures/Figure_adoption_Equipment.png

Panel C: Dedicated equipment

figures/Figure_adoption_Software.png

Panel D: Specialized software

figures/Figure_adoption_Cloud.png

4.4 Factors Adversely Affecting Technology Adoption

The ABS data reveal that a majority of firms, especially small firms, have not adopted advanced technologies. The 2019 ABS asked firms to identify all the factors limiting adoption from a list of 10 options (including costs, lack of data or skills, concerns about safety and regulations), or to indicate that no factors limited their adoption. Half of the firms that did not adopt technologies reported at least one factor that limited their adoption. As summarized in Panel A of Table 4, 45–50% of non-adopters (the majority of firms that reported some limiting factor) report that the advanced technologies in the ABS module are not applicable to their business. Besides lack of applicability, the main adverse factor discouraging adoption is its high cost, with 7–8% of non users (about an eighth of the firms that reported some limiting factor) identifying high costs as the main bottleneck for adoption.

Table 4: Factors limiting the adoption of advanced technologies, ABS data for 2016–2018.

	Artificial Intelligence (1)	Robotics (2)	Dedicated Equipment (3)	Specialized Software (4)	Cloud Computing (5)
	Panel A: firms not using the technology				
No adverse factors	41%	41%	44%	43%	42%
Technology not applicable to this business	49%	50%	47%	46%	44%
Technology too expensive	7%	7%	7%	8%	7%
Technology not mature	2%	1%	0%	0%	1%
Lacked access to required data	1%	0%	0%	0%	1%
Required data not reliable	0%	0%	0%	0%	0%
Lacked access to human capital or talent	1%	1%	1%	1%	1%
Laws and regulations	1%	0%	0%	0%	0%
Concerns regarding safety and security	1%	0%	0%	0%	3%
Lacked access to capital	1%	1%	1%	1%	1%
	Panel B: firms using the technology				
No adverse factors	52%	64%	72%	77%	75%
Technology not applicable to this business	13%	8%	8%	7%	7%
Technology too expensive	17%	17%	12%	9%	6%
Technology not mature	10%	4%	1%	1%	2%
Lacked access to required data	4%	1%	1%	1%	1%
Required data not reliable	4%	2%	1%	1%	1%
Lacked access to human capital or talent	6%	4%	2%	2%	2%
Laws and regulations	4%	2%	2%	2%	2%
Concerns regarding safety and security	6%	3%	2%	3%	7%
Lacked access to capital	7%	7%	5%	3%	2%

Notes: Data from the 2019 ABS technology module based on authors' calculations. The table reports the share of non adopters (Panel a) and adopters (Panel b) that report each of the factors listed in the rows as adversely affecting their adoption of each technology, with separate technologies in different columns. The estimates reported above are based on responses to the following question in the 2019 ABS: "During the three years 2016 to 2018, indicate which factors adversely affected the adoption or utilization of the following technologies to produce goods or services. Select all that apply for each technology."

For firms that adopted the technology, the adverse factors listed may be interpreted as discouraging further adoption or the intensity of use. As summarized in Panel B, adopters faced fewer limitations as a whole, with 52–77% reporting no bottlenecks. On the other hand, some adopters identify lack of applicability (7–13% of firms) and high costs (6–17%) as the main factors limiting further adoption. The case of AI and robotics is particularly interesting, since these are the technologies with the lowest adoption rates and for which users reported the most bottlenecks (48% of AI users and 36% of robotics users reported some adverse factor that limited their adoption, compared to 25% of users for the remaining technologies). In contrast to the remaining technologies, users of AI and robotics see these technologies as lacking maturity, and identify the lack of human capital and financing as important bottlenecks for their adoption and more intense use.

These findings suggest that these advanced technologies have had limited applicability and require a high cost of adoption. This view aligns with our model, which sees advanced technologies as applicable to specific tasks—rather than general purpose technologies increasing the productivity of all firms at all industries irrespective of their task structure—and recognizes that there might be a high fixed cost of adoption. These two factors limit adoption but also imply that adoption concentrates in specific industries (those with the greatest applicability) and among large firms.

5 The Use of Advanced Technologies for Automation and Other Motivations

This section documents the extent to which US firms use advanced technologies for automation and the role of other uses and motivations for adoption.

5.1 Motivations for Technology Adoption

A common view is that advanced technologies facilitate the automation of tasks previously performed by labor. Industrial robots and dedicated equipment are being used in manufacturing to automate tasks such as welding, painting, and assembly. AI is being used to create algorithms capable of achieving human proficiency at predictive tasks, such as controlling automated vehicles, trading, and medical diagnostics. And specialized software systems are capable of handling payrolls and sales. While these examples abound, we do not know the real extent to which firms are using these advanced technologies for automation. It could well be the case that firms use these technologies to control the quality of their processes, replace older vintages of machinery (instead of workers), or expand their offering of goods and services—alternative uses which do not involve the automation of tasks previously performed by labor. The distinction is consequential. As our theory demonstrates, the use of a technology for automation generates distinct effects on firm and worker outcomes.

To understand the importance of automation and other uses of advanced technology, the ABS module asked adopters to identify their motivations for adoption from six possibilities: i. to automate tasks performed by labor; ii. to upgrade outdated processes or methods; iii. to improve the quality or reliability of processes; iv. to expand the range of goods and services provided; v. to adopt standards and accreditation; vi. some other reasons. Adopters were able to select all the motivations that applied.

figures/Figure_motivation_pooled_unw.png

(a) Panel A: Share of user firms

figures/Figure_motivation_pooled_wtd.png

(b) Panel B: Employment-weighted shares

Figure 4: Motivation for technology adoption, ABS data for 2016–2018. Tabulations based on questions E4 of the ABS, which asked firms, for each technology, "During the three years 2016 to 2018, why did this business adopt or use [technology]? Select all that apply."

The share of adopting firms stating these motivations by technology is shown in Figure 4. Panel A reports the share of user firms reporting each motivation, while Panel B reports an employment-weighted share. Improving quality and the reliability of processes is the most common motivator. The employment-weighted shares in Panel B show that 68%–80% of all users cite this as a motivation for using advanced technologies. About 50–64% of firms report using these technologies to upgrade outdated processes or methods, and 20–36% report using these technologies to expand the range of goods and services offered. Adopting standards and accreditation is the least common motivation for all technologies.[23]

In both panels, but especially in Panel B, we see that a significant share of adopters report using advanced technologies to automate tasks performed by labor. AI and robotics are the two technologies with the greatest automation component, with 54% of firms using AI and 66% of the firms using robotics (in an employment-weighted sense) doing so to automate tasks. On the other

[23] The ranking of motivations for technology adoption reported by firms matches the results from the 1991 Survey of Manufacturing Technology. The top benefit from technology use stated by plants in that survey was quality improvement, followed by labor cost reduction and flexibility increase (see Figure 3 in Dinlersoz and Wolf, 2024).

hand, 37% of the firms using dedicated equipment and 32% of the firms using specialized software do so to automate tasks. Cloud computing is the technology least connected to automation, with 24% of firms using it to automate tasks.

The comparison between Panels A and B also shows that, conditional on their adoption, large firms are more likely to use these technologies for automation. For example, the 40% of robotics-using firms adopting the technology for automation (Panel A) account for 66% of employment among robot-using firms (Panel B).

How important is automation as a driver of technology adoption? One challenge in answering this question is that firms were able to select multiple motivations. Most of the firms that report adopting advanced technologies for automation or for introducing new products also indicate that these involved an increase in the quality and reliability of their processes and an upgrade of their methods. To remove this overlap, the figure shows the share of firms that report using the technology to improve the quality of their processes and upgrade their methods but not for automating tasks or introducing new goods and services (firm shares in Panel A and employment-weighted shares in Panel B). We view these shares as measuring other uses of technology different from automation or the introduction of new products. For example, these numbers would capture firms purchasing new dedicated machinery to replace older machines, or using AI algorithms to replace existing software systems—upgrades to their processes that improve quality and reliability but do not involve automation or a change in their product mix. For AI, robotics, and dedicated equipment, automation is more important than these alternative uses of technology. For specialized software, automation is as important as these other uses of technology. For cloud computing, automation is less important than these alternative uses of technology.

In sum, the ABS points to automation being a distinct and important driver of the adoption of advanced technologies. The ABS data also highlights that the extent to which advanced technologies are being used for automation varies by technology, with AI and robotics being more closely linked to automation and software and cloud-computing systems having more diverse uses.[24]

5.2 The Exposure of US Workers to Automation

Using the ABS information on motivation, we can compute the *exposure of US workers to automation*, defined as the share of workers employed at firms using advanced technologies to automate tasks. This measure is informative of the extent of automation in US labor markets.

[24] There are two interpretations of these findings. On the one hand, this could reflect some fundamental and permanent differences across technologies. For example, it might be the case that dedicated equipment and specialized software simply have more diverse applications, while most applications of robotics and AI entail automation. This would also explain the wider adoption of software and dedicated equipment relative to AI and robotics. On the other hand, these differences might be temporary and reflect the maturity of these technologies. For example, it could be the case that technologies are initially deployed with an emphasis on automation, since these applications are more salient and easier to conceive. Over time, and as the technology matures and diffuses, new and more diverse applications of the technology emerge. While the cross-sectional ABS data does not allow us to tease apart these two explanations, we view this as an important question going forward.

Figure 5 reports our estimates of worker exposure to automation. 6.8% of US workers are employed at firms using AI for automation, and this number rises to 10.4% for robotics, 13.5% for dedicated equipment, 20.5% for specialized software, and 14.7% for cloud computing. Even though AI and robotics are more likely to be used to automate tasks, automation via dedicated equipment, specialized software, and cloud-based systems have been more important contributors in the aggregate due to their wider adoption. In total, 30.4% of US workers are employed at firms using advanced technologies for automation.

figures/Figure_Exposure_autom.png

Figure 5: US workers' exposure to automation via advanced technologies, ABS data for 2016–2018. This exposure measure is computed as the share of the US workforce currently employed at firms using each technology for automation.

The ABS data also allow us to gauge the importance of automation in manufacturing and outside of this sector. This is important because most studies have focused on automation via robotics in the manufacturing sector, and relatively less is known about the extent to which automation takes place in services, retail, and other sectors. Exposure to automation is higher in manufacturing, with 52% of manufacturing workers employed at firms using at least one of these technologies for automation. However, automation is not exclusive to manufacturing: 28.3% of US workers outside of manufacturing are employed at firms using at least one of these technologies for automation.

Not all workers employed at firms using these technologies are (or have been) subject to the effects of automation. Still, these high exposure measures suggest that the use of advanced technologies for automation is a relevant force affecting the US labor market, despite their limited adoption across firms. This is because large firms are both more likely to adopt advanced technologies and to use these technologies for automation, and these firms account for a large share of labor demand.

6 Advanced Technologies, Wages, and Labor Productivity

This section documents systematic differences between firms that adopt and use advanced technologies and non-adopters in terms of their labor productivity, labor share and average wages.

6.1 Firm Correlates of Adoption

We first explore the correlation between technology use in 2016–2018 and baseline firm-level characteristics in 2015—a date that preceded the reference period of the ABS.[25] For each technology, we estimate the linear probability model:

$$\text{Adopter}^{\text{tech}}_{f,i,s,a} = \alpha^{\text{tech}}_{i} + \gamma^{\text{tech}}_{s} + \lambda^{\text{tech}}_{a} + \beta^{\text{tech}} \cdot X_f + \varepsilon^{\text{tech}}_{f,i,s,a}. \tag{2}$$

The dependent variable is a dummy for whether firm f in industry i size class s and age a used a given advanced technology during 2016–2018.[26] We explore if adoption correlates with firm characteristics from the LBD, including firm size, age, and average wages paid in 2015 (salaries and wages/employment). We also include two measures that capture the industry diversification of firms and the importance of manufacturing as part of their activities. The first one is a dummy variable that equals 1 for firms that have some (but not all) of their establishments engaged in manufacturing activities. This dummy identifies firms with some manufacturing activity. The second computes

[25] This timing choice does not imply any causality. First, adoption may have taken place prior to the reference period (the ABS only asked firms if they used the technology in 2016–2018, not if they adopted it during this period). Second, even firms that adopted during 2016–2018, might already be different in terms of unobservables by 2015. We interpret the estimates simply as describing the main cross-sectional differences between users and other firms.

[26] We generate separate samples for each technology by dropping firms that answer either "don't know" or left blank questions regarding the intensity of their use of that technology (e.g. a firm that answers "don't know" to whether it uses robotics is not included in the sample for which we analyze robotics adoption). We also generate a separate sample for "any technology" by dropping firms that answer either "don't know" or left blank all technology use intensity questions.

for these multi-sector firms the share of firm's employment classified in manufacturing based on its establishments' industry codes.

All of our specifications control for 6-digit industry dummies α_i^{tech}, size categories γ_s^{tech} defined by employment percentiles in each 6-digit industry, age categories λ_a^{tech} defined by age percentiles in each industry, and firms' employment shares in each US state to account for their location. All regressions use firm weights that are constructed to make the ABS sample representative of the universe of employer firms in the LBD.

Tables 5 presents the estimates of equation (2), with a separate panel for each technology. In line with the theoretical framework and the fact that a significant share of firms use advanced technologies for automation, we find that adopters paid higher wages in 2015. This holds even when comparing firms in the same industry and of similar size and age.

The fact that adopters paid higher wages in 2015 has three plausible interpretations. A first interpretation is that, as emphasized in our theory, higher wages generate incentives for automation. A second interpretation of this finding which is also consistent with firms' assessments in Section 7 is that automation leads to a reallocation of labor from automated tasks to other roles, such as managerial, design, and engineering jobs that typically pay higher wages, which explains the higher mean wages. This effect could be present for firms that adopted some of these advanced technologies before 2015. A third interpretation is that firms that adopt advanced technologies had a more skilled workforce to begin with, as in Doms, Dunne and Troske (1997), which facilitated the adoption of advanced technologies.

The even columns in Table 5 explore the role of industry diversification and the importance of manufacturing in firms' activities. Adopters tend to be diversified and have some manufacturing activities. Still, their share of manufacturing is lower than other multi-industry firms (with the exception of dedicated equipment for which the association is positive), though this relationship is not precisely estimated.[27]

In all specifications, adoption rises with size and decreases with age (with the exception of the oldest firms). Although not reported, all regressions control for detailed industry dummies and employment shares by state. 6-digit NAICS industry dummies account for 66%–88% of the explained variation in adoption; while firm size classes explain 6.3%–23%. On the other hand, once size and industry are accounted for, the geographic location of a firm (measured by its employment shares across states) plays a small role in determining their adoption decisions

The appendix provides related exercises and checks. Tables A-1–A-2 repeat the regression analysis for manufacturing and non-manufacturing industries separately, uncovering similar patterns across sectors, and finding a significant role of wages in 2015 in explaining the use of these

[27] Continuing manufacturing firms have increased their employment of non-manufacturing workers over time, contributing to the process of structural transformation in the economy (see Fort, Pierce and Schott, 2018). Our findings suggest that this firm transformation has coincided with the adoption of advanced technologies.

Table 5: Regressions accounting for the variation in the use of advanced technologies for 2016–2018, ABS data.

Dependent variable:	Artificial intelligence		Robotics		Dedicated equipment		Specialized software		Cloud computing	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Employment percentile 50th-75th	0.008	0.008	0.007	0.007	0.056	0.056	0.109	0.109	0.096	0.096
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Employment percentile 75th-90th	0.012	0.012	0.015	0.014	0.091	0.090	0.170	0.170	0.154	0.154
	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Employment percentile 90th-95th	0.016	0.016	0.025	0.024	0.108	0.107	0.222	0.222	0.208	0.208
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Employment percentile 95th-99th	0.016	0.016	0.028	0.026	0.122	0.121	0.254	0.253	0.258	0.256
	(0.004)	(0.004)	(0.003)	(0.003)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Employment percentile 99th+	0.033	0.031	0.044	0.038	0.173	0.167	0.311	0.309	0.329	0.327
	(0.005)	(0.005)	(0.004)	(0.004)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Age percentile 10th-50th	-0.005	-0.005	-0.002	-0.002	-0.014	-0.014	-0.024	-0.024	-0.045	-0.045
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Age percentile 50th-75th	-0.009	-0.009	-0.004	-0.004	-0.034	-0.034	-0.053	-0.053	-0.090	-0.090
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Age percentile 76th-90th	-0.012	-0.012	-0.007	-0.007	-0.040	-0.040	-0.060	-0.060	-0.117	-0.117
	(0.003)	(0.003)	(0.001)	(0.001)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Age percentile 90th-95th	-0.017	-0.017	.	.	-0.051	-0.051	-0.083	-0.083	-0.136	-0.136
	(0.003)	(0.003)			(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Age percentile 95th-99th	-0.022	-0.022	-0.005	-0.006	-0.070	-0.070	-0.123	-0.123	-0.187	-0.187
	(0.005)	(0.005)	(0.002)	(0.002)	(0.012)	(0.012)	(0.015)	(0.015)	(0.014)	(0.014)
Age percentile 99th+	-0.011	-0.011	.	.	-0.045	-0.046	-0.077	-0.078	-0.125	-0.127
	(0.003)	(0.003)			(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)
log of average wage in 2015	0.003	0.003	0.002	0.002	0.014	0.014	0.047	0.047	0.050	0.050
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Multi-sector dummy		0.036		0.144		0.137		0.061		0.069
		(0.011)		(0.014)		(0.027)		(0.029)		(0.025)
Manufacturing employment share		-0.045		-0.020		0.155		-0.200		-0.334
		(0.029)		(0.048)		(0.105)		(0.127)		(0.104)
R-squared	0.016	0.016	0.051	0.053	0.118	0.118	0.139	0.139	0.142	0.142
Observations (rounded)	117,000	117,000	120,000	120,000	118,000	118,000	117,000	117,000	118,000	118,000

Notes: The table reports results from a regression of firm-level adoption on firm characteristics, 6-digit industry dummies, and employment shares by state. Columns 1–2 report results for the adoption of artificial intelligence. Columns 3–4 report results for the adoption of robotics. Columns 5–6 report results for the adoption of dedicated equipment. Columns 7–8 report results for the adoption of specialized software. Columns 9–10 report results for the adoption of cloud computing. To protect confidentiality, in columns 3–4 the coefficients for firms in the age percentiles 75th to 90th and 90th to 95th are pooled together, as well as firms in the age percentiles 95th to 99th and above the 99th percentile. These coefficients are reported under the row corresponding to firms in the 75th to 90th and 95th to 99th age percentiles, respectively. Robust standard errors are reported in parenthesis.

technologies in 2016–2018.[28]

6.2 Technology, Labor Productivity, and Superstar Firms

We now explore the link between technology use, labor productivity (measured as revenue per worker), and the labor share (measured as payroll over revenue). We document that the use of advanced technologies is associated with higher labor productivity and a lower labor share for adopting firms, both inside and outside of manufacturing.

As noted in Section 3, adopters should achieve higher labor productivity for two reasons. First, when used for automation, advanced technologies allow firms to produce in a more capital-intensive way, by relying more on specialized equipment and software and less on labor. Second, these technologies may reduce employment of less-skilled workers and increase the hiring of skilled workers, and this effect on skill composition can also increase labor productivity. This is very different from a factor-neutral technology, which increases TFP but does not alter labor productivity.

We estimate regressions of the form

$$\text{Log labor productivity}_{f,i,s,a} = \alpha_i + \gamma_s + \lambda_a + \beta \cdot \text{Technology User}_f + e_{f,i,s,a}. \tag{3}$$

This regression explains labor productivity in 2018 (measured from the LBD) as a function of 6-digit industry fixed effects α_i, 2015 size and age categories defined in terms of industries' percentiles γ_s and λ_a, and measures of technology use for 2016-2018 from the 2019 ABS.[29] We interpret this regression as descriptive and emphasize that this approach does not necessarily recover the causal effect of technology adoption on labor productivity.

Table 6 presents our estimates of equation (3). The specification in column 1 explains labor productivity with the size and age percentile categories. Starting at the median firm, there is an increasing relationship between firm size and labor productivity, with the largest firms in each 6-digit industry achieving 22.9 log points (or 25.7%) higher labor productivity than the middle firms in their industry (firms in the 50th–75th employment percentiles). This is the *superstar firm* phenomenon: the rise of large firms with high labor productivity documented by Autor et al. (2020).[30] In addition, labor productivity declines with age (with the exception of the oldest firm group).

[28] To protect confidentiality, the oldest age group now contains firms in the 96+ percentiles of the age distribution within an industry, rather than the 99+ category used in Table 5 for the general samples that include all sectors.

[29] For this exercise, we winsorize the labor productivity and labor share data at the 5th and 95th percentiles of the distribution of these variables by size bin.

[30] Although not reported, these specifications also control for detailed 6-digit industry dummies, which shows that the superstar phenomenon is visible within detailed industries. Industry dummies are the most important factor accounting for differences in labor productivity in our analysis, accounting for more than 80% of the explained variation in all cases. This is not surprising, given the large differences in intermediate input use across industries. Within industries, differences in labor productivity are more comparable. For example, Foster, Haltiwanger and Krizan (2001) present evidence that within detailed industries there is a strong positive correlation between value added per worker and gross output per worker across businesses.

Table 6: Regressions explaining firm labor productivity in 2018 as a function of technology use in 2016–2018, ABS data for 2016–2018.

	Dependent Variable: Log of Labor Productivity in 2018				
	(1)	(2)	(3)	(4)	(5)
Employment percentile 0th-50th	0.047	0.059	0.061	0.062	0.395
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Employment percentile 75th-90th	0.030	0.024	0.022	0.022	-0.184
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Employment percentile 90th-95th	0.065	0.053	0.050	0.048	-0.348
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
Employment percentile 95th-99th	0.137	0.120	0.115	0.111	-0.488
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
Employment percentile 99th+	0.229	0.208	0.201	0.195	-0.781
	(0.032)	(0.031)	(0.031)	(0.031)	(0.033)
Age percentile 10th-50th	-0.016	-0.013	-0.012	-0.011	-0.052
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age percentile 50th-75th	-0.047	-0.039	-0.037	-0.035	-0.095
	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
Age percentile 75th-90th	-0.057	-0.047	-0.045	-0.042	-0.123
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age percentile 90th-95th	-0.119	-0.108	-0.105	-0.101	-0.178
	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)
Age percentile 95th-99th	-0.100	-0.085	-0.080	-0.076	-0.168
	(0.031)	(0.031)	(0.031)	(0.031)	(0.028)
Age percentile 99th+	-0.084	-0.073	-0.070	-0.067	-0.180
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
Technology user		0.108			0.058
		(0.006)			(0.006)
One technology			0.063		
			(0.009)		
Two technologies			0.120		
			(0.007)		
Three technologies			0.139		
			(0.009)		
Four technologies			0.173		
			(0.018)		
Five technologies			0.192		
			(0.033)		
Artificial intelligence				0.020	
				(0.016)	
Cloud computing				0.102	
				(0.007)	
Robotics				0.061	
				(0.017)	
Specialized software				0.046	
				(0.008)	
Dedicated equipment				-0.008	
				(0.008)	
log average wage 2015					0.279
					(0.004)
R-squared	0.323	0.326	0.327	0.327	0.395
Observations (rounded)	103,000	103,000	103,000	103,000	103,000

Notes: The table reports results from a regression of firm labor productivity in 2018 on size and age groups, 6-digit industry dummies, employment shares by state, and measures of technology use from the 2019 ABS for 2016–2018. To protect confidentiality, the number of observations has been rounded. Robust standard errors are reported in parenthesis.

Column 2 explores the contribution of advanced technologies to the observed differences in labor productivity by including a dummy for firms that adopted any of the advanced technologies in the ABS. Technology adoption is associated with a 10.8 log points (or 11.4%) increase in labor productivity.[31]

Column 3 shows that the number of technologies that a firm uses is positively associated with its productivity. Firms using a single technology have a 6.3 log points higher labor productivity than firms with none. Firms using all five technologies have a 19.2 log points (or 21.1%) higher labor productivity than firms with none.

Columns 4 includes separate dummies for each of the five technologies in the ABS. Cloud, robotics, and specialized software have positive and significant association with labor productivity, whereas AI and dedicated equipment are not correlated with labor productivity. One possibility is that the effects of AI on labor productivity and the labor share had not fully materialized by 2018, which aligns with the conclusions in Acemoglu et al. (2022). An alternative interpretation is that the individual technology coefficients are hard to interpret given that many of these technologies are adopted jointly.[32]

The estimates from column 4 imply that, from a descriptive viewpoint, the adoption of advanced technologies by large firms explains between 16% to 30% of the superstar phenomenon. Conditional on the technology measures from the ABS, the largest firms in each industry have a 19.5 log points higher labor productivity than mid-sized firms (as opposed to 22.9 log points when technology is not accounted for in column 1). Thus, technology explains 16% of the labor productivity difference between firms above the 99th employment percentile and mid-sized firms. Likewise, technology explains 20% of the labor productivity difference between firms in the 96th to 99th employment percentile and mid-sized firms, and 30% of the difference between firms in the 90th to 95th employment percentile and mid-sized firms.[33]

For age, we find that differences in technology use between young and old firms account for 27% of the labor productivity difference between firms in the 96th to 99th age percentiles and the youngest firms in the bottom decile of the age distribution in each detailed industry.

Figure 6 illustrates our findings by plotting labor productivity differences as a function of firm-size and age, indicating the share of these differences explained by the measures of technology adoption from the ABS and the part left unexplained.

One concern with the results presented so far is whether they capture the fact that higher productivity firms pay higher wages, and, as we saw in Table 5, higher-wage firms are more likely

[31] These findings are consistent with earlier studies that documented a positive connection between labor productivity and automation technologies in the 1991 *Survey of Manufacturing Technology* (Dinlersoz and Wolf, 2024).

[32] In line with this interpretation, we find that the coefficient on AI rises to 0.041 (se=0.015) once we drop the highly correlated dummy for the use of cloud computing. This is not the case for the labor share regressions, however.

[33] The same calculations show that technology use explains 30% of the labor productivity difference between firms above the 99th employment percentile and firms in the bottom half of the employment distribution, and 60% of the difference between firms in the 96th to 99th employment percentile and firms in the bottom half of the employment distribution.

figures/Figure_labor_productivity_by_size.png figures/Figure_labor_productivity_by_age.png

Panel A: Productivity gaps by firm size

Panel B: Productivity gaps by firm age

Figure 6: Estimates of differences in labor productivity by size and age and the share of these differences explained by the adoption of advanced technologies, as measured in the 2019 ABS.

to adopt these advanced technologies. The last column of Table 6 explores this issue by controlling for the logarithm of the average wage paid by the firm in 2015. The results in this column have to be interpreted with caution, since some of these technologies may have been adopted before 2015, and wages in 2015 are endogenous to past technology adoption, attenuating our estimates of the effects of technology on labor productivity. We find that there is still a sizable positive association between technology use and labor productivity, though it is attenuated relative to earlier specifications.

Tables A-3 and A-4 in the appendix show similar relations between the use of advanced technologies and labor productivity for manufacturing firms and non-manufacturing firms.

Table 7 turns to estimates of (3) using the labor share from the 2018 LBD as outcome variable. Adopters have a 0.7 pp lower labor share by 2018. The more technologies a firm adopts, the lower its labor share, with firms that use all five technologies having a 3.1 pp lower labor share than firms that use none. When we look at the effects of different types of technologies separately, the use of robots has the largest negative association with the labor share, though we also estimate negative coefficients for all other technologies except AI.

Finally, we once again control for the log of the average wage in the firm in 2015, despite its potential endogeneity. In this case, the relationship between technology use and the labor share becomes more negative. Presumably, this reflects the fact that adopters paid higher wages to begin with, which masks the effects of automation on their labor shares.

Tables A-5 and A-6 in the appendix show similar relations between the use of advanced tech-

Table 7: Regressions explaining firm labor share in 2018 as a function of technology use in 2016–2018, ABS data for 2016–2018.

	Dependent Variable: Labor share in 2018				
	(1)	(2)	(3)	(4)	(5)
Employment percentile 0th-50th	-0.060	-0.060	-0.061	-0.061	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Employment percentile 75th-90th	0.022	0.022	0.022	0.022	-0.014
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Employment percentile 90th-95th	0.044	0.045	0.045	0.046	-0.026
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Employment percentile 95th-99th	0.047	0.049	0.049	0.049	-0.058
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Employment percentile 99th+	0.046	0.047	0.049	0.049	-0.126
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Age percentile 10th-50th	0.002	0.002	0.002	0.002	-0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age percentile 50th-75th	0.011	0.011	0.011	0.010	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Age percentile 75th-90th	0.021	0.020	0.020	0.020	0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age percentile 90th-95th	0.034	0.033	0.032	0.032	0.021
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age percentile 95th-99th	0.038	0.037	0.037	0.036	0.023
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Age percentile 99th+	0.038	0.037	0.037	0.037	0.018
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Technology user		-0.007			-0.016
		(0.001)			(0.001)
One technology			-0.002		
			(0.002)		
Two technologies			-0.005		
			(0.002)		
Three technologies			-0.013		
			(0.002)		
Four technologies			-0.022		
			(0.004)		
Five technologies			-0.031		
			(0.008)		
Artificial intelligence				0.000	
				(0.004)	
Cloud computing				-0.006	
				(0.002)	
Robotics				-0.019	
				(0.004)	
Specialized software				-0.002	
				(0.002)	
Dedicated equipment				-0.005	
				(0.002)	
log average wage 2015					0.049
					(0.001)
R-squared	0.300	0.300	0.301	0.301	0.338
Observations (rounded)	103,000	103,000	103,000	103,000	103,000

Notes: The table reports results from a regression of firm labor share in 2018 on size and age groups, 6-digit industry dummies, employment shares by state, and measures of technology use from the 2019 ABS for 2016–2018. To protect confidentiality, the number of observations has been rounded. Robust standard errors are reported in parenthesis.

nologies and firms' labor shares in manufacturing and non-manufacturing.

7 Technology and Changes in Demand for Workers and Skills

This section summarizes firms' self-assessments of the impact of advanced technologies on their workforce. The ABS asked adopting firms to assess the impact that advanced technologies have had on their employment level. Respondents were given 3 options: "Increase," "Decrease," and "Did Not Change." Figure 7 plots these answers separately for each technology. The figure provides the share of firms (both the simple share and an employment-weighted version) reporting an increase or a decrease in employment (with the share of firms reporting no change given by the complement of these two). For brevity, we focus on the employment weighted shares in our discussion.

Across all technologies, most firms claim that the use of advanced technologies did not change their employment levels in recent years, with 67–78% of firms selecting this response. A small share of firms report positive or negative employment changes caused by the adoption of the technologies in the ABS. The employment-weighted share of firms reporting an increase in employment is 26% for users of AI. Robotics is the technology most closely associated with employment decreases: the employment-weighted share of firms reporting a decrease in employment due to the use of robots is 14% (the same share reporting an increase in employment attributed to this technology).[34] One caveat is that these responses reflect self-assessments by firms, and some firms may be particularly reluctant to divulge information on workforce reductions through technology adoption; while other firms might default to reporting no employment changes.

We interpret firms' assessments as pointing to limited and ambiguous employment effects of advanced technologies at the firm level. This finding aligns with the theoretical framework, which highlights the fact that automation will have an ambiguous effect on firm employment. The framework also clarifies that it is reasonable to expect automation to increase employment in some firms while at the same time it reduces employment in others.

The possibility that advanced technologies have a limited effect on employment also underscores the importance of the displacement effects from automation. Consider, for example, a technological improvement that increases productivity in a factor-neutral way but does not involve the automation of tasks performed by labor. Our model shows that these factor-neutral technological developments should always increase sales and employment proportionally.[35]

[34] Figures A-1 and A-2 break down these answers by firm size and age. The 2019 ABS technology module also asked firms to assess the effect of technology on the number of production workers, non-production workers, supervisory workers, and non-supervisory workers. Here too, most firms report no changes in employment levels for these workers. One notable case is that of robotics, where the employment-weighted share of firms reporting a decrease in the employment of production workers exceeds the share reporting an increase.

[35] In the simple model of Section 3, this is always the case since firms face a constant elasticity of demand and have a constant markup, which makes their passthrough of marginal cost to price equal to 1. In practice, firms might expand their sales more than employment if their passthrough of marginal cost to price lies below 1. But for most reasonable values of the demand elasticity and passthrough, we would expect an expansion of both employment and sales in response to higher firm TFP.

figures/Figure_composition.png

Figure 7: Reported changes in employment levels and skill demand by firms adopting advanced technologies, employment-weighted shares from 2019 ABS.

The 2019 ABS technology module also provides information on firms' self-assessments of the impact of advanced technologies on their demand for skills. Firms were asked whether the skill level of their workers changed as a result of technology use, with the response options of "Increase," "Decrease," and "No Change." Panel B in Figure 7 plots the share of reported changes in skill attributed to technology adoption (again, weighted by employment). A sizable share of firms, ranging from 30% to 50% of users in an employment-weighted sense, reports an increase in their demand for skills. Almost no firm reports a reduction in their demand for skills.

Firms' self-assessments indicate that the use of advanced technologies has resulted not so much in changes in firm-level employment but in changes in employment composition, with firms increasing their demand for skills. This finding is in line with the theory, which suggests that the use of advanced technologies involves a reassignment of labor from automated tasks to other complementary roles, including the maintenance, programming, and operation of specialized machinery. Firms' responses also align with recent work highlighting the fact that the adoption of advanced technologies and robots is associated with significant changes in the workforce composition of firms, measured in terms of their occupational structure or the skill level of their workers (see, for example, Dinlersoz and Wolf, 2024; Humlum, 2020; Bonfiglioli et al., 2020; Rodrigo, 2023).[36] The relatively high incidence of skill upgrading reported by firms suggests that the use of advanced technologies might be an important force contributing to the observed changes in the occupational and wage structure of the US economy over the last 40 years, though quantifying the contribution of these technologies to these shifts is beyond the scope of our paper (see Acemoglu and Restrepo, 2022, for more on this question).

8 Conclusion

A lack of comprehensive data at the firm level has precluded a detailed assessment of the current state of advanced technology use by US firms and these technologies' impact on productivity and the workforce. Recent surveys conducted by the Census Bureau in partnership with the National Center for Science and Engineering Statistics (NCSES) as part of the 2018 and 2019 ABS fill this gap and offer new insights. Using the data collected by the technology module included in the 2019 ABS, we have provided new measures of the adoption of five key technologies—AI, robotics, dedicated equipment, specialized software, and cloud—and documented the relationship between their adoption and firm characteristics and workforce outcomes. While these technologies (especially AI and robotics) have low adoption rates among firms, a significant fraction of the US workforce are employed in firms using these technologies.

We documented a number of descriptive facts, which are mostly novel and complement previous work by Zolas et al. (2020):

1. We document that adoption remains limited when measured by the share of firms using these technologies in their processes and methods. This is especially the case for AI and robotics: only 3.2% of firms used AI and 2% used robotics during 2016–2018. While there is wider adoption of the remaining technologies, half of US firms did not use any of these technologies during 2016–2018.

2. Despite the low shares of user firms, adopters account for a sizable share of employment and

[36] These findings contrast with previous work by Doms, Dunne and Troske (1997) using data from the US Survey of Manufacturing Technologies, which suggests that the adoption of new technologies does not increase firms' demand for skills (even though firms that had a more skilled workforce are more likely to adopt these technologies).

economic activity. This is because adoption concentrates in large firms. 12.6% of the US workforce is employed in firms using AI technologies between 2016 and 2018, and this share rises to 15.7% for robotics, 64.4% for specialized software, 36.4% for dedicated equipment, and 61.8% for cloud computing. In manufacturing, worker exposure to advanced technologies is even higher: 22.6% for AI, 45.1% for robotics, 70.7% for dedicated equipment, 72.3% for specialized software, and 62.3% for cloud computing.

3. Large firms are more likely to adopt advanced technologies than other firms in their same detailed industries and cohorts. Conditional on size, younger firms are more likely to adopt advanced technologies than older firms in their same industries.

4. There is considerable variation in adoption rates across detailed industries even within manufacturing.

5. Firms identify automation as an important motivation for the adoption of AI and robotics, and to a lesser extent for dedicated equipment and specialized software. In total, 30.4% of US workers are employed at firms using advanced technologies for automation.

6. In line with the use of advanced technologies for automation, we document that adopters have high labor productivity and lower labor shares, and paid higher wages than the firms with similar age and size in their same detailed industries.

7. Firms' self-assessments point to an increase in the relative demand for skill but limited or ambiguous effects on their employment level. These reports weigh against the view that automation technologies increase employment opportunities for low-skill workers.

Moving forward, there are several directions for future research. Many of these directions will also benefit from future planned ABS modules, which will add a longitudinal dimension. Here we list some of these directions:

- Future work can explore both whether the correlation between advanced technologies and labor productivity is causal at the firm level and how it aggregates to the industry and the economy. Composition effects and impacts of new technologies on markups will be particularly important in understanding these implications.

- Industry-level and aggregate employment implications of new technologies need further study as well. To do this, one can estimate the impact of advanced technologies not just on adopting firms' employment and skill demand, but on their rivals. If effects on rivals are negative and large, advanced technologies can have negative consequences, and whether they do or not and how this varies across different classes of technologies are central questions for future research.

- It would also be interesting to explore how advanced technologies impact the economy by expanding the range of goods and services and enabling quality upgrades. The ABS points to automation being an important driver of the adoption of advanced technologies, with automation being as important as expanding the range of goods and services offered by firms in driving adoption. However, the ABS data also highlights that the extent to which advanced technologies are being used for automation varies by technology and across firms, with a sizable share of firms reporting not using these technologies for automation. Understanding the determinants of these different motivations and uses is a fruitful area of research.

- Another important area is the study of whether labor shortages, such as those caused by the Covid-19 pandemic, trigger further automation and how permanent such shortage-induced adoption decisions will be.[37]

References

Acemoglu, D., G. Anderson, D. Beede, C. Buffington, E. Dinlersoz, L. Foster, N. Goldschlag, J. Haltiwanger, Z. K. P. Restrepo, and N. Zolas (2023): "Advanced Technology Adoption: Selection or Causal Effects?," *AEA Papers and Proceedings*, 113, 210–214.

Acemoglu, D., D. Autor, J. Hazell, and P. Restrepo (2022): "Artificial Intelligence and Jobs: Evidence from Online Vacancies," *Journal of Labor Economics*, 40(S1), S293–S340.

Acemoglu, D., C. Lelarge, and P. Restrepo (2020): "Competing with Robots: Firm-Level Evidence from France," *AEA Papers and Proceedings*, 110, 383–88.

Acemoglu, D., and P. Restrepo (2020): "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 128(6), 2188–2244.

——— (2021): "Demographics and Automation," *The Review of Economic Studies*, 89(1), 1–44.

——— (2022): "Tasks, Automation, and the Rise in US Wage Inequality," *Econometrica*, 90(5), 1973–2016.

Aghion, P., C. Antonin, S. Bunel, and X. Jaravel (2020): "What are the labor and product market effects of automation? new evidence from france," Discussion paper, CEPR Discussion Paper No. DP14443.

Alekseev, G., S. Amer, M. Gopal, T. Kuchler, J. Schneider, J. Stroebel, and N. C. Wernerfelt (2022): "The Effects of COVID-19 on U.S. Small Businesses: Evidence from Owners, Managers, and Employees," *Management Science*, 69(1), 7–24.

Alekseeva, L., J. Azar, M. Giné, S. Samila, and B. Taska (2021): "The demand for AI skills in the labor market," *Labour Economics*, 71, 102002.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020): "The fall of the labor share and the rise of superstar firms," *The Quarterly Journal of Economics*, 135(2), 645–709.

Autor, D., and E. Reynolds (2020): "The Nature of Work after the COVID Crisis: Too Few Low-Wage Jobs," Discussion paper, The Hamilton Project.

Babina, T., A. Fedyk, A. He, and J. Hodson (forthcoming): "Artificial Intelligence, Firm Growth, and Product Innovation," *Journal of Financial Economics*.

[37] Examples of research predicting an increase in investment in automation technologies in response to the Covid pandemic shock and forecasting related impacts include Autor and Reynolds (2020) and Chernoff and Warman (2023). Data enabling direct measurement of the association between the pandemic and technology adoption is still rare. Exceptions include Comin et al. (2022) (conducting a survey of firms in three developing countries and finding that pre-Covid digital technology adopters were better able to weather the pandemic and more likely to increase use of digital technologies than less advanced firms) and Alekseev et al. (2022) (conducting a survey of small businesses and finding that about one-half dealt with the pandemic by providing online services and about one-third expanded digital payments). The US Census Bureau added a question to Phase 7 (November 2021-January 2022) of its experimental Small Business Pulse Survey on whether firms changed any of eight business practices since the onset of the pandemic, including adoption and expansion of digital technologies US Census Bureau (2021).

Basker, E., L. Foster, and S. Klimek (2017): "Customer-employee substitution: Evidence from gasoline stations," *Journal of Economics & Management Strategy*, 26(4), 876–896.

Bessen, J., M. Goos, A. Salomons, and W. Van den Berge (2019): "Automatic reaction-what happens to workers at firms that automate?," Discussion paper, Mimeo, Boston University School of Law.

Bloom, N., T. A. Hassan, A. Kalyani, J. Lerner, and A. Tahoun (2021): "The diffusion of new technologies," Working Paper 28999, National Bureau of Economic Research.

Bonfiglioli, A., R. Crinò, H. Fadinger, and G. Gancia (2020): "Robot Imports and Firm-Level Outcomes," Discussion paper, CEPR Discussion Papers No. 14593.

Brynjolfsson, E., W. Jin, and K. McElheran (2021): "The power of prediction: predictive analytics, workplace complements, and business performance," *Business Economics*, 56(4), 217–239.

Brynjolfsson, E., and A. McAfee (2014): *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. Norton & Company.

Calvino, F., S. DeSantis, I. Desnoyers-James, S. Formai, I. Goretti, S. Lombardi, F. Manaresi, and G. Perani (2022): "Closing the Italian digital gap: The role of skills, intangibles and policies," OECD Science, Technology and Industry Policy Papers 126, OECD Publishing.

Cheng, H., L. A. Drozd, R. Giri, M. Taschereau-Dumouchel, and J. Xia (2021): "The Future of Labor: Automation and the Labor Share in the Second Machine Age," Working Paper 20-11, FRB Philadelphia.

Chernoff, A. W., and C. Warman (2023): "COVID-19 and Implications for Automation," *Applied Economics*, 55(17), 1939–1957.

Cho, J., T. DeStefano, H. Kim, I. Kim, and J. Paik (2023): "What's driving the diffusion of next-generation digital technologies?," *Technovation*, 119(C).

Chow, M. C., T. C. Fort, C. Goetz, N. Goldschlag, J. Lawrence, E. R. Perlman, M. Stinson, and T. K. White (2021): "Redesigning the Longitudinal Business Database," Discussion paper, National Bureau of Economic Research.

Comin, D. A., M. Cruz, X. Cirera, K. M. Lee, and J. Torres (2022): "Technology and Resilience," Working Paper 29644, National Bureau of Economic Research.

Dauth, W., S. Findeisen, J. Suedekum, and N. Woessner (2021): "The adjustment of labor markets to robots," *Journal of the European Economic Association*, 19(6), 3104–3153.

de Souza, G., and H. Li (2023): "Robots, Tools, and Jobs: Evidence from Brazilian Labor Markets," Working Paper 10813, CESifo.

Dechezleprêtre, A., D. Hémous, M. Olsen, and C. Zanella (2021): "Induced automation: evidence from firm-level patent data," Discussion Paper 384, University of Zurich, Department of Economics, Working Paper.

Decker, R. A., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2020): "Changing Business Dynamism and Productivity: Shocks versus Responsiveness," *American Economic Review*, (forthcoming).

Dinlersoz, E. M., and Z. Wolf (2024): "Automation, Labor Share, and Productivity: Plant-Level Evidence from U.S. Manufacturing," *Economics of Innovation and New Technology*, 33(4), 604–626.

Dixon, J., B. Hong, and L. Wu (2021): "The Robot Revolution: Managerial and Employment Consequences for Firms," *Management Science*, 67(9), 5586–5605.

Doms, M., T. Dunne, and K. Troske (1997): "Workers, Wages, and Technology," *Quarterly Journal of Economics*, 112(1), 253–290.

Dunne, T., L. Foster, J. Haltiwanger, and K. R. Troske (2004): "Wage and productivity dispersion in United States manufacturing: The role of computer investment," *Journal of Labor Economics*, 22(2), 397–429.

Eckert, F., S. Ganapati, and C. Walsh (2022): "Urban-Biased Growth: A Macroeconomic Analysis," Working Paper 30515, National Bureau of Economic Research.

Ford, M. (2015): *Rise of the Robots: Technology and the Threat of a Jobless Future*. Basic Books, New York.

Fort, T. C., J. R. Pierce, and P. K. Schott (2018): "New Perspectives on the Decline of US Manufacturing Employment," *Journal of Economic Perspectives*, 32(2), 47–72.

Foster, L., J. C. Haltiwanger, and C. J. Krizan (2001): *Aggregate Productivity Growth: Lessons from Microeconomic Evidence*pp. 303–372. University of Chicago Press.

Genz, S., T. Gregory, M. Janser, F. Lehmer, and B. Matthes (2021): "How Do Workers Adjust When Firms Adopt New Technologies?," Discussion paper, IZA DP No. 14626.

Graetz, G., and G. Michaels (2018): "Robots at Work," *The Review of Economics and Statistics*, 100(5), 753–768.

Hubmer, J., and P. Restrepo (2021): "Not a Typical Firm: The Joint Dynamics of Firms, Labor Shares, and Capital-Labor Substitution," Working Paper 28579, National Bureau of Economic Research.

Humlum, A. (2020): "Robot Adoption and Labor Market Dynamics," Working paper, University of Chicago.

Koch, M., I. Manuylov, and M. Smolka (2021): "Robots and firms," *The Economic Journal*, 131(638), 2553–2584.

Kogan, L., D. Papanikolaou, L. D. W. Schmidt, and B. Seegmiller (2021): "Technology-Skill Complementarity and Labor Displacement: Evidence from Linking Two Centuries of Patents with Occupations," Working Paper 29552, National Bureau of Economic Research.

Leigh, N. G., and B. R. Kraft (2018): "Emerging robotic regions in the United States: insights for regional economic evolution," *Regional Studies*, 52(6), 804–815.

Loucks, J., T. Davenport, and D. Schatsky (2018): *State of AI in the Enterprise, 2nd Edition.* Deloitte Insights.

Mann, K., and L. Püttmann (2019): "Benign effects of automation: New evidence from patent texts," *The Review of Economics and Statistics*, pp. 1–45.

Martinez, J., and J. Moen-Vorum (2022): "A Long-run Anatomy of Task Exposures to Technology," Discussion paper, Mimeo, London Business School.

McElheran, K. (2015): "Do market leaders lead in business process innovation? The case (s) of e-business adoption," *Management science*, 61(6), 1197–1216.

Perla, J., C. Tonetti, and M. E. Waugh (2021): "Equilibrium Technology Diffusion, Trade, and Growth," *American Economic Review*, 111(1), 73–128.

Rodrigo, R. (2023): "Robot Adoption, Organizational Capital, and the Productivity Paradox," *Academy of Management Proceedings*, 2023(1).

Schwab, K. (2017): *The fourth industrial revolution.* Currency.

Susskind, R. E., and D. Susskind (2015): *The future of the professions: How technology will transform the work of human experts.* Oxford University Press, USA.

US Census Bureau (2021): "Questionnaire for Small Business Pulse Survey, Phase 7," .

Zolas, N., Z. Kroff, E. Brynjolfsson, K. McElheran, D. N. Beede, C. Buffington, N. Goldschlag, L. Foster, and E. Dinlersoz (2020): "Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey," Working Paper 28290, National Bureau of Economic Research.

A Appendix A: Development of the ABS 2019 Module

Work on the development of the 2019 ABS module began in the Spring of 2018. The questions for the module were developed over a period of several months in cooperation with NCSES, and with input from economists at Massachusetts Institute of Technology and Boston University.

The initial technologies included in the 2019 ABS module consisted of those relevant for automation: specialized software, specialized equipment, robotics, and artificial intelligence. Cloud computing was added later in the process, as it complements some of these technologies, particularly AI, and facilitates automation.

The initial draft of the module only considered technology adoption and use within the context of the processes for producing goods or services. When confronted with the fact that there is little up-to-date information on which firms actually provide these technologies as their products and services, it was decided to duplicate the questions for firms which identify themselves as sellers of the goods or services embedding the technologies (e.g. providers of machine learning software, or robot producers).

Cognitive testing of the module on a sample of potential respondents took place in late summer and fall of 2018. The testing process revealed some minor changes to the definitions of each of the technologies to make them transparent for respondents, and streamlined parts of the module.

B Appendix B: Additional Empirical Results for the 2019 ABS

This appendix provides additional empirical results:

- Tables A-1 and A-2 reproduce the findings from Table 5 separately for manufacturing and non-manufacturing firms. To protect confidentiality, these table uses a coarser definition of size and age brackets than Table 5.
- Tables A-3 and A-4 reproduce the findings from Table 6 separately for manufacturing and non-manufacturing firms.
- Tables A-5 and A-6 reproduce the findings from Table 7 separately for manufacturing and non-manufacturing firms.
- Figure A-1 reports firms assessments on the effects of technology on their employment level and demand for skills by size. The estimates come from a generalized ordered logit model (controlling for size, age, and sector).
- Figure A-2 reports firms assessments on the effects of technology on their employment level and demand for skills by age. The estimates come from a generalized ordered logit model (controlling for size, age, and sector).

Table A-1: Regressions accounting for the variation in the use of advanced technologies for 2016–2018, ABS data for manufacturing firms.

Dependent variable:	Artificial intelligence	Robotics	Dedicated equipment	Specialized software	Cloud computing
	(1)	(2)	(3)	(4)	(5)
Employment percentile 50th-90th	0.015	0.062	0.156	0.173	0.142
	(0.003)	(0.004)	(0.007)	(0.008)	(0.007)
Employment percentile 90th-95th	0.026	0.146	0.262	0.274	0.204
	(0.006)	(0.011)	(0.016)	(0.016)	(0.016)
Employment percentile 95th-99th	0.046	0.242	0.336	0.335	0.292
	(0.008)	(0.012)	(0.016)	(0.015)	(0.016)
Employment percentile 99th+	0.108	0.403	0.409	0.372	0.380
	(0.015)	(0.023)	(0.023)	(0.023)	(0.025)
Age percentile 10th-50th	-0.009	-0.016	-0.043	-0.042	-0.061
	(0.005)	(0.006)	(0.012)	(0.012)	(0.011)
Age percentile 50th-75th	-0.013	-0.029	-0.072	-0.064	-0.104
	(0.005)	(0.007)	(0.012)	(0.013)	(0.012)
Age percentile 75th-95th	-0.012	-0.030	-0.094	-0.104	-0.130
	(0.005)	(0.008)	(0.013)	(0.015)	(0.013)
Age percentile 95th+	-0.003	0.000	-0.024	0.015	0.011
	(0.005)	(0.008)	(0.013)	(0.014)	(0.013)
log of average wage in 2015	0.007	0.015	0.050	0.066	0.057
	(0.002)	(0.003)	(0.006)	(0.007)	(0.005)
R-squared	0.016	0.097	0.086	0.098	0.090
Observations (rounded)	22,500	23,500	23,000	22,500	23,000

Notes: The table reports results from a regression of firm-level adoption on firm characteristics, 6-digit industry dummies, and employment shares by state. The sample includes firms in the ABS in the manufacturing sector. Column 1 reports results for the adoption of artificial intelligence. Column 2 reports results for the adoption of robotics. Column 3 reports results for the adoption of dedicated equipment. Column 4 reports results for the adoption of specialized software. Column 5 reports results for the adoption of cloud computing. To protect confidentiality, these table uses a coarser definition of size and age brackets than Table 5. Robust standard errors are reported in parenthesis.

Table A-2: Regressions accounting for the variation in the use of advanced technologies for 2016–2018, ABS data for non-manufacturing firms.

Dependent variable:	Artificial intelligence	Robotics	Dedicated equipment	Specialized software	Cloud computing
	(1)	(2)	(3)	(4)	(5)
Employment percentile 50th-90th	0.009	0.007	0.064	0.129	0.115
	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)
Employment percentile 90th-95th	0.015	0.019	0.099	0.217	0.204
	(0.003)	(0.003)	(0.008)	(0.009)	(0.009)
Employment percentile 95th-99th	0.014	0.018	0.110	0.245	0.250
	(0.004)	(0.003)	(0.009)	(0.011)	(0.010)
Employment percentile 99th+	0.029	0.031	0.161	0.304	0.321
	(0.005)	(0.004)	(0.022)	(0.023)	(0.023)
Age percentile 10th-50th	-0.001	-0.002	-0.007	-0.013	-0.026
	(0.002)	(0.002)	(0.005)	(0.006)	(0.006)
Age percentile 50th-75th	-0.005	-0.004	-0.026	-0.041	-0.070
	(0.002)	(0.002)	(0.005)	(0.006)	(0.006)
Age percentile 75th-95th	-0.007	-0.007	-0.029	-0.044	-0.089
	(0.002)	(0.002)	(0.005)	(0.006)	(0.006)
Age percentile 95th+	-0.006	-0.006	-0.026	-0.053	-0.077
	(0.003)	(0.002)	(0.008)	(0.009)	(0.008)
log of average wage in 2015	0.003	0.002	0.013	0.047	0.051
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
R-squared	0.017	0.036	0.111	0.141	0.142
Observations (rounded)	94500	97000	95000	94000	95000

Notes: The table reports results from a regression of firm-level adoption on firm characteristics, 6-digit industry dummies, and employment shares by state. The sample includes firms in the ABS in the non-manufacturing sector. Column 1 reports results for the adoption of artificial intelligence. Column 2 reports results for the adoption of robotics. Column 3 reports results for the adoption of dedicated equipment. Column 4 reports results for the adoption of specialized software. Column 5 reports results for the adoption of cloud computing. To protect confidentiality, these table uses a coarser definition of size and age brackets than Table 5. Robust standard errors are reported in parenthesis.

Table A-3: Regressions explaining firm labor productivity in 2018 as a function of technology use in 2016–2018 for the manufacturing sector, ABS data for 2016–2018.

	Dependent Variable: Log of Labor Productivity in 2018				
	(1)	(2)	(3)	(4)	(5)
Employment percentile 0th-50th	-0.086	-0.069	-0.064	-0.063	0.332
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)
Employment percentile 75th-90th	0.126	0.114	0.108	0.108	-0.133
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Employment percentile 90th-95th	0.284	0.269	0.257	0.256	-0.207
	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)
Employment percentile 95th-99th	0.388	0.363	0.342	0.339	-0.343
	(0.021)	(0.021)	(0.021)	(0.021)	(0.026)
Employment percentile 99th+	0.524	0.494	0.459	0.454	-0.550
	(0.034)	(0.034)	(0.034)	(0.035)	(0.040)
Age percentile 10th-50th	-0.053	-0.043	-0.041	-0.040	-0.115
	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)
Age percentile 50th-75th	-0.101	-0.086	-0.082	-0.081	-0.191
	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)
Age percentile 75th-90th	-0.129	-0.113	-0.109	-0.108	-0.232
	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)
Age percentile 90th-95th	-0.130	-0.106	-0.097	-0.093	-0.217
	(0.064)	(0.065)	(0.065)	(0.065)	(0.061)
Age percentile 95th-99th	0.062	0.090	0.090	0.090	-0.046
	(0.128)	(0.129)	(0.128)	(0.128)	(0.111)
Age percentile 99th+	-0.150	-0.135	-0.131	-0.132	-0.279
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Technology user		0.115			0.053
		(0.010)			(0.010)
One technology			0.055		
			(0.016)		
Two technologies			0.120		
			(0.013)		
Three technologies			0.128		
			(0.014)		
Four technologies			0.229		
			(0.022)		
Five technologies			0.249		
			(0.041)		
Artificial intelligence				-0.002	
				(0.028)	
Cloud computing				0.071	
				(0.012)	
Robotics				0.091	
				(0.018)	
Specialized software				0.081	
				(0.014)	
Dedicated equipment				-0.006	
				(0.013)	
log average wage 2015					0.273
					(0.006)
R-squared	0.204	0.209	0.211	0.212	0.300
Observations (rounded)	20,500	20,500	20,500	20,500	20,500

Notes: The table reports results from a regression of firm labor productivity in 2018 on size and age groups, 6-digit industry dummies, employment shares by state, and measures of technology use from the 2019 ABS for 2016–2018. The relationship is estimated for manufacturing firms. To protect confidentiality, the number of observations has been rounded. Robust standard errors are reported in parenthesis.

Table A-4: Regressions explaining firm labor productivity in 2018 as a function of technology use in 2016–2018 for the non-manufacturing sector, ABS data for 2016–2018.

	Dependent Variable: Log of Labor Productivity in 2018				
	(1)	(2)	(3)	(4)	(5)
Employment percentile 0th-50th	0.053	0.065	0.067	0.068	0.397
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Employment percentile 75th-90th	0.025	0.019	0.018	0.017	-0.187
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Employment percentile 90th-95th	0.056	0.044	0.042	0.039	-0.353
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Employment percentile 95th-99th	0.126	0.109	0.104	0.100	-0.493
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
Employment percentile 99th+	0.218	0.197	0.191	0.186	-0.789
	(0.033)	(0.032)	(0.032)	(0.032)	(0.034)
Age percentile 10th-50th	-0.015	-0.011	-0.011	-0.009	-0.049
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Age percentile 50th-75th	-0.045	-0.037	-0.036	-0.034	-0.091
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Age percentile 75th-90th	-0.054	-0.045	-0.042	-0.039	-0.118
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age percentile 90th-95th	-0.116	-0.106	-0.103	-0.098	-0.175
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Age percentile 95th-99th	-0.098	-0.083	-0.078	-0.074	-0.164
	(0.031)	(0.031)	(0.031)	(0.031)	(0.028)
Age percentile 99th+	-0.082	-0.072	-0.069	-0.066	-0.175
	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)
Technology user		0.107			0.058
		(0.006)			(0.006)
One technology			0.063		
			(0.009)		
Two technologies			0.120		
			(0.008)		
Three technologies			0.138		
			(0.010)		
Four technologies			0.155		
			(0.020)		
Five technologies			0.168		
			(0.036)		
Artificial intelligence				0.024	
				(0.016)	
Cloud computing				0.105	
				(0.008)	
Robotics				0.029	
				(0.021)	
Specialized software				0.044	
				(0.008)	
Dedicated equipment				-0.010	
				(0.009)	
log average wage 2015					0.278
					(0.004)
R-squared	0.329	0.332	0.332	0.333	0.399
Observations (rounded)	82,500	82,500	82,500	82,500	82,500

Notes: The table reports results from a regression of firm labor productivity in 2018 on size and age groups, 6-digit industry dummies, employment shares by state, and measures of technology use from the 2019 ABS for 2016–2018. The relationship is estimated for non-manufacturing firms. To protect confidentiality, the number of observations has been rounded. Robust standard errors are reported in parenthesis.

Table A-5: Regressions explaining firm labor share in 2018 as a function of technology use in 2016–2018 for the manufacturing sector, ABS data for 2016–2018.

	Dependent Variable: Labor share in 2018				
	(1)	(2)	(3)	(4)	(5)
Employment percentile 0th-50th	-0.029	-0.031	-0.031	-0.032	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Employment percentile 75th-90th	-0.010	-0.009	-0.009	-0.008	-0.028
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Employment percentile 90th-95th	-0.033	-0.032	-0.030	-0.029	-0.068
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Employment percentile 95th-99th	-0.047	-0.045	-0.042	-0.040	-0.099
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
Employment percentile 99th+	-0.079	-0.077	-0.070	-0.067	-0.155
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Age percentile 10th-50th	0.022	0.022	0.021	0.021	0.016
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age percentile 50th-75th	0.038	0.037	0.036	0.036	0.029
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age percentile 75th-90th	0.058	0.057	0.056	0.056	0.048
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Age percentile 90th-95th	0.066	0.064	0.063	0.061	0.056
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Age percentile 95th-99th	0.064	0.062	0.062	0.061	0.052
	(0.029)	(0.029)	(0.029)	(0.029)	(0.031)
Age percentile 99th+	0.062	0.061	0.060	0.060	0.050
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Technology user		-0.008			-0.013
		(0.002)			(0.002)
One technology			-0.002		
			(0.004)		
Two technologies			-0.006		
			(0.003)		
Three technologies			-0.009		
			(0.003)		
Four technologies			-0.028		
			(0.005)		
Five technologies			-0.036		
			(0.010)		
Artificial intelligence				0.002	
				(0.006)	
Cloud computing				-0.007	
				(0.003)	
Robotics				-0.027	
				(0.004)	
Specialized software				-0.002	
				(0.003)	
Dedicated equipment				0.001	
				(0.003)	
log average wage 2015					0.021
					(0.002)
R-squared	0.110	0.111	0.112	0.113	0.121
Observations (rounded)	20,500	20,500	20,500	20,500	20,500

Notes: The table reports results from a regression of firm labor share in 2018 on size and age groups, 6-digit industry dummies, employment shares by state, and measures of technology use from the 2019 ABS for 2016–2018. The relationship is estimated for manufacturing firms. To protect confidentiality, the number of observations has been rounded. Robust standard errors are reported in parenthesis.

Table A-6: Regressions explaining firm labor share in 2018 as a function of technology use in 2016–2018 for the non-manufacturing sector, ABS data for 2016–2018.

	Dependent Variable: Labor share in 2018				
	(1)	(2)	(3)	(4)	(5)
Employment percentile 0th-50th	-0.061	-0.062	-0.062	-0.062	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Employment percentile 75th-90th	0.023	0.024	0.024	0.024	-0.014
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Employment percentile 90th-95th	0.048	0.048	0.049	0.049	-0.025
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Employment percentile 95th-99th	0.052	0.053	0.053	0.053	-0.058
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Employment percentile 99th+	0.051	0.052	0.053	0.053	-0.129
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Age percentile 10th-50th	0.002	0.001	0.001	0.001	-0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Age percentile 50th-75th	0.010	0.010	0.009	0.009	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age percentile 75th-90th	0.019	0.019	0.018	0.018	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age percentile 90th-95th	0.032	0.032	0.031	0.031	0.019
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age percentile 95th-99th	0.037	0.036	0.035	0.035	0.021
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age percentile 99th+	0.037	0.037	0.036	0.036	0.018
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Technology user		-0.006			-0.015
		(0.002)			(0.002)
One technology			-0.002		
			(0.002)		
Two technologies			-0.005		
			(0.002)		
Three technologies			-0.013		
			(0.002)		
Four technologies			-0.018		
			(0.005)		
Five technologies			-0.025		
			(0.009)		
Artificial intelligence				-0.001	
				(0.004)	
Cloud computing				-0.006	
				(0.002)	
Robotics				-0.010	
				(0.005)	
Specialized software				-0.002	
				(0.002)	
Dedicated equipment				-0.005	
				(0.002)	
log average wage 2015					0.051
					(0.001)
R-squared	0.308	0.309	0.309	0.309	0.349
Observations (rounded)	82,500	82,500	82,500	82,500	82,500

Notes: The table reports results from a regression of firm labor share in 2018 on size and age groups, 6-digit industry dummies, employment shares by state, and measures of technology use from the 2019 ABS for 2016–2018. The relationship is estimated for non-manufacturing firms. To protect confidentiality, the number of observations has been rounded. Robust standard errors are reported in parenthesis.

figures/Figure_composition_size_wtd.png

Figure A-1: Reported changes in employment levels and skill demand by firms adopting advanced technologies, employment-weighted shares by size from 2019 ABS. The markers provide the employment-weighted responses for firms with 0–9 workers, 10–49 workers, 50–249 workers, and more than 250 workers. The estimates come from a generalized ordered logit model (controlling for size, age, and sector).

figures/Figure_composition_age_wtd.png

Figure A-2: Reported changes in employment levels and skill demand by firms adopting advanced technologies, employment-weighted shares by age from 2019 ABS. The markers provide the employment-weighted responses for firms of 0–5 years, 6–10 years, 11–20 years, and more than 21 years. The estimates come from a generalized ordered logit model (controlling for size, age, and sector).