What determines AI adoption?

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Abstract

The following paper provides one of the first empirical studies on the determinants of AI adoption. The paper relies on novel firm level data of businesses in South Korea for the years 2017 and 2018. Descriptive analysis suggests that the diffusion of AI, similar to previous digital technologies is occurring at faster rates to firms in urban settings and those in data intensive sectors. The econometric assessment identifies a number of firm characteristics important for AI use, notably size and the use of intangible assets. These characteristics are important for AI employment regardless of how they were acquired (either produced in house or purchased from a vendor) or what the technology is applied to (sales, R&D, accounting and so on). Firm partnerships are also important predictors of AI adoption with some evidence that this is driven by joint ventures with foreign firms in different sectors. Moreover, AI is not being adopted in isolation but are acquired with other bundles of digital technologies and services including big data, cloud and the Internet of Things.

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1) Introduction

Artificial intelligence (AI) is becoming a realistic technology choice for firms. This is partially driven by advances in research and development on AI and the degree of investments that are flowing to AI firms. For example the amount of scientific publications in this field quadrupling over the last two decades (OECD 2020) while the sum of venture capital flowing to AI firms is roughly 60 billion dollars over the last 10 years (Schmelzer 2020). This has led to an increase in AI adoption across firms and countries around the world (EU Press 2020; Balakrishnan et al 2020; Brynjolfsson and McAfee 2014). Firms are using AI for a host of business operations including supply chain, product development, marketing, finance and accounting. Advances in data processing capabilities enables AI to be used across a growing number of tasks such making prediction, automating tasks, streamlining processes, classifying text, speech and so on (Iansiti and Lakhani 2020; Davenport and Ronanki 2018; European Parliament 2020).

There is considerable interest in understanding what is driving the diffusion of AI across firms overtime. AI is expected to have a profound impact on the economy, disrupt the way firms compete and organize in the near future with some academics suggesting that it is the next general purpose technology (GPT) (Brynjolfsson and McAfee 2014; Agrawal et al 2018; McElheran 2018; Goldfarb et al 2020; Iansiti and Lakhani 2020). The diffusion of new technologies is important for firms' competitive gains at the micro-level (Jin and McElheran 2018; DeStefano Kneller and Timmis 2018; Cordona et al. 2013; Brynjolfsson and McAfee 2014; Bloom et al 2012; Syverson 2011) and economic growth disparities at the macro-level (Niebel 2018; Fernald 2014; Timmer et al. 2011; O'Mahoney et al. 2008). To date, however there is limited empirical research on what drives AI adoption and much of the existing surveys on AI adoption originate from consultancy reports with limited coverage and sometimes unrepresentative samples (OECD, 2019a).[2]

The objective of this paper is to provide empirical evidence on the drives of AI adoption for firms in South Korea. The research relies on a relatively unused firm level dataset administered by the Office of National statistics in South Korea which contains information on AI use (in 2017 and 2018) along with firm financial information. The dataset contains rich information regarding where the AI is being applied (such as sales, R&D, accounting and so on) and whether it has been

[2] One notable exception is the US Census 2019 (see Zolas at al (2020) for details).

developed in-house or sourced from the third party provider enabling us to assess potential firm differences in AI application and creation. With two years of data, the panel data allows us to control for unobservable time trends which is likely to be present when firms make a decision to use AI. Moreover, the two years of data enables us to assess to date unexplored time dimensions of technology adoption such as when complementary investments (such as big data, IoT and cloud computing) occur and when firm's reorganize (moving, expanding, downsizing and so on) either ex-ante or while adopting AI.

At present there are few papers that examining the diffusion and the determinants of AI adoption. Early work originated from surveys administered by consultancy companies which typically found adoption rates of around 20%-30% (Knight 2020). Later surveys that were administered by national statistical agencies that were representative of firm populations such as in South Korea, the US and Germany found considerably lower rates of adoption, 2-4% (Cho et al 2020; Zolas et al 2021; ZEW paper). One of the early insightful papers by Goldfarb et al (2020) uses job postings for a number of IT positions are early proxies for ML/AI diffusion with the idea being that labor demand can be used to measure technology adoption (Tambe and Hitt 2012). Cho et al (2020) and Zolas et al (2021) rely on a cross-section firm level data to examine the use of AI in South Korea and the US, respectively. Both papers find correlations between AI use and firm size. These studies also provide descriptive evidence for important technology complementariness such as cloud computing and big data. This paper contributes to this work by relying on a panel dataset with rich information on the firm which allows us to assess additional determinants to AI adoption along with details on how firms are reorganizing around the technology overtime.

This paper also contributes to the literature on ICT diffusion more generally. Previous studies using firm-level data have shown that different characteristics of firms (such as size, human capital, intangible assets, R&D, sector heterogeneity and age) determine the use of digital technologies and are important in explaining differences in technological adoption between companies (Bartel and Lichtenberg 1987; Baldwin and Rafiquzzaman 1998; Bresnahan et al. 2002; Gibbs and Kraemer 2004; Giunta and Trivieri 2007, Haller and Siedschlag 2011; Corrado & Hulten, 2010; OECD and World Bank, 2015; Haskel & Westlake, 2017; DeStefano, Kneller and Timmis 2018; OECD 2020).

The types of collaborations firms engage in with other actors can also encourage technology adoption and knowledge spillovers. There is a large literature which has documented positive impacts of joint ventures on technology diffusion, the mechanism of which can flow from bot direct and indirect channels (Javorcik 2004, Keller and Yeaple 2009; Jiang et al 2018). Partnerships amongst firms targeted towards technology development and collaboration may also result in knowledge transfer and subsequent technology creation or adoption (Hottenrott and Lopes-Bento 2016; Zidorn and Wagner, 2013; Hagel and Brown 2005). Using information on whether firms are engaged in joint ventures and technology partnerships this paper also assesses whether such relationships are relevant for AI adoption.

Another important contribution this paper makes is understanding wither AI adoption occurs in isolation or amongst complementary bundles. While empirical studies typically focus on the determinants and performance effects of a single technology (Cordona et al. 2013), in reality, firms likely rely on technologies in bundles. Digital tools generally work together along with various functions, such as creating, collecting, and exploiting large sums of data (Goldfarb et al. 2020; McElheran 2018; Sestino et al. 2020). For example, firms wishing to use AI will require large datasets to train their algorithms, which can be generated and collected at scale by IoT and big data practices and processed and stored on cloud computing services (Iansiti and Lahkani 2020; DeStefano Kneller and Timmis 2020a; OECD 2019a). While likely evident to practitioners, most OECD countries design economic policies to either encourage the use of one particular technology or target capital investments more generally and exclude technology acquired through services such as cloud computing and big data (Tax Foundation 2018; Andres et al. 2020). Our panel data allows us to indentify both the importance to ex-ante technology use i.e. technologies that need to be in place before firms investment in AI and techcnologies that firms are adopting simultaneously with AI. Understadning the nuaces in the timing of technologies is relevent to academics, policy makers and managers alike.

Like previous digital tools, the use of new technologies will require reorganization of the firm (Bresnahan et al 2002: Forman and McElheran 2013). Initial reports suggest that AI use requires considerable firm reorganization. Iansiti and Lahkani (2020) suggest firms need to breakdown siloes, share data across the organization hire skilled data scientists and make adjustments to management practices. This is likely to require firms to downsize particular parts of the organization (such as branchs that carryout repetitive white colar tasks) and expand others (like the IT and data science teams). Today there is a shortage of data scientists and those with AI skills which may also incentivize companies to relocate parts of their operations closer to hubs and/or Universities that lead research in this area including Silicon valley, Boston, Seatle and so on ((Randazzo et al 2021; Heston and Zwetsloot 2020 We contribute to our understanding of how firms are reorganizing around AI use and furthermore identify whether businesses adjust before and/or while they adopt AI.

To preview our results, we find that firms that are large and those that use intangibles intensively are more likely to adopt AI. These results are consistent when we examine the adoption of different AI applications or whether the AI is produced in-house. Firm partnerships are pertinent for AI with some evidence for joint ventures with overseas partners in different sectors. Certain technologies appear to be important complements for AI such as IoT, cloud and big data with the timing of their usage pertinent. Firm reorganization (such as downsizing or moving) is relevant for AI adoption contemporaneously.

The rest of the paper is organized as follows. Section 2 provides some explanation on what is AI. Section 3 discusses the data used while Section 4 highlights the empirical strategy employed in this paper. The descriptive and empirical results are presented in Section 5 and some summation and managerial insights are drawn in Section 6.

2) What is AI

While there is no official definition of AI, the G20 has come up with an understanding of agreement for the technology. Based on their proceedings AI includes the following components (AIGO 2019):

- 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 idea of AI has been around as early as antiquity (Cave et al 2020). However, the basis for our modern understanding of AI originates around the 1950s with people like Turing who proposed a mathematical theory where computers could deduct from simple symbols like 0 and 1. The field of research officially started in 1956 (at a summer workshop on AI at Dartmouth College) with progress slowing by the mid-1970s because of declining research progress and less funding (Anyoha 2017). Recent interest and technological progress in AI began roughly ten years ago facilitated by the emergence of big data sets and cheaper storage and processing capabilities resulting in considerable technological progress (Paik et al 2020).

There are differences in the types of AI/ML tools such as supervised, unsupervised and reinforced learning. Supervised learning algorithms learn from data (with labelled input-output pairs) that enables one to predict outcomes with unforeseen data. Unsupervised learning allows the algorithm to self-discover data on its own to make predictions on outcomes. Reinforced learning is somewhere between the two previous examples where there is a balance between assessing data independently and exploiting available information on inputs and outputs to make predictions (Loukas 2020).

Advances in AI are translating into greater varieties of applications. For example, in product development AI can be used digital testing and prediction of prototypes, defection identification, generative design and so on. The marketing sales and customer management departments are relying more on AI to assist with a host of tasks from transcribing sales calls to analyzing the emotion of callers (Bakken 2019). This technology is also finding growing use cases in the production and logistics process such as predicting depend and supply forecasts, warehouse management, planning performance optimization and so on (Iansiti and Lakhani 2020; Davenport and Ronanki 2018; European Parliament 2020). The richness of the data used in the paper will also us to assess which types of firms adopting various AI applications overtime.

Firms can access AI through two main sources. Firstly, firms can produce their own AI in-house. Firms favoring to build in house typically require AI to drive their core business objectives and are likely to be larger, more data intensive, with higher rates of human capital and deeper financial resources (Forbes 2019). AI is through 3rd party suppliers are more suitable for firms that will use AI for non-essential activities. Thus AI as a service may be more favorable to smaller more financially constrained firms, they may also be appropriate solutions for more technologically sophisticated companies' who are looking for advanced analytical tools for more narrow use cases (Rowan 2020). To date there is little evidence on the rates of in-house versus outsourced AI which represents another contribution from this paper.

3) Data

This paper relies on a firm-level data set called the “Survey of Business Activities” from Statistics Korea (KOSTAT). Since 2005, KOSTAT has conducted comprehensive surveys on business activities. The primary purpose of the survey is to provide detailed data to observe changes in industrial structure and management strategies of the South Korean economy. KOSTAT collects information on various aspects of firm characteristics and business environments, such as business performance, technology use, diversification, partnerships, restructuring and so on. The survey targets corporations with at least 50 full-time employees and capital stock valued at 300 million KRW or more (roughly $250,000 USD), covering approximately 13,000 firms in all industries.[3]

In 2018 and 2019, KOSTAT added questionnaires relating to the use of advanced digital technologies which will be used for the main focus of the paper. This dataset not only identifies firm level AI use but also when AI is being applied and where it is sourced (built in house or as a service). The dataset also collects information on the use of other digital technologies that are likely important complements for AI adoption. These include the Internet of things (IoT), cloud computing, Big Data and 5G (see Table # for these technology definitions). In order to use AI effectively firms need to acquire and maintain large datasets to train its algorithms, which can be generated and collected at scale by IoT, big data practices and mobile technologies (Cho et al 2020). Moreover scalable and flexible data processing and storage will be needed to support the firms' digital infrastructure which is likely to come from cloud computing services (DeStefano et al 2020).

[3] In the meantime, as 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

Table 1Technology 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. (US Census Bureau 2019).
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

Out of the sample, a minority of firms are using AI however the rate nearly doubled between 2017 and 2018 from 1.4% of firms to 2.7%. (See Table 2) These proportions are broadly in line with what Zolas et al (2020) finds for the US. For those that use AI, the preferred source of the technology is self- development at 2.0% while only 0.7% of firms acquire these tools through third party providers. In terms of business applications, the majority of AI users employee them for product development (See Table 3). After which an equal proportion of firms 0.3% use AI in their marketing and strategy, production processes and sales with the least favorable application being organizational management. One simple assessment of this may be that firms are using AI to produce new products and increase scale with less focus on reorganizational and efficiency enhancement.

Table 2 AI use and self-development by count and share

Period	AI use		AI self-development	
Year	# of AI	Share of AI	# of AI	Share of AI
2017	174	1.4%	143	1.1%
2018	355	2.7%	263	2.0%

Source: KOSTAT with calculations made by authors.

Table 3 Share of use by business application

Year	Product/service development	Marketing strategy	Production processes	Organizational management	Sales
2017	1.0%	0.2%	0.1%	0.0%	0.0%
2018	1.7%	0.3%	0.3%	0.1%	0.3%

Source: KOSTAT with calculations made by authors

Table 4 demonstrates that larger firms are more likely to use AI than smaller firms which has become more apparent over the two-year sample. In 2018, firms with 250 or more employees are 5.6% likely to use AI in comparison to 2.0% for those with 50-250 employees and 1.6% for those with 50 employees or less. In terms of age, young firms are adopting AI at a greater rate than mature firms. 5.5% of firms (defined by ones age of being 5 years or less) use AI version 2.6% for mature firms (defined by those older than 5 years). Moreover, considerable heterogeneity in AI use is found across sectors (See Table 6). Not surprisingly data intensive sectors like the information and communication sector has the greatest rate of adoption at 12.6% followed by Financial and Insurance Activities at 8.7%. In addition, a number of sectors have witnessed steady growth in AI use with Education, Professional and Scientific and Technical Activities, Wholesale and Retail and Manufacturing, with rates more than doubling in one year.

Table 4 Share of AI use by firm size, measured by employment

Year	Size	Share of use
2017	Size<50	1.2%
	50<=Size<250	0.9%
	Size>=250	3.1%
2018	Size<50	1.6%
	50<=Size<250	2.0%
	Size>=250	5.6%

Source: KOSTAT with calculations made by authors

Table 5 Share of AI use by firm age, Mature vs Young

Year	Age	Share of use
2017	Mature	1.3%
	Young	3.5%
2018	Mature	2.6%
	Young	5.5%

Source: KOSTAT with calculations made by authors

Table 6 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 business support 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

There also appear to be important complementarities in the adoption. In particular there seems to be considerable overlap in the adoption of AI and Big Data. Interestingly IoT and Mobile technologies appear to be less relevant for AI use. We will explore this more formally in the empirical section below.

Table 7 Technology dyad

Year	AI-IOT	AI-Cloud	AI-Big Data	AI-Mobile	IoT-Cloud	IoT-Big Data
2017	65	80	114	84	102	110
2018	145	163	215	118	209	223

Source: KOSTAT with calculations made by authors

4) Empirical strategy

Baseline regressions

We develop the following model which estimates the firm deterimants of AI adoption (see Equation 1). y_{il} is the dependent variable, signifies changes in AI adoption of firm i at time t. To capture adoption in the data y_{il} =1 if a firm does not use AI in 2017 but does in 2018. While firms which do not use AI in 2017 and 2018 and those that use AI in 2017 and 2018 = 0. In the baseline regression the dependent variable measures the adoption of all types of AI while in subsequent regressions it reflections the adoption of AI relating to specific applications including product/service development,marketing strategy, production processes, organization management. It also reflects the source of AI=0 if its developed in-house and 0 if it is from a 3rd party provider.

$$\Delta y_{it} = \beta_0 + \beta_1 X_{it=2017} + n_j + n_l + \varepsilon_{ijl} \quad (1)$$

X_i represents a vector of firm characteristics in the year 2017. These include (log) number of employees, multi-establishment status, log (age+1), foreign ownership, log labor productivity (measured by value added per worker) and lag intangible asset intensity (reflected by the share of intangible assets over total assets). To control for industrial and regional variation, we use the fixed effects of industries (j) and region (l) 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.

Partnerships

To assess the extent to which firm partnerships and joint ventures impact AI adoption we also a number of variables that capture in our data. These include whether the firm in a strategic partnership, which includes joint technology development, technology collaboration, joint venture ship and whether these relationships are with partners in domestic/foreign countries and if they are in the same or different sectors. Similar to the baseline regressions partnerships are measured at the first year of the sample period in 2017.

Reorganization

The final empirical contribution of the paper is to examine whether firms are reorganizing as a result of AI and when this reorganization is occurring. In terms of reorganization, we examine whether AI is linked with firm restructuring including, downsizing, expanding and moving. Another form of reorganization that we assess is whether firms are using other likely complementary technologies as a result of AI adoption such as cloud computing, big data, IoT, and advanced mobile. We exploit the time dimension of our data to assess whether certain types of firm organization occur before adopting AI or whether they are happening simultaneously. This may be particularly relevant for complementary technologies since it may be the case that the ex-ante use of certain technologies are important predictors of AI adoption, while other technologies need to be adopted simultaneously to support ones AI strategies.

To assess the important of ex-ante reorganization of AI adoption, we include to our baseline an addition covariate Z which measures whether the firm was undertaking a form of reorganization in 2017, the year before firms adopt AI (See Model 2). Note that each regression is run separately for each reorganization variable. Next to whether these reorganization practices are occurring simultaneously, we regression AI adoption on the adoption on each of the organizational variables between 2017 and 2018 (See Equation 3).

$$\Delta y_{it} = \beta_0 + \beta_1 X_{it=2017} + \beta_2 Z_{it=2017} + n_j + n_l + \varepsilon_{ijl} \quad (2)$$

$$\Delta y_{it} = \beta_0 + \beta_1 X_{it=2017} + \beta_2 \Delta Z_{it} + n_j + n_l + \varepsilon_{ijl} \quad (3)$$

5) Empirical results

Baseline firm characteristics and AI use

The following section presents the econometric results on the use of AI. Given the richness of the data we are able to explore a number of important questions around AI use. The first obvious questions, are about which firm characteristics predict AI adoption? As such, we start by assessing the link between firm characteristics at the start of the sample period (size, age, ownership, productivity and investment in intangibles) on AI adoption between 2017 and 2018.

Second, we explore how different characteristics predict AI adoption either self-produced or purchased externally, a question that has not yet been assessed in the literature. On the one hand, some firms may favor producing these in-house with their own IT departments and data scientists, specifically if AI will be used for a core of the business' strategy. On the other hand, others may prefer to simple obtain these tools from third party vendors if the firm last the technical expertise or wants to apply AI more narrowly.

The third part of this section uncovers the links between firm characteristics and the types of AI applications they are adopting. This is particularly relevant for managements that are interested in understanding where in their business operations AI may enhance performance. These applications include AI used in product/service development, marketing strategy, production processes, organizational management and sales.

Table 8 presents our baseline results on the relationship between firm attributes and AI adoption estimated in OLS, Probit and Logit. Consistent with previous digital technologies, firm size is an important determinant for AI adoption, measured by sales and multi-establishment. Investment in intangibles strongly predicts AI adoption. This is consistent with Haskel and Westbrook (2017) who suggest that advanced technology use is corresponding with firms becoming increasingly more reliant on intangible assets such as data, research and development (R&D). We also know that AI is very data intensive and thus firms which employ intangibles more intensely 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.

Surprisingly, labor productivity is negatively correlated with AI adoption which is at first sight a bit surprising but on second though consistent with the literature. The use of AI requires considerable organizational change both before during and after implementation. Therefore, productivity a year before adoption is lower given the need for firm structural adjustment somewhat consistent with Brynjolfsson et al (2018) and Yang and Brynjolfsson (2001). To assess this further, in a subsequent section we will examine whether there is a link between AI adoption and firm reorganization.

Table 8 Firm characteristics and AI adoption

Dependent variable: AI adoption	Model One	Model Two	Model Three
Estimation method	OLS	Probit	Logit
Log(Sales)	0.012***	0.250***	0.559***
	[0.002]	[0.032]	[0.069]
Multi-Establishment	0.004	0.147**	0.344*
	[0.003]	[0.073]	[0.178]
Log(Age+1)	-0.002	-0.053	-0.137
	[0.002]	[0.054]	[0.123]
Foreign Ownership	-0.004*	-0.097	-0.200
	[0.003]	[0.069]	[0.167]
Log(Labor Productivity)	-0.008***	-0.130***	-0.298***
	[0.002]	[0.045]	[0.100]
Intangible	0.081***	1.461***	2.976***
	[0.030]	[0.349]	[0.718]
Observations	11,063	9,300	9,300
R-squared	0.039		

*Note: Regressions cover the years 2017 and 2018. The share of intangibles assets 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.*

[Place AI self-development results here]

[Place AI   application results here]

Strategic partnership and AI

Building off of the baseline results in the previous section, we examine the important for business partnerships and joint ventures on AI adoption. As discussed previously there is considerable amount of literature which finds evidence for partnerships and technology diffusion. However, there is less of an understanding as to whether these business ties matter for technology adoption or AI use. To assess this we include various measures of partnerships to the baseline regressions. The partnership variables include Strategic partnership (which measures whether the firm participates in any of the partnerships), joint technology development, technology collaboration, and joint ventures.

Overall, participating in any form of partnership, measured by strategic partnership is strongly correlated with AI adoption. When we focus in on particular types of partnerships, there is some evidence that joint ventures matter for AI adoption, however the results are somewhat nuanced. For example, joint ventures with overseas partners in different sectors predicts AI adoption while joint ventures with overseas partners in the same sector is negatively correlated with AI use. This may suggest that Korean firms find important synergies with those operating in different spaces which induces them to update their technology and adoption technology. In addition, it may be that firms in the technology intensive sectors are forming relationships and sharing their knowledge with firms in non-technology intensive sectors. We see anecdotal evidence of this in the US with say technology giants forging relationships in the automotive, health, sector (MacDuffies 2021; Drees 2020). It is less clear why there is a negative correlation with joint ventures with overseas partners in the same sector. However, it may that acquirers are targeting less productive entities to form joint ventures with. Further research is needed in this area.

Table 9 Strategic partnerships and AI adoption

Dependent variable: AI adoption	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Estimation method	OLS	Probit	Logit	OLS	Probit	Logit
Strategic partnership	0.017**	0.251**	0.510**			
	[0.008]	[0.105]	[0.238]			
joint technology development w/ overseas in the same industry				0.004	-0.111	-0.051
				[0.025]	[0.353]	[0.847]
joint technology development w/ overseas in a different industry				0.008	-0.710	-2.189
				[0.059]	[0.924]	[1.821]
technology collaboration w/ overseas in the same industry				0.007	0.198	0.288
				[0.020]	[0.362]	[0.879]
technology collaboration w/ overseas in a different industry				0.093	0.854	1.821
				[0.086]	[0.625]	[1.278]
joint venture w/ domestic in the core partners				0.016	-0.120	-0.327
				[0.047]	[0.644]	[1.300]
joint venture w/ domestic in the same industry				0.051	0.993*	2.226*
				[0.046]	[0.512]	[1.163]
joint venture w/ domestic in a different industry				0.016	-0.105	-0.301
				[0.071]	[0.546]	[1.087]
joint venture w/ overseas in the same industry				-0.032**	-0.812*	-1.677
				[0.016]	[0.434]	[1.028]
joint venture w/ overseas in a different industry				0.125	1.014**	2.161**
				[0.079]	[0.468]	[0.960]
Observations	11,063	9,300	9,300	11,063	9,300	9,300
R-squared	0.040			0.042		

*Note: Regressions cover the years 2017 and 2018. The share of intangibles assets 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 technology for AI adoption. In addition, we explore whether the timing of complementary investments (either before or during) matter for AI adoption. While most of the empirical literature typically focuses on the determinants and performance effects of a single technology, in reality firms deploy these technologies in bundles at various points in time. Digital tools generally work together with other tools which create, collect and exploit large sums of data. For example, firms looking to use AI require large datasets to train its algorithms, which can be generated and collected at scale by IoT and big data practices. In turn, they will likely require cloud computing, which facilitates flexible storage and processing of data (Iansiti and Lahkani 2020; DeStefano Kneller and Timmis 2020a; OECD 2019a).

Relying on the rich KOSTAT data which collections information on other advanced digital tools we select a subset of four technologies which we believe may help facilitate AI adoption notably, big data analytics, cloud computing, IoT and mobile communication technology. To assess whether these technologies need to be in place before AI adoption we construct binary variables equally to 1 if the firm used any of these tools in 2017 and 0 if they did not. Alternatively, to uncover whether these potential complements need to be implemented simultaneously we construct binary adoption variables the same way AI adoption is measured; equal to 1 if a firm did not use the technology in 2017 but did in 2018, 0 if the firms did not use the tool in both 2017 and 2018 and if they did used the tool in 2017 and 2018.

The results in Table 10 demonstrate interesting and nuances in terms of the complementarities across technologies and their timing of implementation. The use of ex-ante IoT appears to be an important determinant for subsequent AI adoption. This is somewhat consistent with the function of the technology, i.e. using smart sensors between devices and people that collect and communication data on their actions and responses overtime. These technologies generate large sums of data which is known to be an important pre-requisite for AI implementation. There appears to be less importance however for the other technologies to be in place prior to AI adoption.

However, we find strong empirical support that firms are adopting many of these technologies simultaneously. Notably firms appear to be bundling cloud, big data and IoT along with AI contemporaneously. Given that AI is data intensive means that it is important for firms to also be adopting technology that enhances their ability to collects data such as with IoT, improves the way they assess and exploit large dataset, such as with big data analytics and greater flexibility in how they store and process of large sums of data, like with cloud computing.

Table 10 Technology adoption before and during 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	0.167	0.332			
	[0.022]	[0.180]	[0.420]			
Cloud in 2017	0.001	-0.013	-0.034			
	[0.019]	[0.183]	[0.421]			
IOT in 2017	0.051**	0.472***	0.872**			
	[0.022]	[0.161]	[0.359]			
MOBILE in 2017	0.030*	0.323**	0.524			
	[0.017]	[0.150]	[0.342]			
BIG DATA adoption in 2018				0.236***	1.261***	2.511***
				[0.028]	[0.117]	[0.250]
Cloud adoption in 2018				0.068***	0.572***	1.062***
				[0.022]	[0.137]	[0.310]
IOT adoption in 2018				0.098***	0.626***	1.186***
				[0.025]	[0.141]	[0.319]
MOBILE adoption in 2018				0.025	0.117	0.145
				[0.027]	[0.172]	[0.364]
Observations	11,063	9,300	9,300	11,916	9,865	9,865
R-squared	0.046			0.185		

*Note: Regressions cover the years 2017 and 2018. The share of intangibles assets 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 firm restructuring

The final section examines the extent AI adoption is linked with firm reorganization. The literature finds empirical evidence of firm reorganization of previous digital technologies (Bresnahan et al 2002: Forman and McElheran 2013) while initial analytis suggest that AI use requires considerable firm restructuring (Iansiti and Lahkani 2020). However, to date the is not empirical research on the extent to which firms reorganize around AI, how they organize (such as through expansion, downsizing and/or moving) and when they restructure (before adoption or during). We construct our ex-ante adoption reorganization variables the same way the complementary technology variables.

The results find that AI adoption and firm reorganization is linked but that this occurs during the adoption process rather than before. Neither of the ex-ante reorganization variables are statistically correlated with AI adoption. However, we find that the adoption of reorganization from 2017 to 2018 is correlated with the adoption of AI over the same period. Any form of reorganization (signified by the reorg variable) is positive significant at the 1% level across all estimation methods. When we focus on particular times of reorganization, we find that moving and downsizing and correlated with AI adoption for the Probit and Logit models.

The overall finds suggest that reorganization and adoption is occurring simultaneously, however the relationship is somewhat less pronounced for specific types of restructuring. This may be partial explained by the presence of many zeros in the data. Alternatively and somewhat more consistent with what was found for previous technologies is that much of the reorganization occurs both during but also several years after adopting the technology and thus and are only capturing part of the picture with two years of data.

Table 11 Firm reorganization before and during 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					
VARIABLES	OLS	Probit	Logit	OLS	Probit	Logit	OLS	Probit	Logit	OLS	Probit	Logit
Reorg in 2017	0.008	0.066	0.204									
	[0.012]	[0.189]	[0.423]									
Move in 2017				-0.011	-0.200	-0.751						
				[0.014]	[0.453]	[1.079]						
Downsize in 2017				0.001	0.009	0.072						
				[0.009]	[0.260]	[0.588]						
Expand in 2017				0.003	0.144	0.240						
				[0.011]	[0.234]	[0.603]						
Reorg in 2018							0.050***	0.572***	1.155***			
							[0.016]	[0.129]	[0.275]			
Move in 2018										0.043	0.537**	1.249**
										[0.027]	[0.233]	[0.490]
Downsize in 2018										0.015	0.387**	0.793*
										[0.010]	[0.178]	[0.418]
Expand in 2018										0.015	0.281	0.619
										[0.012]	[0.173]	[0.391]
Observations	11,063	9,300	9,300	11,063	9,300	9,300	11,916	9,865	9,865	11,916	9,865	9,865
R-squared	0.039			0.039			0.050			0.048		

*Note: Regressions cover the years 2017 and 2018. The share of intangibles assets 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.*

6) Conclusion

Advances in the development of AI are increasing the functionality of the technology and making it easier for firms to adopt. Businesses are using AI for a host of business operations across and increased variety of tasks such making prediction, automating tasks, streamlining processes and classifying. AI is expected to have a profound impact on the economy, disrupt the way firms compete and organize in the near future with some academics suggesting that it is the next general-purpose technology. This is likely to create a winner take all scenario potentially benefiting a minority of early adopters. As a result, there is considerable interest from managers, academics and policy makers alike to understand how and where the technology is being adopted.

The following paper attempts to fill this knowledge gap by providing early empirical evidence on the firm determinants of AI adoption. The analysis relies on novel firm level data for 2017 and 2018 which contains details information on the use of AI and complementary technologies, firm characteristics and partnership and organizational changes. We use this to econometrically estimate the relationship between firm types and AI adoption. We exploit the time dimension of the data to examine whether firm adjustment (measured by investments in complementary technologies and reorganization) is necessary before or during AI adoption.

Overall, we find that firms that are large and those that use intangibles intensively are more likely to adopt AI. These results are consistent when we examine different AI applications or whether the AI is produced in-house. Certain types of technologies are found to be important complements to adoption. Firm partnerships are pertinent for AI with some evidence for joint ventures with overseas partners in different sectors. Having technology in place that allows for the collection of large amounts of data, like IoT is important before firms adopt AI. In addition, cloud, big data and IoT are also being adopted simultaneously alongside AI. Moreover, firm reorganization is relevant for AI adoption however it is something that is taking place during the adoption rather than before and consists most of downsizing and moving.

These results provide some interesting insights into the ways in which firms are adopting AI however more effort is needed in this area. At present there are few representative surveys on AI use across different jurisdictions making it difficult to make cross-country comparisons. In addition, the datasets which exist contain little to know information on the quality of technology being adopted given the difficulty in quantifying AI investments and acquisitions. In addition to the adoption question, considerable research is needed to understand how AI is impacting firm performance and how these impacts differs by firms across space and time. If AI truly is a GTP and the evidence suggests that it is, firms that are able to effectively implement these tools will likely achieve considerable competitive gains against those that do not.

7) References

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Appendix