What determines AI adoption?

Jaehan Cho, Timothy DeStefano, Hanhin Kim, Jin Paik[1]

Abstract

The following paper comprises one of the first empirical studies on the firm determinants of AI adoption. The analysis relies on novel firm-level data on AI use by application and source for businesses in South Korea from 2017 and 2018. The econometric assessment identifies several firm characteristics important for AI use, specifically firm size and use of intangible assets. These characteristics are significant for AI adoption regardless of the technology's source (i.e., produced in-house or obtained from a vendor) with some heterogeneity across different operational applications (i.e., product/service development, sales, organizational management, and so on). Furthermore, AI is adopted in tandem with bundles of other digital technologies including big data, cloud computing, and the Internet of Things that facilitate data collection, usage, and processing. Finally, AI adoption corresponds with contemporaneous firm reorganization, however the channel through which this occurs is unclear.

Keywords: AI, Digital technology, Technology diffusion, Firm, Reorganization

[1] Jaehan Cho, Korea Institute for Industrial Economics and Trade: jhcho@kiet.re.kr
Timothy DeStefano, Harvard Business School: tdestefano@hbs.edu
Hanhin Kim, Korea Institute for Industrial Economics and Trade: hh.kim@kiet.re.kr
Jin Paik, Harvard Business School: jpaik@hbs.edu

Acknowledgements include Andrea Blasco, Jackie Lane, Michael Menietti, Rachel Mural, Wei Yang Tham and Jonathan Timmis.

1) Introduction

Artificial intelligence (AI) is becoming an obtainable technology for firms. This is in part driven by advances in AI research, increased investments in AI firms, and more cost-effective access to computing and storage technology delivered by the cloud (OECD 2020; Schmelzer 2020; Iansiti and Lakhani 2020). Firms embed AI into a host of business operations by applying AI-based techniques to a growing number of tasks, including prediction, automation, process optimization, text classification, and text-to-speech conversion (Iansiti and Lakhani 2020; Davenport and Ronanki 2018; European Parliament 2020). In the coming years, AI will dramatically change how firms organize, compete, and engage with customers, with some suggesting that AI is the next general-purpose technology (GPT) (Iansiti and Lakhani 2020; Goldfarb, Taska and Teodoridis 2020; Agrawal, Gans, and Goldfarb 2018; Brynjolfsson and McAfee 2014).

Survey research provides some insights into the use of AI. Early surveys (administered by consultancy companies) which targeted larger firms and had small samples, typically found unexpectedly high adoption rates ranging from 20 to 30 percent (Knight 2020). More recently, national statistical agencies administered surveys to a representative sample of firms in the United States (US) and Germany. These studies reveal important AI use patterns: i) usage rates are considerably lower than found by previous surveys, and ii) descriptive analysis suggests the importance of firm size and technology complementarity (such as big data and the cloud) for AI use (Cho et al. 2021; Zolas et al. 2020; Rammer et al. 2021). However, due to the preliminary nature of these AI-related surveys, much of the data is cross-sectional, thus empirical evidence on AI adoption is limited.[2]

This paper conducts one of the first studies on firm-level AI adoption, relying on a relatively unused firm-level dataset on AI usage administered by the Office of National Statistics in South Korea. Data includes detailed information on AI use, firm financials, organizational changes, and complementary technology usage for the years 2017 and 2018. Using this data, we identify the firm characteristics that influence AI adoption and determine whether heterogeneity exists in terms of where AI is being implemented (such as sales, product/service development,

[2] One early and insightful exception is Goldfarb et al (2020), which uses job postings for a number of IT positions as proxy for ML/AI diffusion, suggesting that labor demand can be used to measure technology adoption (Tambe and Hitt 2012).

organizational management, etc.) and where it is sourced (developed in-house or an external provider). This paper also explores the extent to which external partnerships matter for AI adoption, whether complementarities exist with other emerging technologies such as cloud computing, big data, and the Internet of Things (IoT) and if reorganization is occurring alongside AI implementation. The panel data enables us to assess relatively unexplored time dimensions of AI technology adoption, such as whether complementary investments and firm reorganization are a precursor to AI adoption or if they occur contemporaneously.

We are motivated to understand what drives AI adoption for several reasons. First, the use of new technologies is important for firms' competitive gains and innovativeness at the micro-level (Jin and McElheran 2018; Cardona, Kretschmer and Strobel 2013; Brynjolfsson and McAfee 2014; Bloom, Sadun and Van Reenen 2012; Syverson 2011) and economic growth disparities at the macro-level (Niebel 2018; Fernald 2014; Timmer et al. 2011; O'Mahoney, Van Ark and Timmer 2008). The implementation of this technology may therefore lead to concentrated job losses (Acemoglu et al. 2020; Acemoglu and Restrepo 2020; Silva et al. 2019; Frey and Osborne 2017; Brynjolfsson and McAfee 2014) and widening income inequality (Bessen, Denk and Meng 2021; Van Reenen 2011; Aghion, Howitt and Violante 2002). Moreover, history provides numerous examples of social upheavals coinciding with the diffusion of GPTs (Fischer 1966; Foster 2003; Berlanstein 1992).

When firms adopt AI, they face a cost/benefit tradeoff where certain attributes are more complementary to AI-driven performance gains; therefore, firms with those characteristics may be more likely to adopt the technology. Firm size is an important deterimant of technology adoption, as larger firms tend to have greater amounts of knowledge-based capital, accumulated technology, and financial strength (Gibbs and Kraemer 2004; Claessens and Tzioumis 2006; Hall and Lerner 2010). Firm age is also a likely determinant for technology adoption, since young firms are thought to have newer assets and more flexible business models which may be more compatible with newer technologies (DeStefano, De Backer and Moussiegt 2017; Haller and Siedschlag 2011; Luque 2000; Baldwin and Rafiquzzaman 1998).[3] The diffusion of frontier digital technology also corresponds with firms becoming increasingly more reliant on intangibles such as data, intellectual property, and R&D, thus pointing to the importance of intangible assets for AI adoption (Haskel

[3] However, older firms may have greater amounts of accrued know-how, potentially allowing them to adopt and exploit advanced technology more effectively than young firms (Arvanitis & Hollenstein, 2001).

and Westlake 2017; Byrne and Corrado 2017; Bryne et al. 2018; Andres, Niebel and Viete, 2020; DeStefano et al. 2020). In addition, foreign-owned firms are typically found to exhibit higher levels of productivity and use more technology, which may also be related with AI adoption (Lopez-Acevedo 2002; Griffith, Redding and Simpson 2002). This paper contributes to the literature on digital diffusion by assessing the extent to which these characteristics matter for AI adoption.

The use of complementary technologies is also likely to determine AI adoption, notably those which facilitate data collection, analysis, and processing/storage. Anecdotally, firms wishing to use AI require large datasets to train their algorithms, which are collected and assessed at scale by IoT and big data practices and processed and stored on cloud computing services (Firouzi et al. 2021; Iansiti and Lahkani 2020; Ramraj 2020; OECD 2019a).[4] While likely evident to practitioners, academic papers on digital diffusion tend assess the adoption and/or performance effects of a single technology rather than bundles (Cordona et al. 2013). Similarly, amongst policymakers, most Organization for Economic Cooperation and Development (OECD) member countries design policy frameworks to either encourage the use of one particular technology or target capital investments more generally, while excluding technology acquired through services such as cloud computing and big data (Tax Foundation 2018; Andres et al. 2020; DeStefano et al 2020).[5] This paper tests the importance of technology complementarities for AI and identifies whether timing (ex-ante or contemporaneous) matters for adoption. Insights gained from this paper will inform both managers considering whether to use AI and policymakers trying to foster technology diffusion.

As with previous digital tools, implementing new technologies will likely require firm restructuring (Bresnahan et al. 2002: Forman and McElheran 2013; Brynjolfsson et al. 2019). Recent work by Iansiti and Lahkani (2020) suggests that AI use requires considerable firm reorganization, including breaking down siloes, sharing data across the organization, hiring skilled data scientists, and adjusting management practices. These activities may induce firms to downsize parts of the organization (such as branches that carry out repetitive white-collar tasks) while expanding others (like the IT and data science teams). However, when making such changes, firms are faced with various supply-side constraints. For example, the current shortage of data scientists

[4] A recent paper by Firouzi et al 2021 discusses, in detail, the interplay between, IoT, cloud computing, data practices and AI.

[5] This has been found to discourage firms from adopting cloud computing and data analytics (DeStefano et al. 2020; Andres, et al. 2020).

and skilled AI workers may require companies to relocate parts of their operations closer to technology hubs and/or universities, including Silicon Valley, Boston, Seattle, etc (Randazzo et al. 2021; Heston and Zwetsloot 2020). We examine the relationship between AI and firm reorganization and identify when these changes occur in the adoption process.

To preview our results, we find that the types of firms that are adopting AI are those that are large and those that use intangibles intensively. These results are consistent when we examine the adoption by source (either produced in-house or outsourced) with some heterogeneity by application. We also identify several technologies which appear to be important complements for AI, notably IoT, cloud computing, and big data; the timing of technology application plays a role as well. Finally, our analysis finds evidence that firm reorganization is correlated with contemporaneous AI adoption however it is not clear through which channel restructuring is occurring.

The rest of the paper is organized as follows. In Section 2, we define AI and discuss the history around the technology. In Section 3, we discuss the data used, while Section 4, highlights the empirical strategy used in this paper. The descriptive and empirical results are presented in Section 5. In Section 6, we provide a summary of the results with some insights for future research.

2) What is AI?

While there is no internationally recognized definition for AI, a G20 Memorandum of Agreement offers the following agreement on the basic components of AI. (OECD 2019b):

- *Machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments.*
- *Uses machine and/or human-based inputs to perceive real and/or virtual environments; abstract such perceptions into models (in an automated manner, e.g., with ML or manually)*
- *Uses model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy*

The concept of AI has its roots in antiquity (Cave et al. 2020); however, the basis for our modern understanding originates in the 1950s from researchers such as Alan Turing, who proposed a mathematical theory where computers could deduct information from simple symbols such as 0 and 1. While the field of research commenced in 1956 (at a summer workshop on AI at Dartmouth College), development stalled in the mid-1970s due to slow research progress and declining funding (Anyoha 2018). Renewed interest in AI occurred roughly a decade ago and coincided with greater availability of data, cheaper storage techniques, and advanced processing capabilities (Paik et al. 2020).

AI advances are translating into greater varieties of applications and is expected to increase in the future.[6] For example, in product development, AI can be used for digital testing, making prototype predictions, identifying defections, facilitating generative designs, and so on. Marketing, sales, and customer management operations employ AI to assist with tasks ranging from transcribing sales calls to analyzing callers' emotions (Balkken 2019). Firms are finding a growing number use cases for AI within production and logistics processes, such as predicting demand and supply forecasts, assisting with warehouse management, planning performance optimization, and so on (Iansiti and Lakhani 2020; Davenport and Ronanki 2018; European Parliament 2020). The

[6] There are differences in the types of AI/machine learning (ML) commonly used in firms, such as supervised, unsupervised, and reinforced learning. Supervised learning algorithms learn from known data (with labeled input-output pairs) to predict outcomes within unforeseen data. Unsupervised learning allows the algorithm to self-discover data to make outcome predictions. Reinforced learning lies between the two previous examples; the system makes predictions by independently assessing data and exploiting available input/output information (Loukas 2020).

richness of the data used in this paper allows us to assess the firm determinants of different AI applications over time.

Businesses acquire AI through two main sources. First, firms can produce their own AI in-house. Firms that tend to build AI in-house typically use the technology to drive their core business objectives. Moreover, they tend to be large, data-intensive, have more human capital, and enjoy deeper financial resources (Forbes 2019). AI acquired through third-party suppliers tends to be used for less-essential activities. Thus, AI as a service may be better-suited to younger, smaller firms with limited access to finance. However, they may also be appropriate solutions for large and technologically-sophisticated companies seeking advanced analytical tools for more specialized use cases (Rowan 2020). To date, there is scant research on the rates of in-house versus outsourced AI deployment and the determinants of their adoption. This paper aims to contribute to this area.

3) Data

This paper relies on a firm-level dataset from the Survey of Business Activities from Statistics Korea (KOSTAT), the national statistical agency of the government of South Korea. Since 2005, KOSTAT has conducted comprehensive surveys on business activities for a representative sample of firms. The aim of the survey is to provide detailed data on changes in the South Korean economy's, industrial structure. KOSTAT collects information on various aspects of firm characteristics and business environments, such as business performance, technology use, diversification, partnerships, restructuring patterns, etc. The survey targets corporations with at least 300 million KRW (roughly 250,000 USD) in capital stock, thereby covering approximately 11,063 firms across all industries in our sample.[7] [8] The survey is conducted by either firm visitation or online-based questionnaires and supplemented with administrative data on business information.

In 2018 and 2019, KOSTAT added questionnaires on the use of advanced digital technologies to track the diffusion of Industry 4.0 technologies. This dataset contains information on firm-level AI use, both by applications, and sourcing. The KOSTAT data also features

[7] For enterprises in wholesale and retail trade and other service industries, enterprises with fewer than 49 full-time employees are included in the target population if their capital stock is valued at one billion KRW or more.
[8] Summary statistics can be found in Table A1 in the Appendix.

information on the use of other emerging digital technologies, including (but not limited to) IoT, cloud computing, big data, and 5G (see Table 1 for definitions of these technologies).[9] The inclusion of these technologies in the dataset enables us to test the perceived importance of technology bundling when adopting AI.

Table 1 Technology definitions

Technology Type	Definitions
Artificial Intelligence	A technology that enables machines to become intelligent, including the ability to learn, deduce, perceive, and understand natural language through computer programs, to perceive, analyze, determine response and act appropriately in its environment. For a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments (OECD, 2019a).
Internet of Things (IoT)	Smart sensors and services that communicate information between people to people, people to things, and things to things by interconnecting all objects via the Internet. (OECD 2017b).
Cloud Computing	Cloud computing is a service delivered by third-party providers which enables pay as you go on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction (NIST 2011)
Big Data	The practice of collecting, processing, and analyzing large volumes of digital data on a massive scale. The types of data may include numerical, text and imagery data (both structured and unstructured). (OECD 2017b).
Mobile	The next-generation mobile technologies and services being deployed (including 5G).

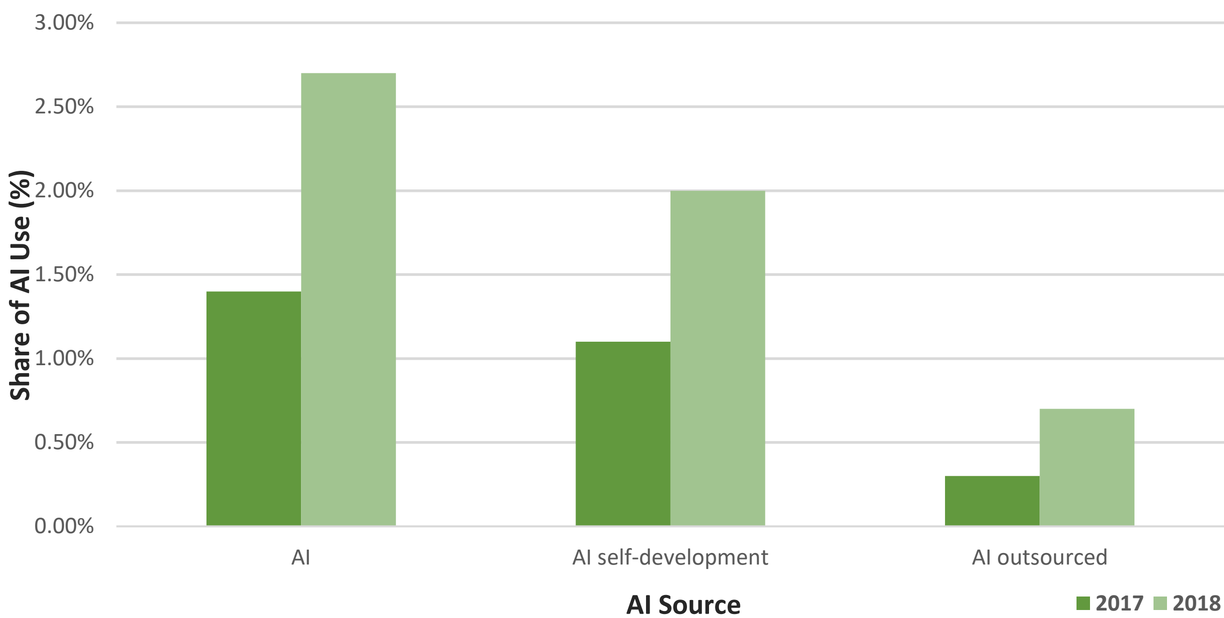
Descriptive statistics

A minority of firms in the sample use AI, but the rate nearly doubled between 2017 and 2018, from 1.4 percent to 2.7 percent (see Figure 1). For those utilizing AI, self-development represents the preferred source of the technology, with 2.0 percent of firms developing AI in-house and only 0.7 percent of firms acquiring AI through third-party providers in 2018. Among AI users,

[9] These and other technologies were selected as the core technologies believed to facilitate Industry 4.0 through internal discussion by relevant experts.

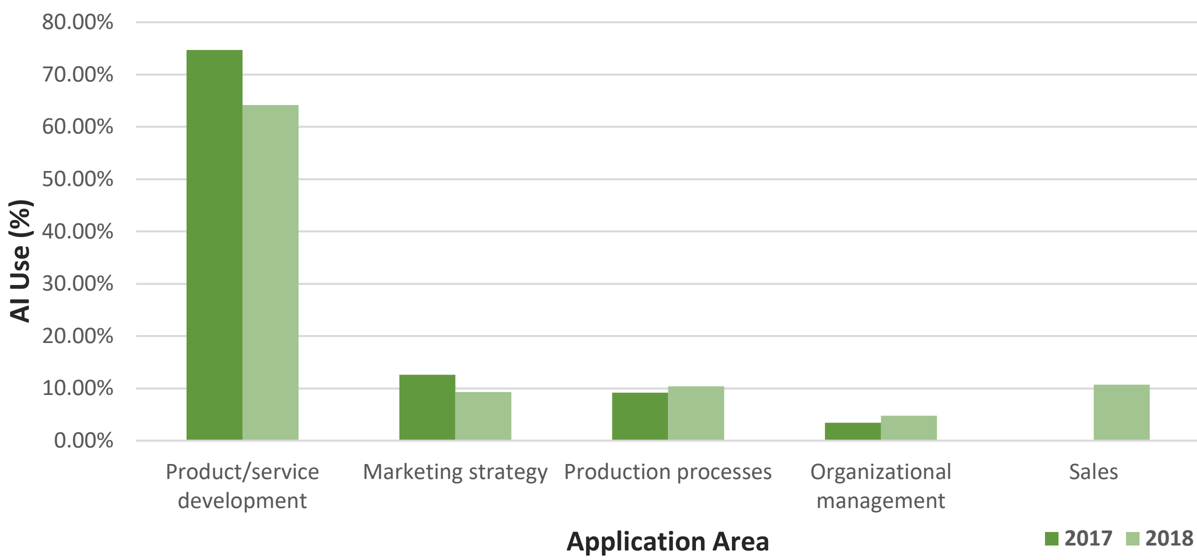
most firms (about 64.2 percent in 2018) employ the technology for product/service development (see Figure 2). Between 2017 and 2018 the increased reliance on AI for sales applications (with usage rising from nearly 0 percent in 2017 to 10.7 percent in 2018) indicates AI resources are shifting more to production and sales of new products rather than towards management and efficiency-enhancement applications. Additionally, given the proportional change in application over time, it appears that firms are still in the process of experimenting with the technology.

Figure 1: Share of AI use by source in 2017 and 2018



Source: KOSTAT with calculations made by authors

Figure 2: AI by application amongst AI users in 2017 and 2018

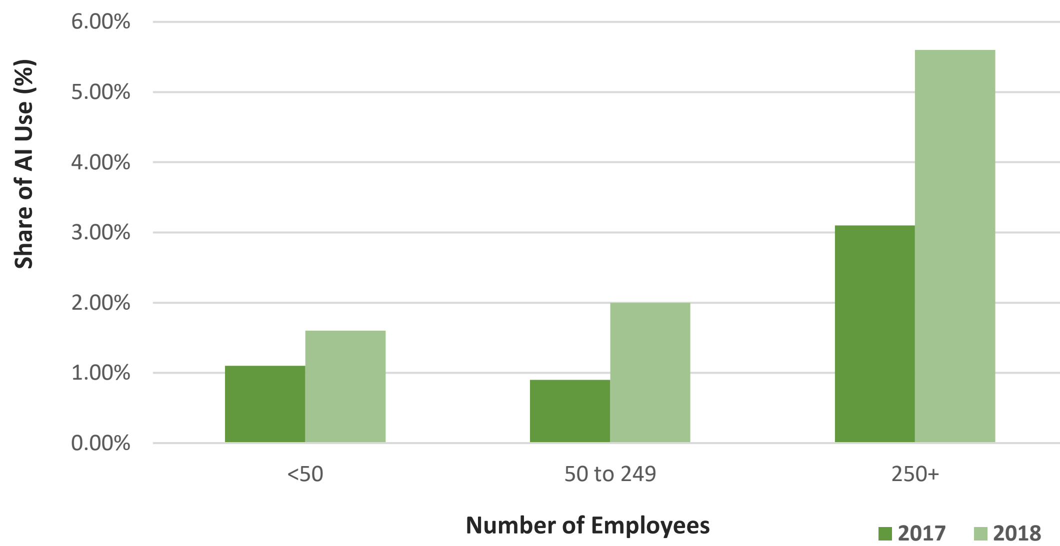


Source: KOSTAT with calculations made by authors

Figure 3 illustrates the use of AI by firm size over the sample period. Overall, larger firms are more likely to use AI than smaller firms, a trend that has strengthened over time. In 2018, 5.6 percent of large firms (250+ employees) used AI in comparison to 2.0 percent for medium firms (50 to 250 employees) and 1.6 percent for small firms (<50 employees). At the same time, AI use across all size cohorts increased between 2017 and 2018.

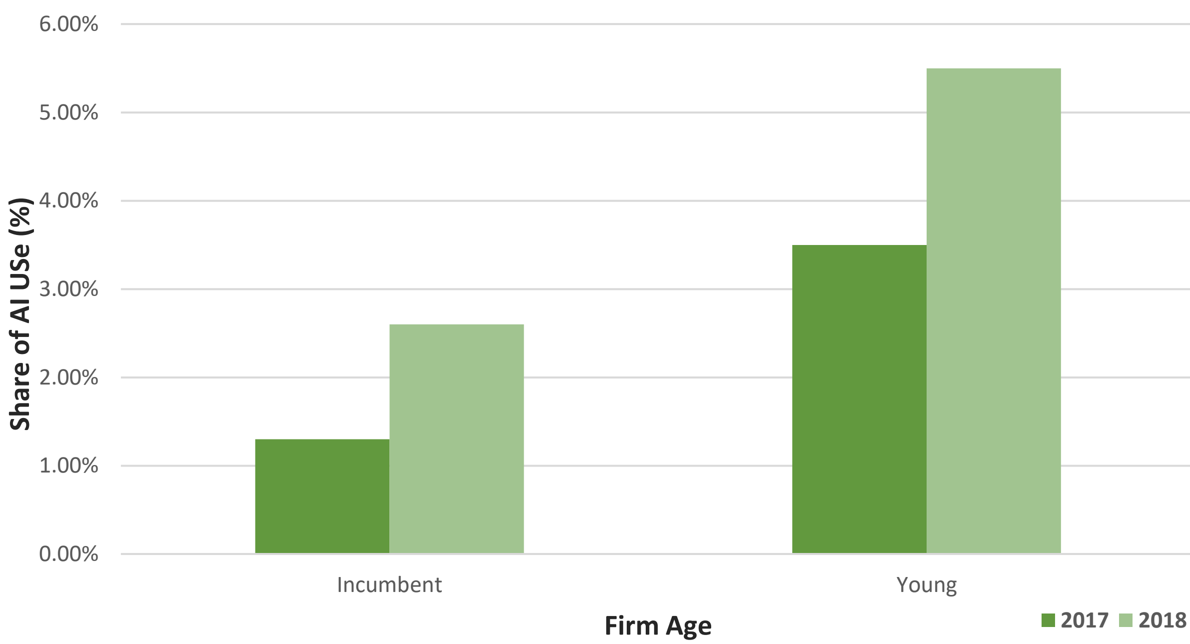
In terms of age, young firms are adopting at a greater rate than mature firms in both sample periods (See Figure 4). In 2018, 5.5 percent of young firms (those five years old or less) used AI versus 2.6 percent for mature firms (those older than five years). Considerable heterogeneity in AI use is found across sectors (See Table 2). Unsurprisingly, data-intensive sectors, such as the information and communication industry, have the greatest proportion of adoption at 12.6 percent, followed by financial and insurance at 8.7 percent. Over the sample period, steady growth in AI use is observable in a number of sectors, including education, professional, scientific and technical services, wholesale and retail and manufacturing, with rates of use more than doubling in one year.

Figure 3: Share of AI use by firm size, in 2017 and 2018



Source: KOSTAT with calculations made by authors

Figure 4: Share of AI use by firm age, in 2017 and 2018



Source: KOSTAT with calculations made by authors

Table 2: AI use by sector, 2017 and 2018

Sector classification: 1 digit	**2017**	**2018**
Agriculture, forestry and fishing	0.0%	0.0%
Mining and quarrying	0.0%	0.0%
Manufacturing	0.8%	1.7%
Electricity, gas, steam and air conditioning supply	3.4%	3.2%
Water supply; sewage, waste management, materials recovery	0.0%	0.0%
Construction	0.4%	1.6%
Wholesale and retail trade	0.9%	2.3%
Transportation and storage	0.1%	0.4%
Accommodation and food service activities	0.6%	0.6%
Information and communication	6.8%	12.6%
Financial and insurance activities	6.1%	8.7%
Real estate activities	0.0%	0.0%
Professional, scientific and technical activities	1.3%	2.6%
Business facilities management and services; rental and leasing activities	1.0%	1.1%
Education	1.2%	4.5%
Human health and social work activities	0.0%	0.0%
Arts, sports and recreation related services	0.0%	0.0%
Membership organizations, repair and other personal services	1.1%	1.1%

Source: KOSTAT with calculations made by authors

4) Empirical strategy

Baseline regressions

We develop the following model to examine the firm determinants of AI adoption (see Equation 1). y_{it} is the dependent variable, which signifies AI adoption of firm *i* at time t. To capture adoption in the data, y_{it} =1 if a firm does not use AI in 2017 but does in 2018. Firms that do not use AI in either 2017 or 2018 are coded 0, while those that use AI in both 2017 and 2018 are dropped. In the baseline regression, the dependent variable measures the adoption of all types of AI while in subsequent regressions it reflects the adoption of AI by specific application (including product/service development, marketing strategy, production processes, organization management) or the source of the technology (in-house or outsourced).

<u>Equation 1</u>

$$\Delta y_{it} = \beta_0 + \beta_1 X_{it=2017} + n_j + n_l + \varepsilon_{ijl}$$

X_i represents a vector of firm characteristics for the year 2017. These include (log) sales, multi-establishment status, log (age+1), foreign ownership, log labor productivity (measured by value added per worker), and log intangible asset intensity (reflected by the share of intangible assets over total assets). To control for industrial and regional variation, we use industries (j) and region (l) fixed effects denoted by n_j and n_l, which are dummy variables based on the two-digit code level of the Korean Standard Industry Classification (KSIC) and regions based on the administrative districts at the state-level. ε_{it} is the error term. Regressions are clustered at the firm level.

Firm restructuring: Complementary technology use and firm reorganization

The paper also examines whether restructuring is correlated with AI adoption. We assess restructuring in two ways. First, we examine whether the use of perceived complementary technologies is important for AI adoption. Second, we analyze whether reorganization (such as moving, downsizing, or expanding) correlates with AI implementation. The availability of panel data allows us to build off the baseline analysis by exploiting the time dimension to assess whether certain types of firm restructuring are precursors to AI adoption or whether they are happening simultaneously. The timing of implementation may be particularly relevant for complementary technologies, as certain technologies need to be in place before using AI (such as tools that facilitate data collection, an important prerequisite for AI adoption) while others are more likely to be adopted contemporaneously alongside AI. Furthermore, existing scholarship carries few implications for the timing of reorganization (measured as expanding, contracting, and relocating in our data) for AI adoption. For example, if the supply of human capital is critical to a firm's goals, they may relocate to obtain talent before adoption. Other adjustments, such as expanding or contracting, may be more likely to occur during the AI adoption process than before. [10]

To assess the timing of restructuring and AI adoption, we use two different empirical specifications. To evaluate the possible importance of ex-ante restructuring and AI adoption, we include in our baseline model an additional covariate Z, which measures whether the firm underwent a form of restructuring in 2017 (See Equation 2). Next, to assess whether these restructuring practices are occurring simultaneously, we regress AI adoption on the adoption of each restructuring variable between 2017 and 2018 (See Equation 3).

<u>Equation 2</u>

$$\Delta y_{it} = \beta_0 + \beta_1 X_{it=2017} + \beta_2 Z_{it=2017} + n_j + n_l + \varepsilon_{ijl}$$

<u>Equation 3</u>

$$\Delta y_{it} = \beta_0 + \beta_1 X_{it=2017} + \beta_2 \Delta Z_{it} + n_j + n_l + \varepsilon_{ijl}$$

[10] It may also be the case that the relationship between AI use and reorganization is apparent several periods after adoption. Unfortunately, we are unable to explore this question with only two years of data.

5) Empirical results

Baseline firm characteristics and AI adoption

In this section, we present the econometric results on the adoption of AI. We start by examining the link between firm characteristics and AI adoption. Next, we explore how firm characteristics predict AI adoption either self-produced or purchased externally. We then uncover the links between firm characteristics and the types of AI applications adopted, including product/service development, marketing strategy, production processes, organizational management, and sales applications.

Table 3 presents our baseline results on the relationship between firm attributes and AI adoption estimated using OLS, Probit, and Logit. Consistent with previous digital technologies, firm size is an important determinant for AI adoption, measured by sales and multi-establishment status. Moreover, investment in intangibles strongly predicts AI adoption.[11] This is consistent with Haskel and Westbrook (2017), which suggests that the use of frontier digital technology corresponds with firms becoming increasingly more reliant on intangible assets. We also know that AI is very data intensive, and thus firms which employ intangibles more intensively are more likely to have a more conducive environment for adoption. Age does not appear to be strongly correlated with AI, although the coefficient is negative, suggesting younger firms are more likely to adopt AI.[12] The results are also somewhat inconclusive for foreign ownership.[13]

Somewhat unexpectedly, labor productivity is negatively correlated with AI adoption. Typically, the relationship between digital technology and productivity is found to be positive (Syverson 2011). One explanation may be that firms with lower levels of productivity are adopting AI to improve their efficiency, however this is unobservable in the data. To explore this further, we examine whether this result holds when assessing those at the top of the productivity

[11] We find consistent results when restricting the sample to firms in data/technology intensive sectors (see Table A2 in the Appendix). Eckert et al (2019) provides a definition for these sectors which include Information, Finance and Insurance, Professional, Scientific and Technical Services and Management Services sectors.

[12] To further assess this result, we construct a dummy variable which captures whether a firm is young, defined as those aged 5 years or younger. These results do not reveal any conclusive relationship between being young and adopting AI. Results are available upon request.

[13] While the results for foreign ownership suggest limited relevance for AI adoption, it may be the case that the origin of the parent company (such as being in a high-income country) matters for AI use. We test this by including an indicator variable equal to one if the parent of the foreign-owned firm is from a high-income country (as defined by the World Bank 2020). The results are in Table A4 of the Appendix. We find no evidence between ownership by firms in high-income country and AI adoption.

distribution. To do so we interact the labor productivity variable with a dummy variable equal to one if a firm is at the top 10 percent of the distribution at the start of the sample period and zero otherwise (see Table A3 in the Appendix). The positive and significant coefficient of the interaction terms suggest that while the effect of productivity is on average negative, for those at the top of the distribution, productivity positively matters for AI adoption. We explore these results further by examining adoption by source and application type in the next section.

Table 3: Firm characteristics and AI adoption

Dependent variable: AI adoption	Model One	Model Two	Model Three
Estimation method	OLS	Probit	Logit
Log(Sales)	0.012***	0.006***	0.005***
	[0.002]	[0.001]	[0.001]
Multi-Establishment	0.004	0.004**	0.003*
	[0.003]	[0.002]	[0.002]
Log(Age+1)	-0.002	-0.001	-0.001
	[0.002]	[0.001]	[0.002]
Foreign Ownership	-0.004*	-0.002	-0.002
	[0.003]	[0.002]	[0.002]
Log(Labor Productivity)	-0.008***	-0.003***	-0.003***
	[0.002]	[0.045]	[0.001]
Intangible Intensity	0.081***	0.036***	0.027***
	[0.030]	[0.009]	[0.007]
Observations	11,063	9,300	9,300
R-squared	0.039		

*Note: The dependent variable is AI adoption between 2017 and 2018. All independent variables are measured in 2017 levels. Intangible intensity is the share of intangible assets over total assets. Labor productivity is value added per worker. All models include region and sector fixed effects. Robust standard errors clustered at the firm level are in brackets. *** p<0.01, ** p<0.05, * p<0.10.*

AI adoption by source and application

When assessing the determinants of AI adoption by source (See Table 4), we find consistent results with the baseline, larger firms and those intensively using intangibles are more likely to adopt AI through either in-house production or from vendors. Domestic-owned firms in South Korea are more likely to adopt AI developed in-house, but this does not appear to predict outsourcing AI. Labor productivity negatively predicts the adoption of self-developed AI but is not significantly correlated with non-self-developed AI. However as with self-developed AI, the coefficient is negative.

The Probit and Logit estimated regressions in Table 5 assess the relationship between firm characteristics and AI adoption by application.[14] Firm size is a relevant determinant for the adoption of all application types except organizational management. Intangible use appears relevant for product and process applications but not important for marketing strategies and negatively correlated with organizational management. The results also suggest that young firms are more likely to adopt AI in the context of organizational management. This may be because younger firms have less rigid organizational structures, making it easier for them to adopt these technologies (Iansiti and Lakhani 2020). While labor productivity is found to negatively relate to the adoption of AI overall (in the baseline), when we disaggregate by application, it appears this is mostly driven by product/service development applications, with a less-distinct relationship across other applications.[15]

---

[14] Table A5 in the Appendix aggregates by applications by those relating to sales (product/service development and marketing strategy) and organization (product process and organization management).

[15] The corresponding OLS results can be found in Table A6 the appendix.

Table 4: Firm characteristics and AI adoption by source

Variable	(1) In-hour	(2) In-hour	(3) In-hour	(4) Outsource	(5) Outsource	(6) Outsource
Estimation method	OLS	Probit	Logit	OLS	Probit	Logit
Log(Sales)	0.009***	0.004***	0.004***	0.003***	0.002***	0.002***
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]
Multi-Establishment	0.003	0.003**	0.003*	0.001	0.001	0.001
	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
Log(Age+1)	-0.000	-0.001	-0.001	-0.001	-0.001	-0.001
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Foreign Ownership	-0.005**	-0.003*	-0.002	0.000	0.000	0.000
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Log(Labor Productivity)	-0.006***	-0.003***	-0.002***	-0.001	-0.001	-0.001
	[0.002]	[0.0001]	[0.001]	[0.001]	[0.001]	[0.001]
Intangible	0.064**	0.028***	0.021***	0.017	0.011**	0.009**
	[0.027]	[0.008]	[0.006]	[0.012]	[0.004]	[0.004]
Observations	11,063	8,387	8,387	11,063	6,812	6,812
R-squared	0.031			0.016		

*Note: The dependent variable is AI adoption between 2017 and 2018. All independent variables are measured in 2017 levels. Intangible intensity is the share of intangible assets over total assets. Labor productivity is value added per worker. All models include region and sector fixed effects. Robust standard errors clustered at the firm level are in brackets. *** p<0.01, ** p<0.05, * p<0.10.*

Table 5 Firm characteristics and AI adoption by application, Probit and Logit estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**Product/Service Development**		**Marketing Strategy**		**Product Processes**		**Organization Management**	
Estimation method	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
Log(Sales)	0.004***	0.003***	0.002*	0.001	0.002***	0.001***	0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]
Multi-Establishment	0.003*	0.003*	-0.000	-0.000	0.001	0.001	-0.001	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
Log(Age+1)	-0.001	-0.001	-0.000	-0.000	0.001	0.000	-0.002*	-0.001*
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Foreign Ownership	-0.001	-0.000	-0.006***	-0.006**	-0.001	-0.000	-0.001	-0.001
	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
Log(Labor Productivity)	-0.003***	-0.002***	-0.001	-0.001	0.000	0.000	-0.000	-0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
Intangible Intensity	0.019***	0.014***	0.011	0.009	0.015***	0.012**	-0.017	-0.015
	[0.007]	[0.005]	[0.008]	[0.006]	[0.005]	[0.005]	[0.012]	[0.012]
Observations	7,424	7,424	2,381	2,381	4,568	4,568	1,925	1,925

*Note: The dependent variable is AI adoption between 2017 and 2018. All independent variables are measured in 2017 levels. Intangible intensity is the share of intangible assets over total assets. Labor productivity is value added per worker. All models include region and sector fixed effects. Robust standard errors clustered at the firm level are in brackets. *** p<0.01, ** p<0.05, * p<0.10.*

AI adoption and complementarities

Technology bundling

In this section, we examine the importance of complementary technologies for AI adoption. In addition, we explore whether the timing of complementary investments (either before or during adoption) relates to the adoption of AI. While most of the empirical literature focuses on the determinants and performance effects of a single technology, firms often deploy these technologies in bundles at various points in time. The same is likely true for AI. Practitioners suggest that AI requires large datasets to train algorithms (Paik et al. 2020). To obtain such data, firms likely require technologies that collect information (either on the firms themselves or their customers), such as IoT. Given the data intensity of AI, it is also likely that firms require flexible and scalable hardware services delivered through the cloud, along with data practices for using and assessing large amounts of information, such as with big data analytics (Iansiti and Lahkani 2020; Firouzi, Farahani, and Marinšek 2021).

The results in Table 6 demonstrate the relationship between complementary technology and AI adoption, both ex-ante and contemporaneously. There is some evidence that the use of ex-ante IoT is a determinant for AI adoption, which is consistent with the function of the technology i.e. using smart sensors between devices and people that collect and communicate data on their actions and responses over time (OECD 2017b). These technologies generate large quantities of data, which appears to be a prerequisite for AI. However, having the other technologies in place prior to AI adoption seem less important.

On the other hand, our results underscore the potential importance of adopting these technologies contemporaneously with AI. Notably, firms appear to be simultaneously implementing cloud computer, big data, and IoT technologies along with AI. Given AI's data intensity, these findings imply that firms should also be 1) adopting technology that enhances their ability to collect data (i.e., through IoT), 2) improving how they assess and exploit large datasets (i.e., big data analytics), and 3) enhancing their flexibility in how they store and process of large sums of data (i.e., cloud computing).

Table 6: Complementary technologies and AI adoption

Dependent variable: AI adoption	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Technology adoption **before** AI adoption			Technology adoption **during** AI adoption		
Estimation method	OLS	Probit	Logit	OLS	Probit	Logit
Big data in 2017	0.021	0.005	0.004			
	[0.022]	[0.006]	[0.005]			
Cloud in 2017	0.001	-0.000	-0.000			
	[0.019]	[0.004]	[0.004]			
IoT in 2017	0.051**	0.019*	0.012			
	[0.022]	[0.010]	[0.008]			
Mobile in 2017	0.030*	0.011	0.006			
	[0.017]	[0.007]	[0.005]			
Big data adoption: 2017-2018				0.232***	0.087***	0.065***
				[0.029]	[0.019]	[0.017]
Cloud adoption: 2017-2018				0.058***	0.014**	0.009*
				[0.022]	[0.007]	[0.005]
IoT adoption: 2017-2018				0.089***	0.024***	0.018***
				[0.021]	[0.008]	[0.007]
Mobile adoption: 2017-2018				0.011	0.002	0.000
				[0.021]	[0.003]	[0.002]
Observations	11,063	9,300	9,300	11,063	9,300	9,300
R-squared	0.046			0.171		

*Note: The dependent variable captures AI adoption between 2017 and 2018. For regressions 1-3, explanatory technology variables are binary for the year 2017. For regressions 4-6, explanatory technology variables reflect adoption between 2017 and 2018. Regressions include the same firm characteristics measured in 2017 as the baseline models, including log sales, multi-plant status, log (age+1), labor productivity, foreign ownership, and intangible intensity. All models include region and sector fixed effects. Robust standard errors clustered at the firm level are in brackets. *** p<0.01, ** p<0.05, * p<0.10.*

AI adoption and firm restructuring

The final section examines the relationship between firm restructuring and AI adoption. The literature demonstrates empirical evidence of firm reorganization of previous digital technologies (Bresnahan et al. 2002: Forman and McElheran 2013), with initial analysis suggesting that AI use requires considerable firm restructuring (Iansiti and Lahkani 2020). However, limited empirical research on the extent to which, how, and when firms reorganize around AI is problematic.

The restructuring variable used in our analysis indicates whether a firm has undergone any form of restructuring. This variable is then disaggregated into indicate particular type of restructuring and includes relocating, downsizing, and expanding.[16] We construct our ex-ante and adoption reorganization variables consistent with the previous section.

Neither of the ex-ante reorganization variables are statistically correlated with AI adoption. However, we find that contemporaneous changes in reorganization between 2017 to 2018 are correlated with the adoption of AI over the same period. Restructuring generally (signified by the reorganize variable) is positive and significant at the 5 percent level across all estimation methods. Focusing on particular types of reorganization, the coefficients are positive or all forms but not statistically significant below the 10% level.

This research suggests that although reorganization and AI adoption occur simultaneously, the relationship is somewhat less pronounced for specific types of restructuring. Nonetheless, it is likely that more substantial reorganizational changes may occur several years after adopting AI; given that our dataset only spans two years, we are unable to assess these potential long-term changes.

[16] Relocation measures any geographical movement either by the firm or its establishments in the stated year.

Table 7: Firm reorganization before and during AI adoption

Dependent variable: AI adoption	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
	Organizational change **before** AI adoption						Organizational change **during** AI adoption					
Estimation method	OLS	Probit	Logit	OLS	Probit	Logit	OLS	Probit	Logit	OLS	Probit	Logit
Reorganize in 2017	-0.000	0.001	-0.000									
	[0.006]	[0.004]	[0.004]									
Move in 2017				-0.011	-0.004	-0.005						
				[0.014]	[0.007]	[0.005]						
Downsize in 2017				0.001	0.000	0.001						
				[0.009]	[0.006]	[0.006]						
Expand in 2017				0.003	0.004	0.002						
				[0.011]	[0.008]	[0.007]						
Reorganize in 2017							0.017**	0.012**	0.010**			
							[0.008]	[0.006]	[0.267]			
Move between 2017-2018										0.044	0.024	0.021
										[0.029]	[0.017]	[0.014]
Downsize between 2017-2018										0.011	0.009	0.007
										[0.010]	[0.008]	[0.007]
Expand between 2017-2018										0.015	0.010	0.008
										[0.012]	[0.008]	[0.007]
Observations	11,063	9,300	9,300	11,063	9,300	9,300	11,063	9,300	9,300	11,063	9,300	9,300
R-squared	0.039			0.039			0.039			0.040		

*Note: The dependent variable captures AI adoption between 2017 and 2018. For regressions 1-6, explanatory reorganization variables are binary for the year 2017. For regressions 7-12, explanatory reorganization variables reflect adoption between 2017 and 2018. Regressions include the same firm characteristics measured in levels in 2017 as the baseline models, including log sales, multi-plant status, log(age+1), labor productivity, foreign ownership, and intangible intensity. All models include region and sector fixed effects. Robust standard errors clustered at the firm level are in brackets. *** p<0.01, ** p<0.05, * p<0.10.*

6) Conclusion

Advances in AI development are increasing the technology's functionality, making it more obtainable to firms. Businesses are beginning to use AI for a host of operational capabilities across an increasing variety of projection, automation, optimization, and classification tasks. AI is expected to have a profound impact on the economy, altering the way firms compete and organize in the near future. These changes may create a winner-take-all scenario potentially benefiting a minority of early adopters. As a result, managers, academics, policymakers should remain attentive to understanding how and when technology adoption occurs.

This paper provides one of the first empirical studies on the determinants of AI adoption. The analysis relies on novel firm-level data from 2017 and 2018, which contains detailed information on the use of AI and complementary technologies, firm characteristics, external partnerships, and organizational changes. Using this data, we econometrically estimate the relationship between firm types and AI adoption. We exploit the data's time dimension to examine whether firm restructuring (measured by the use of complementary technologies and reorganization) is pertinent either before or contemporaneously with AI adoption.

Overall, we find that large firms and those that use intangibles intensively are more likely to adopt AI. These results are consistent when we examine the adoption by source with some heterogeneity by application. The use of data collection technologies (such as IoT) appears to be an important precursor for AI adoption. In addition, we find evidence that the contemporaneous use of cloud, big data, and IoT predict AI adoption.

The results in this paper provide new insights into the ways in which firms are adopting AI. However further study is needed in this area. There are few representative surveys on AI use across different jurisdictions, thereby complicating cross-country comparisons. In addition, the existing datasets contain little-to-no information on the quality of technology being adopted due to the challenges of measuring AI investments and acquisitions. In addition to the adoption question, considerable research is needed to understand how AI impacts firm performance and how these impacts differ across space and time. If AI is a GTP (and the evidence suggests that it is), firms that can implement these technologies effectively will likely achieve considerable competitive gains against those that do not. We hope to address these questions in future research.

7) References

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, *128*(6), 2188-2244.

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2020). *AI and jobs: Evidence from online vacancies, w28257*. National Bureau of Economic Research.

Aghion, P., Howitt, P., & Violante, G. L. (2002). General purpose technology and wage inequality. *Journal of Economic Growth*, *7*(4), 315-345.

Agrawal, A., Gans, J. S., & Goldfarb, A. (2018). Human Judgment and AI Pricing. *AEA Papers and Proceedings*, *108*, 58–63. https://doi.org/10.1257/pandp.20181022

Agrawal, A., Gans, J., & Goldfarb, A. (2019). Economic policy for artificial intelligence. *Innovation Policy and the Economy*, *19*(1), 139–159. https://doi.org/10.1086/699935

Ajay Agrawal, Joshua S. Gans, and A. G. (2017). *What to Expect From Artificial Intelligence*. MIT Sloan Management Review. https://sloanreview.mit.edu/article/what-to-expect-from-artificial-intelligence/

Andres, R., Niebel, T., & Viete, S. (2020). Firm-level cloud adoption: the role of firm characteristics and policy environment. Paper presented at the 30th ITS European Conference Espoo, Finland, 16th - 19th June 2019.

Anyoha, R. (2018). *The History of Artificial Intelligence - Science in the News*. Science in the News. https://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/

Balakrishnan, T., Chui, M., Hall, B., & Henke, N. (2020). Global survey: The state of AI in 2020. *Mckinsey Analytics*, *November*, 13. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2020

Baldwin, J. R., & Rafiquzzaman, M. (1998). The determinants of the adoption lag for advanced manufacturing technologies. *Statistics Canada Working Paper*, *117*.

Balkken, R. (2019). *Business Applications for Artificial Intelligence: An Update for 2020*. - Professional Development | Harvard DCE. https://professional.dce.harvard.edu/blog/business-applications-for-artificial-intelligence-an-update-for-2020/

Bartel, A., statistics, F. L.-T. R. of E. and, & 1987, undefined. (n.d.). The comparative advantage of educated workers in implementing new technology. *JSTOR*. Retrieved May 28, 2021,

Baptista, R. (2000). Do innovations diffuse faster within geographical clusters?. *International Journal of industrial organization*, *18*(3), 515-535.

Berlanstein, L.R. (1992). *The Industrial Revolution and Work in Nineteenth-Century Europe (1st ed.).* Routledge. https://doi.org/10.4324/9780203415917

Bessen, J. E., Denk, E., & Meng, C. (2021). Firm differences: skill sorting and software. *Research Paper, 18*, Boston University School of Law. https://doi.org/10.2139/SSRN.3862782

Bloom, N., Sadun, R., & Van Reenen, J. (2012). Americans do IT better: US multinationals and the productivity miracle. In *American Economic Review* (Vol. 102, Issue 1, pp. 167–201). https://doi.org/10.1257/aer.102.1.167

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Quarterly Journal of Economics*, *117*(1), 339–376. https://doi.org/10.1162/003355302753399526

Brynjolfsson, E., Mcafee, A., & Wheeler, J. C. (2014). *The Second Machine Age by*. https://books.google.fr/books?hl=en&lr=&id=WiKwAgAAQBAJ&oi=fnd&pg=PA1&dq=brynjolfsson+mcafee&ots=4_VpTd4ugg&sig=PSQltpwhCSBtOnUFnImSLgPeFvw

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). *Title: Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics: Vol. Publisher*. University of Chicago Press. https://www.degruyter.com/document/doi/10.7208/9780226613475-003/html

Byrne, D. M., & Corrado, C. A. (2017). ICT Services and Their Prices: What Do They Tell Us About Productivity and Technology?. *Finance and Economics Discussion Series*, 015r1. https://doi.org/10.17016/FEDS.2017.015R1

Byrne, D., Corrado, C., & Sichel, D. E. (2018). *The rise of cloud computing: minding your P's, Q's and K's*. *NBER Working Papers, 25188*.

Cardona, M., Kretschmer, T., & Strobel, T. (2013). ICT and productivity: conclusions from the empirical literature. *Information Economics and Policy*, *25*(3), 109-125.

Claessens, S., and Tzioumis (2006). Measuring firms' access to finance. *The World Bank Group,* https://www.researchgate.net/profile/Stijn-Claessens-2/publication/255580619_Measuring_firms%27_access_to_finance/links/54295ff50cf26120b7b6672d/Measuring-firms-access-to-finance.pdf

Cho, J., DeStefano, T., Kim, H., Kim, I., & Paik, J. (2021). *What's Driving the Diffusion of Next-Generation Digital Technologies?*

Corrado, C. A., & Hulten, C. R. (2010). How do you measure a "technological revolution"?" *American Economic Review*, *100*(2), 99–104. https://doi.org/10.1257/aer.100.2.99

Davenport, T. H., & Ronanki, R. (2018). *3 Things AI Can Already Do for Your Company*. Harvard Business Review. https://hbr.org/2018/01/artificial-intelligence-for-the-real-world

DeStefano, T., Kneller, R., & Timmis, J. (2018). *Cloud Computing and Firm Growth*, CESifo Working Paper. No 8306

DeStefano, T., Johnstone, N., Kneller, R., & Timmis, J. (2020). *Capital incentives in the age of intangibles*, GEP Research Paper 2020/06. https://www.nottingham.ac.uk/gep/documents/papers/2020/2020-06.pdf

DeStefano, T., K. De Backer and L. Moussiegt (2017), "Determinants of digital technology use by companies", *OECD Science, Technology and Industry Policy Papers*, No. 40, OECD Publishing, Paris, https://doi.org/10.1787/a9b53784-en.

Drees, J. (2020). *11 recent big tech partnerships in healthcare: Apple, Amazon, Google & more*. Becker's Healthcare. https://www.beckershospitalreview.com/digital-transformation/11-recent-big-tech-partnerships-in-healthcare-apple-amazon-google-more.html

Eaton, J., & Kortum, S. (1999). International technology diffusion: Theory and measurement. *International Economic Review*, *40*(3), 537-570.

Eckert, F., Ganapati, S., & Walsh, C. (2020). Skilled scalable services: the new urban bias in economic growth, 8705. https://papers.ssrn.com/abstract=3736487

European Parliament. (2020). *What is artificial intelligence and how is it used?* News | European Parliament. https://www.europarl.europa.eu/news/en/headlines/society/20200827STO85804/what-is-artificial-intelligence-and-how-is-it-used

Fernald, J. (2014). Productivity and potential output before, during, and after the great recession. *NBER Macroeconomics Annual*, *29*(1), 1-51, edited by Jonathan A. Parker and Michael Woodford. Cambridge, MA: MIT Press.

Firouzi, F., Farahani, B., & Marinšek, A. (2021). The convergence and interplay of edge, fog, and cloud in the AI-driven Internet of Things (IoT). *Information Systems*, 101840. https://doi.org/10.1016/J.IS.2021.101840

Fischer, W. (1966). Social Tensions at Early Stages of Industrialization. *Comparative Studies in Society and History*, *9*(1), 64–83. https://doi.org/10.1017/S0010417500004357

Forbes Insights. (2019). *Should You Build Or Buy Your AI?* https://www.forbes.com/sites/insights-intelai/2019/05/22/should-you-build-or-buy-your-ai/?sh=5b269b75441d

Forman, C., & McElheran, K. (2013). The Digital Reorganization of Firm Boundaries: IT Use and Vertical Integration in US Manufacturing *. In *frbatlanta.org*.

https://www.frbatlanta.org/-/media/documents/news/conferences/2013/caed/I1McElheran.pdf

Foster, J. (2003). Class Struggle and the Industrial Revolution : Early Industrial Capitalism in Three English Towns. 1–341. https://doi.org/10.4324/9780203222379

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. *Technological Forecasting and Social Change*, *114*, 254-280.

Gibbs, J. L., & Kraemer, K. L. (2004). A Cross-Country Investigation of the Determinants of Scope of E-commerce Use: An Institutional Approach. *Electronic Markets*, *14*(2), 124–137. https://doi.org/10.1080/10196780410001675077

Goldfarb, A., Taska, B., & Teodoridis, F. (2019). Could Machine Learning Be a General-Purpose Technology? Evidence from Online Job Postings. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3468822

Goldfarb, A., Taska, B., & Teodoridis, F. (2020). Artificial Intelligence in Health Care? Evidence from Online Job Postings. *AEA Papers and Proceedings*, *110*, 400–404. https://doi.org/10.1257/pandp.20201006

Giunta, A., & Trivieri, F. (2007). Understanding the determinants of information technology adoption: Evidence from Italian manufacturing firms. *Applied Economics*, *39*(10), 1325–1334. https://doi.org/10.1080/00036840600567678

Griffith, R., Redding, S., & Simpson, H. (2002). Productivity convergence and foreign ownership at the establishment level. *CEPR Discussion Paper, 3765*.

Hagel, J., & Brown, J. S. (2005). Productive friction how difficult business partnerships can accelerate innovation. In *Harvard Business Review* (Vol. 83, Issue 2, pp. 82–91, 148). https://europepmc.org/article/med/15724576

Hall, B. and J. Lerner (2010), "Chapter 14 - The Financing of R&D and Innovation" In Handbook of the Economics of Innovation, edited by Bronwyn H. Hall and Nathan Rosenberg, 1:609–39. Handbook of the Economics of Innovation, Vol. 1. North-Holland.

Haller, S. A., & Siedschlag, I. (2011). Determinants of ICT adoption: Evidence from firm-level data. *Applied Economics*, *43*(26), 3775–3788. https://doi.org/10.1080/00036841003724411

Haskel, J., & Westlake, S. (2017). *Capitalism without capital*. Princeton University Press.

Heston, R and Zwetsloot, A. (2020). *Mapping U.S. Multinationals' Global AI R&D Activity CSET Issue Brief*. https://cset.georgetown.edu/wp-content/uploads/CSET-Mapping-U.S.-Multinationals-Global-AI-RD-Activity-1.pdf

Hottenrott, H., & Lopes-Bento, C. (2016). R&D Partnerships and Innovation Performance: Can There Be too Much of a Good Thing? *Journal of Product Innovation Management*, *33*(6), 773–794. https://doi.org/10.1111/jpim.12311

Iansiti, M., & Lakhani, K. (2020). *Competing in the age of AI: strategy and leadership when algorithms and networks run the world*.

Jaffe, A. B., & Trajtenberg, M. (1999). International knowledge flows: Evidence from patent citations. *Economics of innovation and new technology*, *8*(1-2), 105-136.

Javorcik, B. S. (2004). Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages. *American Economic Review*, *94*(3), 605-627.

Jiang, K., Keller, W., Qiu, L., & Ridley, W. (2018). *International Joint Ventures and Internal vs. External Technology Transfer: Evidence from China*. https://doi.org/10.3386/w24455

Jin, W., & McElheran, K. (2018). Economies Before Scale: Survival and Performance of Young Plants in the Age of Cloud Computing. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3112901

Keller, W. (2002). Geographic localization of international technology diffusion. *American Economic Review*, *92*(1), 120-142.

Keller, W., & Yeaple, S. R. (2009). Multinational enterprises, international trade, and productivity growth: Firm level evidence from the United States. *Review of Economics and Statistics*, *91*(4), 821–831. https://doi.org/10.1162/rest.91.4.821

Knight, W. (2020). *AI Is All the Rage. So Why Aren't More Businesses Using It?* Wired. https://www.wired.com/story/ai-why-not-more-businesses-use/

LaBerge, L., O'Toole, C., Schneider, J., & Kate Smaje. (2020). *COVID-19 digital transformation & technology | McKinsey*. McKinsey. https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/how-covid-19-has-pushed-companies-over-the-technology-tipping-point-and-transformed-business-forever

Liveley, G., & Thomas, S. (2020). Homer's Intelligent Machines. In *AI Narratives* (pp. 25–48). Oxford University Press. https://doi.org/10.1093/oso/9780198846666.003.0002

López-Acevedo, G. (2002). Determinants of technology adoption in Mexico. *Policy Research Working Paper, 2780*. World Bank, Washington, DC.

Loukas, S. (2020). *What is Machine Learning: Supervised, Unsupervised, Semi-Supervised and Reinforcement learning methods | by Serafeim Loukas | Towards Data Science*. https://towardsdatascience.com/what-is-machine-learning-a-short-note-on-supervised-unsupervised-semi-supervised-and-aed1573ae9bb

Luque, A. (2000). An option-value approach to technology adoption in us manufacturing: evidence from plant-level data. *CES Working* Paper, 12. Center for Economic Studies, Washington, DC.

MacDuffie, J. (2021). *Who Is Shaping the Future of Autos – Tech Firms or Automakers? - Knowledge@Wharton*. Knowledge@Warton. https://knowledge.wharton.upenn.edu/article/who-is-shaping-the-future-of-autos-tech-firms-or-automakers/

McElheran, K. (2018). *Economic measurement of AI*. NBER

National Institute of Standards and Technology (NIST). (2011). The NIST definition of cloud computing. Retrieved: http://csrc.nist.gov/publications/nistpubs/800-145/SP800-145.pdf.

Niebel, T., Rasel, F., & Viete, S. (2018). Understanding the link between big data analytics and innovation BIG data-BIG gains? *Taylor & Francis*, *28*(3), 296–316. https://doi.org/10.1080/10438599.2018.1493075

OECD. (2019). *Measuring the Digital Transformation: A Roadmap for the Future*. OECD Publishing, Paris,.

OECD. (2019b). Scoping the OECD AI principles: Deliberations of the Expert Group on Artificial Intelligence at the OECD (AIGO). *OECD Digital Economy Papers, 291*. https://doi.org/10.1787/d62f618a-en

OECD. (2020). OECD Digital Economy Outlook 2020. In *OECD Digital Economy Outlook 2020*. OECD. https://doi.org/10.1787/bb167041-en

OECD and World Bank. (2015). *Inclusive Global Value Chains Policy Options in Trade and Complementary*. https://scholar.google.fr/scholar?hl=en&as_sdt=0%2C22&q=Inclusive+global+value+chains+%3A+policy+options+in+trade+and+complementary+areas+for+GVC+integration+by+small+and+medium+enterprises+and+low-income+developing+countries&btnG=

OECD. (2017). *Determinants of digital technology use by companies*. OECD Science, Technology and Industry Policy Papers, No. 40, OECD Publishing, Paris,. https://doi.org/https://doi.org/10.1787/a9b53784-en

O'Mahoney, M., Van Ark, B., & Timmer, M. P. (2008). The productivity gap between Europe and the United States: trends and causes. *Journal of Economic Perspectives*, *22*(1), 25-44.

Paik, J. H., Randazzo, S., & Hoffman, J. (2020). *AI in the Enterprise: How Do I Get Started?*

Press, G. (2020). *AI Stats News: Only 14.6% Of Firms Have Deployed AI Capabilities In Production*. Forbes. https://www.forbes.com/sites/gilpress/2020/01/13/ai-stats-news-only-146-of-firms-have-deployed-ai-capabilities-in-production/?sh=41ebc40c2650

Rammer, C., Czarnitzki, D., & Fernández, G. P. (2021). Artificial intelligence and industrial innovation: Evidence from firm-level data. *ZEW-Centre for European Economic Research Discussion Paper, 36*.

Ramraj, A. (2020). *Cloud AI Can Help You Survive The Storm*. Forbes. https://www.forbes.com/sites/forbestechcouncil/2020/10/05/cloud-ai-can-help-you-survive-the-storm/?sh=682bea067d06

Randazzo, S., Ham, H., & Paik, J. (2021). *What is a data scientist?*

Rowan, I. (2020). *Make or Buy AI?. The decision to build AI from scratch*. Towards Data Science. https://towardsdatascience.com/make-or-buy-ai-7b8d1f48ef21

Sestino, A., Prete, M. I., Piper, L., & Guido, G. (2020). Internet of Things and Big Data as enablers for business digitalization strategies. In *Technovation* (Vol. 98). https://doi.org/10.1016/j.technovation.2020.102173

Schmelzer, R. (2020). *The Changing Venture Capital Investment Climate For AI*. Forbes. https://www.forbes.com/sites/cognitiveworld/2020/08/09/the-changing-venture-capital-investment-climate-for-ai/?sh=1c96531765b3

Syverson, C. (2011). What determines productivity. In *Journal of Economic Literature* (Vol. 49, Issue 2, pp. 326–365). https://doi.org/10.1257/jel.49.2.326

Tambe, P., & Hitt, L. M. (2012). Now IT's Personal: Offshoring and the Shifting Skill Composition of the U.S. Information Technology Workforce. *Management Science*, *58*(4), 678–695. https://doi.org/10.1287/mnsc.1110.1445

Tax Foundation. (2018). Capital cost recovery across the OECD. *Fiscal Fact*, 590. Retrieved from https://taxfoundation.org/capital-cost-recovery-across-oecd-2018/

Timmer, M. P., Inklaar, R., O'Mahony, M., & Van Ark, B. (2011). Productivity and economic growth in Europe: A comparative industry perspective. *International Productivity Monitor, 21*, 3.

Van Ark, B., O'Mahony, M., & Timmer, M. P. (2008). The productivity gap between Europe and the United States: Trends and causes. *Journal of Economic Perspectives*, *22*(1), 25–44. https://doi.org/10.1257/jep.22.1.25

Van Reenen, J. (2011). Wage inequality, technology and trade: 21st century evidence. *Labour Economics*, *18*(6), 730-741.

Yang, S., & Brynjolfsson, E. (2001). Intangible assets and growth accounting: evidence from computer investments. *Academia.Edu*. Retrieved December 16, 2020, from http://www.academia.edu/download/30661553/10.1.1.130.7826.pdf

Zidorn, W., & Wagner, M. (2013). The effect of alliances on innovation patterns: An analysis of the biotechnology industry. *Industrial and Corporate Change*, *22*(6), 1497–1524. https://doi.org/10.1093/icc/dts042

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D., Buffington, C., Goldschlag, N., Foster, L., & Dinlersoz, E. (2020). *Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey* (WORKING PAPER 28290). https://doi.org/10.3386/w28290\

Appendix

Table A1 Firm descriptives

Variable	Obs	Mean	Median	SD	p1	p99
Log(Sales)	11,065	10.62	10.49	1.46	7.5	15.01
Multi-Establishment	11,065	0.43	0	0.49	0	1
Log(Age+1)	11,065	3.01	3.04	0.58	1.38	4.14
Foreign Ownership	11,065	0.41	0	0.49	0	1
Log(Labor Productivity)	11,065	5.86	5.83	1.07	3.36	8.74
Intangible intensity	11,065	0.02	0.001	0.07	0	0.36

Table A2 Firm characteristics and AI adoption, Scalable Tradeable Sectors

Dependent variable: AI adoption	Model One	Model Two	Model Three
Estimation method	OLS	Probit	Logit
Log(Sales)	0.018***	0.260***	0.506***
	[0.005]	[0.056]	[0.114]
Multi-Establishment	0.013	0.153	0.340
	[0.010]	[0.127]	[0.279]
Log(Age+1)	-0.009	-0.106	-0.216
	[0.009]	[0.098]	[0.206]
Foreign Ownership	-0.011	-0.107	-0.219
	[0.009]	[0.122]	[0.265]
Log(Labor Productivity)	-0.018***	-0.263***	-0.522***
	[0.005]	[0.075]	[0.158]
Intangible intensity	0.125**	1.421***	2.472***
	[0.063]	[0.504]	[0.953]
Constant	0.004	-2.523***	-4.569***
	[0.045]	[0.500]	[1.048]
Observations	1,822	1,480	1,480
R-squared	0.050		

*Note: The dependent variable is AI adoption between 2017 and 2018. All independent variables are measured in 2017 levels. Intangible intensity is the share of intangible assets over total assets. Labor productivity is value added per worker. STS sectors are classified by Eckert et al (2019) and include Information, Finance and Insurance, Professional, Scientific and Technical Services and Management Services sectors All models include region and sector fixed effects. Robust standard errors clustered at the firm level are in brackets. *** p<0.01, ** p<0.05, * p<0.10.* ***The probit and logit results reflect coefficients and not marginal effects. The marginal effect results are in the process of being released by the South Korean statistical authorities.***

Table A3 Firm characteristics and AI adoption, Labor productivity heterogeneity

Dependent variable: AI adoption	Model One	Model Two	Model Three
Estimation method	OLS	Probit	Logit
Log(Sales)	0.012***	0.251***	0.559***
	[0.002]	[0.032]	[0.070]
Multi-Establishment	0.004	0.149**	0.348*
	[0.003]	[0.073]	[0.179]
Log(Age+1)	-0.002	-0.052	-0.135
	[0.002]	[0.054]	[0.123]
Foreign Ownership	-0.004*	-0.096	-0.200
	[0.003]	[0.069]	[0.167]
Log(Labor Productivity)	-0.008***	-0.153***	-0.347***
	[0.002]	[0.053]	[0.118]
Intangible intensity	0.001	0.013	0.029
	[0.001]	[0.018]	[0.044]
Labor Productivity * Top 10%	0.081***	1.458***	2.953***
	[0.030]	[0.350]	[0.725]
Constant	-0.071***	-3.389***	-6.878***
	[0.019]	[0.455]	[1.041]
Observations	11,063	9,300	9,300
R-squared	0.039		

*Note: The dependent variable is AI adoption between 2017 and 2018. All independent variables are measured in 2017 levels. Intangibles intensity is the share of intangible assets over total assets. Labor productivity is value added per worker. Top 10% is an indicator variable equal to one if a firm is at the top 10% of the labor productivity distribution at the start of the sample period. All models include region and sector fixed effects. Robust standard errors clustered at the firm level are in brackets. *** p<0.01, ** p<0.05, * p<0.10.* ***The probit and logit results reflect coefficients and not marginal effects. The marginal effect results are in the process of being released by the South Korean statistical authorities.***

Table A4 Firm characteristics and AI adoption, High Income Country Owner

Dependent variable: AI adoption	Model One	Model Two	Model Three
Estimation method	OLS	Probit	Logit
Log(Sales)	0.012***	0.254***	0.566***
	[0.002]	[0.033]	[0.070]
Multi-Establishment	0.003	0.129*	0.296
	[0.003]	[0.076]	[0.185]
Log(Age+1)	-0.002	-0.053	-0.135
	[0.002]	[0.053]	[0.122]
HIC owners	-0.011**	-0.222	-0.558
	[0.004]	[0.150]	[0.375]
Log(Labor Productivity)	-0.008***	-0.129***	-0.292***
	[0.002]	[0.045]	[0.102]
Intangible intensity	0.081***	1.433***	2.941***
	[0.030]	[0.348]	[0.718]
Constant	-0.080***	-3.552***	-7.263***
	[0.018]	[0.422]	[0.948]
Observations	11,063	9,300	9,300
R-squared	0.039		

*Note: The dependent variable is AI adoption between 2017 and 2018. All independent variables are measured in 2017 levels. Intangibles intensity is the share of intangible assets over total assets. Labor productivity is value added per worker. HIC is an indicator variable equal to one if the parent company is based in a high-income country (World Bank 2020) All models include region and sector fixed effects. Robust standard errors clustered at the firm level are in brackets. *** p<0.01, ** p<0.05, * p<0.10.* ***The probit and logit results reflect coefficients and not marginal effects. The marginal effect results are in the process of being released by the South Korean statistical authorities.***

Table A5 Firm characteristics and AI adoption by sales and efficiency applications, Probit and Logit estimation

	(1)	(2)	(3)	(4)
Variables	Product/Service Development + Marketing Strategy		Product Processes + Organization Management	
Estimation method	Probit	Logit	Probit	Logit
Log(Sales)	0.206***	0.475***	0.286***	0.720***
	[0.038]	[0.086]	[0.052]	[0.124]
Multi-Establishment	0.160*	0.374*	0.024	0.095
	[0.086]	[0.220]	[0.132]	[0.391]
Log(Age+1)	-0.053	-0.130	-0.087	-0.215
	[0.062]	[0.149]	[0.095]	[0.250]
Foreign Ownership	-0.104	-0.247	-0.111	-0.244
	[0.082]	[0.203]	[0.135]	[0.393]
Log(Labor Productivity)	-0.168***	-0.395***	-0.040	-0.089
	[0.055]	[0.132]	[0.064]	[0.149]
Intangible intensity	1.112***	2.338***	1.136*	3.016*
	[0.362]	[0.746]	[0.636]	[1.686]
Constant	-2.813***	-5.682***	-5.312***	-12.009***
	[0.451]	[1.041]	[0.553]	[1.463]
Observations	8,392	8,392	5,628	5,628

*Note: The dependent variable is AI adoption between 2017 and 2018. All independent variables are measured in 2017 levels. Intangibles intensity is the share of intangible assets over total assets. Labor productivity is value added per worker. All models include region and sector fixed effects. Robust standard errors clustered at the firm level are in brackets. *** p<0.01, ** p<0.05, * p<0.10* ***The probit and logit results reflect coefficients and not marginal effects. The marginal effect results are in the process of being released by the South Korean statistical authorities.***

Table A6 Firm characteristics and AI adoption by application, OLS estimation

	Model One	Model Two	Model Three	Model Four	Model Five	Model Six
VARIABLES	Product/Service development	Marketing Strategy	Product Processes	Organization management	Product/Service development + Marketing Strategy	Product Processes + Organization management
Log(Sales)	0.006***	0.001	0.003***	0.001**	0.007***	0.004***
	[0.002]	[0.001]	[0.001]	[0.000]	[0.002]	[0.001]
Multi-Establishment	0.003*	-0.000	0.000	-0.000	0.003	-0.000
	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]
Log(Age+1)	-0.001	-0.000	0.001	-0.001*	-0.001	-0.001
	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]
Foreign Ownership	-0.002	-0.002***	-0.001	-0.000	-0.003*	-0.001
	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]
Log(Labor Productivity)	-0.005***	-0.001	-0.001	-0.000	-0.005***	-0.001
	[0.001]	[0.001]	[0.001]	[0.000]	[0.002]	[0.001]
Intangible intensity	0.040**	0.007	0.016*	-0.005**	0.047**	0.011
	[0.019]	[0.008]	[0.009]	[0.002]	[0.021]	[0.009]
Observations	11,063	11,063	11,063	11,063	11,063	11,063
R-squared	0.030	0.008	0.011	0.011	0.032	0.012

*Note: The dependent variable captures AI adoption between 2017 and 2018. All independent variables are measured levels in year 2017. Intangible intensity is the share of intangible assets over total assets. Labor productivity is value added per worker. All models include region and sector fixed effects. Robust standard errors clustered at the firm level are in brackets. *** p<0.01, ** p<0.05, * p<0.10.*