Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey[1]

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Abstract: We introduce a new survey module intended to complement and expand research on the causes and consequences of advanced technology adoption. The 2018 Annual Business Survey (ABS), conducted by the Census Bureau in partnership with the National Center for Science and Engineering Statistics (NCSES), provides comprehensive and timely information on the diffusion among U.S. firms of advanced technologies including artificial intelligence (AI), cloud computing, robotics, and the digitization of business information. The 2018 ABS is a large (over 850,000), nationally representative sample of firms covering all private, non-agricultural sectors of the economy. We describe the motivation for and development of the technology module on the ABS, as well as provide a first look at technology adoption and use patterns across firms and sectors. We find that technology adoption is consistent with a skewed and hierarchical pattern of increasing technological sophistication, in which leading adopters tend to be large. Most firms that adopt AI or other advanced business technologies utilize other, more widely-diffused technologies such as cloud computing or digital information. Finally, we find that while firm exposure to advanced technologies is limited, worker exposure to these technologies may be significantly higher. This new data will be available to qualified researchers on approved projects in the Federal Statistical Research Data Center network.

[1] Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this data product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. (DRB Approval Number CBDRB-FY20-095 and CBDRB-FY20-331). We thank Scott Ohlmacher, John Eltinge, Rob Seamans, John Haltiwanger, Susan Helper and Pascual Restrepo for excellent comments and feedback, as well as participants in the 2020 AEAStat session.

Introduction

Measuring firms' adoption and use of advanced technologies is critical for understanding the current state of the U.S. economy and for planning for the future; but owing to a lack of comprehensive data on firms' adoption and use of such technologies, we are "flying blind into what has been called the fourth industrial revolution" (Brynjolfsson and Mitchell 2017b).[2] This data gap hinders evidence-based decision making at all levels of government and society. Datasets that provide detailed information on the diffusion of new technologies are rare, and those that are available often suffer from coarse aggregation (to industry classification levels), have response and sampling biases, fail to capture the non-manufacturing economy, and/or miss key emerging technologies. Consequently, we have limited knowledge about the decision to adopt these technologies or their prevalence across firms with different characteristics.

We describe the U.S. Census Bureau's recent efforts to fill this data gap by collecting information on adoption and use of several advanced technologies from a large, nationally representative sample of firms covering the private non-agricultural sectors of the economy. Our contributions to the literature are threefold. First, our discussion concerning the challenges faced in this collection provide context in analyzing the results of our surveys and other surveys that attempt to measure rapidly evolving technologies. Second, we provide a detailed first glimpse at the adoption of several key technologies that may shape the future, including artificial intelligence (AI) and robotics. Third, we provide useful guidance for future researchers to use this data in their own research through the Federal Statistical Research Data Center (FSRDC) network.[3]

With the caveat that this is a new data collection, we find that adoption of advanced technologies is relatively low and skewed, with heavy concentration among older and larger firms, with firm size and age being key determinants of adoption. We also find that technology adoption displays features of a hierarchical pattern, with stages of technology adoption of increased sophistication that appear to build on one another. Unlike frontier applications of technology, more basic digitization of business information is very widely adopted. Adoption of

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[2] The National Academy of Sciences (NAS) panel report in 2017 titled "Information Technology and the U.S. Workforce: Where Are We and Where Do We Go from Here?" makes a similar point about the paucity of data in this area and calls for a comprehensive and holistic approach to filling this data gap.

[3] Qualified researchers on approved projects can use these data and other Census Bureau micro data through the FSRDC network. See https://www.census.gov/fsrdc.

cloud services displays an intermediate level of adoption, with a large set of firms electing to host at least one or more IT functions in the cloud. Notably, for firms that do adopt the latest business technologies, the majority of these firms have also adopted digitization and cloud services, suggesting a cumulative progression.

An extensive literature amassed over the last decade argues that technology adoption and use by firms has significant impacts on the labor market and on the economy overall.[4] Despite this growing literature and an accelerating pace of technological change, measurement of technology adoption and use at the firm-level has lagged. Scarcity of firm-level data has been cited as a bottleneck in developing a better understanding of these technologies' impacts on workers and firms (see, for example, Seamans and Raj, 2018).

In the absence of detailed, firm-level data, researchers have relied primarily on highly aggregated data or small-scale surveys focused on specific types of firms and technologies. For instance, recent research has utilized broad nationwide or industry-level measures of robot diffusion (Acemoglu and Restrepo 2019, Graetz and Michaels 2017), information technology (Bessen 2002), or industry-level total factor productivity and patents as proxies for automation (Autor and Salomons 2018). Yet, because the relationship between labor and capital at the heart of much recent research occurs within highly heterogeneous firms, it is important to have accurate and comprehensive data at the firm level.[5] A recent paper combining firm-level investments in IT with worker earnings highlights the importance of obtaining accurate firm-level measures of software investments (Barth et al. 2020). Variation among firms in adoption and use of technology is critical for understanding the underlying mechanisms at work. Only with a higher-resolution lens will it be possible to characterize accurately broader effects at the industry level and higher levels of aggregations, which reflect general equilibrium considerations involving product, labor, and capital markets that are influenced by these mechanisms.

We introduce the technology module from the Annual Business Survey (ABS) and present the first results from this module. This survey represents a partnership between the Census Bureau and the National Science Foundation's National Center for Science and

[4] Acemoglu and Autor (2011), Brynjolfsson et al. (2017), Brynjolfsson and Mitchell (2017a), Acemoglu and Restrepo (2019), and Agrawal, Gans, and Goldfarb (2019) all provide excellent reviews of current and future research issues pertaining to the diffusion of various advanced technologies.

[5] This heterogeneity is highlighted as one of the key determinants in worker wages at both the firm (Song et al. 2019) and establishment-level (Barth et al. 2016).

Engineering Statistics (NCSES) and consolidates three surveys: the Survey of Business Owners (SBO), the Annual Survey of Entrepreneurs (ASE), and the Business R&D and Innovation Survey for Microbusinesses (BRDI-M).[6] The ABS captures important characteristics of the business context in which technology adoption and use take place. It asks businesses about company information (such as the type of ownership), owner characteristics, innovation, research and development, technology and intellectual property, and finance and other business characteristics. The longer-term goal is to measure changes over time, with the ABS currently planned to be conducted annually for five years with rotating modules about particular topics (such as technology or globalization), allowing for longitudinal analysis. In most years, the ABS will be mailed to a nationally representative sample of approximately 300,000 companies across all private non-agricultural sectors in the United States.

The sample in its initial year was larger than is planned for subsequent years, with approximately 850,000 employer businesses.[7] The ABS was mailed in June 2018 with data collection taking place through the end of the calendar year (the primary reference period is calendar year 2017). The sample size and timeliness make it the largest and most up-to-date data set available on advanced technology adoption. Response to the ABS is required by law, reducing selection bias, a topic often glossed over in much empirical work or work with private surveys. Finally, it is more representative than most existing surveys due to its coverage of small and young firms. This is important because we have reason to believe these firms respond differently to new technological advances in general (Hitt and Tambe 2016) and new technologies such as cloud computing, in particular (Jin and McElheran 2017).

The economy-wide, large sample of 850,000 firms allows for the tabulation and publication of novel data on nascent and growing technology use by U.S. businesses that smaller samples would not support. Also, the large sample size has the potential to identify at a disaggregated level (e.g., 6-digit NAICS) the industries in which these nascent technologies are being adopted at a higher rate, or in which only a few businesses are adopting but are having a major impact within that industry. Thus, the large sample size may help inform sampling

[6] The SBO and ASE are run independently from NCSES

[7] The reason for this unusually large sample in its first year is that it coincided with the quinquennial Economic Census and is intended to provide data that had previously been provided by the SBO, but is no longer, due to the SBO being rolled into the ABS.

strategies for future ABS data collections and the development of skip patterns for industries and firms for which the technology is less relevant and thereby reduce respondent burden.

The technology module contains three detailed questions related to technology: digital format of information, expenditure on cloud services, and use of advanced business technologies. Taking these in turn, the first question explores firms' reliance on digital information, which is widely regarded as a necessary input to more-advanced uses of digital technologies (Brynjolfsson and McAfee 2014, Brynjolfsson and McElheran 2019). Brynjolfsson and McAfee (2014) argue that in order for firms to adopt artificial intelligence technologies, the necessary ingredients are massive amounts of digital information ("big data") and sufficient computing power. In broad terms, digital information is defined as "the representation of information in bits."[8] In addition to its importance as prerequisite for AI adoption, digital representation of information is a key ingredient to several business functions, such as electronic commerce, supply chain management, customer relations and marketing, and human resources. Recent research based on the U.S. Census Bureau's Management and Organizational Practices Survey (MOPS) has shown that decision making that relies on digital information ("data-driven decision making") has been rapidly diffusing, and has important implications for firm performance (Brynjolfsson and McElheran 2016 and 2019).

The second question explores the extent to which firms rely on cloud computing, which has shifted the cost structure and use of IT by a broad range of firms (Armbrust et al. 2009, Brynjolfsson et al. 2010) and is widely viewed as a key enabler of digital transformation (Forrester 2017). Also, a second necessary ingredient for adopting AI technologies is sufficient computing power to handle the inflow of massive quantities of digital information. Much of this computing power has been beyond the reach of all but the largest, most technologically advanced firms until the mid-2000's. The advent of cloud computing services made highly scalable computing resources available on-demand, fundamentally changing the economics of IT use from an ownership model with high up-front fixed costs to an outsourced model with highly elastic variable costs (Armbrust et al. 2010).

Cloud services may substitute for firms' fixed investments in their own physical data centers and owned IT resources, including software. Yet, while cloud services provide firms with the flexibility to scale up and down the volume of IT services they purchase, the solutions

[8] Goldfarb and Tucker (2019) provide a comprehensive review of the economics of digital technologies.

offered are less tailored to an individual firm's needs (Staten 2012, Schneier 2015). To the extent that cloud services enable outsourcing of major IT functions, smaller and younger firms have become able to access computing capabilities that may be too costly to implement in-house. Consistent with this role, Jin and McElheran (2017) find that outsourced IT since the rise of cloud computing is significantly correlated with improved survival and productivity of young establishments.

Finally, the third question asks directly about the use of AI technologies and other advanced "business technologies." Respondents are presented with a list that covers robotics (i.e., "automatically controlled, reprogrammable, and multipurpose machines"), various artificial intelligence (AI) technologies (i.e., enabling machines to "perceive, analyze, determine response and act appropriately in [their] environment"), radio frequency identification, touchscreens/kiosks for customer interface, automated storage and retrieval systems, and automated guided vehicles. This question is aimed at pinning down where the frontier of technology use actually lies and understanding interrelationships among different applications, while informing future surveys' sampling methodology and content.

Many of these business technologies have been the focus of recent research. For instance, Acemoglu and Restrepo (2017), Graetz and Michaels (2018), and Acemoglu et al. (2020) show that the diffusion of robots have had important labor and productivity consequences across regions and nations. Similarly, using data on the introduction of a machine translation system in a digital international trade platform, Brynjolfsson, Hui, and Liu (2019) find significant economic effects arising from artificial intelligence technologies. Their analysis indicates that machine translation has so far had economically significant impact on trade volume on the platform by reducing language-related frictions.

Using the data collected on the three sections of technologies, this paper provides, as a first look, some key statistics on the diffusion of the technologies described above across firms and sectors. The diffusion rates are presented using tabulation weights constructed from the Longitudinal Business Database (LBD) to give estimates for the entire population of U.S. firms. In addition, estimates using both tabulation and employment weights are provided to offer a picture on the fraction of workers employed by firms using the technologies. The analysis documents the prevalence of the technologies across firm size and age categories, and the co-presence patterns for the technologies at the firm level. It also identifies which technologies are in the early stages of adoption as indicated by the rates of testing of technologies by firms versus the rates of actual adoption and use. The firm-level connection between innovation and advanced technology presence is also briefly explored.

Since the data introduced may provide a valuable resource to the research community, we also engage in some speculative discussion of our results as they relate to a number of open questions and theories concerning firm technology use and adoption. We highlight just a few of these potential areas of inquiry including: (a) dynamics and diffusion, (b) technology hierarchy and value chains, (c) technology as the "great equalizer" removing barriers for small and young firms, (d) technology complementarities, (e) technology and innovation, and (f) technology and the worker, specifically, the macro and distributional effects of new technology adoption, including how new technologies may substitute for or complement workers in various occupations (Barth et al. 2020). We do not intend to draw conclusions regarding these increasingly-salient topics, but instead highlight how ABS data might be used to address some of these open questions.

The remainder of the paper is organized as follows. Section 2 provides context for the ABS by reviewing existing related surveys and measures. Section 3 discusses the technology module and the overall results. We then turn to providing detailed results from each of the three questions in Sections 4-6. In Section 7 we provide speculative discussion of our findings in light of open questions concerning technology. We provide concluding remarks in Section 8.

2 Review of Existing Surveys

We start by reviewing existing business technology surveys. While we restrict our attention to business surveys, we acknowledge that household surveys can also provide important complementary information.[9] We start by discussing Census Bureau surveys and then discuss other efforts.

A. *Census Bureau Surveys*

[9] The Census Bureau through the American Community Survey (ACS) and periodic supplements to the Current Population Survey (CPS, jointly sponsored by the Bureau of Labor Statistics and the National Telecommunications and Information Administration) collects data on household technology (i.e., computer and Internet) adoption and use. The ACS and CPS also collect data on workers in technology-intensive occupations (e.g., computer programmers) and industries (e.g., computer systems design and related services). The Bureau of Labor Statistics

The Census Bureau has collected data on advanced technologies over the past three decades through various surveys (see Table 1). We start by describing three relatively short-lived surveys that focused on technologies. The Survey of Manufacturing Technology (SMT) was an extensive survey on the adoption and use of advanced technologies in the manufacturing sector. The SMT collected information from establishments within selected manufacturing subsectors[10] about current and planned use of 17 technologies across 5 categories: design and engineering (e.g., computer-aided design); fabrication/machining and assembly (e.g., numerically controlled/computer numerically controlled machines); automated materials handling (e.g., automated guided vehicle systems); automated sensor-based inspection or testing; and communications and control (e.g., local area networks). While providing rich details on technology adoption, use, benefits, and costs at the plant level, the SMT was collected only for three years (1988, 1991, 1993) before it was discontinued. It remains, however, as one of the most comprehensive surveys on advanced technologies, and in particular, on automation-related technologies. We describe how we use the SMT and ABS aggregated to comparable industry subsectors to assess changes over time in the use rates of robotics and automated guided vehicles in section 7A.

The Computer Network Use Supplement (CNUS), which asked plants about their e-commerce activities and e-business processes, was a supplement to the 1999 Annual Survey of Manufactures (ASM). While it provided the most detailed insights to date on early applications of the commercial internet, it was restricted to the manufacturing sector. E-commerce data persists for subsequent years, but the detailed survey was not repeated after its initial year. Lastly, the Information and Communication Technology Survey (ICTS) was a supplement to the Annual Capital Expenditure Survey (ACES) from 2003 to 2013.[11] The ICTS asked for information regarding purchases and expenses for four types of ICT equipment and software: computer and peripheral equipment; ICT equipment excluding computer and peripheral equipment; electro-medical and electrotherapeutic apparatus; and computer software. The ACES

collects data on workers by occupation, including technology-intensive occupations, in its Occupational Employment Survey. The Pew Research Center also collects household data on this subject.

[10] Sampled establishments were from one of the following subsectors: fabricated metal products (SIC 34); industrial machinery and equipment (SIC 35); electronic and other electric equipment (SIC 36); transportation equipment (SIC 37); instruments and related products (SIC 38). These major industry groups accounted for about 43% of all employees and value added as reported in the 1987 Census of Manufactures.

[11] The ICTS for 2012 was suspended for budgetary reasons, was briefly reinstated for the year 2013, and then discontinued.

is a nationally representative annual survey of around 50,000 firms and, from 2002 onward, includes capitalized IT expenditure.

In addition to the Census surveys geared specifically toward measuring technology, there are many other Census collections with selected questions about technology. Most of these questions ask about firms' software use or e-commerce activities. For example, the following contain at least one question about either software use or e-commerce activities: Annual Retail Trade Survey (ARTS), Annual Survey of Entrepreneurs (ASE), Annual Wholesale Trade Survey (AWTS), Business R&D and Innovation Survey (BRDIS), Census of Construction Industries (CCN), Census of Manufacturing (CMF), Service Annual Survey (SAS), and Survey of Business Owners (SBO).

Other surveys ask about complementary subjects. The 2014 ASE module on R&D and Innovation asks about process innovations (including automation). The Management and Organizational Practices Survey (MOPS) asks how establishments utilize data to support decision making.[12] Beginning in 2014, the Business R&D and Innovation Survey for Microbusinesses (BRDI-M) asks whether processes were improved by increasing automation. The BRDIS (newly renamed the Business Enterprise Research & Development Survey (BERD)) has targeted technology questions for a number of years, with special emphasis on R&D expenditures related towards specific technologies, including biotechnology and nanotechnology (2008-2016) and artificial intelligence (2017, 2018). Finally, some information on robotics and automation-related imports by firms can be obtained from the Longitudinal Firm Trade Transactions Database (LFTTD) which contains administrative data on trade transactions by U.S. firms.

As the above descriptions make clear, earlier Census Bureau data collections on technology were generally not repeated over time and did not necessarily focus on emerging technologies that might have the largest impact on business operations.[13] These data collection efforts also did not measure the consequences of technology adoption and use for worker outcomes at the business level (something that the ABS is scheduled to do in the 2019 version), though certain insights are possible by linking disparate data sets (e.g., Barth et al. 2020).

[12] MOPS is a relatively newer ASM supplement that has been collected for years 2010 and 2015.
[13] There is wide opinion on which technologies to focus on in a limited space and very difficult to predict in advance which emerging technologies will have the largest impact on business operations

Furthermore, most technology data collection efforts have focused on manufacturing and not on the diffusion of emerging technologies in other sectors. For example, data was not systematically collected on the diffusion of radio-frequency identification (RFID) and barcodes in retail and wholesale trade and other services that now collectively account for a larger share of GDP than manufacturing.

The Census Bureau has recently begun multiple efforts on collecting new data to improve its measurement of technology. These efforts are intended to address some of the shortcomings of the earlier collections. In addition to the module on the 2018 ABS, technology-related questions were added to the ACES, the ASM, and the MOPS. The 2018 ACES and ASM have included questions regarding purchases of robotic equipment. The 2020 MOPS is currently being developed and will likely include some questions about the use of AI in decision making.

Lastly, the 2019 ABS includes a technology module with a focus on workers. It asks firms about the effects of technology adoption and use on their workers' numbers, types, and skills. These questions offer a unique opportunity to document firms' own assessment of how technology impacts their workforce. While workforce-related questions only have qualitative response categories, firms' responses can be compared with the quantitative responses provided by the same firms in other survey and administrative data. This last point highlights an important strength of Census data, which is that it is possible to link data from multiple surveys. Finally, in order to address the shortcoming of a lack of a longitudinal component, which is especially important for understanding the diffusion of technology, the ABS technology modules are scheduled to be repeated over three-year cycles.[14] While the sample of respondents will differ over this time period, Census expects there to be considerable overlap, thereby providing a glimpse for how technology adoption changes over time for a select group of firms.

B. *Other Surveys*

We highlight a few alternative surveys in this section (see Table 2). Helper (1995) uses her survey of 499 automotive suppliers regarding their use of computer numeric control (CNC) machines and the applicability of this technology in their typical production[15] to show that

[14] That is, the first technology module from 2018 will be repeated in 2021 and the second technology module from 2019 will be repeated in 2022.

[15] Helper excluded 213 of these respondents because the technology was either unknown to them or reportedly not applicable to their business. Details about this survey can be found in Helper's NBER working paper #5278.

arm's-length supplier/customer relationships inhibit the adoption of CNC technology. The global marketing services company Harte Hanks administered an international survey to make up the Computer Intelligence Technology Database (CITDB) from 1996 until 2015. This survey samples establishments of firms across 20 European countries and the United States. The CITDB contains information on IT adoption in areas such as PCs/laptops, servers, IT employees, software and hardware, and (more recently) cloud computing.[16]

Some recent surveys focus on various automation technologies. The Georgia Tech Survey of Advanced Technology and Robotics in U.S. Manufacturing was conducted in 2018 by Green Leigh of the Georgia Institute of Technology. This survey "was conducted to better understand U.S. manufacturers' use of robotics and automation technology and to generate real knowledge about their impacts on employment and manufacturing competitiveness."[17] Green Leigh surveyed 428 U.S. manufacturing firms regarding their use of rapid prototyping, additive manufacturing, computer-aided design and manufacturing (CAD/CAM), machine vision and real-time monitoring, advanced materials, CNC machines, and robots.

Finally, Helper, Seamans, Reichensperger, and Bessen collected responses to the National Survey of Auto Suppliers for 2018. The National Survey of Auto Suppliers includes a plant, human resources, and sales survey form administered to firms in "any tier of the supply chain for new cars or light trucks." This survey asks auto suppliers about their use of various automation technologies and how automation has impacted their employment, robots' effects on certain performance outcomes, and their gathering and analysis of operations data.[18]

Researchers have also relied on data collections by trade associations. For instance, country- and industry-level data on robot installations are published by the International Federation of Robotics. UN Comtrade provides data on robot imports, and country-level numbers of robotics patents filed are available from the U.S. Patent and Trademark Office (USPTO). In addition, some major consulting firms have also collected data on technology adoption and use. For example, Deloitte collected information from about 1,100 US-based

[16] For more information about the CITDB, see Bloom et al. (2014), McElheran (2014), Bloom et al. (2016), and Haug et al. (2016). Other notable works using CITDB include Bresnahan et al. (2002), Brynjolfsson and Hitt (2003), Forman et al. (2009), Mahr (2010), Bloom et al. (2012), Forman et al. (2012), and Kretschmer et al. (2012).
[17] Details about this survey can be found at https://planning.gatech.edu/gatech_survey_mfg_tech/.
[18] For more information on this survey, visit http://sites.bu.edu/tpri/auto-survey/.

companies representing 10 industries in 2018 and published adoption rates for advanced technologies in *State of AI in the Enterprise.*[19]

3 Technology Module and Overall Results

With this context serving as background, we now turn to how we developed the technology module for the ABS. As the ABS was being developed, a team of researchers within and outside of Census[20] had the opportunity to develop a limited set of questions as a module. Three main criteria were considered in the development process: appropriateness, consistency, and optimality. Content must be appropriate with regard to the Census Bureau's mission and its role in the larger Federal Statistical System, consistent with the instrument on which it would appear (in terms of goals of the instrument and its format), and optimal in terms of weighing the benefits (i.e., filling existing gaps in our knowledge) against the costs (i.e., respondent burden) of the additional data collection.

Three questions were developed for inclusion on the 2018 ABS. As is standard practice with the Census Bureau collections, these questions were subject to cognitive testing. The decision to add the technology module to the ABS came relatively late in the survey cycle, which meant weighing the benefit of quickly responding to an emerging data need and the opportunity that the large sample presented against the drawbacks of only conducting one round of cognitive testing.[21] One set of interviews took place in August 2017 during the second round of ABS cognitive testing, and a second set took place in Boston during the same month as part of a debriefing of high tech companies who participated in the Business R&D and Innovation Survey (BRDIS). A detailed description of the results and recommendations from cognitive testing are in the Appendix.

The final resulting questions are shown in Text Box 1. The first question asks about the intensity of digitization of six critical business activities (personnel, financial, customer

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[19] For more information see the report at https://www2.deloitte.com/content/dam/insights/us/articles/4780_State-of-AI-in-the-enterprise/DI_State-of-AI-in-the-enterprise-2nd-ed.pdf.

[20] Catherine Buffington, Lucia Foster, and Scott Ohlmacher from Census, along with Erik Brynjolfsson and Kristina McElheran.

[21] Census typically requires two rounds of cognitive testing for new survey content. The first round is exploratory and is used to identify problems with the content including cognitive difficulty or excessive burden as well as whether the respondent has the information needed to answer the question. The second round is confirmatory and is used to confirm that changes made to the content based on findings and recommendations from the first round do in fact correct the problems uncovered in testing.

feedback, marketing, supply chain, and production) and allows for a write-in for "other" activities. The second question asks about the intensity of cloud services purchases for eight business functions and allows for a write-in for "other" functions.[22] These two questions have check boxes for four percentage ranges (None, Up to 50%, More than 50%, and All) along with "Don't know" and "N/A" options. The third questions concerns the testing and intensity of use of nine advanced business technologies (including augmented reality, machine learning, and robotics) in the production of goods or services. For each of the nine technologies, there are checkboxes for "Testing," four intensity percentage ranges (No use, Less than 5%, 5%-25%, and More than 25%), and "Don't know" options.

The ABS was collected from June through December 2018. The response rate for the portion of the survey used in the paper was 68.7%, slightly lower than the usual response rate for Census Bureau surveys (see Table 3). However, as shown in Table 4, when weighted by tabulation weights the size and age distributions of responders align closely with the national set of firms.[23] The firms included in the sample for the 2018 ABS had a mean employment of about 89 (or 26 by tabulation weight), and a mean age of 16 years (the same as with tabulation weights).[24] About 67% of the firms sampled had fewer than 10 employees (75% by tabulation weight), and 3% had 250 or more (1% by tabulation weight). The oldest firms (21+ years) represented about 33% of the sample (31% by tabulation weight), while young firms (0-5 years) accounted for 25% (27% by tabulation weight). These distributions fall well within the national size and age distributions for firms. The 19 two-digit NAICS sectors sampled in the survey were aggregated to form 13 sectors for the purposes of the subsequent analysis. The largest shares of firms in the sample fall into Professional Services, Retail Trade, and Other (Arts, Food, Other Services) sectors. Going forward, we rely primarily on the tabulation weights when describing response rates as well as extensive and intensive technology adoption rates.

One concerning aspect of the survey is the item non-response rate and the share of "Don't Know" responses to the technology module. The item response rate to the technology module does not differ dramatically from other parts of the survey (nearly 95%). The cumulative

[22] Cloud services are "[information technology [IT] services provided by a third party that [a] business accesses on-demand via the internet."
[23] The firm size, age and industry composition of the non-responses also closely aligns with the size, age and industry distribution of responders.
[24] Firm size and age information is derived from the Longitudinal Business Database (LBD).

responses are displayed in Figure 1. In the item responses there is a somewhat high (and consistent) rate of "Don't Know" responses for each of the technology questions. A small but significant share of firms answered "Don't Know" for *all* of the categories within a technology question. Firms responding "Don't Know" tend to be larger and older.[25] The rate of "Don't Know" responses affects each of the three technology questions differently. Digitization had the fewest firms responding "Don't Know" to all question categories. The size distribution of these firms, however, is much more skewed toward larger firms when compared to the overall distribution. This means that while the "Don't Know" responses likely have relatively little effect on overall firm digitization rates, they may have a significant effect on estimates of the association between adoption and firm size. Compared to digitization, cloud services had a larger number of firms responding "Don't Know" to all question categories, and their size distribution is even more skewed toward larger firms. Business technologies had the most firms respond "Don't Know" to all question categories (roughly three times as many firms as for digitization). However, the size distribution of the "Don't Know" firms is very similar to that of the overall sample distribution. So while the overall levels of business technology adoption may be—of the three technology questions—most affected by the rate of "Don't Know" responses, we expect size predictors of business technology use to be the least affected by "Don't Know" responses.

Missing responses are another dimension worth considering. Unlike the "Don't Know" responses, firms that leave the technology questions blank are generally the same firms across digitization, cloud services, and business technology questions. These firms are much more likely to be large, with the share of 250-employee firms skipping this module more than two times the share of 250-employee firms in the overall sample. For this reason, missing responses may have a significant effect on estimates of how size predicts adoption of digitization, cloud services, and business technologies. Thus considering the issue of "Don't Know" responses together with item non-response, we note that the size analysis on the business technologies

[25] The reason why this particular set of questions receives higher than usual "Don't Know" responses may be due to the persons filling out the survey (usually financial analysts), who are unlikely to have reliable measures of intensive (or extensive) use for the various technologies, as this is not typically a line-item found on a balance sheet. Note also that Census was unable to perform a follow-up to the item non-response for the technology module in the 2018 ABS. However, in the follow-up year of the ABS (2019 ABS), we find that the number of "Don't Know" responses declined.

question should be—of the three technology questions—least affected by the combined effect of item non-response and "Don't Know" issues.

As we highlight below, our preliminary analysis reveals that both size and age appear to be significant predictors of various forms of technology adoption. Excluding the "Don't Know" or missing responses from the sample may bias our findings and paint an incorrect picture of the types of firm that adopt frontier technologies. To address this, we impute responses for firms who left an item as "Missing" or "Don't Know" across the usage categories based on identifiable firm characteristics, while simultaneously reporting an estimated lower bound on usage rates.[26] The lower bound of the range is determined by assuming all of the missing and "Don't Know" responses are "Do Not Use" and are reported throughout the tables in parentheses. The imputed response for each firm is determined by performing an ordered probit on each of the usage categories based on firm size, average payroll per employee, age and 2-digit industry. For cloud services, we also use the responses for digitization as an explanatory variable; for business technologies, we further use the responses for both digitization and cloud services.[27] The ordered probit provides a set of probabilities for each of the usage categories for all three technology questions. These corresponding probabilities are then combined with the tabulation weights and tabulated. Note that for firms who responded to one of the usage categories (as either "None" or some usage), their values are kept as-is. It is only firms who left the item blank or responded with "Don't Know" for whom probabilities are tabulated in the analysis below.

Lastly we describe our process for creating tabulation weights using the 2017 Longitudinal Business Database (LBD). Because the ABS has replaced the SBO, which is designed to represent the economy's set of business *owners*, the survey weights assigned to firms in the ABS are in part determined by business owner characteristics. This type of sampling frame—along with the fact that our final sample is only the subset of firms that actually responded to the survey—means that the weighted distribution of certain firm characteristics

[26] For the digitization and cloud services questions, the usage categories consist of "None", "Less than 50%", "More than 50%" and "All". For the business technologies questions, the usage categories consist of "None", "Testing", "Up to 5%", "Between 5% and 25%" and "More than 25%".

[27] We first group all of the response options into the usage categories, counting the "Not Collected" option from the Digitization question as "None" and the "Do not use IT function" from the Cloud Services question into "None". As we demonstrate later in the paper, the technology categories appear hierarchical, implying that firms will be more (less) likely to purchase (not purchase) cloud services if they have (do not have) information in a digital format and so forth.

may not actually be representative of the economy. We confirm this by comparing the distributions of weighted firm counts and employment across NAICS sectors to their respective distributions in the 2017 LBD.[28] Thus, to better represent the entire economy in our analysis, we construct tabulation weights based on the universe of firms in the 2017 LBD. Our weights are calculated by stratifying the firms in the 2017 LBD and our final sample of firms in the ABS into strata characterized by firm size, age, and industry. These strata are defined by the 19 two-digit NAICS sectors, and the 12 firm size and 12 firm age groups used in the Business Dynamics Statistics (BDS). All firms in a given stratum are assigned the same weight, which is calculated by dividing the number of firms in that stratum from the 2017 LBD by the number of firms in that stratum from the ABS sample.[29] With these new tabulation weights, we match much more closely the firm and employment distributions in the 2017 LBD.

We now turn to detailed analysis of the three questions in the next three sections. Given the abundance of results, we have organized each of the sections in the same manner. Each section has the same set of subsections: summary of the results (subsection A), adoption and use rates (subsection B), industry breakdown (subsection C), relation to firm size and age (subsection D), and summary remarks.

4. Digital Share of Information by Business Activity

The first question on the 2018 ABS technology module queried firms on the type of information stored digitally.

A. *Summary of Responses*

Figure 1 contains the frequencies of responses for the digital share of information by business activity or function. The responses signal that digitization is widely adopted across the majority of firms, with most firms electing to store their personnel and financial information digitally. Other types of information, such as supply chain and production information, were less

[28] Note that the LBD is the underlying data used in creating the Business Dynamics Statistics (BDS), which reports economy-wide statistics on firms and establishments.
[29] To account for unusually large weights caused by too few ABS firms in a stratum, we also winsorize the tabulation weights at the 99.99th percentile.

likely to be stored digitally mainly due to firms not collecting those types of information in any format.

For firms that did respond in the affirmative for each type of information, the most frequent response is “more than 50%”, followed by “all”, and then “up to 50%.” In particular, there is a large number of firms indicating full digital information use for personnel and financial business activities. These categories represent the highest overall use of digital information, followed by customer feedback and marketing. Table 5 lists the three most common information types digitized by sector. In all sectors financial and personnel information are the most likely to be digitized.

B. Adoption and Use Rates

Table 6 contains the adoption and intensive use shares for digital information by business function. A firm is considered an adopter if its response indicates at least some use of digital information in a business function. According to our tabulation weights, 79.1% (65.5% non-imputed) of firms have stored at least one type of information in digital format. Consistent with the frequencies in Table 5, the highest rates of adoption are in financial, personnel, and marketing activities. The relatively high rates of adoption in these categories are not surprising, as most firms rely on basic financial and personnel functions, regardless of sector. On the other hand, the lowest rates of adoption are observed in production and supply chain activities, in part driven by the fact that these activities are more concentrated in the manufacturing sector, which does not comprise a large share of firms in the U.S. economy. Also shown in Table 6, the incidence of intense use (more than 50% or all) parallels the basic adoption rates by function. The most intense use is in financial functions, where nearly 62% of the firms use digital information at high intensity. In contrast, supply chain function has the lowest incidence of intense use at about 19%.

Table 7 highlights the five business function pairs that have the highest co-presence (correlation) with adoption of digital information. This The correlations indicate the extent to which the two functions as a pair together rely on digital information and potentially highlights any complementarities between the information types. The highest correlation (0.70) occurs in the financial and personnel pair, which is consistent with the fact they are the top two adoption rates in Table 6. The next pair is marketing and feedback, which have a correlation of 0.69. The high correlation for this pair is sensible if firms that use digital information in their marketing activities also tend to have digitized customer feedback platforms. The relatively high correlation for the pair supply chain and production is also intuitive. Production and supply chain activities complement one another and the reliance on digital information in production pairs well with digitization of information in the supply chain.

C. Industry Breakdown

Figure 2 is a butterfly chart of adoption and use rates for digital information by sector. The right panel of the chart represents, by sector, the adoption rate of digital information across all surveyed information types. The adoption rate is highest (about 90%) in Information, followed by Professional Services and Education. The sectors with the lowest adoption rates are Transportation & Warehousing, Retail Trade, and Other (Arts, Food, Other). The segments within each bar in the chart capture adoption rates by the number of information types in digital format. The leftmost segment in the right panel indicates the share of firms that have digitized at least three types of information, the next segment adds firms with exactly two information types digitized, and the final segment represents with only one type of information digitized. In all sectors, a large share of the adopters report having three or more types of information digitized.

The left panel of Figure 2 represents intense use of digitization (defined as “50% or more” or “all”) by sector. Once again, Information leads with nearly 85% of firms indicating intense use. In general, the ranking of sectors by adoption and use rates parallel each other. Similar to the extensive margin measures, most firms report digitizing at least three types of information, regardless of sector. In fact, the fraction of firms digitizing only one type of information is relatively small in each sector. Overall, digitization appears to be highly prevalent across sectors and information types.

D. Relation to Firm Size and Age

Table 8 provides the coefficients of the connection between the adoption of digital information, on the one hand, and firm size and age, on the other. Specifically, the table reports the estimated coefficients[30] from a Linear Probability Model (LPM) where the data are centered, the dependent variable is an indicator of whether a firm uses at least one type of digital information, and the independent variables are pairwise interactions of four size categories and four age categories (16 size-age cells in total). [31] The estimated coefficients for size-age cells indicate that for a given size level, the presence of digital information slightly increases with firm age, with the exception of the smallest size category, where the use indicator actually declines with age. This observation is consistent with research that old, small firms are a relatively low-growth and less advanced segment of the firm population, and thus may be less reliant on digital information in business functions, which has been supported in Jin and McElheran (2017). In general, the adoption pattern is monotonic according to size, with the largest firms having the highest rates of adoption. With age, the general pattern is more nuanced. For smaller firms (1-9 employees), age is negatively associated with adoption rates, with a smaller proportion of old small firms adapting their information digitally than young firms. However, as the size increases, this pattern changes, with age positively associated with increased adoption of digitization.

To summarize, the majority of firms have digitized at least one source of information. Both financial and personnel information are the most likely sources of information to be digitized, with both information types intensively digitized. Manufacturing, Information and Professional Services are among the highest adopters of digitization, with size being a key determinant of adoption. The next section looks at cloud service purchases.

5. Cloud Service Purchases by IT Function

This section describes the adoption patterns for cloud service purchases across size, age and sector. We see similar, but lower, rates of adoption across the categories of cloud services, with firms electing to host multiple IT functions in the cloud rather than concentrating cloud purchases within a single IT function.

[30] All coefficients are statistically significant at a 1% level of significance.

[31] The results from a Probit specification yield essentially identical estimates for the digital information technology, and for most of the other technologies discussed below. Hence, we uniformly use an LPM for all specifications that follow later in the paper. For further information on limitations and potential biases introduced from estimating a probability model using ordinary least squares (OLS) see Horrace and Oaxaca (2006).

A. *Summary of Responses*

Based on our tabulation weights, the majority of firms (59.7% (43% non-imputed)) purchase at least one cloud service. These purchases vary across several functions, with almost no concentration in a specific function, as found in Figure 3. In addition, a large number of firms also indicated that they did not know whether they had any cloud purchases. For many IT functions, the frequency of responses was typically highest for “up to 50%” category followed by “more than 50%”, and “all”. Exceptions to this are in Security or Firewall and Billing and Account functions, and to some extent in Servers. For these functions, more firms reported in the “all” category compared to “more than 50%.” The Data Analysis function has the lowest number of firms reporting some cloud purchase, whereas Billing and Account Management had the highest number of firms, closely followed by Security or Firewall and Collaboration and Synchronization functions.

B. *Adoption and Use Rates*

Table 9 contains the adoption and intensive use shares for purchased cloud services by business function. A firm is considered an adopter if its response indicates at least some use of cloud services in a business function. First, when all functions are considered, both the adoption rates of cloud services and their intense-use rates tend to be generally lower than the adoption of digital information in Table 6. The highest adoption and intense-use rates are observed for Billing, Security and Synchronization, whereas the lowest rates are in Customer Relations and Data Analysis. The lowest adoption and intense-use rates in Data Analysis may be an indication that not many firms are using this specialized IT function. The rates in Table 9 indicate that purchased cloud services are more prevalent in relatively basic IT functions such as Billing and Security, and adoption and intensity are lower in more-specialized functions. Overall, about a quarter of the firms have indicated adoption of purchased cloud services in All IT functions.

One notable pattern for cloud services purchased is the lack of a single mass concentration for a particular type of service. This suggests that firms are utilizing the cloud for a variety of business processes and perhaps speaks to the flexibility and adaptability of the cloud. The ranking of the intense-use rates (intense defined as “50% or more” and “all”) is similar to the ranking of the adoption rates, with a few exceptions. In particular, intense usage in Data

Storage and Servers services are higher than Synchronization and All IT cases. Data Analysis is lowest ranked in terms of intense use, as with its ranking in the adoption rates.

Table 10 shows the top five business function pairs that have the highest co-presence (correlation) in terms of adoption of purchased cloud services. As in Table 7, the correlations indicate the extent to which the two functions in a pair tend to rely (or not rely) on cloud service purchases. The highest correlation (0.74) occurs in the Servers and Security pair, which may be driven by the fact that Security, which has the highest rate of adoption for cloud services, could go hand-in-hand with a need to protect servers. The relatively high correlations between All IT functions and Security, Servers, and Storage may not be too surprising, as these functions are often times bundled together in cloud-hosting services. The third-highest correlation is for the pair Servers and Storage (0.68), which is consistent with servers unsurprisingly needing storage services.

C. *Industry Breakdown*

Similar to Figure 2, Figure 4 provides the butterfly chart for adoption and intense-use rates across sectors in the case of purchased cloud services. Similar to digitization, the highest adoption and intense-use rates are in Information, followed closely by Professional Services and Education. The lowest rates are in Agriculture, Mining and Utilities, Retail Trade, and Transportation & Warehousing, in addition to the Other category. These ranking are consistent with a prior that IT-intensive sectors such as Information, Professional Services, Education and Health Care should have more reliance on cloud services. Figure 4 also reveals that cloud services purchases have much lower diffusion rates compared to the diffusion rates of digital information for any given sector. For instance, in the Information sector, the digital information diffusion rate based on at least some use in a business activity is about 90%, compared to the diffusion rate of purchased cloud services, which is about 79%.

As in the case of digital information use, for all sectors there is a large fraction of firms relying on cloud services for 3 or more IT functions, indicating that conditional on using some cloud services, firms tend to use those services for many IT functions, regardless of sector. Table 11 shows that Billing and Security are the most common IT functions for most sectors, with certain sectors predominantly relying on the cloud to perform collaborative or synchronized tasks. Almost half the sectors list “All IT functions” as the third most common use in the cloud.

This seems to be suggestive that digitization and cloud usage is most efficient when used and shared across multiple platforms. This may be due to a variety of reasons such as shared infrastructure, personnel, lower marginal costs or complementarities in functionality.

D. Relation to Firm Size and Age

The adoption rate coefficients of purchased cloud services by size and age are shown in Table 12. As in Table 8, the cells contain the magnitudes of the estimated coefficients[32] from a Linear Probability Model, where the dependent variable is an indicator for a firm purchasing cloud services for at least one IT function and the independent variables are 16 size-age bins. While the adoption rates for cloud services are generally lower than for digital information across all cells, the patterns are broadly similar. For the smallest size category (1-9 employees), the adoption rate declines with age, from 0.61 to 0.5, moving from the youngest (0-5 years old) to the oldest (21+ years old) firms. For the middle size categories (10-49 or 50-249 employees), the variation across age categories is much less. For the largest size category (250+ employees), there is a non-monotonic pattern, with adoption rate increasing with age first and then declining. The smallest-oldest category has the lowest adoption rate, consistent with the pattern for digital information. The highest rates occur for firms in the higher size categories, again consistent with digitization patterns. The relatively higher rates of adoption for middle- and high-size categories may indicate that these firms are most likely to outsource IT services to a cloud computing provider, while smaller firms may either perform IT functions internally, not have a need for cloud computing and storage services or simply be somewhat slower to adopt.[33]

To summarize, the adoption rates for business IT functions in the cloud is significantly lower than the adoption rates of storing information digitally. However, this technology is fairly widespread, as nearly a third of every kind of IT function is being performed in the cloud and used intensively. We see a monotonic pattern of adoption by size similar to digitization, where the largest firms are the most likely to adopt some form of cloud computing services. The next section looks at business technologies and their patterns of adoption.

[32] All coefficients are statistically significant at a 1% level of significance.
[33] If it is the latter, we may be able to capture this in the follow-up year adoption patterns.

6. Advanced Business Technologies

In this section we analyze firm responses to the business technologies question. Due to their wide technological scope, we link the responses here with the previous technology adoption questions and perform a deeper set of analysis assessing the range of response categories

A. *Summary of Responses*

The frequency of responses in Figure 5 indicates that an overwhelming number of firms do not use the business technologies included in the module and many answered “Don’t know”. Based on our tabulation weights, only 8.6% (8.4% non-imputed) of firms adopt at least one of the listed advanced business technologies. Given the advanced and specialized nature of at least some of the technologies, it is not surprising that only a relatively small number of firms indicate any type of use: fewer than 7 percent of businesses report using any given technology, and most adoption rates are less than 2 percent on an unweighted basis. The highest use frequencies are observed in automated storage, touchscreens and machine learning. However, our analysis of the responses to the automated storage question indicated that firms most likely interpreted automated storage as mainly data storage and not the physical storage and retrieval systems the question was intended to measure.[34] As a result, the responses for this technology are not considered reliable and are dropped from the analysis.

B. *Adoption and Use Rates*

Table 13 provides the use and testing rates for each business technology. Perhaps not surprisingly, the highest use and testing rates are observed for the Touchscreen/Kiosks technology, which is relatively less specialized. Even so, the adoption rate is only 5.9% for this technology and the testing rate is quite small (0.9%). Machine learning technology comes second in use and testing rates, but the rates are quite low at 1.7% and 0.4%, respectively. Voice Recognition and Machine Vision, which are closely related to Machine Learning and can be considered as its application, have the next two highest use and testing rates.

[34] We performed multiple sets of analyses identifying the sectors and industries most likely to use automated storage and retrieval systems, and looked at technological similarities that were correlated with automated storage and retrieval systems. We found the publishing sector is the largest adopter and most likely to adopt automated storage. We also found a significantly higher correlation between automated storage and “data storage” in cloud computing than would be predicted. As a result, we concluded that subsequent analyses using automated storage as an outcome variable are likely to be invalid.

While robots are usually singled out as a key technology in studies of automation, the overall diffusion of robotics use and testing is very low across firms in the U.S. The use rate is only about 1.3% and the testing rate is 0.3%. This pattern seems to be driven by robots primarily being concentrated in manufacturing and in larger firms. In other words, the distribution of robots among firms is highly skewed, and the skewness in favor of larger firms can have a disproportionate effect on the economy that is otherwise not obvious from the relatively low overall diffusion rate of robots. The least-used technologies are relatively more specialized, such as RFID (1.1%), Augmented Reality (0.8%), and Automated Vehicles (0.8%). Looking at the pairwise adoption of these technologies in Table 14, we find that use or testing of Machine Learning and Machine Vision are most coincident. We find that use or testing of Automated Guided Vehicles is closely associated with use and testing of Augmented Reality and RFIDs.

Next, we turn to testing versus use rates across different technologies to assess which technologies are in earlier phase of diffusion (that is, where testing is high relative to use). In Figure 6, the y-axis represents the ratio of the fraction of firms testing to the fraction of firms using. The technologies are represented by the circles. The size of each circle corresponds to the use rate for that technology, with larger circles representing higher rates of use. Technologies are ordered in the figure by usage rate, low to high. As shown in panel a, the technology with the highest testing-to-use ratio is Augmented Reality, where nearly half as many firms as those using the technology report testing it. The next highest ratios are observed in RFID and Natural Language Processing and the lowest ratios are in technologies that are relatively more diffused, such as Touchscreens, Machine Learning and Machine Vision. For Touchscreens, for instance, only about 15 firms report testing the technology for every 100 that use it. It is notable that most testing-to-use rations are below 0.3, indicating that there are fewer than 30 firms testing the technology for every 100 using it.

The remaining panels of Figure 6 plot the testing-to-use ratio for technologies by firm size, age and manufacturing status. Panel b displays ratios by firm size, where small firms are defined as those with 1-9 employees and large firms are those with at least 250 employees. The blue circles capture usage among large firms and the orange circles represent usage among small firms. The sizes of the circles are smaller for small firms for each technology, consistent with the earlier finding that larger firms tend to use the business technologies at a higher rate, in general.

Interestingly, testing-to-use ratios are higher for small firms for Robotics and RFID technologies, but lower for Machine Learning, Voice Recognition, Natural Language Processing, Automated Vehicles, and Augmented Reality. The ratios are similar for large and small firms for Touchscreens and Machine Vision.

Panel c in Figure 6 shows the ratios by firm age. Young firms are defined as those that are 0-5 years old and old firms are the ones that are 21 years or older. Strikingly, testing-to-use ratios are almost uniformly higher for young firms compared to the old firms, in some cases substantially so. In the case of Augmented Reality, Natural Language Processing and Automated Vehicles, the ratios for the young are nearly double those for the old. The only technology where the two ratios are similar is Touchscreens, the less-specialized technology. It is interesting to note that circle sizes are similar across the two groups, reflecting the earlier finding that firm age is less of a predictor for technology use than is firm size. Overall, the patterns in Figure 6, panel c indicate that within the population of young firms there is a high rate of testing compared to use, whereas older and larger firms tend to either experiment less with these technologies or the diffusion of these technologies among the set of older and larger firms is mostly complete.

Finally, panel d in Figure 6 presents the testing-to-use ratios for manufacturing versus non-manufacturing industries. More of the technologies tend to be adopted and used within manufacturing, as indicated by the much larger circles for manufacturers (with the exception of Voice Recognition, Touchscreens, and Natural Language Processing). For the technologies most closely associated with automation, such as Machine Learning, Robotics and Machine Vision, manufacturing firms show significantly higher usage, as well as usage rates as compared to non-manufacturing firms. This seems to indicate that the these specific technologies have already found their place within or were designed specifically for use in the production process for manufacturing firms, while non-manufacturing firms are still experimenting with how these technologies can be implemented for their business. The largest differences in testing-to-use ratios across the two sector-based groups are in Voice Recognition, where testing is relatively more prevalent in manufacturing, and Natural Language Processing, where testing is relatively more intense in non-manufacturing.

C. Industry Breakdown

The butterfly chart in Figure 7 provides sectoral diffusion rates for all business technologies considered together. Manufacturing leads with about 15% of firms indicating use of at least one business technology, followed by Health Care (14%), Information (12%), Education (11%) and Professional Services (10%). The lowest diffusion rates for the technologies are in Construction, Agriculture, Mining and Utilities, Management and Administrative, and Finance, Insurance and Real Estate sectors. The rates of use in these sectors hover around 5%. Note that conditional on adoption, most firms across all sectors report using one technology, in stark contrast to the use of digital information and cloud services. It may be that the benefits of digital information and cloud services across business functions are much higher than for the use of these business technologies, either because they are more "general" in their application or because there are economies of scope in their adoption

The testing rates on the left panel of the figure reveals an interesting pattern. While Manufacturing leads sectors in the rates of adoption, the testing rate in manufacturing is not the highest. In fact, Information has the highest testing rate at about 6%, followed by Professional Services. These two sectors also have the highest testing-to-use ratio (0.48 and 0.36, respectively). The lowest ratios are in Health Care, Retail Trade and the Other (Arts, Food, and others).

Looking at the most common types of business technologies adopted by sector in Table 15, we find that there is substantial variation. The trade sector (retail, wholesale and more) primarily adopts touchscreens, followed by machine learning. Manufacturing is most likely to adopt machine learning followed by touchscreens and robotics. RFIDs are mostly commonly used in Retail, Wholesale, and Transportation sectors.

The three industries (4-digit NAICS) which have the highest adoption rate for a given technology are shown in Table 16. Some of these industries are those that we might expect to observe. Robotics use is highest in three manufacturing industries, with the highest rate in Motor Vehicle Parts Manufacturing (17%).[35] Machine Learning is most prevalent in Metalworking Machinery Manufacturing (12.3%) and Machine Shops (11.6%). Firms in these two industries provide pre-packaged and customized software to clients, and likely embed machine learning

[35] This finding is consistent with the preliminary findings from the Robotics question in the 2018 ASM on which manufacturing industries are the largest adopters, with a similar ranking across 4-digit NAICS

algorithms in the software products they design to address consumer and business needs. RFID use is most common in Warehousing and Storage (6%).

D. Relation to Firm Size and Age

How does the use of business technologies vary by firm size and age? Table 17 provides the estimated coefficients from a Linear Probability Model where the dependent variable is whether a firm uses at least one of the business technologies, and the explanatory variables are 16 size-age categories, as in Tables 8 and 12. A clear pattern emerges. First, the smallest firms have the lowest use rates, and the use rates tend to increase with size. Second, for small firms (less than 50 employees) use rates tend to decline with age, with oldest small firms having the lowest adoption rates in general. For larger firms (50+ employees), use rates exhibit the opposite pattern: as firm age increases, so does the use rate. The highest use rates are in largest and oldest firms. Another notable feature of the table is that for each age category, the use rate increases with size. Overall, these patterns suggest that size is an important predictor of business technology use, and the connection between age and technology use depends on size.

7. Discussion of Results in Light of Open Questions

The technology module of the 2018 ABS reveals several interesting patterns of technology adoption across firm size, age, and sector. Most notably, we find that adoption for the latest advanced technologies appears to be quite low, with adoption mainly being led by the largest and oldest firms. This is consistent with much prior work on IT adoption, which documents advantages for incumbent firms (albeit sometimes with a lag) due to mechanisms such as economies of scale or complementary organizational capital (Bertschek and Kaiser 2004, Tambe and Hitt 2012, Saunders and Brynjolfsson 2016). We also capture technologies at different states of diffusion, with digitization and cloud computing taking on relatively large and significant roles in business and, within adopting firms, across business functions.

The technology module, in its current state, can be used to address several open empirical questions related to technology adoption across firms. These include questions relating to dynamics and diffusion, ordering of technology adoption and the organizational capabilities and/or infrastructure required to adopt the most-advanced technologies. This data is also informative about technological complementarities (Milgrom and Roberts 1990 & 1995, Bertschek and Kaiser 2004, Brynjolfsson and Milgrom 2013), which have already been mentioned in describing some of the notable pairwise correlations. In addition to these questions, the module sheds light on technology's role in stimulating innovation. Finally, and most relevant, the module provides a glimpse into the macro-economic and distributional effects of technology use. Each of these questions are discussed below.

A. Technological Hierarchies

The three technology categories listed in the technology module seem to require different levels of technological sophistication for adoption, with digitization being the first step, and culminating in one of the advanced business technologies. This "hierarchy" in technological sophistication is apparent in Figure 8, which plots a Sankey diagram of firm counts that adopt each of the different technology categories. From the diagram, we can see that the vast majority of firms who utilize the cloud for their IT services also digitize their information. Similarly, we see that for the vast majority of firms that adopt at least one advanced business technology, they almost always purchase cloud services.

This clear evidence of hierarchy points to some of the challenges that firms may face, as well as barriers to technology adoption. In the firm size and age exercises, we found that the largest and oldest firms are by far the most likely to adopt at least one business technology, implying that scale effects may be an important determinant of technology adoption. And while it has been speculated that cloud services can "open" up unlimited computing power to smaller firms, the uptake of this technology and other advanced, nascent technologies is still very low, suggesting that the rates of return to investing in these technologies for smaller firms is not high enough to justify the costs. This may be due to the return being dependent on the scale of the data being used. Firms with small amounts of digital data have little reason to invest in high-powered computing or apply the latest machine learning algorithms to their data. On the other hand, the returns to access to high-powered computing and the latest advances in AI become much more apparent as digitization scales.

In panel b. of Figure 8, we plot a similar Sankey diagram for firms who test or use "Machine Learning", one of the core technologies associated with artificial intelligence. In this example, the majority of firms who adopt machine learning have multiple cloud computing purchases (usually 3 or more IT functions hosted on the cloud) and multiple pieces of their data digitized. Related to this idea of technological hierarchies, are technological complementarities, which we discuss in the next subsection.

B. Technological Complementarities

We started to explore the notion of technological complementarities when we listed the top five pairwise technological correlations within each category of technology. The idea behind technological complementarities is that adopting one kind of technology is likely to lead to adopting another type, or that certain technology types require adoption of multiple technologies in order to fully benefit.

To further explore this idea, we look at the highest cross-category pairwise correlations with each of the advanced business technologies. We find that for many of the core elements of artificial intelligence, namely machine learning, machine vision, and natural language processing, the associated technology categories associated with these include digitizing production information and performing their data analysis on the cloud. These complementarities tell us that certain technologies may need to be adopted in tandem to fully reap the benefits of the technology.

C. Technology and Innovation

Adopting technologies is often associated with improvements in productivity and efficiency. However, it is not clear what mechanism within the firm causes these improvements, as adoption is also associated with higher labor costs (for higher skilled workers), training and learning, significant capital investments and perhaps changing some of the underlying fundamentals for the firm. These factors may also force the firm to innovate so that it can effectively adopt the new technology.

As an exercise, we look at how technology adoption is associated with measures of both product and process innovations within the ABS.[36] We estimated a linear probability model looking at whether a firm responded positively to producing a product or process innovation in the last three years based on their technology adoption, controlling for their size, age and

[36] Product innovation is defined as the business having introduced or significantly improved a new good or service, while process innovation is defined as the business having introduced or significantly improved their method of manufacturing, logistics, delivery or distribution methods or support activities.

industry. We group each of the firms into eight different technology categories: None (no use across all technology categories), Digitization Only, Cloud Only, Business Technology Only, Digitization and Cloud, Digitization and Business Technology, Cloud and Business Technology, All.

We plot the coefficients for these technology groupings in Figure 9.We see that as the technological sophistication increases, the magnitudes of the coefficients for both product and process innovations increases, indicating a positive association between technology adoption and innovation. We further decompose these regressions to each of the subcategories in panel b., looking at the adoption of each technology type on any (product or process) innovation. We see a surprising amount of heterogeneity across each technology type, with certain technologies having stronger and positive associations with innovation than others.

D. Macro/Distributional Outcomes of Technology Use

While a survey can tell us firm exposure to certain technologies, it does not tell the whole story for the worker and the technologies to which workers are exposed. In this section, we weigh some of the key statistics by employment and demonstrate how some of the key advanced business technologies, despite having relatively low adoption rates at the firm-level, have significantly higher worker exposure rates for certain technologies.

Weighted by the tabulation weights, the adoption rates of digitization, cloud services and at least one advanced business technology are 79.1% (65.5%), 59.7% (43%) and 8.6% (8.4%) respectively. However, if we assume that each worker within the firm is exposed to the technology, then the adoption rates for digitization, cloud services and at least one business technology change to 93.7%, 90.1% and 42.4%. The employment-weighted shares of adoption for all technology types differ quite dramatically from the weighted results, with the employment-weighted adoption rates for advanced business technologies being nearly 5x higher. Therefore, while the firm-level adoption rates for advanced business technologies is quite low, more than 4 of 10 workers are part of firms that have adopted at least one of the technologies. Second, more than 9 out of 10 workers are in firms that have adopted at least one form digital information and purchased cloud services. These findings raise some important questions regarding the macroeconomic/distributional impacts of these technologies, especially if we believe that these technologies will someday substitute for labor.

Taking a closer look at each of the business technologies in Table 19, we find that the business technologies with the highest discrepancies between the firm-weighted adoption rates and employment-weighted adoption rates are Robotics and RFID, each of which has an 8x higher employment-weighted adoption rate. One of the limitations of the survey is that it is an enterprise-level survey, while adoption of certain technologies may take place only at the establishment, suggesting that the employment-weighted exposure measures listed here are an upper bound. Nevertheless, the key message is that while firm exposure to advanced technologies tends to be concentrated and limited to a relatively small subset of firms, worker exposure to the technologies may in fact be significantly higher.

E. Technology as Equalizer

One of the key reasons why economists believe that technology adoption is important is that technology is often seen as the “great equalizer”. Young and small firms, who are usually seen as being more nimble, are able to quickly scale up using the cost savings and efficiency improvements from adopting the latest technologies as compared to old, large incumbents. One worrying aspect that this survey reveals, however, is that the latest technology adoption is mostly being done by the largest and older firms, potentially leading to increased separation between the typical firm and “superstar” firms.

One of the reasons for this may actually be driven by the technology itself, as much of the latest technology relies on scale effects to be useful. For instance, machine learning and artificial intelligence requires vast amounts of data in order to be effect and smaller firms may be unable to provide the necessary data where adopting these technologies proves efficient. This is worrying in the age of “superstar” firms, where the large firms can continuously reap efficiency gains from adopting and refining the latest technologies, which in turn, makes them larger and then makes the technology more and more productive.

8. **Conclusion**

We have provided an introduction to the technology module in the 2018 ABS and placed it in the larger context of related work at the Census Bureau to collect comprehensive data on technology adoption and use by U.S. firms in order to provide a more accurate picture of the state of advanced technology use in the U.S. economy. Because of the large pool of respondents (about 850,000 firms) in the 2018 ABS, the module represents a unique opportunity to offer insights on technology adoption and use across all sectors of the economy and across a variety of key firm characteristics.

Using this new collection, we provide a first look at the diffusion of digital information use, cloud computing purchases, and several new and emerging business technologies. A few key observations emerge. While the use of digital information in business functions and cloud computing purchases for many IT functions are highly prevalent across firms, the diffusion of the business technologies is very limited. However, employment-weighted diffusion rates indicate that the presence of many of these technologies in large firms exposes many workers in the economy to these technologies. Further insights into how these new technologies impact the skill composition and demand for these workers will be unveiled in the 2019 ABS. In addition, there are important differences in the diffusion and intensive use rates across sectors. The analysis of the connection between the prevalence of different technologies and firm life-cycle indicators (firm size and age) reveals that technology adoption and use is not always monotonically related to these indicators.

In general, the business technologies explored in the module's third question are more prevalent in larger and older firms. This skewness in technology prevalence implies that generally low adoption rates for these technologies do not necessarily mean low economic impact overall. As the concentration of economic activity in larger and older firms in the U.S. economy increases over time, the effects of technology adoption by these firms will likely have growing influence on key economic aggregates, such as employment and productivity. It is our hope that this paper serves as an impetus for further research using this new data set to help answer these important questions.

Looking towards the future, we will continue to validate the responses from the survey by incorporating and comparing output from existing Census data on technology use such as the 2018 ASM, 2018 BRDIS (and 2019 BERD) and 2018 ACES. We also plan to utilize administrative data, such as patents linked to Census data (see Graham et al. 2018) to help validate responses and look outside towards external researchers utilizing the Federal Statistical Research Data Centers (FSRDC) network to contribute their ideas on validating and improving the data. Finally, looking even further in the future, the same technology module is expected to be a part of the 2021 Annual Business Survey, providing a panel dimension for the set of firms queried on both modules.

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Text Box 1: 2018 Annual Business Survey Technology Questions

DIGITAL SHARE OF BUSINESS ACTIVITY

In 2017, how much of each type of information was kept in digital format at this business? ***Select one for each row.***

	None	Up to 50%	More than 50%	All	Don't know	This type of information not collected by this business
A. Personnel	☐	☐	☐	☐	☐	☐
B. Financial	☐	☐	☐	☐	☐	☐
C. Customer Feedback	☐	☐	☐	☐	☐	☐
D. Marketing	☐	☐	☐	☐	☐	☐
E. Supply Chain	☐	☐	☐	☐	☐	☐
F. Production	☐	☐	☐	☐	☐	☐
G. Other: (specify) ____________________	☐	☐	☐	☐	☐	☐

CLOUD SERVICE PURCHASES

Considering the amount spent on each of these IT functions, how much was spent on cloud services? (Cloud services are services provided by a third party that this business accesses on-demand via the internet.) ***Select one for each row.***

	None	Up to 50%	More than 50%	All	Don't Know	Don't use this IT function
A. All IT functions	☐	☐	☐	☐	☐	☐
B. Security or firewall	☐	☐	☐	☐	☐	☐
C. Servers	☐	☐	☐	☐	☐	☐
D. Data storage and management (Examples:	☐	☐	☐	☐	☐	☐

	Amazon Web Services, IBM Bluemix, Microsoft Azure)						
E.	Collaboration and file synchronization (Examples: Dropbox, OneDrive, Google Drive)	☐	☐	☐	☐	☐	☐
F.	Data Analysis	☐	☐	☐	☐	☐	☐
G.	Billing and account management	☐	☐	☐	☐	☐	☐
H.	Customer relationship management	☐	☐	☐	☐	☐	☐
I.	Other: (specify) ________________	☐	☐	☐	☐	☐	☐

BUSINESS TECHNOLOGIES

In 2017, to what extent did this business use the following technologies in producing goods or services? ***Select one for each row.***

	No use	Testing, but not using in production or service	In use for less than 5% of production or service	In use for between 5% – 25% of production or service	In use for more than 25% of production or service	Don't know
A. Augmented reality	☐	☐	☐	☐	☐	☐
B. Automated guided vehicles (AGV) or AGV systems	☐	☐	☐	☐	☐	☐
C. Automated storage and retrieval systems	☐	☐	☐	☐	☐	☐
D. Machine learning	☐	☐	☐	☐	☐	☐
E. Machine vision software	☐	☐	☐	☐	☐	☐
F. Natural language processing	☐	☐	☐	☐	☐	☐
G. Radio-frequency identification (RFID) inventory system	☐	☐	☐	☐	☐	☐
H. Robotics	☐	☐	☐	☐	☐	☐
I. Touchscreens/kiosks for customer interface (Examples: self-checkout, self-	☐	☐	☐	☐	☐	☐

Text Box 2: 2018 Annual Business Survey Technology Definitions

Augmented reality	Technology that provides a view of a real-world environment with computer-generated overlays.
Automated guided vehicles (AGV) or AGV systems	A computer-controlled transport vehicle that operates without a human driver. AGVs navigate facilities through the use of software and sensors.
Automated storage and retrieval systems	Technology that locates, retrieves, and replaces items from predetermined storage locations.
Machine learning	Computer algorithms that use data to improve their predictive performance without being reprogrammed.
Machine vision	Technology used to provide image-based automatic inspection, recognition or analysis.
Natural language processing	Technology that allows a computer to process human speech or text.
Radio-frequency identification (RFID) system	A system of tags and readers used for identification and tracking. Tags store information and transmit them using radio waves. Readers maybe be mobile or fixed in place.
Robotics	Reprogrammable machines capable of automatically carrying out a complex set of actions.
Touchscreens/kiosks for customer interface (Examples: self-checkout, self check-in, touchscreen ordering)	A computer with a touchscreen that allows a customer to receive information or perform tasks related to the business such as registering for a service or purchasing items.
Voice recognition software	Software that converts speech to text or executes simple commands based on a limited vocabulary or executes more complex commands when combined with natural language processing.

Table 1: U.S. Census Bureau Surveys with Technology Information

Survey	Years	Topics
Annual Business Survey (ABS)	2017-2018	Software, Data Processing, Digitization, Cloud Services, Automation, AI, Robotics
Annual Capital Expenditures Survey (ACES)	2018	Robotics
	2002-2018	Software
Annual Retail Trade Survey (ARTS)	1999-2018	E-Commerce
	2002, 2017	Software, Data Processing
Annual Survey of Entrepreneurs (ASE)	2014-2016	E-Commerce, Tech on Profits
	2014	Software, Automation
Annual Survey of Manufactures (ASM)	2018	Robotics
	2000-2018	Data Processing
Annual Wholesale Trade Survey (AWTS)	1999-2018	E-Commerce
Business Research & Development and Innovation Survey (BRDIS)	2008-2016	Software
Business R&D and Innovation Survey - Microbusiness (BRDI-M)	2014, 2016	Software, Automation
Census of Construction Industries (CCN)	2012	Software, Data Processing
	2002	E-Commerce
Census of Manufacturing (CMF)	2002, 2007, 2012	E-Commerce, Data Processing
Census of Retail Trade (CRT)	2017	Self-service technologies
Computer Network Use Supplement (CNUS)	1999	E-Commerce
Information and Communication Technology Survey (ICTS)	2003-2011, 2013	ICT, Software
Management and Organizational Practices Survey (MOPS)	2010, 2015	Data-Driven Decisions
Service Annual Survey (SAS)	2005-2016	E-Commerce
Survey of Business Owners (SBO)	2007, 2012	E-Commerce
Survey of Manufacturing Technology (SMT)	1988, 1991, 1993	Software, Automation, Robotics

Table 2: Relevant Other Surveys on Technology Use

Source (Authors)	Years	Observation Count/Type	Topics
Helper, Seamans, Reichensperger, and Bessen	2018	Ongoing/Establishment	Automation, Robotics, Data Processing
Nancy Green Leigh	2017	428/Establishment	Automation, Robotics
Harte Hanks	1996-2015	?/Establishment	ICT, Software, Cloud Services
Susan Helper	1989	286/Firm	Automation
Deloitte - State of AI in the Enterprise	2018	1,100/Firm	AI
Narrative Science in Partnership with National Business Research Institute	2017	197/Firm	AI
Accenture – Technology Vision	2019	6,672/Firm	AI
McKinsey Digital Manufacturing Global Expert Survey	2018	<700/Firm	Digital Manufacturing
McKinsey – Global Lighthouse Network	2018-2019	44/Site	Business processes, management for manufacturing establishments that have scaled “4th industrial revolution” solutions

Table 3: Response Rates and Sample Construction*

	# of Responses
Initial Mailout (June 2018)	850,000
Response[37]	583,000
Linked to 2017 Longitudinal Business Database (LBD)	573,000

[37] Survey response is determined by whether the respondent answered question 1 of the survey, which asks whether the business has ceased operations. Note that there are several instances and sections of the survey where responses are missing or left blank. These are classified as “item non-response”. If the firm ceased operations at the time of the survey and are matched to the LBD, we retain the records for that firm and that firm is still included in our main sample.

Table 4: Summary Statistics and Distributions of ABS Respondents*

a. Firm Level Statistics

Mean	ABS Responses	ABS Responses (Weighted)	2016 BDS
Employment	89.32	26.28	24.05
Age	16.33	15.61	n.a.

b. Firm Distributions (in %)

By Size	ABS Sample (Raw)	ABS Sample (Weighted)	National (2016 BDS)
1 to 9	67	75	76
10 to 49	21	20	20
50 to 249	8	4	4
250+	3	1	1

By Age	ABS Sample (Raw)	ABS Sample (Weighted)	National (2016 BDS)
0 to 5	25	27	33
6 to 10	16	17	17
11 to 20	25	25	23
21+	33	31	27

c. Sectoral Distribution (in %)

Sector	ABS Sample (Raw)	ABS Sample (Weighted)
Agriculture, Mining, Utilities	2	1
Construction	10	11
Education	1	2
Finance, Insurance, Real Estate	10	9
Health Care	9	11
Information	2	1
Management & Administrative	5	6
Manufacturing	8	4
Other (Arts, Food, Other Services)	14	23
Professional Services	17	13
Retail Trade	13	11
Transportation & Warehousing	4	3
Wholesale Trade	5	5

*Note: Tables tabulated from linked 2018 ABS data with the 2017 Longitudinal Business Database (LBD). The 2017 size, age and industry figures from the LBD are the figures listed in the tables. Firms that did not respond to any of the 2018 ABS survey are excluded. Industry tabulations for multi-unit firms are generated from the largest payroll industry within the firm (if there is a tie, then the largest employer is used).

Table 5: Top Use Digitized Information by Business Function by Sector

	Business Function		
Sector	1st	2nd	3rd
Agriculture,..., Mining, Utilities	Financial	Personnel	Production
Construction	Financial	Personnel	Marketing
Manufacturing	Financial	Personnel	Production
Wholesale Trade	Financial	Personnel	Marketing
Retail Trade	Financial	Personnel	Marketing
Transportation & Warehousing	Financial	Personnel	Marketing
Information	Financial	Personnel	Marketing
Finance, Insurance, Real Estate	Financial	Personnel	Marketing
Professional Services	Financial	Personnel	Marketing
Management & Administrative	Financial	Personnel	Marketing
Education	Financial	Personnel	Marketing
Health Care	Financial	Personnel	Marketing
Other (Arts, Food, Other)	Financial	Personnel	Marketing

Notes: "Use" is defined as having responded with "Up to 50%", "More than 50%" or "All" for the information category listed on "Digital Share of Business". Shares are computed using the tabulation weights of firm counts, divided by the total number of firms (including those that left the responses as "Don't Know" or missing). Imputed responses for Missing and "Don't Know" categories are used in the numerator.

Table 6: Use of Digital Information by Business Function

Business Function	% Use	% Intensive Use
Financial	73.2 (62.4)	61.8 (52.5)
Personnel	59.8 (50.4)	44.2 (37.3)
Marketing	43.2 (35.5)	31.3 (25.9)
Feedback	37.8 (30.5)	27.6 (22.2)
Production	28.2 (23.6)	22.0 (18.3)
Supply Chain	26.4 (21.6)	19.3 (15.7)
Other	7.0 (5.6)	5.8 (4.6)

Notes: "Use" is defined as having responded with "Up to 50%", "More than 50%" or "All" for the information category listed on "Digital Share of Business". "Intensive Use" is defined as having responded with "More than 50%" or "All". Shares are computed using the tabulation weights of firm counts, divided by the total number of firms (including those that left the responses as "Don't Know" or missing). Listed shares are imputed shares, with raw values in parentheses.

Table 7: Top Pairwise Correlated Digitized Information Use by Business Functions

Function 1	Function 2	Correlation
Financial	Personnel	0.698 (0.737)
Marketing	Feedback	0.686 (0.678)
Supply Chain	Production	0.600 (0.598)
Supply Chain	Marketing	0.521 (0.521)
Supply Chain	Feedback	0.485 (0.484)

Notes: "Use" is defined as having responded with "Up to 50%", "More than 50%" or "All" for the information category listed on "Digital Share of Business". Correlation is defined as cross-category responses (Use/No Use) at the firm-level. Imputed values are listed, while raw values are in parentheses.

Table 8: Size-Age Coefficients for Digital Share of Business Activity

	Firm Size			
Firm Age	**1 to 9**	**10 to 49**	**50 to 249**	**250+**
0 to 5	0.75 (0.65)	0.85 (0.71)	0.89 (0.66)	0.89 (0.55)
6 to 10	0.73 (0.64)	0.84 (0.73)	0.90 (0.72)	0.92 (0.67)
11 to 20	0.71 (0.63)	0.85 (0.75)	0.91 (0.76)	0.91 (0.67)
21+	0.67 (0.59)	0.84 (0.75)	0.91 (0.79)	0.92 (0.72)

Notes: Size-Age coefficients generated from linear probability model (LPM) where the outcome variable is "Use/No Use" for at least one type of information that is digitized. Independent variables are the 16 size-age categories assigned to each firm and the LPM is weighted by the tabulation weights. All coefficients are significant to the 0.1%. All firms are included (including "Don't Know" and missing) with the dependent variable being imputed for firms whose responses are missing or "Don't Know".

Table 9: Cloud Service Purchases by IT Function

Cloud Service Purchased	% Use	% Intensive Use
Billing	39.0 (30.9)	25.7 (20.5)
Security	37.3 (27.6)	23.2 (17.2)
Synchronization	34.0 (26.1)	17.1 (13.2)
All IT	32.8 (24.7)	18.1 (13.7)
Data Storage	31.5 (24.1)	18.5 (14.2)
Servers	30.3 (23.0)	18.8 (14.3)
Customer Relations	26.1 (20.3)	15.3 (12.0)
Data Analysis	20.3 (15.3)	11.8 (9.0)
Other	4.8 (3.7)	3.3 (2.5)

Notes: "Use" is defined as having responded with "Up to 50%", "More than 50%" or "All" for the category listed on "Cloud Service Purchases". "Intensive Use" is defined as having responded with "More than 50%" or "All". Shares are computed using the tabulation weights of firm counts, divided by the total number of firms (including those that left the responses as "Don't Know" or missing). Listed shares are imputed shares, with raw values in parentheses.

Table 10: Top Pairwise Correlations among Cloud Service Purchases

Technology 1	Technology 2	Correlation
Servers	Security	0.741 (0.731)
Security	All IT	0.739 (0.716)
Servers	Data Storage	0.683 (0.669)
Servers	All IT	0.682 (0.659)
Data Storage	All IT	0.681 (0.664)

Notes: "Use" is defined as having responded with "Up to 50%", "More than 50%" or "All" for the category listed on "Cloud Service Purchases". Correlation is defined as cross-category responses (Use/No Use) at the firm level. Imputed values are listed, while raw values are in parentheses.

Table 11: Top Use Sub-Categories for Cloud Services by Sector

	Cloud Services		
Sector	**1st**	**2nd**	**3rd**
Agriculture,..., Mining, Utilities	Billing	Security	Synchronization
Construction	Billing	Security	Synchronization
Manufacturing	Security	Billing	Synchronization
Wholesale Trade	Security	Billing	Synchronization
Retail Trade	Billing	Security	Synchronization
Transportation & Warehousing	Billing	Security	Synchronization
Information	Synchronization	All IT	Billing
Finance, Insurance, Real Estate	Security	Billing	Synchronization
Professional Services	Synchronization	Security	All IT
Management & Administrative	Billing	Security	Synchronization
Education	Synchronization	Billing	Security
Health Care	Billing	Security	All IT
Other (Arts, Food, Other)	Billing	Security	All IT

Notes: "Use" is defined as having responded with "Up to 50%", "More than 50%" or "All" for the category listed on "Cloud Service Purchases". Shares are computed using the tabulation weights of firm counts, divided by the total number of firms (including those that left the responses as "Don't Know" or missing). Imputed responses for Missing and "Don't Know" categories are used in the numerator.

Table 12: Size-Age Coefficients for Cloud Service Purchases

	Firm Size			
Firm Age	**1 to 9**	**10 to 49**	**50 to 249**	**250+**
0 to 5	0.61 (0.45)	0.71 (0.52)	0.78 (0.50)	0.83 (0.43)
6 to 10	0.58 (0.42)	0.70 (0.53)	0.78 (0.54)	0.84 (0.52)
11 to 20	0.55 (0.40)	0.69 (0.53)	0.78 (0.57)	0.82 (0.50)
21+	0.50 (0.34)	0.67 (0.51)	0.77 (0.58)	0.81 (0.51)

Notes: Size-Age coefficients generated from linear probability model (LPM) where the outcome variable is "Use/No Use" for at least one type of cloud service purchase. Independent variables are the 16 size-age categories assigned to each firm and the LPM is weighted by the tabulation weights. All coefficients are significant to the 0.1%. All firms are included (including "Don't Know" and missing) with the dependent variable being imputed for firms whose responses are missing or "Don't Know".

Table 13: Business Technology Use Rates by Type

Business Technology	**% Use**	**% Testing**
Touchscreens	5.9 (4.6)	0.9 (0.7)
Machine Learning	2.8 (2.2)	0.7 (0.5)
Voice Recognition	2.5 (2.0)	0.7 (0.5)
Machine Vision	1.7 (1.4)	0.4 (0.3)
Robotics	1.3 (1.0)	0.3 (0.2)
Natural Language	1.2 (1.0)	0.4 (0.3)
RFID	1.1 (0.9)	0.3 (0.3)
Augmented Reality	0.8 (0.6)	0.4 (0.3)
Automated Vehicles	0.8 (0.6)	0.2 (0.2)

Notes: "Use" is defined as having responded with "In use for less than 5% of production or service", "In use for between 5% - 25% of production or service" or "In use for more than 25% of production or service " for the category listed on "Business Technologies" (excluding "Automated Storage and Retrieval Systems"). "Testing" is defined as having responded with "Testing but not using in production or service". Shares are computed using the tabulation weights of firm counts, divided by the total number of firms (including those that left the responses as "Don't Know" or missing). Listed shares are imputed shares, with raw values in parentheses.

Table 14: Top Pairwise Correlations among Business Technologies

Technology 1	**Technology 2**	**Correlation**

Machine Learning	Machine Vision	0.526 (0.516)
Automated Vehicles	Augmented Reality	0.492 (0.489)
Machine Vision	Natural Language	0.402 (0.395)
RFID	Automated Vehicles	0.390 (0.386)
Machine Vision	Automated Vehicles	0.386 (0.380)

Notes: Correlations are for whether a firm lists "Use" for a technology category. "Use" is defined as having responded with "In use for less than 5% of production or service", "In use for between 5% - 25% of production or service" or "In use for more than 25% of production or service " for the category listed on "Business Technologies" (excluding "Automated Storage and Retrieval Systems"). Imputed values are listed, while raw values are in parentheses.

Table 15: Top Use Sub-Categories for Business Technologies by Sector

	Business Technology		
Sector	**1st**	**2nd**	**3rd**
Agriculture,..., Mining, Utilities	Touchscreens	Machine Learning	Automated Vehicles
Construction	Touchscreens	Machine Learning	Voice Recognition
Manufacturing	Machine Learning	Robotics	Touchscreens
Wholesale Trade	Touchscreens	Machine Learning	RFID
Retail Trade	Touchscreens	Machine Learning	RFID
Transportation & Warehousing	Touchscreens	Machine Learning	RFID
Information	Touchscreens	Machine Learning	Voice Recognition
Finance, Insurance, Real Estate	Touchscreens	Voice Recognition	Machine Learning
Professional Services	Touchscreens	Voice Recognition	Machine Learning
Management & Administrative	Touchscreens	Machine Learning	Voice Recognition
Education	Touchscreens	Machine Learning	Voice Recognition
Health Care	Touchscreens	Voice Recognition	Machine Learning
Other (Arts, Food, Other)	Touchscreens	Machine Learning	Machine Vision

Notes: "Use" is defined as having responded with "In use for less than 5% of production or service", "In use for between 5% - 25% of production or service" or "In use for more than 25% of production or service " for the category listed on "Business Technologies" (excluding "Automated Storage and Retrieval Systems"). Shares are computed using the tabulation weights of firm counts, divided by the total number of firms (including those that left the responses as "Don't Know" or missing). In this scenario, "Use" for a business technology includes "Testing". Imputed responses for Missing and "Don't Know" categories are used in the numerator.

Table 16: Top 3 Industry Use Rates for Each Business Technology

Augmented Reality		Mean (All Industries)	0.009 (0.007)
5121	Motion Picture and Video Industries		0.040 (0.035)
5112	Software Publishers		0.030 (0.025)
5414	Specialized Design Services		0.027 (0.023)
Automated Guided Vehicles		Mean (All Industries)	0.008 (0.007)
1151	Support Activities for Crop Production		0.064 (0.059)
4245	Farm Product Raw Material Merchant Wholesalers		0.040 (0.039)
2379	Highway, Street and Bridge Construction		0.030 (0.028)
Machine Learning		Mean (All Industries)	0.032 (0.025)
3335	Metalworking Machinery Manufacturing		0.123 (0.108)
3327	Machine Shops; Turned Products; Screw, Nut and Bolt Manufacturing		0.116 (0.105)
3344	Semiconductor and Other Electronic Component Manufacturing		0.100 (0.083)
Machine Vision		Mean (All Industries)	0.020 (0.016)
3344	Semiconductor and Other Electronic Component Manufacturing		0.136 (0.123)
3335	Metalworking Machinery Manufacturing		0.111 (0.098)
3363	Motor Vehicle Parts Manufacturing		0.096 (0.084)
Natural Language Processing		Mean (All Industries)	0.014 (0.011)
5112	Software Publishers		0.060 (0.049)
5191	Other Information Services		0.054 (0.046)
5182	Data Processing, Hosting, and Related Services		0.049 (0.042)
RFID		Mean (All Industries)	0.014 (0.011)
4931	Warehousing and Storage		0.062 (0.056)
4248	Beer, Wine, and Distilled Alcoholic Beverage Merchant Wholesalers		0.056 (0.048)
3363	Motor Vehicle Parts Manufacturing		0.052 (0.045)
Robotics		Mean (All Industries)	0.018 (0.014)
3363	Motor Vehicle Parts Manufacturing		0.174 (0.158)
3261	Plastics Product Manufacturing		0.166 (0.151)
3335	Metalworking Machinery Manufacturing		0.141 (0.128)
Touchscreens		Mean (All Industries)	0.064 (0.049)
6231	Nursing Care Facilities (Skilled Nursing Facilities)		0.207 (0.155)
3121	Beverage Manufacturing		0.169 (0.147)
7139	Other Amusement and Recreation Industries		0.151 (0.125)
Voice Recognition		Mean (All Industries)	0.026 (0.021)
6215	Medical and Diagnostic Laboratories		0.176 (0.154)
6211	Offices of Physicians		0.139 (0.122)
6214	Outpatient Care Centers		0.083 (0.072)

Notes: “Use” is defined as having responded with “In use for less than 5% of production or service”, “In use for between 5% - 25% of production or service” or “In use for more than 25% of production or service ” for the category listed on “Business Technologies” (excluding “Automated Storage and Retrieval Systems”). Shares are computed using the tabulation weights of firm counts, divided by the total number of firms (including those that left the responses as “Don’t Know” or missing). Means generated from cross-industry means. In this scenario, “Use” for a business technology includes “Testing”. Imputed responses for Missing and “Don’t Know” categories are used in the numerator.

Table 17: Size-Age Coefficients for Business Technologies

	Firm Size			
Firm Age	**1 to 9**	**10 to 49**	**50 to 249**	**250+**
0 to 5	0.1 (0.08)	0.19 (0.14)	0.25 (0.16)	0.31 (0.15)
6 to 10	0.09 (0.07)	0.17 (0.13)	0.24 (0.17)	0.3 (0.18)
11 to 20	0.08 (0.06)	0.16 (0.13)	0.23 (0.17)	0.31 (0.19)
21+	0.07 (0.05)	0.14 (0.12)	0.26 (0.21)	0.37 (0.26)

Notes: Size-Age coefficients generated from linear probability model (LPM) where the outcome variable is "Use/No Use" for at least one type of business technology. Independent variables are the 16 size-age categories assigned to each firm and the LPM is weighted by the tabulation weights. All coefficients are significant to the 0.1%. All firms are included (including "Don't Know" and missing) with the dependent variable being imputed for firms whose responses are missing or "Don't Know".

Table 18: Technological Complementarities with Business Technologies

Business Technology	Most Correlated Digital Information	Correlation	Most Correlated Cloud Service	Correlation
Augmented Reality	Other Information	0.101 (0.083)	Other IT Functions	0.127 (0.105)
Automated Vehicles	Other Information	0.093 (0.079)	Other IT Functions	0.118 (0.102)
Machine Learning	Production	0.147 (0.129)	Data Analysis	0.172 (0.147)
Machine Vision	Production	0.131 (0.114)	Data Analysis	0.144 (0.122)
Natural Language	Other Information	0.100 (0.083)	Data Analysis	0.135 (0.114)
RFID	Supply Chain	0.118 (0.099)	Data Analysis	0.121 (0.101)
Robotics	Production	0.123 (0.107)	Data Analysis	0.103 (0.085)
Touchscreens	Feedback	0.194 (0.171)	Data Analysis	0.203 (0.17)
Voice Recognition	Feedback	0.108 (0.098)	All IT Functions	0.144 (0.124)

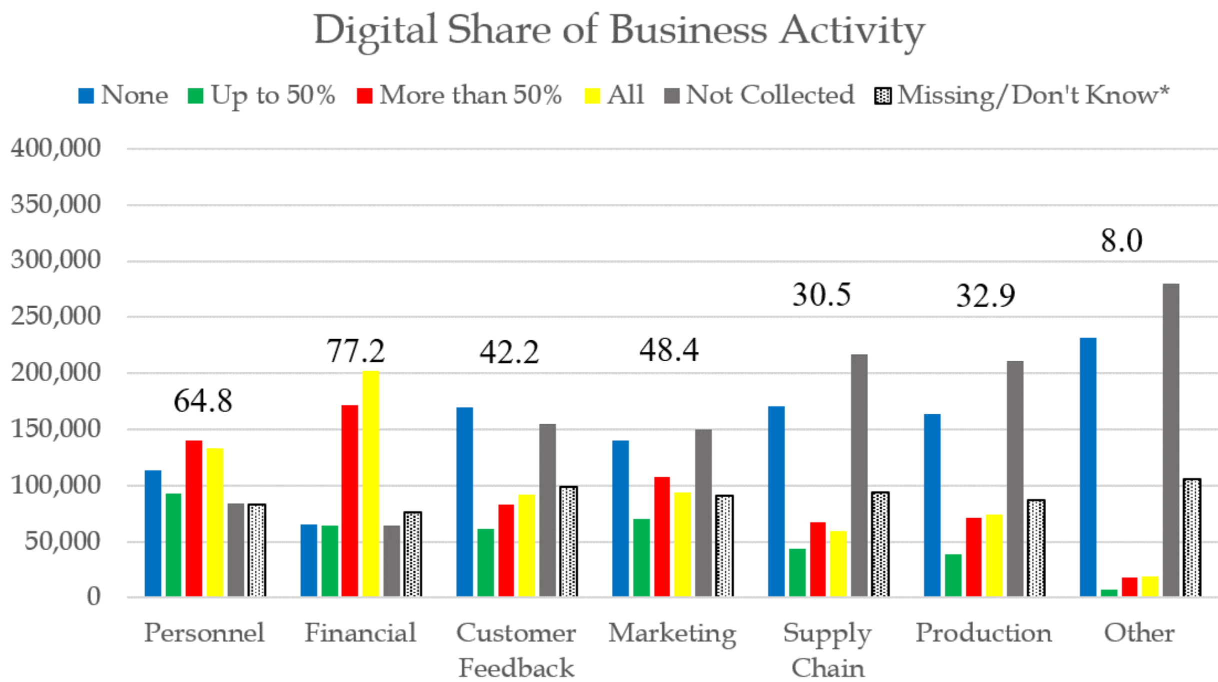
Notes: Correlations are for whether a firm lists “Use” for a technology category with “Use” in another technology category (Digitization or Cloud Computing). In this scenario, “Use” for a business technology includes “Testing”. Imputed values are listed, while raw values are in parentheses.

Table 19: Firm-Weighted versus Employment-Weighted Adoption Rates for Business Technologies

Business Technology	% Use (Tab-Weighted)	% Use (Employment-Weighted)	Difference Ratio
Touchscreens	5.9 (4.6)	25.7 (13.6)	4.4 (2.9)
Machine Learning	2.8 (2.2)	8.9 (5.2)	3.2 (2.4)
Voice Recognition	2.5 (2.0)	7.5 (5.9)	3.1 (3.0)
Machine Vision	1.7 (1.4)	5.6 (3.1)	3.3 (2.3)
Robotics	1.3 (1.0)	10.4 (6.4)	8.0 (6.1)
Natural Language	1.2 (1.0)	4.3 (3.5)	3.5 (3.5)
RFID	1.1 (0.9)	9.6 (4.9)	8.7 (5.6)
Augmented Reality	0.8 (0.6)	2.0 (1.4)	2.5 (2.2)
Automated Vehicles	0.8 (0.6)	2.2 (1.6)	2.8 (2.5)

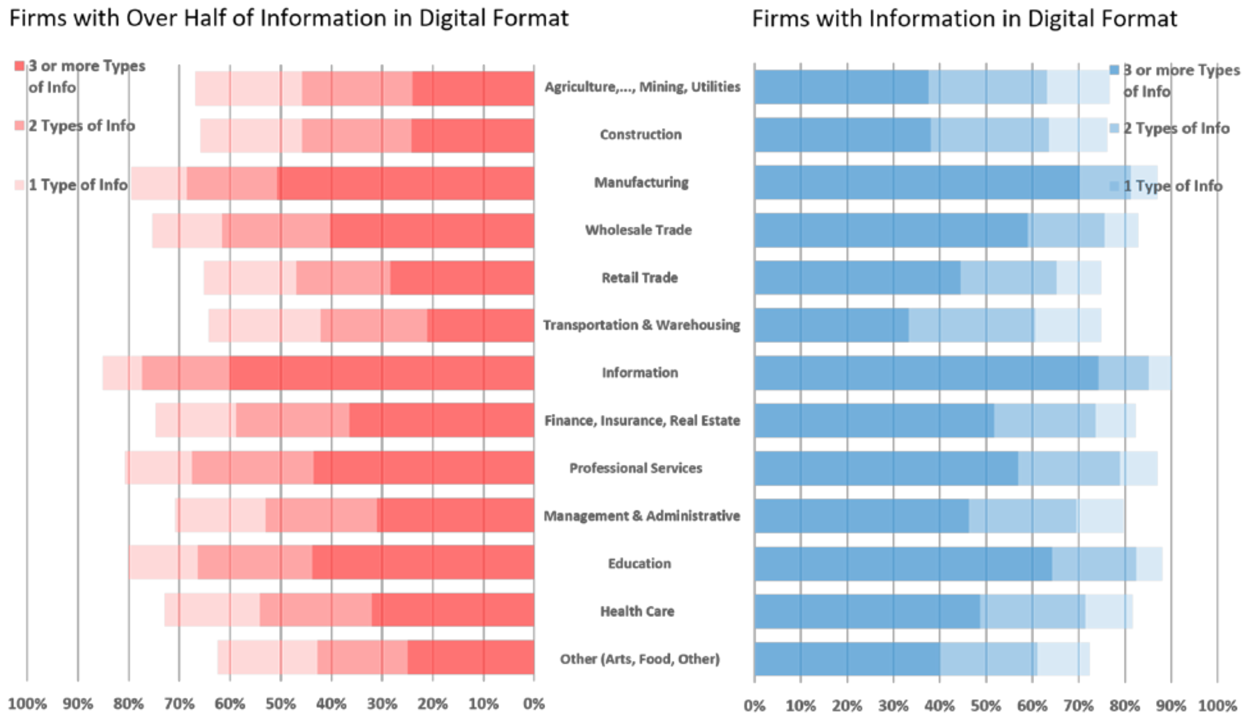
Notes: “Use” is defined as having responded with “In use for less than 5% of production or service”, “In use for between 5% - 25% of production or service” or “In use for more than 25% of production or service ” for the category listed on “Business Technologies” (excluding “Automated Storage and Retrieval Systems”). “Testing” is defined as having responded with “Testing but not using in production or service”. Shares are computed using the tabulation weights of firm counts, divided by the total number of firms (including those that left the responses as “Don’t Know” or missing). Employment weights are combined with the tabulation weights and the difference ratio is computed by dividing the Employment Weighted Use rate by the Tabulation-Weighted Use rate. Imputed values are listed, while raw values are in parentheses.

Figure 1: Firm Responses to Digital Share of Information by Business Activity



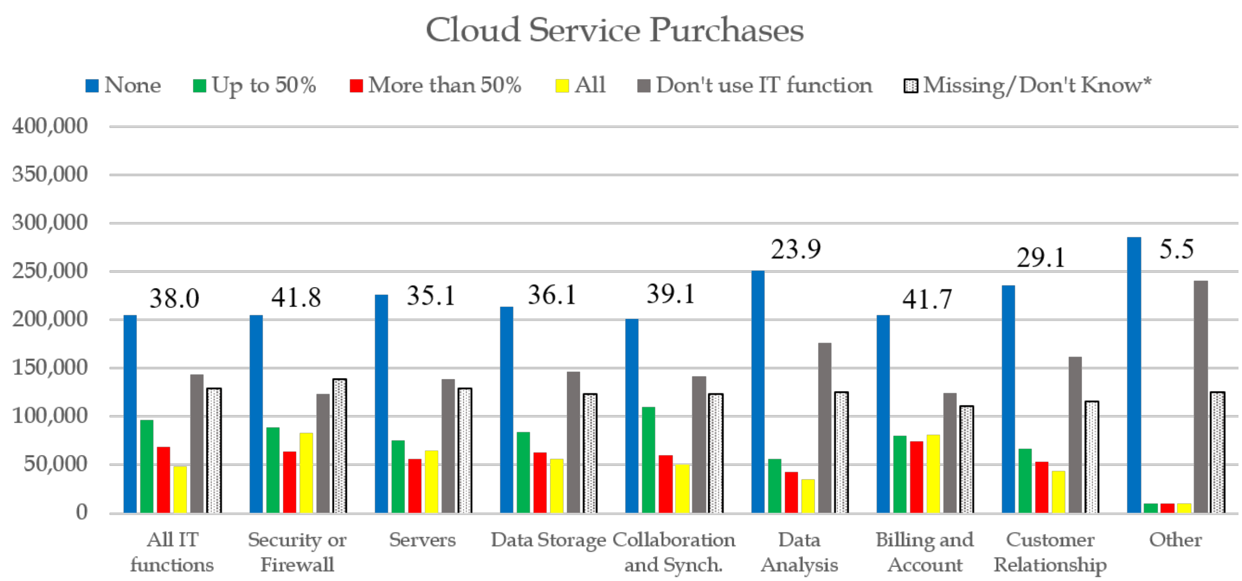
Notes: Tabulations based on unweighted responses. The number listed on top of the bar charts indicates the percentage of firms that responded to digitizing some form of information (either "Up to 50%", "More than 50%" or "All") as a share of the entire set of firms (unweighted).Missing/Don't Know responses are imputed across the other four response options ("None", "Up to 50%", "More than 50%" and "All").

Figure 2: Extensive and Intensive Margin Measures of Digitized Information by Sector



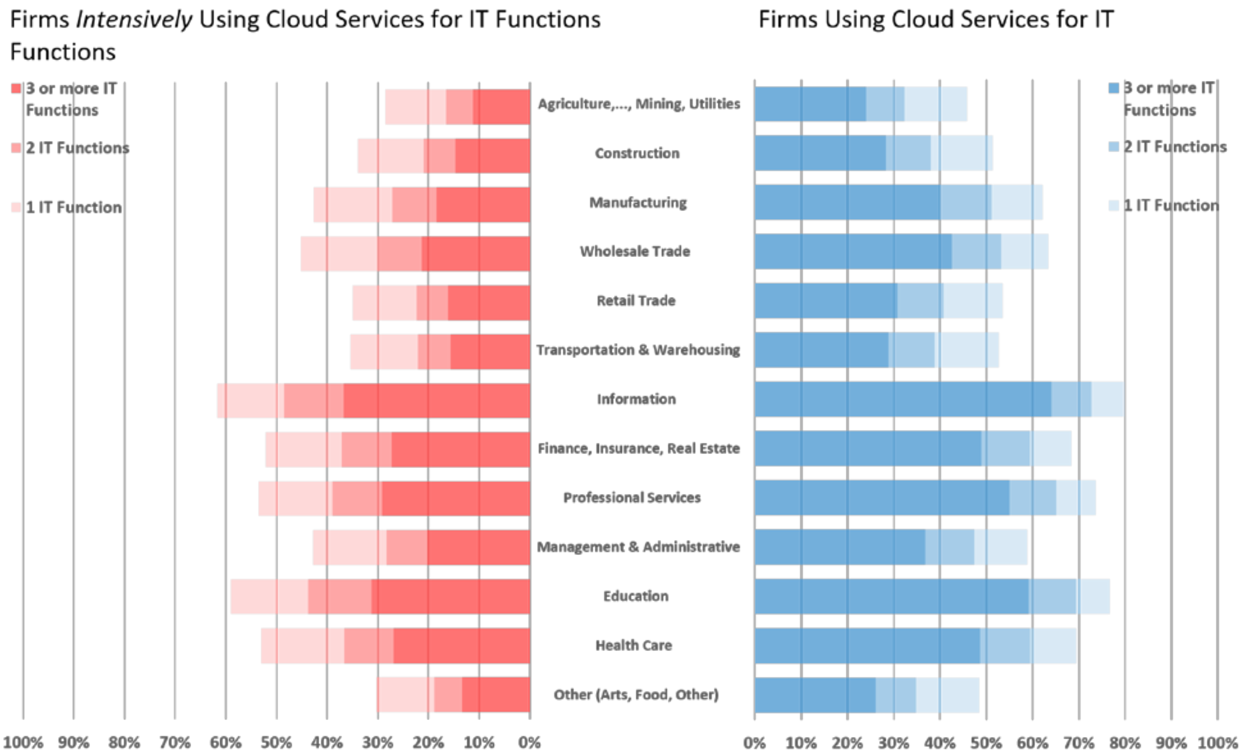
Notes: "Use" is defined as having responded with "Up to 50%", "More than 50%" or "All" for the information category listed on "Digital Share of Business". "Intensive Use" is defined as having responded with "More than 50%" or "All". Shares are computed using the tabulation weights of firm counts, divided by the total number of firms (including those that left the responses as "Don't Know" or missing). Sectors are defined by combined 2-digit NAICS and assigned for multi-unit firms by largest payroll industry by firm. Original responses classified as "Missing" or "Don't Know" are imputed.

Figure 3: Firm Responses to Purchases of Cloud Service



Notes: Tabulations based on unweighted responses. The number listed on top of the bar charts indicates the percentage of firms that responded to digitizing some form of information (either “Up to 50%”, “More than 50%” or “All”) as a share of the entire set of firms (unweighted). Missing/Don’t Know responses are imputed across the other four response options (“None”, “Up to 50%”, “More than 50%” and “All”).

Figure 4: Extensive and Intensive Margin Measures of Use Rates for Cloud Service Purchases by Sector

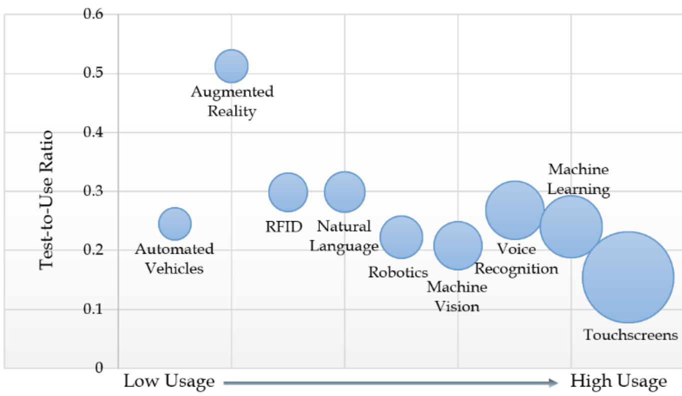


Notes: "Use" is defined as having responded with "Up to 50%", "More than 50%" or "All" for the category listed on "Cloud Service Purchases". "Intensive Use" is defined as having responded with "More than 50%" or "All". Shares are computed using the tabulation weights of firm counts, divided by the total number of firms (including those that left the responses as "Don't Know" or missing). Sectors are defined by combined 2-digit NAICS and assigned for multi-unit firms by largest payroll industry by firm. Original responses classified as "Missing" or "Don't Know" are imputed.

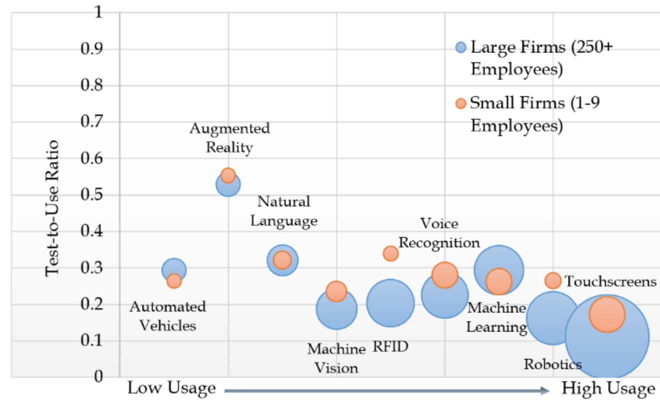
Figure 5: Firm Responses to Business Technologies

Notes: Tabulations based on unweighted responses. The number listed on top of the bar charts indicates the percentage of firms that responded to imputed "use" for a business technology as a share of the entire set of firms (including "Don't' Know and missing"). Missing responses are imputed across the other five response options ("None", "Testing", "Less than 5%", "Between 5% and 25%" and "More than 25%").

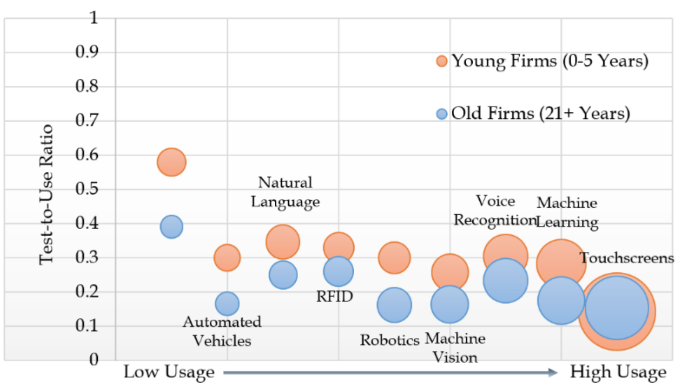
Figure 6: Testing-to-Use Ratios



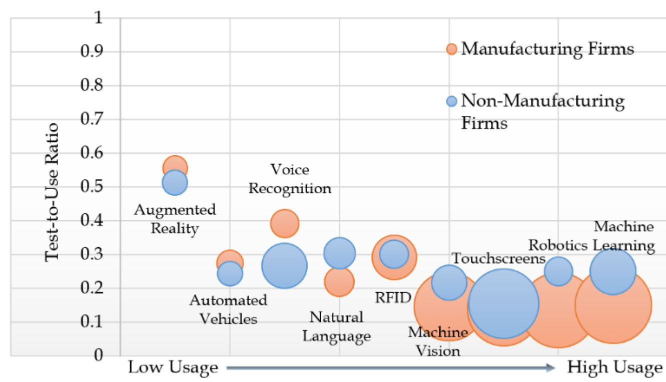
a. Testing-to-Use Ratios for all Business Technologies (All Firms)



b. Testing-to-Use Ratios for all Business Technologies (By Size)



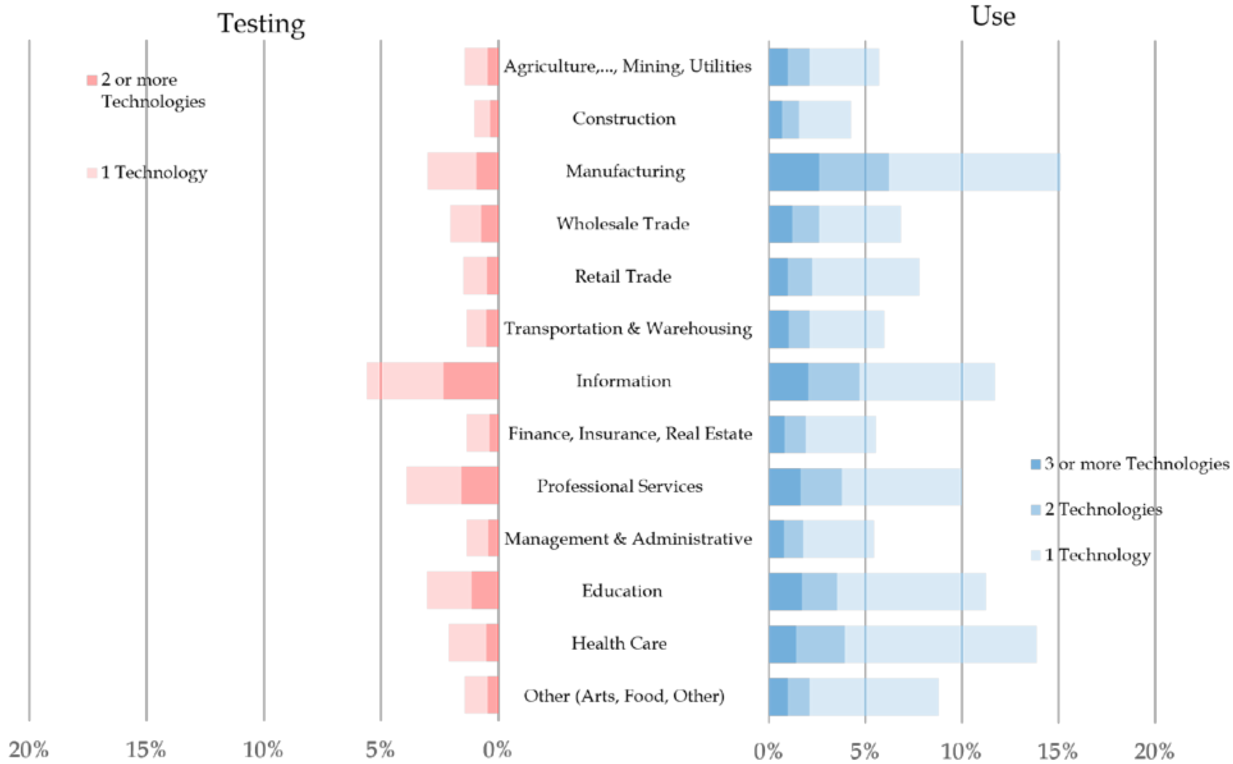
c. Testing-to-Use Ratios for all Business Technologies (By Age)



d. Testing-to-Use Ratios for all Business Technologies (By Manufacturing Status)

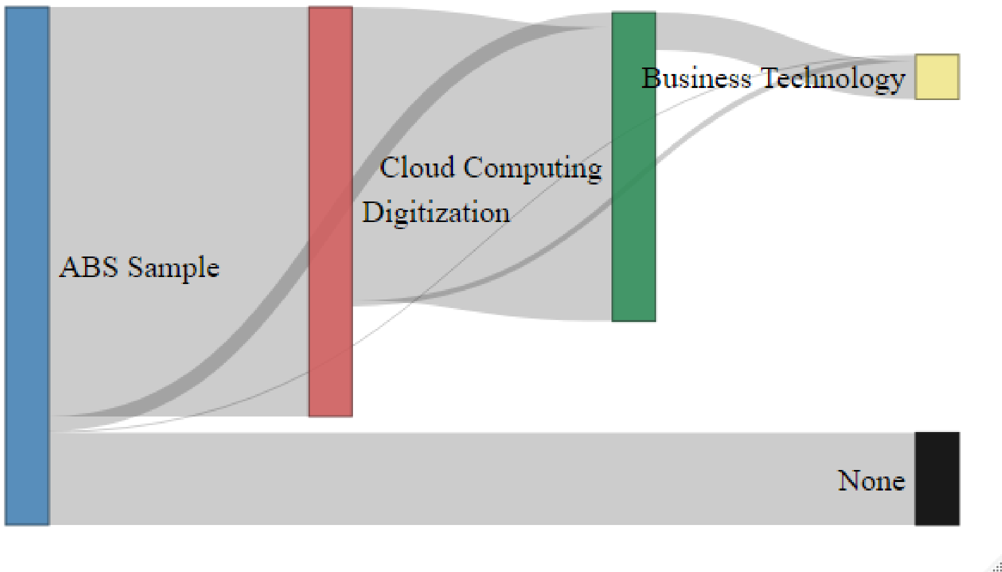
Notes: "Use" is defined as having responded with "In use for less than 5% of production or service", "In use for between 5% - 25% of production or service" or "In use for more than 25% of production or service " for the categories listed on "Business Technologies" (excluding "Automated Storage and Retrieval Systems"). "Testing" is defined as having responded with "Testing but not using in production or service". Bubble size is determined by number of firms who respond to "Use" for the listed technology. Categories are sorted by use rates for large firms in panel b., old firms in panel c. and manufacturing firms in panel d. All ratios here are calculated using imputed response for "Missing" responses.

Figure 7: Extensive and Intensive Margin Measures of Use and Testing Rates for Business Technologies by Sector



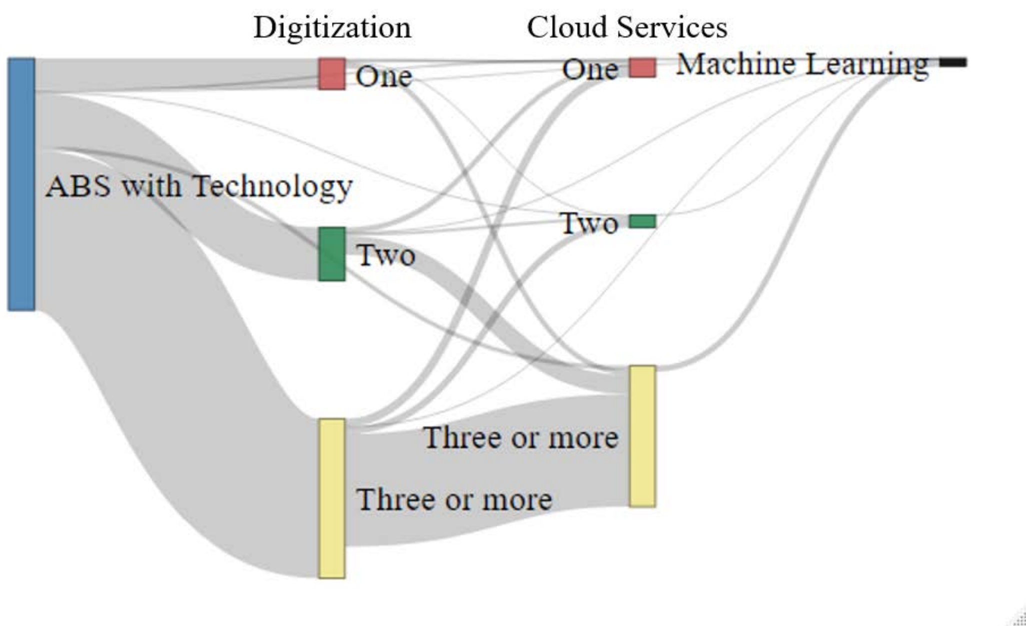
Notes: "Use" is defined as having responded with "In use for less than 5% of production or service", "In use for between 5% - 25% of production or service" or "In use for more than 25% of production or service " for the category listed on "Business Technologies" (excluding "Automated Storage and Retrieval Systems"). "Testing" is defined as having responded with "Testing but not using in production or service". Sectors are defined by combined 2-digit NAICS and assigned for multi-unit firms by largest payroll industry by firm. Original responses classified as "Missing" are imputed.

Figure 8: Technological Hierarchies[38]



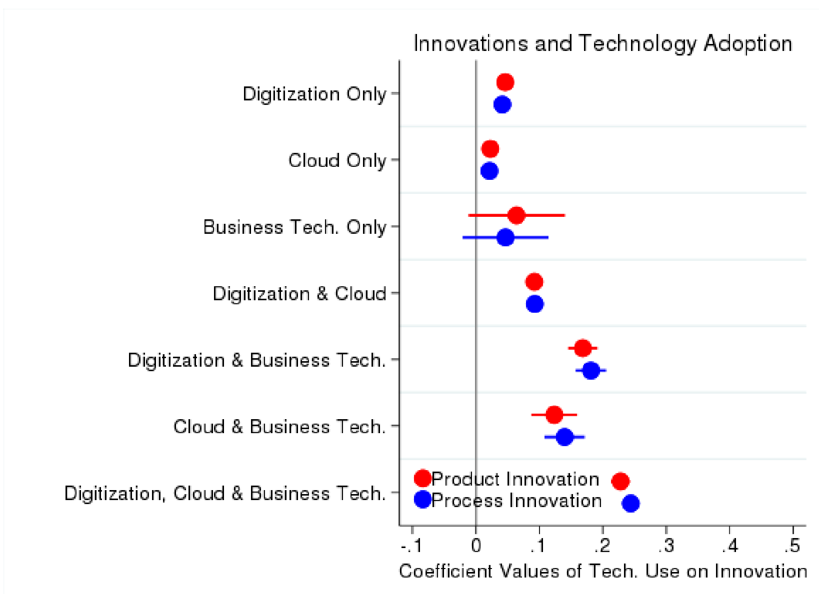
a. Sankey Diagram for Business Technologies (Any)

[38] The Sankey diagrams visually represents firm counts as they progress from no technology adoption to business technology and machine learning technology adoption. The size of the grey area is representative of the number of firm counts progressing to the next stage. Note that the calculations are made using imputed responses for "Missing".

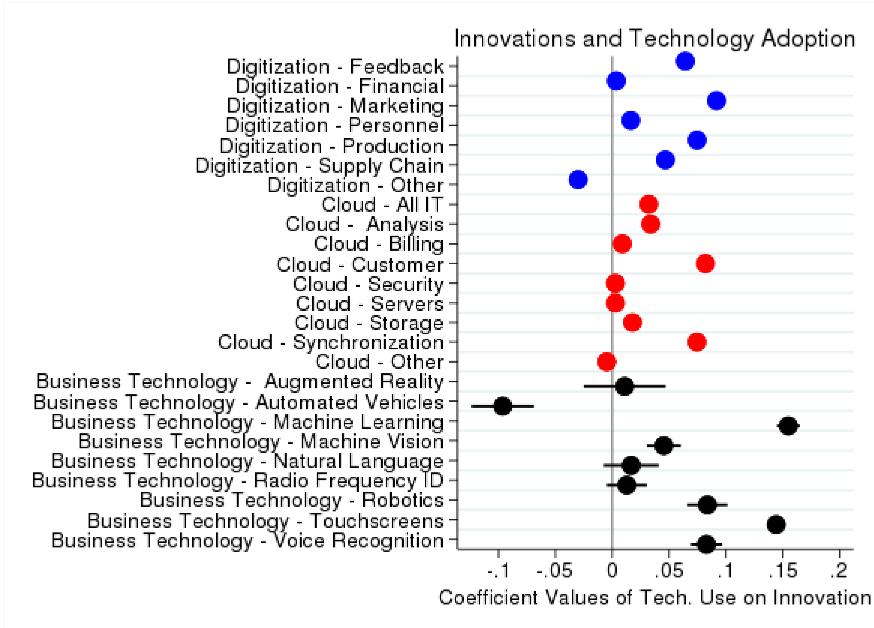


b. Sankey Diagram for Machine Learning

Figure 9: Technology Adoption and Innovation



a. Technology Adoption and Innovation Outcomes



b. Technology Adoption and Innovation Outcomes (Any)

Notes: The figures visually represent the coefficients from a LPM where the dependent variable is a 1/0 for whether the firm conducted a Product or Process Innovation (defined as having responded "Yes" to one of the categories listed under Product or Process Innovation in the ABS). Panel b. considers the subset of firms who use a technology category (i.e. Digitization or Cloud Computing) and looks at how the individual subcategories is associated with any type of innovation (either product or process). The independent variables include the technology use categories, along with firm size and age controls, and industry fixed effects. All coefficient plots are calculated using imputed independent variables for "Missing".

Appendix: Cognitive Testing

First Week

The second round of cognitive testing for the ABS, which was the first set of interviews to include the three technology questions, occurred in Nashville in mid-August. Nine companies participated in the testing. Each was given three questions relating to its use of digital information, cloud services, and business automation technologies. Two versions of Question 1 were tested to determine both the most preferred wording (i.e., "digital" vs. "digitized"), as well as the best method to measure the use of digitized data. Version A used the term "digitized" and asked what *shares* of different types of data were digitized; and version B used the term "digital" and asked how the business *changed* its availability of different types of digital data. Question 2 asked about the extent to which the establishment purchased cloud services for various IT functions. Question 3 asked about how intensively the business used various technologies (mainly relating to automation; e.g., automated guided vehicles (AGVs), machine learning, robotics, etc.). The column choices for each of the three questions included both qualitative (i.e., "slight," "moderate," "extensive," etc.) and quantitative (i.e., percentage range) measures of technology use. Appendix A contains the original versions of the questions tested.

Results from testing Question 1 showed that respondents generally preferred version A (i.e., they preferred being asked about *how much* of their data was digitized, as opposed to being asked about how its availability changed), but they also typically preferred the word "digital" over "digitized." As a consequence, the version A measure of digitized data use was recommended, replacing the term "digitized" with "digital," and including a definition of digital data. Including examples of personnel data to clarify its meaning was also recommended. For Question 2, respondents overall understood the concept of cloud services and were able to answer confidently whether they used them. In some cases, however, respondents either were not sure in which category to include a service or did not know whether the cloud service was free or purchased. Recommendations for this question included adding a clearer definition of cloud services and including examples of name-brand products in applicable categories. In answering Question 3, many of the technological terms were unfamiliar to some respondents, however they were generally able to answer confidently and accurately regarding the technologies they *did not* use. For technologies that *were* utilized by participant firms, respondents occasionally misunderstood the question's intended scope (e.g., employees using touchscreen technology in settings other than labor substitution). Here, the sole recommendation was to include examples that would clarify the intended scope of the question.

Second Week

The second set of interviews for the technology questions took place in Boston in late-August. Six companies included in the BRDIS were given revised versions of the three technology questions (see Appendix B). Question 1 now had a single version, asking about the share of different types of "information" (term substituted for "data") that was "digital" (term substituted for "digitized"). The columns no longer included qualitative measures, but rather solely percentage ranges. The percentage ranges themselves were also adjusted, and a "Not Applicable" column was added. Similarly to Question 1, the revision to Question 2 removed all qualitative descriptors and asked simply for percentage ranges of cloud services shares (with respect to spending). For clarity, the revision also included product examples for the "Data storage and management" and "Collaboration and file synchronization" categories. In revising Question 3 the phrase "for customer interface," along with some examples, was added for clarification to the "Touchscreens/kiosks" category. Also, unlike the previous two questions, the revision of Question 3 removed the quantitative descriptors (i.e., percentage ranges) of automation technology use, in addition to adding a column with "Not currently using, but planning future use."

The responses to the revised version of Question 1 seemed generally more confident. With the revised wording, the overall understanding of the question was good. Almost all respondents easily answered "More than 50%" for every category, and many stated confidently that simply "Everything is digital." The revised version of Question 2 was better understood than the original, however all but one individual responded that they would need to consult their firm's IT group to accurately answer the question. The revised version of Question 3 was relatively difficult for respondents to answer. The fact that there were only qualitative descriptions to measure overall use of different technologies made it unclear how to answer the questions if, for example, a technology is used extensively in one part of the company but little or not at all in another.

Text Box A1: First Version of the Technology Questions

1A) What share of each of the following types of data is digitized at this business?

	Data Not Digitized	Slightly Digitized (less than 5% of this kind of data)	Moderately Digitized (6-50% of this kind of data)	Heavily Digitized (50-99% of this kind of data)	Entirely Digitized
Personnel					
Financial					
Customer feedback					
Marketing					
Supply chain					
Production					
Other (write-in)					

1B) During the three years from 2015 to 2017, to what extent did this business change the availability of digital data of each of the following types?

	Digital Data Not Used	Decreased Availability	No Change in Availability	Slight Increase in Availability	Moderate Increase in Availability	Extensive Increase in Availability
Personnel						
Financial						
Customer feedback						
Marketing						
Supply chain						
Production						
Other (write-in)						

2) In 2017, to what extent did this business purchase **cloud services** for the following information technology (IT) functions?

	Not Used	Did not purchase as cloud service	Slight Use (less than 5% of spending for this function)	Moderate Use (6-50% of spending for this function)	Intensive Use (More than 50% of spending for this function)
Security or firewall					
Servers					
Data storage and management					
Collaboration and file synchronization					
Data analysis					
Billing and account management					
Customer relationship management					
Other (write-in)					

3) In 2017, to what extent did this business use the following technologies?

	Not Used	Slight Use (Piloting or using in less than 5% of production or service)	Moderate Use (In use for between 5-25% of production or service)	Intensive Use (In use for more than 25% of production or service)
Augmented reality				
Automated guided vehicles (AGV) or AGV system				
Automated storage and retrieval systems				
Cloud-based servers, storage and data management				
Machine learning				
Machine vision software				
Natural language processing				
Radio-frequency identification (RFID) inventory system				
Robotics				
Touchscreens/kiosks				
Voice recognition software				

Text Box A2: Revised Version of the Technology Questions

Question 1

In 2017, what share of each of the following types of information was **digital** at this business?

Mark one box for each row

	Data not digital	Less than 25%	More than 25%, but less than 50%	More than 50%	Not Applicable
Personnel					
Financial					
Customer feedback					
Marketing					
Supply chain					
Production					
Other (write-in)					

Question 2

In 2017, what share of spending on the following information technology (IT) functions at this business was used to purchase **cloud services**?

Cloud services are services provided by a third party that this business accesses on-demand via the internet.

Mark one box for each row

	Did not purchase as cloud service	Less than 25%	More than 25%, but less than 50%	More than 50%	Not applicable
Security or firewall					
Servers					
Data storage and management (Examples: Amazon Web Services, IBM Bluemix, Microsoft Azure)					
Collaboration and file synchronization (Examples: Dropbox, OneDrive, Google Drive)					
Data analysis					
Billing and account management					
Customer relationship management					
Other (write-in)					

Question 3

In 2017, to what extent did this business use the following technologies?

Mark one box for each row

	Not currently using, but planning future use	Some experimental use	Limited use in production or services	Extensive use in production or services	Not applicable
Augmented reality					
Automated guided vehicles (AGV) or AGV systems					
Automated storage and retrieval systems					
Cloud-based servers, storage and data management					
Machine learning					
Machine vision software					
Natural language processing					
Radio-frequency identification (RFID) inventory system					
Robotics					
Touchscreens/kiosks for customer interface (Examples: self-checkout, touchscreen ordering)					
Voice recognition software					

Table 1A: Summary of Recommended Changes based on Cognitive Testing

Section	Question	Recommendation	Accepted?	Notes
Business Structure	*For the person(s) owning the largest percentage(s) in this business in 2017, please list the percentage owned by each person and his or her name.*	Put the column designated for a name before the column for percent ownership.	**Yes**	
	In 2017, did two or more members of one family own the majority of this business?	Consider including "step" relationships to this definition.	**No**	
	Did spouses/unmarried partners jointly own this business; Was this business operated equally by both spouses/unmarried partners?	Consider specifying what time frame is relevant to the questions.	**Yes**	
Owner Characteristics	*What was the highest degree or level of school Owner X completed prior to establishing, purchasing, or acquiring this business?*	For individuals who have received an associate degree, it may be helpful to explicitly state that associate degrees are to be excluded.	**Yes**	
	Prior to establishing, purchasing, or acquiring this business, what was the field of the highest degree completed for Owner X?	Consider changing or adding to "field of the highest degree completed" to include "major" or some other simplifying term.	**No**	
	How important to Owner X are each of the following reasons for owning this business?	Consider additional response categories to include: "carrying on the family business," and "Helping and/or becoming more involved in my community."	**Yes**	Both suggested categories were included.

	Does Owner X have any of the following difficulties?	Add response category for “None of the Above” to differentiate between having no disability and item nonresponse. Additionally, specifically mention “even when using a hearing aid” for the hearing difficulty response category.	**N/A**	This question was not included in the final version.
Other Business Characteristics	*In 2017, which of the following types of workers were used by this business? Select all that apply.*	Consider adding category for workers who receive a commission, seasonal employees, workers who are on call/demand, etc.	**No**	
	In 2017, did this business use any of the following to promote or conduct business?	Since participants selected the option for “company website” even if they didn’t use it to promote or conduct business, perhaps the words “promote” and “conduct” should be in bold print or underlined to emphasize what this question is asking.	**N/A**	This question was not included in the final version.
Business Financing	*For 2017, what was the total amount of money that the owner(s) personally put into the business? Your best estimate is fine.*	Due to the fact that there was some confusion regarding whether to report the amount that each owner put in to the company, or to sum those amounts, it may be beneficial to bold and/or italicize the word “total” in the question.	**No**	
	In 2017, did this business attempt to establish any new funding relationships (for example, loans, investments, or gifts) with any of the following sources?	Specify whether new financing with a bank the owner already has a relationship with would still qualify as an affirmative response. Consider adding a definition for the term “crowdfunding.”	**N/A**	This question was not included in the final version.

	For 2017, what was the total amount of money this business received from angel investors, venture capitalists, or other businesses in return for a share of ownership in this business?	Consider adding a definition for the term “angel investor.”	**Yes**	
	For 2017, what was the total amount of money this business borrowed from a bank or other financial institutions, including business loans, a business credit card carrying a balance, or a business line of credit? Include all draws on a business line of credit, even if paid off during the year.	This question may benefit by having a list for respondents to reference of specifically what to include and exclude in their response.	**No**	
	For 2017, what was the total amount of money this business received from family, friends, and employees?	Instead of “total amount of money” consider using “capital or investment funds” from family etc.	**Yes**	The term “investment funds” was chosen.
	At any time during 2017, did this business need additional financing?	Perhaps consider moving this question sooner if including the previous question or specify not to include what was already covered by the previous question if that is the intent of this question.	**No**	

Business Performance	*For 2017, which of the following negatively impacted the profitability of this business?*	Prior to asking this question, consider asking respondents first a yes/no question regarding whether they experienced any negative impacts on their profit. Regarding the subjectivity of the question, it may help to include a qualifier stating something akin to "please only include factors that impacted profit."	**No** **Yes**	