AI Adoption in America: Who, What, and Where[1]

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Abstract: Artificial intelligence (AI) is perhaps one of the most important advanced technologies of our era. Using some of the first comprehensive measures of firm-level adoption of advanced technologies in the United States collected by the U.S. Census Bureau, we find that nationwide prevalence of AI is low yet highly concentrated within a subset of economically important firms. Early AI use is an attribute of innovative, venture-funded, and early-growth firms. Founder characteristics and aspirations matter, too. Firms founded by younger, yet also more-educated and more-experienced leaders are more likely to adopt rising technologies in the AI space such as machine learning, voice recognition, machine vision, natural language processing, and automated vehicles. Founders focused on bringing new ideas to market, inspired by an entrepreneurial role model, or seeking to help the community are also more likely to use AI. This work is the first to map out important connections between startup characteristics, firm strategies, and frontier use of a technology hypothesized to be an important driver of changes in work, productivity, and society.

[1] Any opinions and conclusions expressed herein are those of the authors and do not 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, CBDRB-FY20-331, CBDRB-FY21-041 and CBDRB-FY22-074). We thank John Eltinge, John Jankowski, John Haltiwanger, Susan Helper, Nathan Goldschlag, Scott Ohlmacher , Pascual Restrepo, Rob Seamans for excellent comments and feedback, as well as participants in the 2020 AEAStat session.

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1 Introduction

Artificial Intelligence (AI) is potentially the most transformative technology of our era, but little is known about the extent to which machine learning, machine vision, natural language processing - and other, related technologies such as robotics and automated vehicles - are being used by firms, far less which types of firms are adopting them. Yet limited understanding of adoption and diffusion patterns make it difficult to anticipate the economic implications of this fast-emerging technology. What will an AI-enabled future entail in terms of innovation, prosperity, inequality, or the increasingly-discussed "future of work"? AI is often argued to be a General-Purpose Technology (GPT)—flexible, ubiquitous, and potentially high economic impact –yet thus far it has had seemingly minimal impact on measured economic activity (Brynjolfsson et al. 2021; Furman and Seamans 2019). This failure to find AI in the productivity data suggests that the technology remains in its genesis, firms are having trouble deploying the technology, and/or – as we argue, here – researchers have yet to look in the right places.

This lack of empirical traction is understandable, given the absence of comprehensive data on firms' adoption and use of emerging technologies such as AI. However, guideposts are essential if we are to avoid "flying blind into what has been called the Fourth Industrial Revolution" (Brynjolfsson and Mitchell (2017b).[2] Evidence-based decision making at all levels of government, firm leadership, and society is affected by this data gap. Although efforts have been made to triangulate on AI adoption and exposure using indirect measures such as O*NET task descriptions (Brynjolfsson, Mitchell, and Rock 2017, Felten, Raj, and Seamans 2021), online job postings (Alekseeva et al. 2021), or patents (Webb 2019), datasets that provide direct and nuanced firm-level information on the diffusion of these new technologies are rare. Those that are available often suffer from coarse (industry)/occupation aggregation, have non-response and sampling biases, fail to capture activity outside of the manufacturing sector, or miss key dimensions of this flexible class of technologies. Consequently, we have limited insight into who the early AI adopters are, which industries, technologies, or geographies are leading the diffusion curve, or what aspirations or strategies of firm leaders are associated with AI use. This study provides rich answers to these questions, throwing up much-needed signposts on a landscape urgently in need of systematic exploration.

[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.

The recent release of a new nationally representative survey, the 2018 Annual Business Survey (ABS), conducted jointly between the Census Bureau and the National Center for Science and Engineering Statistics (NCSES) within the National Science Foundation (NSF), helped to fill this data gap and provides a rich platform for our investigation. The ABS collects information on adoption and use of several advanced technologies from a large, nationally representative sample of firms covering the private nonfarm sectors of the economy.[3] Initial analysis of this survey indicated that, despite increasingly widespread interest in technologies such as machine learning, robotics, automated vehicles, natural language processing, and machine vision and voice recognition, their adoption rates across firms remain relatively low, on average (Zolas et al. 2020). However, nationwide averages rest on a denominator that risks obscuring the firms most-central to the growth and dynamism of the U.S. economy. Just focusing attention on larger, older firms - a relatively small segment of the firm population – we find that worker exposure to AI across the country is much higher. Narrowing the lens further onto firms and founders that prioritize innovation and economic growth, a far different picture of AI prevalence begins to emerge.

In this study, we provide a higher-resolution image of early AI use by documenting novel and important characteristics of early AI adopters and, by association, key implications for economics and strategic management. Who adopts AI can matter greatly for the economy. For instance, if AI adoption is concentrated in a niche of firms that are productive, large, and innovative, the potential effects of AI use can be much more consequential than if adoption is more diffuse. Further, the types of outcomes may vary if leaders of adopting firms have certain fixed characteristics or are committed to certain aspirations or strategies. It is often overlooked that the way in which technology is deployed in firms is subject to the choices of managers, and complementary strategic and human resources decisions are likewise subject to managerial discretion. Inequality linked to between-firm differences is on the rise, with technology increasingly implicated as a core driver of unequal outcomes for workers (Andrews et al. 2015; Autor and Salomons 2018; Autor et al. 2020). However, some workers in some firms are benefitting from rising digitization (Barth et al. *forthcoming*). How this will play out for AI is an open question. Yet, knowing where the leading AI adoption is taking place can inform what "lamppost" to look under for this, and other phenomena of vital interest. We anticipate that a

[3] The ABS covers all nonfarm employer businesses filing the 941, 944, or 1120 tax forms (see https://www.census.gov/programs-surveys/abs/about.html for more details about the ABS).

better-illuminated landscape will enable more-rapid traction for a wider range of impactful research questions and data collection efforts.

Our large-scale survey approach has a number of advantages worth emphasizing. For one, the Annual Business Survey (ABS) consolidates three prior 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)—into one, providing data on a number of factors related to the owners of the firms, funding at the time of founding, innovation activities, and other firm strategies. This rich information allows us to identify a wide range of novel organizational characteristics – including, but not limited to, those associated with "high growth entrepreneurship" (e.g., Guzman and Stern 2020) – that have been linked to important economic outcomes. We link these to AI use and compare across drivers and complements of AI use to arrive at a number of key insights. In addition to richly describing the who, what, and where of AI use, we show that a number of quasi-fixed organizational factors are important intangible drivers of AI adoption, that later-stage growth is significantly and separately correlated with AI use, and that a range of important firm strategies - notably innovation and aspirations to give back to local communities that bode well for inclusive prosperity – are also key ingredients of leading AI "recipes." Some of our results remain preliminary (with a few still pending disclosure review by Census). Taken together, though, they point to a compelling role for AI in a number of important – and arguably, desirable - economic outcomes. They also provide guidance for what types of firm strategies "play nicely" with AI, in practice.

Our contributions to the literature are several. By tying together early AI adoption with quasi-fixed founding and ownership characteristics, we build on the growing literature on leadership/top management teams and firm performance (see, e.g., Choi, Goldschlag, Haltiwanger, and Kim 2021, Azoulay, Jones, Kim, and Miranda 2021, Ewens and Marx 2017)**.** We also offer new insight on the link between leader characteristics and tech adoption that might drive or mediate differences in firm performance. There is a related literature on the drivers of economic dynamism in the U.S. (see, e.g., Decker, Haltiwanger, Jarmin, and Miranda 2017, 2020), and we argue that a potential driver related to the "fixed-at-birth" characteristics and skewed economic outcomes is rooted in the propensity to adopt important, scale-biased technologies. When exploring complementarities with other dimensions of firm strategy and performance, we find AI adoption to be linked with both product and process innovations, as well as "growth-oriented innovation" (as opposed to innovation driven towards "efficiency").[4] This contributes to some of the key insights brought up in Song et al. (2018), who argue that if high-performing firms are more likely to adopt performance-enhancing and scale-biased technology, this self-selection could reinforce inequality driven by between-firm differences. Unpacking the difference between firm exposure and worker exposure is therefore critical to understanding distributional implications of AI.

We make a number of key observations related to adoption of AI. As evidenced in Zolas et al. (2020), advanced technology adoption exhibits a hierarchical pattern, with the most-sophisticated technologies being present most often only when more-basic technologies are as well. We highlight how attempts to predict AI use based on commonly observed firm characteristics such as size, industry and age have had limited success. While our early measures of firm aspirations and quality adds substantially to explaining variation in adoption, there remains still a huge amount of unexplained heterogeneity in adoption, indicating that unobserved firm-specific features are dominant. Finally, our approach allows us to assess who the potential adopters ("at-risk" firms) are. This assessment is critical for getting the "denominator" right in linking AI adoption to outcomes of interest (e.g., economic dynamism, job growth), and describing the niche of the economy that is most relevant to study for the consequences of AI adoption.

The rest of this paper is organized as follows. In Section 2, we describe the 2018 Annual Business Survey and its contents along with some summary tables of technology adoption and preliminary findings. In Section 3, we go over our methodology for assessing who the early adopters are and our predictive model for early adoption. In Section 4, we discuss our results, before concluding.

2 The 2018 Annual Business Survey

Our primary dataset relies on the recently released Annual Business Survey (ABS), which was first conducted in 2018. This survey represents a partnership between the Census Bureau and the National Center for Science and Engineering Statistics (NCSES) within the

[4] We define "growth-oriented" innovation as a focus on opening up new domestic or export markets, introducing new goods or services, or reaching new customer groups.

National Science Foundation (NSF) 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), and adds a new and expanded collection on nationally representative business innovation statistics.[5] The ABS captures many important characteristics of the business context in which technology adoption and use take place.[6]

The survey was sent to 850,000 nationally representative firms, with approximately 590,000 responses, of which 573,000 can be linked to the Longitudinal Business Database (LBD) – the primary source of firm-level information on key outcomes such as employment, revenue, and payroll. A summary of the respondents' characteristics can be found in Table 1.[7] The sectoral and age distribution coincides with national averages and thus the vast majority of firms in the sample are small (more than ¾ of the sample have fewer than 10 employees).

Technology Module

The technology module in the 2018 ABS contains three detailed questions: the availability of information in digital format (digitization), expenditure on cloud computing services, and use of several advanced business technologies – the definitions of these technologies are provided in Text Box 1. Taking the three questions in turn, the first question explores firms' reliance on digital information, widely regarded as a prerequisite to more-advanced uses of digital technologies (Brynjolfsson and McAfee 2014, Brynjolfsson and McElheran 2019). The second question explores the extent to which firms rely on cloud computing, which has shifted the cost structure and use of IT for a broad range of firms (Armbrust et al. 2010, Brynjolfsson et al. 2010) and is viewed as a key enabler of digital transformation (Forrester 2017, Sunyaev 2020). A second necessary ingredient for adopting AI technologies is sufficient computing power to handle and exploit massive quantities of digital information.

[5] The SBO was conducted by the Census Bureau. The ASE was conducted by the Census Bureau in partnership with the Ewing Marion Kauffman Foundation and the Minority Business Development Agency. The BRDI-M was conducted by the Census Bureau under a partnership with NCSES.
[6] For more information on the ABS technology module and past history of efforts to collect national statistics on technology adoption, see Zolas et al. (2020).
[7] Note that due to the relatively low response rate, respondents were reweighted to better coincide with national averages in size, age and industry according to the Business Dynamic Statistics. For more information, see Zolas et al. (2020)

Finally, the third question, and the primary focus of this paper, asks directly about the use of advanced "business technologies," including those typically categorized as "AI." The AI-related technologies include machine learning, machine vision, natural language processing, voice recognition software, and automated guided vehicles.[8] A summary of responses can be found in Figure 1, which indicates that only a very small percentage of respondents use any of the AI-based advanced business technologies. In Table 2, we combine the different measures of intensity into an aggregate "use" value and find that the adoption rate for each of the 5 AI-based technologies is less than 3%.

As Zolas et al. (2020) point out, some of these adoption patterns can be explained by size and age differences across firms: adoption is highly skewed and concentrated in the larger (and older) firms in the economy. This is readily apparent in Figure 2, which reports the adoption rates for any of the AI-based technologies by firm size. This skewness in adoption rates underscores the impact of this technology on workers. As Table 3 shows, despite the relatively low across-firm adoption rate, due to the concentration of AI in the right tail of firm size distribution, the worker exposure to these technologies can be considerably higher.[9] This impact is more pronounced for some sectors of the economy.

Founding Characteristics

A key advantage of the ABS is that, in addition to the technology module, it contains useful information related to the owners of the firm, reasons for starting the business, the capitalization/funding required to start the firm, as well as innovation strategies and outcomes of the firm. This information, not typically available in large firm surveys and administrative data, is highly relevant in understanding the types of firms that are among the early adopters of AI-based technologies. It also reveals some key characteristics about the firm itself, like the potential growth trajectory.

Table 4a provides some summary statistics (based on our analysis sample described in Section 3) of these intangible factors, such as whether the primary owner[10] has an advanced

[8] Other technologies queried include augmented reality, robotics, touchscreens, automated storage and retrieval systems and radio frequency identification (RFID). While some of these other advanced technologies may also contain an AI-related component, they are less likely to rely heavily on AI-based algorithms or software compared to the ones we include as AI-intensive.
[9] It is assumed that workers at firms that adopt the technology are "exposed".
[10] Denoted as the owner with the largest share of the business (usually Owner 1).

degree[11], has owned a business previously, and their reasons for starting the business, along with some capitalization measures and innovative strategies of the firm. These tabulations are then separated by whether or not the business utilizes any of the AI-based technologies defined earlier. We see some stark differences in these intangible factors across the adopters and non-adopters, which we discuss in the next section.

Similarly, Table 4b highlights the differences in AI usage by various firm characteristics as in Table 4a. We note that the usage rates between firms that possess a characteristics versus those that do not differ substantially in some cases. The differences are especially pronounced for owner having an advanced degree, presence of VC funding, high startup funding amounts, and nearly all characteristics in the innovative strategies and outcomes category. Interestingly, businesses motivated to help or become involved in a community also have a higher AI usage rate, compared to businesses that are not motivated by this goal.

3 Methodology

Our methodology for understanding the nature of the early AI adopters extends the work first performed in Zolas et al. (2020), who use observable firm characteristics to first tabulate the users of advanced business technologies, and then extend their analysis to impute some of the non-missing and “don’t’ know” response options collected in the survey. Their tabulations highlight the skewness in patterns of adoption where adoption seemed primarily determined by the size and age profiles of the firm, along with industry. However, these observable factors were only able to explain relatively little of the variation in adoption patterns, even when including high-dimensional controls, such as detailed industry by state. As an extension, here we explore how the organizational factors and early-stage startup characteristics described in the previous section may play a role in early adoption patterns and whether they can explain an important portion of the remaining variation in adoption.

There is a growing literature that suggests that some key organizational factors, which are mostly fixed at birth for the firm, can signify both the “quality” of the firm and the growth trajectory of the firm (see, e.g., Schoar, 2010; Guzman & Stern, 2020; Haltiwanger et al., 2016 Sterk, Sedlacek, and Pugsley 2021, Botelho, Fehder, and Hochberg 2021, Kerr, Kerr, and Xu 2018). The key message from this body of work is that high-growth entrepreneurs exhibit certain

[11] Defined as having either a Master’s Degree, Doctorate Degree, or Professional Degree.

early features which are not captured in the usual observable firm characteristics (size, age, payroll, industry, and location). These same features for high-growth entrepreneurship may also be relevant for technology adoption. Thus, our contribution is to assess whether the "quasi-fixed" organizational features that can predict high-growth or high-quality firms, such as owner education, intellectual property (IP) and "innovativeness", serial entrepreneurship, and motivations for starting the business and capitalization requirements, can simultaneously predict early adoption of AI. At the same time, we explore whether technology presence has an independent connection to firm growth even after controlling for the initial characteristics that predict high growth. If AI adoption is strongly connected to these initial characteristics but also contributes to future growth, then we should still see some connection between AI use and *later* firm growth even after controlling for these initial firm-level high-growth characteristics – though a more causal statement requires further analysis.

Due to restrictions in the revenue information of the LBD—which does not include revenue information prior to 1997—we rely on a subset of the full ABS sample: firms born in or after 1997. And because of the ownership characteristics we also include, we further restrict our sample to firms who reported having at least one owner owning a non-zero share of the firm.

Examining the sample described, we find that early high-growth firms are more likely to be adopters of AI, by using direct measures of early firm revenue growth. We then add controls for the characteristics of firm "leadership" or ownership (e.g., whether the primary owner has an advanced degree, has prior experience founding firms, etc.), startup "capitalization", and "innovative complementarities". By adding each set of controls, we can de-couple the early growth trajectories of the firm from its most recent economic activity (e.g., latter revenue gains and technology adoption).

The following sub-sections delve into how the controls were selected from the information available in ABS, and how we expect them to relate to the patterns of early adoption based on existing findings in the literature.

Leadership Variables

Owner characteristics matter for the performance of the firm, consistent with the findings on the role of leadership and top teams in firm performance (see, e.g., Choi, Goldschlag, Haltiwanger, and Kim 2021, Azoulay, Jones, Kim, and Miranda 2020, Ewens and Marx 2017).

Several features of the owner may play a role, including education, age, prior experience, and reasons for starting the business.

The goals and motivations of entrepreneurs are also important in the trajectory of the firm, and the literature has noted a clear delineation between "lifestyle" entrepreneurship and "high-growth" entrepreneurship (Schoar 2010; Hurst & Pugsley 2010). We therefore incorporate some of the reasons for starting the business in our analysis to differentiate between these two firm types.

When thinking about the age of the owner, Choi et al. 2021 identified a "sweet spot" for owner age and innovation. This finding is consistent with the idea of "vintage-specific human capital" whereby much older cohorts of founders and managers may lack the tech-specific facility combined with important (potentially complementary) experience or tacit "know how" that takes time to accumulate (Barth et al. 2020)

For education, firms with owners that possess advanced degrees are more likely to innovate (Brayman et al. 2011). There is also a relationship between serial entrepreneurship and higher quality firms (LaFontaine and Shaw 2016).

Capitalization

There are numerous indicators at the founding of the firm that may hint at the firm's potential. Some of these factors include the sources of funding (e.g., firms funded via venture capital or through outside investors have greater potential than firms funded through the owner's capital), as well as the funding amount.[12]

Non-TFP Objectives

Besides ownership and capitalization, other attributes of the firm beyond the usual firm characteristics can describe the quality of the firm. For instance, Guzman & Stern (2020) rely on the startup filing a trademark or owning a patent as key indicators for the quality of the firm. Hard-to-measure complementarities may exist elsewhere, such as in the innovation strategy of the firm and importance of IP. In the Annual Business Survey, the survey queries firms on their

[12] See, e.g., Kortum and Lerner (2000), Nanda and Rhodes-Kropf (2013), Catalini, Guzman, and Stern (2019), Lerner and Nanda (2020), and Botelho, Fehder, and Hochberg (2021). Akcigit, Dinlersoz, Greenwood and Penciakova (2019) find that both selection by venture capitalists and the synergies between venture capitalists and entrepreneurs are an important contributor to US economic growth.

intention for innovating new products or services. These intentions can be linked to either cost reductions (efficiency gains) or growth (market or product expansion). These differing strategies may reveal different firm types.

4 Results

We begin by establishing the predictive ability of these leadership, high-growth, and non-TFP-related characteristics on the early quality of firms. We measure initial firm quality by taking the growth rate of average annual revenue as defined[13] by Davis, Haltiwanger and Schuh DHS) (r) over the first three years of an employer firm's life:

$$g = \frac{1}{3}\sum_{t=1}^{3}\frac{r_t - r_{t-1}}{0.5(r_t + r_{t-1})}$$

We regress this growth rate, g, on our three broad groups of firm characteristics—first on each individual group, and then on all groups together—controlling for standard fixed observables like state-by-industry and cohort (firm age).

Column 1 of Table 5 reports the estimated coefficients of leadership characteristics. The owner characteristics include an indicator for holding an advanced degree, an indicator for having previously owned a business, and indicators for owner age being 35–54 or over 55. As expected, an owner holding an advanced degree or previously owning a business is associated with a higher startup revenue growth rate. We also find that a business with an owner of age 35 or older is more likely to have a lower startup revenue growth rate than a firm with a primary owner younger than 35 (and we note that firms with owners 55 or older are even more likely than those with owners aged 35–54).

Column 2 of Table 5 similarly reports estimates where startup revenue growth is regressed on founding characteristics which we expect to be related to entrepreneurs with high-growth aspirations. These characteristics include an indicator for the primary owner listing a lifestyle-related reason (i.e., either "flexible hours" or "balance work and family") as a "very important" reason for owning the business, an indicator for using investment by venture capitalist(s) as a source of startup capital, and indicators for startup capital amounts of $25,000–

[13] Davis, Haltiwanger and Schuh define a measure of revenue growth given by: $(REV_t - REV_{t-1})/(0.5 * REV_t + REV_{t+1})$.

$999,999 or $1,000,000 or more. Having a "lifestyle" reason as being very important for starting the business has a negative point estimate but is not statistically significant when included only with the other high-growth entrepreneurship characteristics. Receiving venture capital investment and requiring larger amounts of startup capital are both associated with higher startup revenue growth.

Column 3 of Table 5 reports coefficients for non-TFP investments, which include indicators for a firm participating in process innovation or product innovation, owning patents or having any patents pending, or responding that any of a list of types of IP protection was "very important" to the business.[14] We also included an indicator for a firm responding that introducing new goods or services, reaching new customer groups, or opening up new domestic or export markets were "very important" focuses. Each of these non-TFP investment characteristics is associated with a higher startup revenue growth.

Lastly, in Column 4 of Table 5, we include all three types of firm characteristics together and find that almost all relationships shown in Columns 1–3 are robust to including all of the characteristics together. The two exceptions are the indicator for previously owning a business, which is still positive but no longer statistically significant; and the indicator for reporting a "lifestyle" reason as being "very important" for starting the business, which is still negative but stronger in magnitude and statistically significant. Adding AI presence to Column 4 (as shown in Column 6) indicates that use of AI does not contribute additionally to early growth next to the three groups of characteristics we examined – a caveat to this exercise is that the timing of adoption for AI is not known, so adoption may have occurred after the first three years of a firm.

Having established that our three groups of firm characteristics are indeed statistically significant predictors of firm quality at startup, we next look at how well these high-growth characteristics account for the effect of early firm quality in predicting the use of AI in 2017. Column 1 in Table 6 highlights that being a high-growth firm early in the firm's lifecycle is positively and significantly associated with the adoption of AI. Along with the state-industry (6-digit NAICS) and age fixed effects, these factors can explain 14.1% of the variation in adoption rates of AI among U.S. firms.

[14] The types of IP protection which firms were asked about in the ABS are utility patents, design patents, trademarks, copyrights, trade secrets, and nondisclosure agreements.

We then add each of the variables associated with the different categories of firms listed above, beginning with ownership characteristics. As we layer on additional explanatory variables, the intention here is to de-couple the attributes (e.g., Owner characteristics, Capitalization, and Non-TFP objectives) from high-growth status, and to assess the cumulative impact on adoption. Columns 2–4 show the results from adding each element. Note that the association of revenue growth with adoption weakens as each additional element is included. When non-TFP objectives are included, revenue growth actually becomes insignificant. When all of the factors are included together, revenue growth has no statistically significant relationship with AI adoption. Our fullest specification (column 5) can explain 16.4% of the variation in AI presence, an increase of nearly 20% over the initial specification. While the additional firm characteristics we bring to the analysis beyond typical firm observables contribute significantly to the explanatory power of the model, there remains a substantial portion of variation in AI adoption unexplained by all the controls we use, pointing to a large amount of unobserved heterogeneity among firms that drives AI presence.

In Table 7, we include not only the revenue growth from the initial years of the firm, but also the average annual DHS revenue growth rate from the 3 most recent years for which revenue information is currently available, 2014–2016. Similar to Table 6, in Column 1 we see a positive and statistically significant relationship between revenue growth (both early and late) and AI use. As we include leadership, capitalization and non-TFP objectives in Columns 2–5, the coefficient on early revenue growth loses significance like in Table 6. However, the coefficient on the most recent measure of revenue growth remains statistically significant even when controlling for our full three groups of firm characteristics. While we do not observe the precise timing of firms' AI adoption (we only know whether or not they were using AI in 2017), the fact that this later period of revenue growth could potentially fall into post-adoption period suggests that the use of AI itself could have contributed to the improved performance of the firms who adopted AI—though make no claims for a causal link (future work), and the reverse causality may also be relevant here: growing firms in later stages may have a greater need, and the necessary scale, for AI adoption.

Overall, our specifications have identified some key firm-level characteristics that are clearly associated with early revenue growth of firms, and these characteristics are at the same time highly correlated with AI adoption. These characteristics include the primary owner holding an advanced degree and having had experience starting a business (e.g., serial entrepreneur), along with the primary owner being relatively young (under 35 years of age). Other key factors include being funded by venture capital and having a high initial capitalization. Finally, it appears that the characteristics most closely associated with both high-growth and technology adoption are indicators of innovative activity, specifically process innovation and possessing patents. Each of these factors has been shown to be positively correlated with high-quality and high-growth firms.

Summary of Findings

The results from our full specification in Table 7 (Column 5) can be summarized as follows:

Result #1 – AI Adoption is low on average and skewed towards large firms

The evidence suggests that overall AI adoption by firms is very low and it is concentrated in larger firms that are influential for the economy.[15] Therefore, as in the case of many other firm outcomes that exhibit a high degree of skewness, the low adoption rate does not necessarily make AI irrelevant for aggregate economy. For instance, the exposure to AI by workers is likely much higher than its adoption rate among firms, as our employment-weighted adoption rates indicate. The question naturally turns to why is adoption rate so low and why does this matter?

There are several impediments to AI adoption that seem to limit its diffusion. These include scale effects (many businesses may not possess the vast amounts of data to utilize AI applications), as well as a clear hierarchy of technology adoption needed for proper deployment of AI applications (see Figure 3). For instance, the digitization of various information a firm possesses is a key prerequisite for AI adoption.

The second question of "why it matters" is important in the context of future attempts at trying to measure adoption and the types of firms that are "at-risk" of adoption. If AI is only going to fit among a group of firms that are highly specialized in a certain industry, or in certain product/process types within an industry, then policy makers need to realign their expectations of what they believe AI can accomplish. Many types of firms may never end up adopting AI for a variety of reasons, some of which were discussed above. In other words, perhaps it is not yet fair

[15] This result matches the prior observations from Zolas et al. (2020), where AI tends to be more prevalent among very large and older.

to classify AI as being a potential GPT, or perhaps it is too early to consider its effects on the larger economy.

Result #2 – Observable firm characteristics have limited success in predicting AI adoption

The results from Column 1 of Table 6 indicate that our usual controls do a relatively poor job of describing variation in AI adoption across firms. Even with high-dimensional controls (state-industry controls at the 6-digit NAICS), along with controls for firm size and age, we can only explain around 14% of firm variation in adoption. This low explanatory power indicates that there remains significant unobserved heterogeneity behind AI adoption among firms. Including additional, harder-to-measure factors from ABS related to leadership, capitalization, and innovative strategies contribute significantly to the explanatory power (an increase of almost 20% from the baseline specification in Column 1). This improvement in explanatory power becomes more apparent among the firms that are among the most likely to adopt AI.

In Figure 4, we plot the F1 score (a weighted average between the precision and recall score for individual firms and their predicted AI adoption rate) between the most basic specification (Column 1, Table 6) and the fullest specification (Column 6, Table 6). Our exercise trained our model on 70% of the data and created predicted likelihoods of AI adoption on the remaining 30%, from which we were able to compute the precision/recall for the adopters and non-adopters. The figure shows how the cumulative prediction rate increases for the most likely adopters of AI when we include the Leadership factors, capitalization and non-TFP objectives.

Result #3 – Owner's education, prior startup experience, and age are significant predictors of AI adoption

Prior experience of an entrepreneur has been identified as one of the key predictors of firm survival and performance in the literature on firm dynamics (see, e.g., Nanda and Sorensen 2010, Lindquist, Sol, and Van Praag 2015, Lafontaine and Shaw 2016, Eesley and Wang 2017). In addition, serial entrepreneurship may also be correlated with a better assessment and exploitation of business opportunities advanced technologies offer, or it may reflect the adaptability of an entrepreneur to new technology. It is therefore not surprising that prior startup experience is also positively associated with AI adoption.

Higher levels of education are also positively associated with AI. One possible explanation for this pattern is that higher education may be a proxy for the complexity of products and services offered by the firm that require a higher degree of education and, at the same time, advanced technology to be produced. For instance, a management consulting firm that offers predictive analytics services (a high-end business service) would likely demand Ph.D. degree for owners and managers (see, e.g., Baumol 2005, Lerner and Malmendier 2013, Boudreau and Marx 2019).

The finding that firms with owners younger than 35 are more likely to adopt AI is also intuitive. Younger cohorts of entrepreneurs are likely more avid and sophisticated users of advanced technology and may be more open to adopting these technologies in their businesses (see, e.g., Liang, Wang, and Lazear 2018, Azoulay, Jones, Kim, and Miranda 2020).

Result #4 – Firms with high capitalization requirements are more likely to adopt AI.

Higher initial capital levels required for a startup is also associated with higher probability of AI use. This finding is consistent with the prior literature that indicates businesses with higher capital intensity or capital-to-labor ratio tend to adopt and use advanced technologies more intensively (see, e.g., Dinlersoz and Wolf 2019). Firms receiving VC investment as a startup are also more likely to adopt AI. VC-funded startups tend to be high-growth, innovative startups even before VC-funding (see, e.g., Akcigit et al. 2019 for an analysis of this selection). In addition, much of VC funding goes to startups that are users and producers of advanced technology in high-tech industries. Venture capitalists generally have expertise on identifying the underlying promise of a startup. Hence, VC funding could be a signal of firm quality not captured by other observables used in the analysis. Overall, the characteristics of VC-funded firms are in general highly conducive and complementary to advanced technology use, including AI.

Result #5 – Innovativeness matters for AI adoption

Our results also suggest that innovativeness of a firm matters for AI adoption. Both product and process innovation are positively correlated with AI adoption, but the latter has a much higher correlation. The estimated coefficient for process innovation suggests that firms with this type of innovation are 5.8 percentage points more likely to adopt AI—a magnitude that is roughly equivalent to the overall adoption rate of AI for the firms in our sample. Similarly, firms that possess patents are more likely to adopt (by 3.2 percentage points), and firms that identify IP protection as very important have an additional 5.7 percentage points higher probability of being AI users.

Conclusion and Discussion

As AI rapidly advances its capabilities and becomes more integrated into the workplace, there is an ongoing debate about whether AI technologies will lead to further prosperity and enhance our productivity or whether they will lead to mass joblessness and wage stagnation (Brynjolfsson and McAfee, 2014; Aghion et al. 2017). Central to this debate is obtaining reliable measures on the pervasiveness of AI among the U.S. firm population, and identifying firm characteristics associated with the presence of AI so that we can begin to gauge its impact.

In a 2017 report by the National Academies of Science, Engineering, and Medicine (NASEM) entitled, “Information Technology and the U.S. Workforce: Where Are We and Where Do We Go From Here?”, an expert panel acknowledges the potential of AI to transform the economy, but notes that accurate forecasts of these effects are limited due to the absence of reliable data on the use of AI in the economy. The ABS closes this gap in the data by providing a first glimpse as to the spread of AI across a nationally representative set of firms and identifying a set of firms that are leading the race in its adoption.

From the set of business technologies, we have identified five potential technologies that incorporate elements of AI. These include: Automated Guided Vehicles, Machine Learning, Machine Vision, Natural Language Processing, and Voice Recognition. Across all AI-related technologies, the aggregate adoption rate for all firms in the economy is only 6.6% (4.5% non-imputed), meaning that approximately 1 in 16 firms in the US are utilizing some form of AI in the workplace. This adoption rate is significantly lower than the adoption rate highlighted in the AI survey by the European Commission and other private surveys by McKinsey, Deloitte, and PwC. However, it is important to consider the sampling methods of those surveys. Neither of the other surveys claim to be nationally representative and tend to focus on larger, publicly traded companies. In contrast, ABS sample includes many small firms where AI adoption is very low.

AI adoption rate indeed varies greatly by firm size. Figure 2 charts the adoption rate of AI (for the whole ABS sample) across 12 different size categories used in the BDS. Adoption rates (defined as usage or testing) monotonically increase from 5.3% for the group of firms with the smallest number of employees to 62.5% for firms with 10,000+ employees. In other words, scale appears to be a primary correlate of AI usage, likely due to both the large quantities of data and computing power required to fully realize the most popular types of AI currently available. However, despite this strong relationship, there appears to be a substantial amount of heterogeneity among firms who report using AI.

Our analysis finds that standard observable characteristics of firms, such as size, age, location (state), and industry do not go far in explaining the heterogeneity in AI adoption. Leveraging the richness of firm characteristics in ABS that are not typically available in other firm-level surveys, we show that firm intangibles such as ownership characteristics, innovation, and startup capitalization add significantly to our ability to capture variation in AI adoption. Taken together, early AI adopters tend to be among the largest firms in the economy, but also among the highest quality and highest growth firms. The complementarity between AI use and measures of firm quality and growth potential suggests that while the diffusion rate of AI is low and may remain low, AI's impact on the economy can be disproportionately large because it is concentrated in a niche of startups that are innovative, highly capitalized, and fast-growing—the type of firms that contribute significantly to aggregate growth and productivity. The findings also suggest an "AI divide" between two segments of the firm population: one characterized by low growth ambitions, life-style-oriented entrepreneurship, and little innovation; the other with ambitions to expand, innovation-driven, and the ability to transform the economy and propel growth. The distance between these two segments is also likely growing in part due to the use of advanced technologies like AI. Identifying and quantifying this role of advanced technologies is a key challenge for future work.

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Text Box 1: 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: Summary Statistics and Distributions of ABS Respondents*

a. Firm-Level Statistics

Mean	ABS Sample (Raw)	ABS-LBD Sample (Weighted)	National (2017 BDS)
Employment	89.32	26.28	24.24
Age	16.33	15.61	n.a.

b. Firm Distributions (in %)

By Size	ABS Sample (Raw)	ABS-LBD 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 (in %)	ABS Sample (Raw)	ABS-LBD Sample (Weighted)	National (2017 BDS)
0 to 5	25	27	33
6 to 10	16	17	16
11 to 20	25	25	23
21+	33	31	28

*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).

**The firm size categories reported in Table 1b were created based on size categories used in a previous (legacy) BDS. With the release of the 2017 and 2018 BDS came updated size categories which make it impossible to compare the publicly available size categories to the size categories used here. For this reason, we compare to the legacy 2016 BDS instead of the new 2017 BDS.

Table 2: AI-Based Business Technology Use Rates by Type

Business Technology	% Use	% Testing
Machine Learning	2.9 (2.9)	0.7 (0.7)
Voice Recognition	2.5 (2.6)	0.7 (0.7)
Machine Vision	1.8 (1.8)	0.4 (0.4)
Natural Language	1.3 (1.3)	0.4 (0.4)
Automated Vehicles	0.8 (0.8)	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 LBD 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 weighted values in parentheses.

Table 3: Firm-Weighted versus Employment-Weighted Adoption Rates for AI-Based Business Technologies

Business Technology	% Use (Tab-Weighted)	% Use (Employment-Weighted)	Difference Ratio
Machine Learning	2.9 (2.2)	8.9 (5.2)	3.1 (2.4)
Voice Recognition	2.5 (2)	7.5 (5.9)	3 (3)
Machine Vision	1.8 (1.4)	5.6 (3.1)	3.2 (2.3)
Natural Language	1.3 (1.0)	4.3 (3.5)	3.3 (3.5)
Automated Vehicles	0.8 (0.6)	2.2 (1.6)	2.7 (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 LBD 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 LBD tabulation weights and the difference ratio is computed by dividing the Employment Weighted Use rate by the LBD Tabulation-Weighted Use rate. Imputed values are listed, while raw weighted values are in parentheses.

Table 4a: Firm Characteristics by AI User Status (%)

	Full Sample	Use AI	Do not use AI	Difference
Primary Owner Characteristics				
Hold Advanced Degree	22.5	34.6	21.7	12.9
Owned Prior Business	35.2	37.4	35.0	2.3
Missing Age	6.6	7.6	6.5	1.1
Owner Age (0–34)	3.9	3.8	3.9	-0.1
Owner Age (35–54)	49.1	49.5	49.1	0.3
Owner Age (55+)	40.6	39.0	40.7	-1.7
Reasons for Starting the Business				
Wanted to be own boss	65.6	65.4	65.6	-0.2
Flexible Hours	53.1	52.2	53.2	-1.0
Balance work and family	55.7	54.9	55.7	-0.8
Opportunity for greater income	62.9	63.7	62.8	0.9
Best avenue for ideas/goods/services	57.2	62.6	56.9	5.7
Unable to find employment	6.4	7.1	6.3	0.8
Working for someone else not appealing	30.9	30.8	30.9	-0.1
Always wanted to start own business	47.6	48.4	47.6	0.8
Entrepreneurial role model	23.7	26.4	23.6	2.8
Carry on family business	10.1	11.0	10.1	0.9
Help or become involved in community	21.6	28.0	21.2	6.8
Other reasons	7.5	10.1	7.4	2.7
Startup Costs and Funding				
Funded by VC	0.5	1.2	0.5	0.7
Missing Startup Capitalization	8.2	5.8	8.4	-2.6
Startup Capitalization <25K	36.5	34.6	36.6	-2.0
Startup Capitalization 25K–1M	37.8	42.9	37.4	5.4
Startup Capitalization 1M+	2.1	2.7	2.0	0.7
Don't Know Startup Capitalization	15.6	13.7	15.7	-2.0
Innovative Strategies & Outcomes				
Process Innovation	17.8	37.4	16.6	20.8
Product Innovation	49.7	63.2	48.9	14.3
Patents Owned or Pending	1.9	4.7	1.7	3.0
IP is very important	17.1	35.2	16.0	19.1
Growth-oriented innovation strategy	64.4	73.1	63.9	9.2

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 any of the AI-based Business Technologies. The "Growth-oriented innovation strategy" indicator is equal to 1 if a firm responded that a focus on introducing new goods or services, reaching new customer groups, or opening up new domestic or export markets was a "very important" innovation strategy for the business.

Table 4b: AI Usage Rates by Firm Characteristics

	AI Usage Rate (%)		
Full Sample	5.8		-
	Yes	**No**	**Difference**
Primary Owner Characteristics			
Hold Advanced Degree	8.9	4.9	4.0
Owned Prior Business	6.1	5.6	0.6
Missing Age	6.6	5.7	0.9
Owner Age (0–34)	5.6	5.8	-0.1
Owner Age (35–54)	5.8	5.7	0.1
Owner Age (55+)	5.5	5.9	-0.4
Reasons for Starting the Business			
Wanted to be own boss	5.7	5.8	0.0
Flexible Hours	5.7	5.9	-0.2
Balance work and family	5.7	5.8	-0.2
Opportunity for greater income	5.8	5.6	0.2
Best avenue for ideas/goods/services	6.3	5.0	1.3
Unable to find employment	6.5	5.7	0.8
Working for someone else not appealing	5.7	5.8	0.0
Always wanted to start own business	5.8	5.7	0.2
Entrepreneurial role model	6.4	5.6	0.8
Carry on family business	6.3	5.7	0.5
Help or become involved in community	7.5	5.3	2.2
Other reasons	7.7	5.6	2.1
Startup Costs and Funding			
Funded by VC	12.8	5.7	7.1
Missing Startup Capitalization	4.1	5.9	-1.8
Startup Capitalization <25K	5.5	5.9	-0.5
Startup Capitalization 25K–1M	6.5	5.3	1.2
Startup Capitalization 1M+	7.6	5.7	1.9
Don't Know Startup Capitalization	5.1	5.9	-0.8
Innovative Strategies & Outcomes			
Process Innovation	12.1	4.4	7.7
Product Innovation	7.3	4.2	3.1
Patents Owned or Pending	14.4	5.6	8.8
IP is very important	11.8	4.5	7.3
Growth-oriented innovation strategy	6.5	4.4	2.2

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 any of the AI-based Business Technologies. The "Growth-oriented innovation strategy" indicator is equal to 1 if a firm responded that a focus on introducing new goods or services, reaching new customer groups, or opening up new domestic or export markets was a "very important" innovation strategy for the business.

Table 5 – Determinants of High-Growth Firms

Description	(1) Revenue Growth (First 3 years)	(2) Revenue Growth (First 3 years)	(3) Revenue Growth (First 3 years)	(4) Revenue Growth (First 3 years)	(5) Revenue Growth (First 3 years)
Use AI (1/0)					0.0032
					(0.0042)
Advanced Degree (1/0)	0.0127***			0.0073**	0.0072**
	(0.0031)			(0.0031)	(0.0031)
Prior Business (1/0)	0.0086***			0.0031	0.0031
	(0.0022)			(0.0022)	(0.0022)
Owner Age (35–54)	-0.0547***			-0.0538***	-0.0538***
	(0.0058)			(0.0058)	(0.0058)
Owner Age (55+)	-0.0996***			-0.0982***	-0.0982***
	(0.0060)			(0.0060)	(0.0060)
Lifestyle Reason (1/0)		-0.0017		-0.0126***	-0.0126***
		(0.0020)		(0.0021)	(0.0021)
Funded by Venture Capital (1/0)		0.0753***		0.0551***	0.0550***
		(0.0166)		(0.0166)	(0.0166)
Startup Capitalization 25K–1M (1/0)		0.0397***		0.0351***	0.0351***
		(0.0025)		(0.0025)	(0.0025)
Startup Capitalization 1M+ (1/0)		0.0677***		0.0611***	0.0611***
		(0.0071)		(0.0071)	(0.0071)
Process Innovation (1/0)			0.0241***	0.0214***	0.0212***
			(0.0028)	(0.0028)	(0.0028)
Product Innovation (1/0)			0.0061***	0.0042**	0.0042**
			(0.0021)	(0.0021)	(0.0021)
Patents Owned or Pending (1/0)			0.0677***	0.0613***	0.0612***
			(0.0091)	(0.0091)	(0.0091)
IP is very important (1/0)			0.0323***	0.0282***	0.0280***
			(0.0029)	(0.0029)	(0.0029)
Growth-oriented innovation strategy (1/0)			0.0279***	0.0254***	0.0253***
			(0.0021)	(0.0021)	(0.0021)
Owner Gender (1 = Female, 0 = Male)	-0.0026	0.0008	-0.0020	0.0006	0.0006
	(0.0024)	(0.0024)	(0.0023)	(0.0024)	(0.0024)
State-by-Ind Controls	Yes	Yes	Yes	Yes	Yes
Firm Age Controls	Yes	Yes	Yes	Yes	Yes
Observations (rounded)	170,000	170,000	170,000	170,000	170,000
R-squared	0.144	0.143	0.144	0.151	0.151

Notes: Standard errors in parentheses. *, ** and *** denotes significance at the 10, 5 and 1% respectively. Revenue growth refers to the Davis, Haltiwanger and Schuh measure of growth given by: $(REV_t - REV_{t-1}) / (0.5 * REV_t + REV_{t+1})$. "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 any of the AI-based Business Technologies (Automated Guided Vehicles, Natural Language Processing, Machine Learning, Machine Vision and Voice Recognition). State-by-Ind controls refers to state and 6-digit NAICS industry dummies.

Table 6 – Determinants of AI Adoption (High-Growth Firms (First 3 years))

Description	(1) Use AI	(2) Use AI	(3) Use AI	(4) Use AI	(5) Use AI	(6) Use AI
Revenue Growth (First 3 years)	0.0093***	0.0087***	0.0076***	0.0023	0.0014	-0.0013
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Advanced Degree (1/0)		0.0157***			0.0099***	0.0096***
		(0.0021)			(0.0021)	(0.0021)
Prior Business (1/0)		0.0115***			0.0062***	0.0054***
		(0.0014)			(0.0014)	(0.0014)
Owner Age (35–54)		-0.0057*			-0.0019	-0.0019
		(0.0034)			(0.0034)	(0.0034)
Owner Age (55+)		-0.0101***			-0.0039	-0.0032
		(0.0035)			(0.0035)	(0.0035)
Lifestyle Reason (1/0)			0.0000		-0.0023*	-0.0017
			(0.0013)		(0.0013)	(0.0013)
Funded by Venture Capital (1/0)			0.0553***		0.0362***	0.0345***
			(0.0115)		(0.0113)	(0.0113)
Startup Capitalization 25K–1M (1/0)			0.0178***		0.0106***	0.0079***
			(0.0017)		(0.0017)	(0.0017)
Startup Capitalization 1M+ (1/0)			0.0269***		0.0117**	0.0030
			(0.0049)		(0.0049)	(0.0050)
Process Innovation (1/0)				0.0590***	0.0578***	0.0569***
				(0.0022)	(0.0022)	(0.0022)
Product Innovation (1/0)				0.0096***	0.0095***	0.0095***
				(0.0013)	(0.0013)	(0.0013)
Patents Owned or Pending (1/0)				0.0358***	0.0325***	0.0318***
				(0.0073)	(0.0073)	(0.0073)
IP is very important (1/0)				0.0584***	0.0566***	0.0550***
				(0.0023)	(0.0023)	(0.0023)
Growth Strategy (1/0)				0.0105***	0.0099***	0.0087***
				(0.0013)	(0.0013)	(0.0013)
State-by-Ind Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Size Controls	No	No	No	No	No	Yes
MU Status Control	No	No	No	No	No	Yes
Observations (rounded)	170,000	170,000	170,000	170,000	170,000	170,000
R-squared	0.141	0.142	0.143	0.162	0.164	0.164

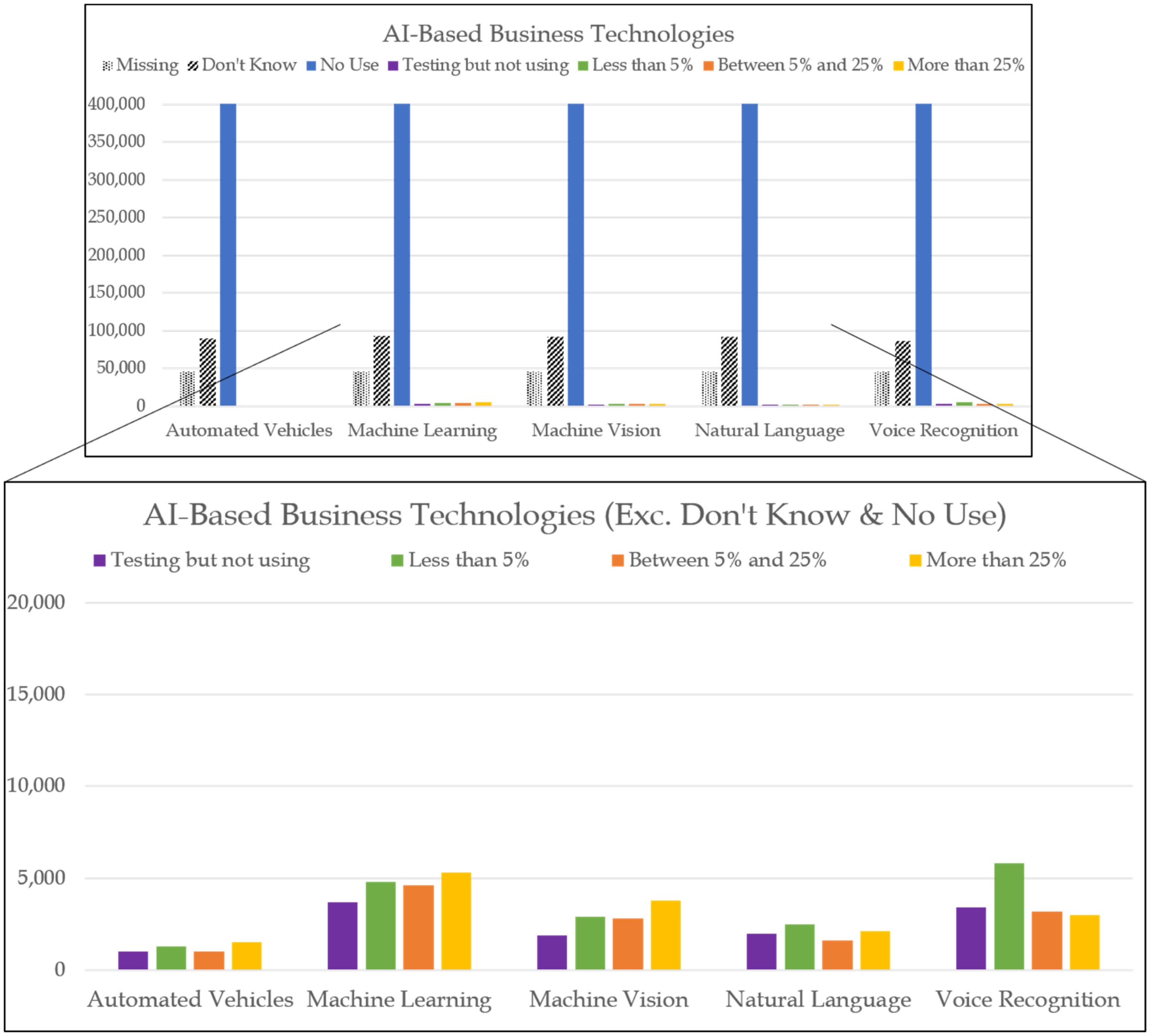
Notes: Standard errors in parentheses. *, ** and *** denotes significance at the 10, 5 and 1% respectively. Revenue growth refers to the Davis, Haltiwanger and Schuh measure of growth given by: $(REV_t - REV_{t-1})/(0.5 * REV_t + REV_{t+1})$. “Use” is defined as having responded with “In use for less 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 any of the AI-based Business Technologies (Automated Guided Vehicles, Natural Language Processing, Machine Learning, Machine Vision and Voice Recognition). State-by-Ind controls refers to state and 6-digit NAICS industry dummies. Firm size controls refers to size at time of the ABS survey (reference year 2017).

Table 7 – Determinants of AI Adoption (High-Growth Firms (First 3 years & Most Recent))

Description	(1) Use AI	(2) Use AI	(3) Use AI	(4) Use AI	(5) Use AI	(6) Use AI
Revenue Growth (First 3 years)	0.0074***	0.0070***	0.0058***	0.0014	0.0005	-0.0022
	(0.0020)	(0.0020)	(0.0020)	(0.0019)	(0.0019)	(0.0020)
Revenue Growth (Last 3 years)	0.0082***	0.0078***	0.0081***	0.0043**	0.0043**	0.0038*
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Advanced Degree (1/0)		0.0157***			0.0099***	0.0096***
		(0.0021)			(0.0021)	(0.0021)
Prior Business (1/0)		0.0114***			0.0062***	0.0054***
		(0.0014)			(0.0014)	(0.0014)
Owner Age (35–54)		-0.0053			-0.0017	-0.0017
		(0.0034)			(0.0034)	(0.0034)
Owner Age (55+)		-0.0095***			-0.0036	-0.0029
		(0.0035)			(0.0035)	(0.0035)
Lifestyle Reason (1/0)			-0.0000		-0.0023*	-0.0017
			(0.0013)		(0.0013)	(0.0013)
Funded by Venture Capital (1/0)			0.0549***		0.0360***	0.0344***
			(0.0115)		(0.0113)	(0.0113)
Startup Capitalization 25K–1M (1/0)			0.0179***		0.0107***	0.0079***
			(0.0017)		(0.0017)	(0.0017)
Startup Capitalization 1M+ (1/0)			0.0269***		0.0118**	0.0031
			(0.0049)		(0.0049)	(0.0050)
Process Innovation (1/0)				0.0590***	0.0578***	0.0569***
				(0.0022)	(0.0022)	(0.0022)
Product Innovation (1/0)				0.0096***	0.0095***	0.0095***
				(0.0013)	(0.0013)	(0.0013)
Patents Owned or Pending (1/0)				0.0357***	0.0324***	0.0318***
				(0.0073)	(0.0073)	(0.0073)
IP is very important (1/0)				0.0584***	0.0565***	0.0550***
				(0.0023)	(0.0023)	(0.0023)
Growth Strategy (1/0)				0.0105***	0.0099***	0.0086***
				(0.0013)	(0.0013)	(0.0013)
State-by-Ind Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Size Controls	No	No	No	No	No	Yes
MU Status Control	No	No	No	No	No	Yes
Observations (rounded)	170,000	170,000	170,000	170,000	170,000	170,000
R-squared	0.141	0.142	0.143	0.162	0.164	0.164

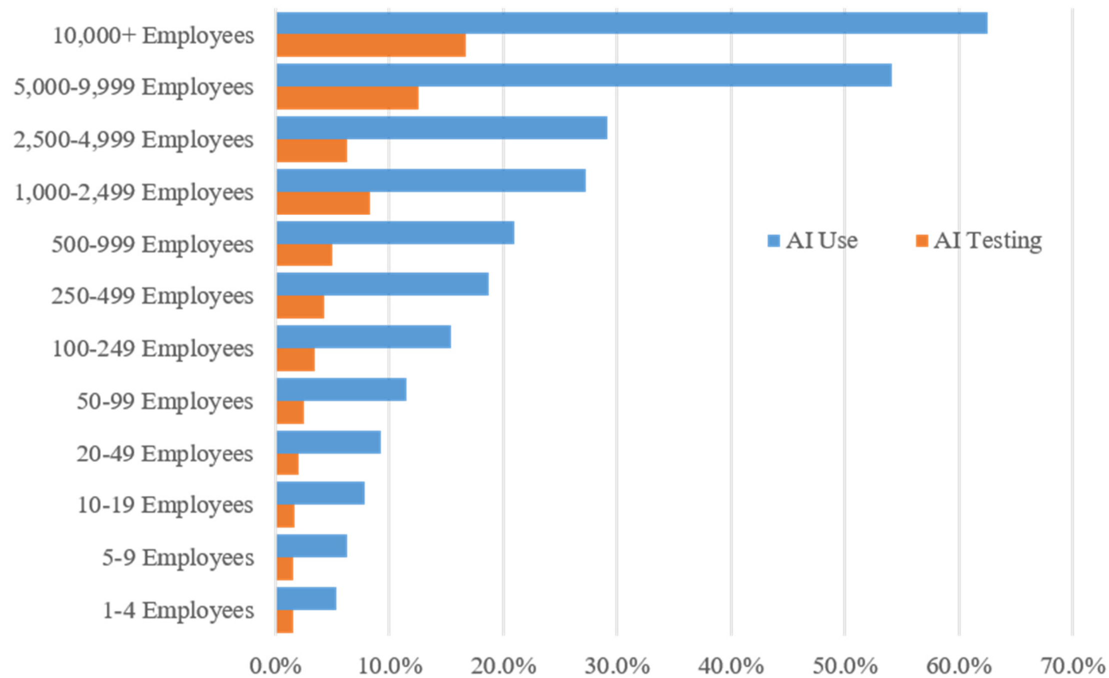
Notes: Standard errors in parentheses. *, ** and *** denotes significance at the 10, 5 and 1% respectively. Revenue growth refers to the Davis, Haltiwanger and Schuh measure of growth given by: $(REV_t - REV_{t-1})/(0.5 * REV_t + REV_{t+1})$. “Use” is defined as having responded with “In use for less 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 any of the AI-based Business Technologies (Automated Guided Vehicles, Natural Language Processing, Machine Learning, Machine Vision and Voice Recognition). State-by-Ind controls refers to state and 6-digit NAICS industry dummies. Firm size controls refers to size at time of the ABS survey (reference year 2017).

Figure 1: ABS Responses to AI-Based Business Technologies



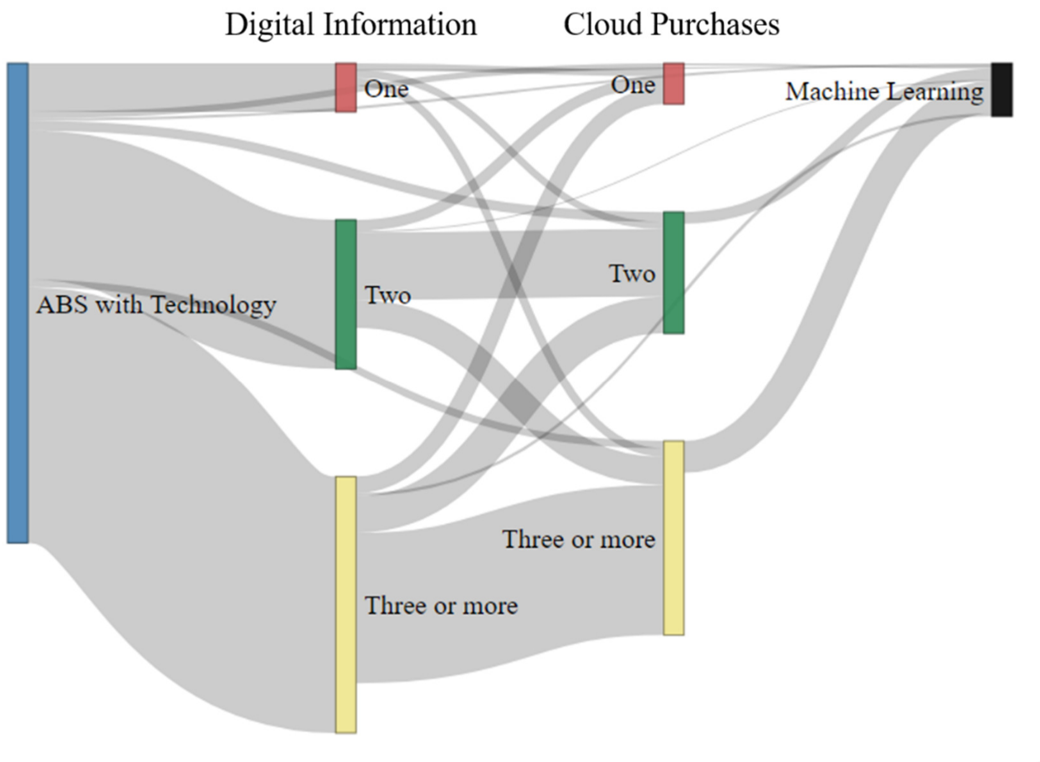
Note: Tabulations based on unweighted and unimputed responses.

Figure 2: AI Usage across size Categories (Weighted)



Notes: The figures visually represent the share of firms (weighted by survey-LBD weights) that indicate use or test at least 1 of the following business technologies: Automated Guided Vehicles, Machine Learning, Machine Vision, Natural Language Processing and Voice Recognition. Values are based on the imputed probabilities for respondents who answered “Missing” or “Don’t Know” to 1 or more of the aforementioned business technologies.

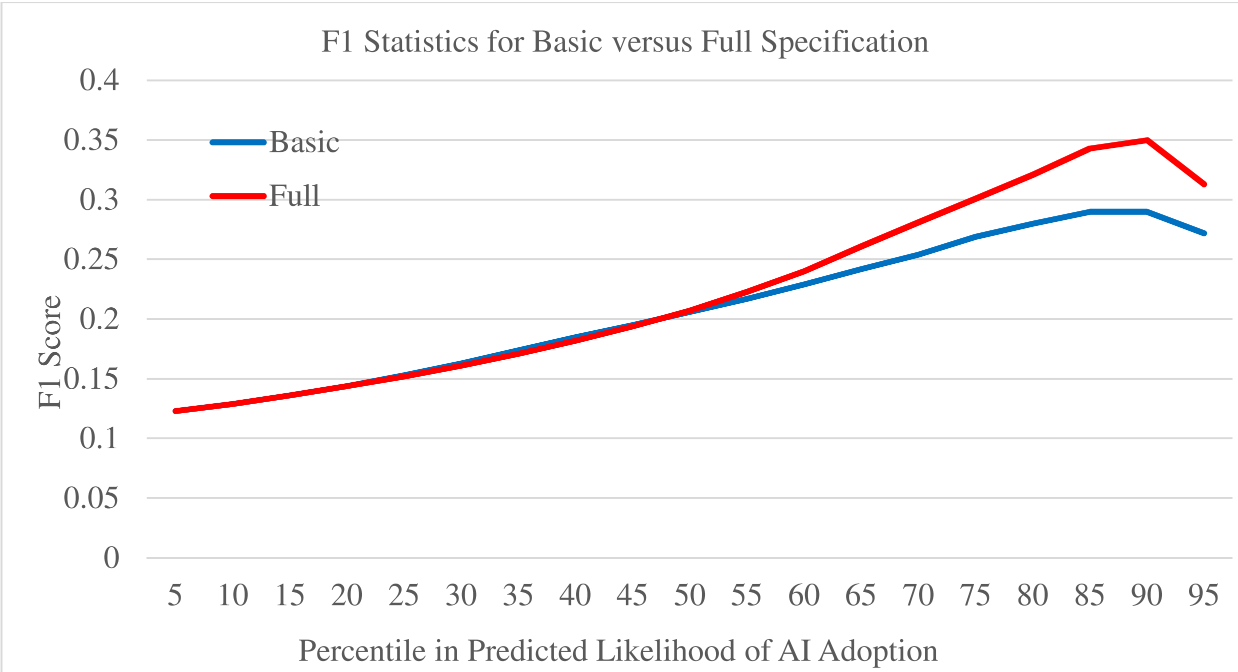
Figure 3: Technological Hierarchies[16]



a. Sankey Diagram for Machine Learning

[16] 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".

Figure 4 – F1 Score for Basic versus Full Specification



Appendix

Table A1– Determinants of High-Growth Firms (Detailed Reasons for Owning Business)

Description	(1) Revenue Growth (First 3 years)
Wanted to be own boss (1/0)	0.0082***
	(0.0028)
Flexible hours (1/0)	-0.0158***
	(0.0028)
Balance work and family (1/0)	-0.0086***
	(0.0027)
Opportunity for greater income (1/0)	0.0043*
	(0.0026)
Best avenue for ideas/goods/services (1/0)	0.0031
	(0.0024)
Unable to find employment (1/0)	-0.0108**
	(0.0043)
Working for someone else not appealing (1/0)	-0.0013
	(0.0024)
Always wanted to start own business (1/0)	0.0089***
	(0.0025)
Entrepreneurial role model (1/0)	0.0022
	(0.0027)
Carry on family business (1/0)	-0.0137***
	(0.0037)
Help or become involved in community (1/0)	0.0107***
	(0.0027)
Other reasons (1/0)	-0.0040
	(0.0039)
Advanced Degree (1/0)	0.0075**
	(0.0031)
Prior Business (1/0)	0.0024
	(0.0022)
Owner Age (35-54)	-0.0539***
	(0.0058)
Owner Age (55+)	-0.0979***
	(0.0060)
Funded by Venture Capital (1/0)	0.0542***
	(0.0166)
Startup Capitalization 25K - 1M (1/0)	0.0343***
	(0.0025)
Startup Capitalization 1M+ (1/0)	0.0605***
	(0.0071)
Process Innovation (1/0)	0.0206***
	(0.0028)
Product Innovation (1/0)	0.0038*
	(0.0021)
Patents Owned or Pending (1/0)	0.0616***
	(0.0091)
IP is very important (1/0)	0.0272***
	(0.0029)
Growth-oriented innovation strategy (1/0)	0.0218***
	(0.0022)
Owner Gender (1 = Female, 0 = Male)	0.0030
	(0.0024)
State-by-Ind Controls	Yes
Firm Age Controls	Yes
Observations (rounded)	170,000
R-squared	0.152