# Does Artificial Intelligence Enhance Firm Productivity?

Iulia Siedschlag[a,b] and Juan Durán[a,b]

[a] Economic and Social Research Institute, Dublin, Ireland

[b] Department of Economics, Trinity College Dublin, Ireland

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## Abstract

This paper examines the adoption of Artificial Intelligence (AI) across firms and explores the relationship between using AI and firm productivity. The data used in the empirical analysis are linked firm-level data sets from Ireland over 2020-2021. Our results indicate that using AI is not widely spread across firms and it is concentrated in large firms and knowledge-intensive sectors. Descriptive statistics indicate that the adopters of AI differ systematically from non-adopters: they are larger, younger, have higher productivity and a larger market share within industry; they use a larger number of other digital technologies such as Internet of Things (IoT), cloud computing services, and software for sharing electronic information within the firm; and AI adopters have a larger share of sales linked to e-commerce. Estimation results indicate that the propensity of firms to adopt AI is positively associated with firm size, within industry market share and the adoption of other digital technologies. Estimates obtained with a production function econometric model indicate that using AI and the intensity of using AI are positively associated with firm productivity over and above other capital inputs. However, when additional factors that influence productivity are taken into account the statistical significance of this relationship holds only for the intensity of using AI.

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Corresponding author: iulia.siedschlag@esri.ie

## 1 Introduction

Artificial intelligence (AI) is seen as a modern general-purpose technology (GPT) with the potential to enhance innovation and productivity across enterprises and sectors (Brynjolfsson et. al. 2019). However, the effects of AI on innovation and productivity are likely to be delayed in time due to adjustment costs and additional complementary investments in other intangible assets such as human capital and organisational change which are needed (Brynjolfsson et al. 2021).

There are several channels through which AI can enhance innovation and productivity. First, AI enables firms to put in place new combinations of existing technologies leading to higher productivity (Agrawal et al. 2019). Second, AI systems have a lower error rate than humans and thus they can perform co-ordination tasks rather than routine tasks (Brynjolfsson et. al. 2018). Third, AI (machine learning and deep learning) can be used to learn from the production patterns using data (Brynjolfsson and Mitchell, 2018) and further to perform tasks that involve prediction aspects (Agrawal et al. 2017). Fourth, AI allows firms to produce in a more capital-intensive and less labour-intensive way by using more specialised equipment and software and which are productivity-enhancing (Acemoglu et al. 2022a). Finally, using AI could lead to changes in the skill composition at firm level with a higher share of high-skilled employees which increases productivity (Acemoglu et al. 2022a).

AI can be deployed in the production of goods and services affecting economic growth (Aghion et al. 2019). Babina et al. (2022) find that AI investments at firm level (measured using worker resume data and demand for AI skills from job posting data) have increased across sectors in the US. Further, they estimate that firms investing in AI have increased growth in sales, employment and market valuation. Their results show that this growth comes mainly through product innovation. Growth driven by AI is concentrated among larger firms leading to higher industry concentration and the emergence of superstar firms. They find no effect of AI investment on firm productivity. The authors suggest that the benefits of AI depend to a large extent on the ownership of big data, the key input to AI technologies (Fedyk 2016).

Evidence on the relationship between using AI and firm productivity is scarce due to a lack of data to measure the use of AI. Previous empirical studies have focused on the effects of information and communications technology (ICT) on firm productivity. An earlier body of literature has discussed the emergence of ICT during the 1990s as general-purpose technologies having the potential to enhance productivity growth (Bresnahan and Trajtenberg 1995). Following on empirical studies have established that ICT have a positive and statistically significant effect on productivity and that this effect has increased over time (for a review of this evidence, see for example Cardona et al. 2013). Studies that found a positive significant effect of ICT on productivity include among others: Bertschek and Kaiser (2004); Black and Lynch (2004); Bloom et al. (2012); Brynjolfsson and Hitt (2000, 2003); O'Mahony and Vecchi (2005).

Another related literature strand has examined the effects of investment in intangible assets on firm productivity. Di Ubaldo and Siedschlag (2021) employ a dynamic production function empirical approach accounting for path dependency and endogeneity and firm-level data from Ireland over 2006-2012. They estimate that on average, *ceteris paribus*, investment in intangible assets increases firm productivity: a 10% increase in investment in intangible assets increases firm productivity by 3%. Examining investment in specific intangible assets, the estimates indicate that investment in computer software has the largest effect on firm productivity: over and above other factors, investment in computer software leads to higher productivity gains, 16% in response to a 10% increase in investment in computer software. This effect is driven by foreign-owned firms, while the effect is not statistically significant for Irish-owned firms. Borowiecki et al (2021) provides evidence from the Netherlands showing that digital skill intensity (as a proxy for intangibles) have a positive and significant effect on firm-level productivity in the service sector and for younger firms. Productivity is also positively associated with investment in ICT hardware and the uptake of high-speed broadband.

A recent literature has examined the relationship between digitalisation and firm productivity. Cette et al. (2021) find that across firms in France, using ICT specialists and digital technologies improved labour productivity by 23% and total factor productivity by 17% over and above other factors. Erjavec et al. (2023) examine the effects of digitalisation on the performance of small and medium-sized enterprises (SMEs) using a range of merged firm-level data sets from Slovenia over 2007-2020. Key findings indicate that although SMEs lag behind large firms with respect to the use of ICT, the use of ICT and other new technologies increases the productivity of SMEs especially when combined with investment in intangible assets that enhance the contribution of ICT and other new technologies. The results show that firms using intangible capital (based on occupations, workers in ICT, organisational and R&D capital occupations) more intensively have a higher productivity compared with firms with low technology intensity and no intangible assets over the analysed period. In particular smaller firms lag behind large firms with respect to investments in intangible capital that enable firms to use digital technologies more efficiently.

There are only a few studies examining the relationship between using AI and firm productivity. These are recent contributions using data from firm-level surveys which have become available recently. Czarnitzki et al. (2023) employ a production function approach and exploit firm-level survey data from Germany's Community Innovation Survey for 2018. They find that firms using AI had a higher productivity. Specifically, firms using AI had higher sales and generated higher value added than firms which did not use AI. This result holds when AI usage is measured with a continuous variable, an AI intensity index (the number of AI technologies and areas out of all possible combinations). The positive and significant effects of using AI on firm productivity are robust to a range of econometric methods accounting for the potential endogeneity of using AI.

Calvino and Fontanelli (2023) provide cross-country evidence on the adoption of AI and firm productivity from 11 countries using survey data. Their results indicate that the use of AI is more widespread in large firms and across young firms. AI users tend to be more productive, particularly the largest AI users. The relationship between productivity and using AI is conditioned by complementary assets such as employing ICT specialists, having high-speed digital infrastructure (fixed broadband), and the use of other digital technologies (such as Internet of Things and Cloud Computing). While the relationship between AI and productivity remains positive, its magnitude and statistical significance decline when these other factors are controlled for. This evidence is consistent with productivity gains being delayed in time due to adjustment costs and other complementary investments which are needed as discussed by Brynjolfsson et al. (2021).

Nucci et al. (2023) use firm-level data from Italy over 2015-2018 and find that adoption of digital technologies increased total factor productivity (TFP) by nearly one percentage point (0.97 percentage points). The effect is larger, 2.20 percentage points, for investment in at least one AI technology. They estimate that the effect of digital adoption on TFP increases with firm size, age and it is larger in the service sectors.

Coyle at al. (2022) use firm-level data from the UK and find that large firms are more digital intensive than small ones and that adopters of digital technologies have a higher productivity than non-adopters. They find that the relationship between digitalisation and TFP is conditioned by firm's internal capabilities. While having in-house ICT specialists is associated with higher TFP, firms which purchased digital services from external suppliers had a lower productivity.

Acemoglu et al. (2022a) use data from the US and examine the relationship between the adoption of advanced technologies and labour productivity over the period 2016-2018. The advanced technologies considered include AI, robotics, dedicated equipment, specialised software and cloud computing. The adoption rates are limited, particularly for AI and robotics: 3.2% in of firms adopted AI and 2% adopted robotics over the analysed period. Estimates obtained with separate panel regressions for each technology indicate that adoption rates increase with firm size and, with the exception of oldest firms, decrease with age. In regressions controlling for firm size and industry, the geographical location is less important. Firms using advanced technologies have a higher labour productivity by 11.4% than non-adopters. A higher number of adopted technologies is associated with higher labour productivity. Firms using all five advanced technologies are more productive by 21.1% than firms using none while the productivity premium for firms using only one advanced technology is lower. Looking at each technology separately, the correlations between using cloud computing, robotics, and specialised software are positive and statistically significant. Using AI and dedicated equipment is not significantly correlated with labour productivity. These results are consistent with evidence of a time lag between the adoption of AI and productivity effects as documented in previous studies (Brynjolfsson et al. 2021; Acemoglu et al. 2022b). An alternative interpretation is related to the difficulty to disentangle the effects on productivity of specific technologies given that these technologies are adopted jointly with other advanced technologies.

Yang (2022) examines data on patents granted to firms from the electronic industry in Taiwan over 2002-2018 and finds that using AI technology is positively associated with firm productivity and employment. Using a fixed effects panel estimator and controlling for non-AI patents and firm characteristics (firm size, age, export intensity, number of foreign affiliates), the results indicate that firms having AI patents have a higher total factor productivity by 7.8% than firms without patents. Over and above other factors that influence firm productivity, a 10% increase in the number of AI patents is associated with higher productivity by 0.6%. This effect of the number of AI is still positive and significant (0.4%) when accounting for potential endogeneity of the AI variable and it is larger than the effect of non-AI patents (0.3%).

Against this background, this paper contributes to filling the gap in the literature on the adoption of AI and its effect on firm productivity. Specifically, we use firm-level data from Ireland over 2020-2021 to address two questions:

- Which firms use AI and other digital technologies?
- Does using AI and other digital technologies enhance firm productivity?

In addition to Artificial Intelligence (AI), we examine the use of other digital technologies including Internet of Things (IoT), cloud computing services and software for sharing information electronically within the enterprise (ERP software for integrating internal processes; and CRM software for integrating with customers and suppliers).

Our research results indicate that in 2021 just 7% of all firms reported using AI. The use of AI is concentrated across firms, sectors and space. The rates of AI adoption are highest for firms which are large, young, most productive and firms in knowledge-intensive sectors. Descriptive statistics indicate that on average, firms using AI differ systematically from firms which do not use AI: they are larger, younger, have higher productivity and a larger market share within industry; they adopt more digital technologies such as Internet of Things (IoT), cloud computing services, and software for sharing electronic information within the firm; have a larger share of sales linked to e-commerce. Estimation results indicate that the propensity to adopt artificial intelligence technologies is positively associated with firm size, within industry market share and the adoption of other digital technologies. Using a production function framework, our estimates indicate that using AI and the intensity of using AI are positively and statistically significantly associated with firm productivity over and above other capital inputs. However, when additional factors that influence productivity are taken into account the statistical significance of this relationship holds only for the intensity of using AI.

The rest of the paper is organised as follows. Section 2 describes the data and measuring the adoption of AI across firms. Section 3 presents descriptive evidence on the adoption of AI across groups of firms, sectors and regions. The descriptive evidence is then complemented with estimates from a regression analysis of factors that influence the propensity of firms to adopt AI. Section 4 examines the relationship between the use of AI and firm productivity. The analysis is based on an augmented production function model, with AI as an intangible input. The identification strategy exploits the variation in the adoption of AI at industry level to account for the potential endogeneity of AI. Finally, Section 5 concludes and discusses limitations and directions for future research.

## 2 Data and Measurement

### 2.1 Data Sources

Our empirical analysis uses four linked micro-data sets available from Ireland's Central Statistics Office (CSO). The main data source is the E-commerce and ICT Survey 2021. The survey size is a representative sample of approximately 4,000 firms in the business sector with 10 or more persons employed (the business sector includes manufacturing, utilities, construction and selected services; financial and insurance services are not included in the survey). The data set contains information on the usage of AI, IoT (data collected for the first time in 2021) and other digital technologies including cloud computing services and software for sharing information electronically within the firm such as Enterprise Resources Planning (ERP) and Customer Relationship Management (CRM) software. The response rate to the 2021 E-commerce and ICT Survey was 49.7%. The sample for the analysis contains information from 1,554 firms.[1] Using a common firm identifier, we link these data with data from three other surveys containing data for 2020: the Census of Industrial Production (CIP), the Annual Services Inquiry (ASI), and the Business Register (BR). The CIP and ASI Surveys contain data on changes in capital assets, wages, sales, purchases of goods and services for firms in the industry sector (mining and quarrying, manufacturing, and utilities) and for firms in the distribution and services sectors (financial

[1] Due to confidentiality reasons, the largest firms are not included in the Research Microdata File (RMF) made available by the CSO to researchers.

and insurance services not included), respectively. Finally, we merge these data with data from the Business Register and exploit information on the date of firm registration and location.

### 2.2 Measuring the Adoption of AI across Firms

Artificial Intelligence is defined in the E-commerce and ICT Survey as "systems that use technologies such as: text mining, computer vision, speech recognition, natural language generation, machine learning, deep learning to gather and/or use data to predict, recommend or decide, with varying levels of autonomy, the best action to achieve specific goals". Artificial intelligence technologies are defined as follows:

- Technologies performing analysis of written language (data mining)
- Technologies converting spoken language into machine-readable format (speech recognition)
- Technologies generating written or spoken language (natural language generation)
- Technologies identifying objects or persons based on images (image recognition, image processing)
- Machine learning (e.g. deep learning) for data analysis
- Technologies automating different workflows or assisting in decision-making (Artificial Intelligence based software robotic process automation)
- Technologies enabling physical movement of machines via autonomous decisions based on observation of surroundings (autonomous robots, self-driving vehicles, autonomous drones)

AI systems can be software-based (e.g. data analysis based on machine learning, machine translation software) or embedded in devices (e.g. autonomous robots for production assembly).

The survey data also provides information about the purposes for using AI in each firm, namely: organisation of business administration; marketing or sales; production process; management; ICT security; human resources (HR) management or recruiting; and logistics. Multiple purposes/responses are possible. We use these data to construct a measure of the intensity of AI as the ratio of the number of business areas where AI is used and the total number of business areas (seven).

## 3 AI Adoption Across Firms

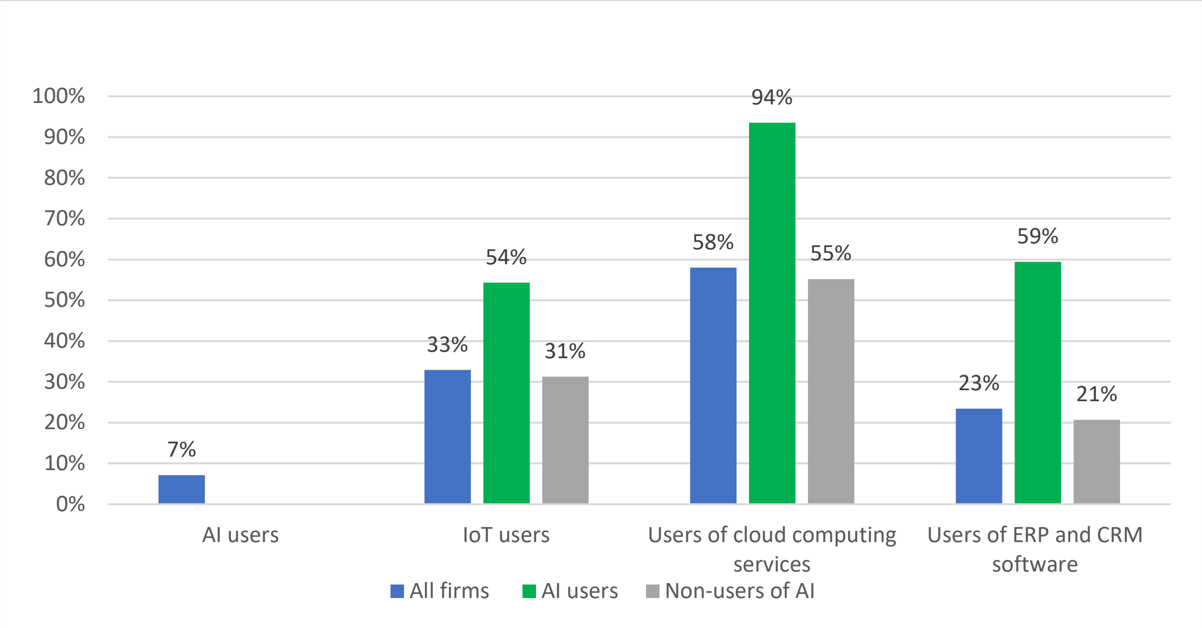
This section first examines the adoption of AI across groups of firms, sectors and regions. Further, we employ regression analysis to better understand factors that influence the propensity of firms to use AI.

### 3.1 Descriptive Evidence

We begin with a set of descriptive statistics of the use of AI across groups of firms, sectors and regions. Figure 1 shows the adoption rates across enterprises of AI and other digital technologies in 2021. While only 7% of all firms use AI, the other digital technologies are used more widely: the highest adoption rates were for cloud computing services (58%) followed by Internet of Things (IoT) (33%) and software for sharing electronically information within the enterprises (23%).

Enterprises which used AI were also using other digital technologies. Among the enterprises using AI, 94% used also cloud computing services; 54% used Internet of Things (IoT) and 59% used software for sharing electronically information within the enterprise. The adoption rates of other digital technologies by enterprises using AI were higher in comparison to the adoption rates of other digital technologies by enterprises which did not use AI. Among the enterprises that did not use AI, 55% used cloud computing services, 31% used IoT and 21% used software for sharing electronically information within the enterprise.

**Figure 1: The use of AI and other digital technologies, 2021**

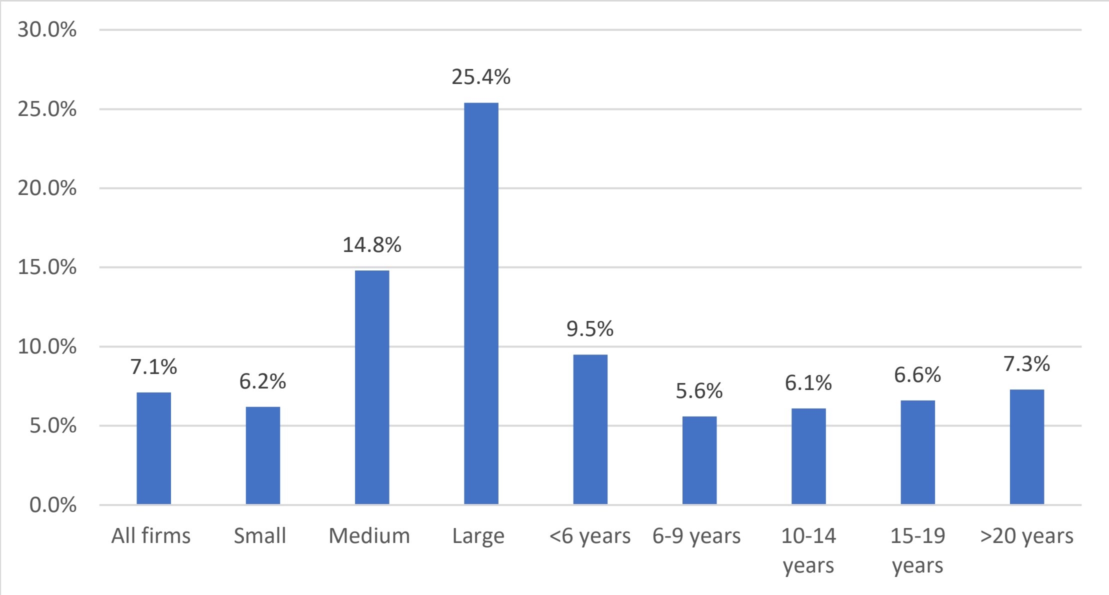



Note: Weighted summary statistics using survey sampling weights.

*Source*: Authors' calculations based on microdata from the E-commerce and ICT Survey 2021 provided by the Central Statistics Office, Ireland.

Figure 2 shows the diffusion of AI across enterprise groups by firm size and age groups. The AI adoption rates increase with firm size. While a quarter of large firms use AI, only 6.2% of small firms and 14.8% of medium-sized firms use AI. The youngest firms, with less than 6 years of business operations have the highest AI adoption rate, 9.5%, while only 7.3% of mature firms (having been in business more than 20 years) use AI.

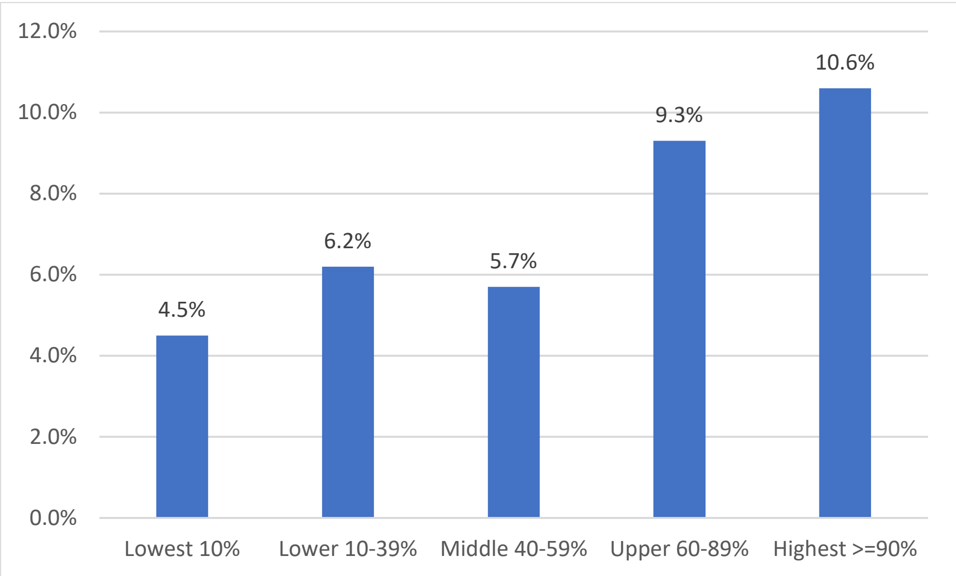
**Figure 2: The use of AI by firm size and age groups**




Note: Weighted summary statistics using survey sampling weights.
*Source*: Authors' calculations based on microdata from the E-commerce and ICT Survey 2021 provided by the Central Statistics Office, Ireland.

Figure 3 shows that AI usage is the highest for most productive firms, those in the top 10% percentile of productivity.

**Figure 3: The use of AI across firms by productivity percentiles**

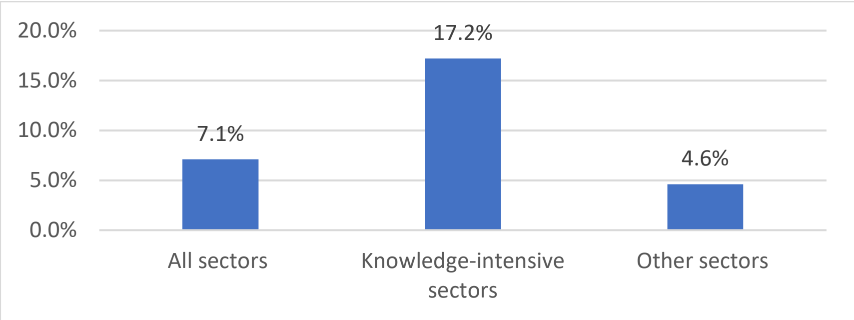



Note: Weighted summary statistics using survey sampling weights.

*Source*: Authors' calculations based on microdata from the E-commerce and ICT Survey 2021 provided by the Central Statistics Office, Ireland.

Figure 4 shows that the AI is used more widely in knowledge-intensive sectors (17.2% of firms) compared to the other sectors (4.6% of firms). Knowledge-intensive sectors are identified using the Eurostat classification[2] and include high-tech industries and knowledge-intensive service sectors.

**Figure 4: The use of AI across firms by knowledge-intensity of sector**

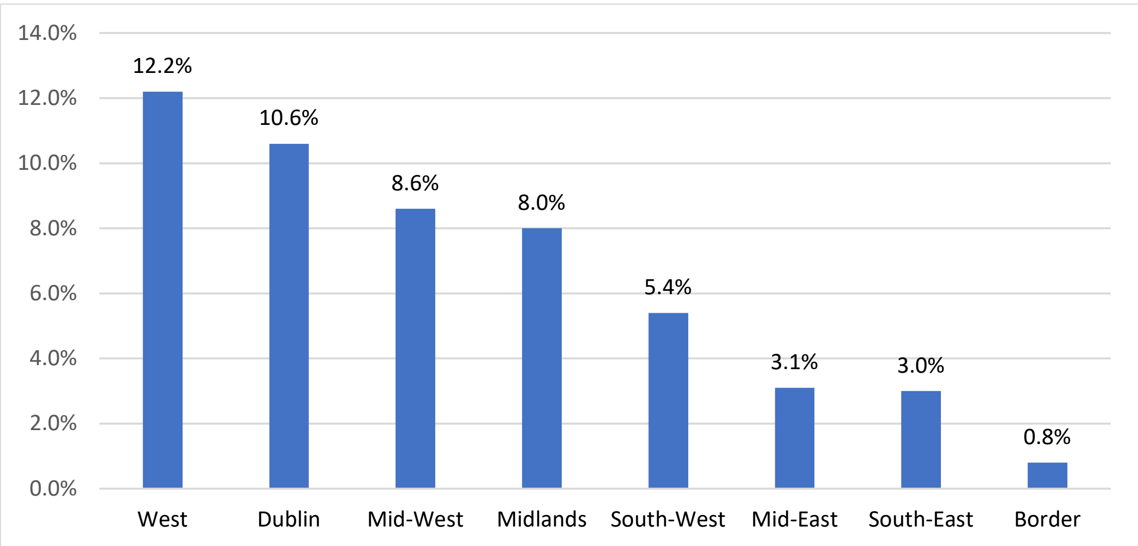



Note: Weighted summary statistics using survey sampling weights.

*Source*: Authors' calculations based on microdata from the E-commerce and ICT Survey 2021 provided by the Central Statistics Office, Ireland.

As shown in Figure 5, AI usage is concentrated geographically. The West and Dublin regions have the highest AI usage rates, 12.2% and 10.6% respectively, while the Mid-West and Midlands regions have AI usage rates above the national average, 8.6 and 8.0% respectively. In the Border region less than 1% of firms use AI. Firms located in the Mid-East and South-East regions have also low AI usage rates, 3.1% and 3.0% respectively. This geographical distribution of AI usage follows most likely the sectoral pattern of regions, with high-tech sectors located in the West and Dublin region.

**Figure 5: The use of AI across firms by region**



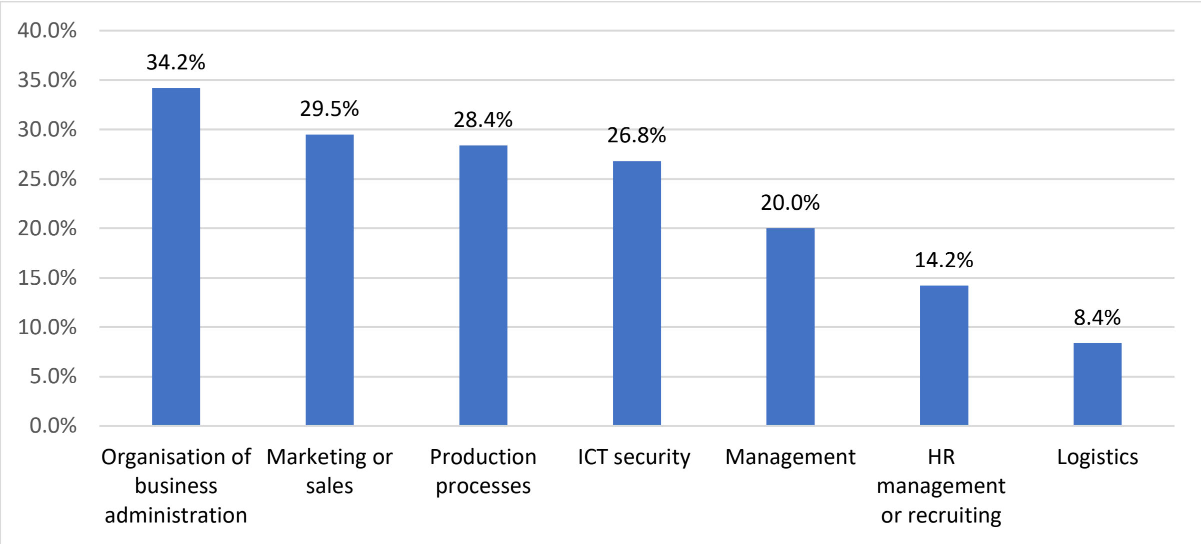

Note: Weighted summary statistics using survey sampling weights.

[2] Knowledge-intensive business sectors are those with at least 33% of employees with tertiary education. Full details of sectors classified as knowledge-intensive are available from the following web link: https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an_8.pdf

*Source*: Authors' calculations based on microdata from the E-commerce and ICT Survey 2021 provided by the Central Statistics Office, Ireland.

Figure 6 shows the use of AI across several business purposes. The top three largest AI usage rates are for organisation of business administration (34.2% of AI users), marketing or sale (29.5% of AI users) and production purposes (28.4% of AI users). It is also worth noting that 26.8% of AI users use AI for ICT security, while only 14.2% of AI users use AI for HR management and recruiting while 8.4% of AI users use AI for logistics purposes.

**Figure 6: AI usage by purpose area**




Note: Weighted summary statistics using survey sampling weights (same figures when unweighted).

*Source*: Authors' calculations based on microdata from the E-commerce and ICT Survey 2021 provided by the Central Statistics Office, Ireland.

Table 1 compares summary statistics for characteristics of enterprises using AI and enterprises which do not use AI. Relative to firms that do not use AI, firms using AI are larger, younger, have a larger market share within industry, and have a larger share of sales linked to e-commerce. The intensity of AI usage is 0.17 which is equivalent to 1.2 AI purposes for the average AI user.

**Table 1: Adopters of AI vs non-adopters – summary stats of firm characteristics**

| | | Number of firms | Mean | Standard deviation (SD) |
|---|---|---|---|---|
| AI users | | | | |
| | Employees | 190 | 67.23 | 250.22 |
| | Age | 190 | 16.32 | 11.15 |
| | Turnover (million €) | 190 | 92.40 | 571.00 |
| | Industry market share (%) | 190 | 3.38 | 13.90 |
| | E-commerce share in sales (%) | 190 | 49.60 | 50.10 |
| | Intensity of using AI | 190 | 0.17 | 0.11 |
| Non-users of AI | | | | |
| | Employees | 1,364 | 32.55 | 193.51 |
| | Age | 1,364 | 17.51 | 12.49 |
| | Turnover (million €) | 1,364 | 7.79 | 63.00 |
| | Industry market share (%) | 1,364 | 1.11 | 5.03 |
| | E-commerce share in sales (%) | 1,364 | 35.40 | 47.80 |
| | Intensity of using AI | 1,364 | 0.00 | 0.00 |
| All firms | | | | |
| | Employees | 1,554 | 35.02 | 198.22 |
| | Age | 1,554 | 17.42 | 12.40 |
| | Turnover (million €) | 1,554 | 13.80 | 165.00 |
| | Industry market share (%) | 1,554 | 1.28 | 6.12 |
| | E-commerce share in sales (%) | 1,554 | 36.40 | 48.10 |
| | Intensity of using AI | 1,554 | 0.01 | 0.05 |

Note: Weighted summary statistics using survey sampling weights.

*Source*: Authors' calculations based on microdata from the E-commerce and ICT Survey 2021 provided by the Central Statistics Office, Ireland.

### 3.2 Determinants of AI Adoption: Regression Analysis

In this section we examine the probability of firms to adopt AI conditional on firm characteristics such as firm size, age, and within industry competition. The baseline model that we estimate is specified as follows:

$$Prob\left(Y_{it} = 1 \middle| \beta X_{it-1}, \sigma_k, \rho_j, \varepsilon_{it}\right) = F(\beta X_{it-1} + \sigma_k + \rho_j + \varepsilon_{it}) \qquad (1)$$

$Y_{it}$ is a binary variable equal to 1 if firm *i* reported using AI in year *t* (2021) and 0 otherwise; $X_{it-1}$ is a vector of control variables in year *t* (2020) associated with the usage of AI by a given firm *i*; $\beta$ are parameters to be estimated. $\sigma_k$ controls for unobserved sector-specific fixed effects; $\rho_j$ controls for unobserved region-specific fixed effects; $\varepsilon_{it}$ is an error term capturing unobserved omitted variables associated with the adoption of AI such as managerial quality. Further, given the descriptive evidence discussed in Section 4.1, we estimate the propensity of firms to use AI conditional on using other digital technologies including cloud computing services, Internet of Things, software for sharing information electronically within the firm, and e-commerce.

Table 2 shows the estimates of the probability of firms to use AI. Column 1 shows the estimates of the baseline model described by Eq. 1. The estimates of the augmented model specification are shown in column 2.

Estimates shown in column (1) indicate that controlling for firm age, and market share within industry as well as industry and region fixed effects, the probability to use AI is positively associated with firm size. Specifically, relative to small firms, the probability to use AI is significantly higher for medium-sized firms by 5.1 percentage points (pp) and for large firms by 13.6 pp. Over and above other control factors, the estimates for age groups are all negative indicating that, youngest firms are more likely to adopt AI than the older firms. However, these estimates are not statistically significant. Over and above firm size and firm age, firms with a higher market share within their industry are more likely to use AI. As shown in column (2), conditional on the usage of other digital technologies and other control factors, the probability to use AI is higher by 4.8 pp for large firms relative to small firms. Further, over and above other control factors, the probability to use AI is higher for firms with a large market share within their industry.

**Table 2: Estimated determinants of the propensity of firms to use AI**

| | (1) | (2) |
|---|---|---|
| Firm Size | | |
| 50 to 249 employees | 0.051** | 0.012 |
| >=250 employees | 0.136*** | 0.048* |
| Firm Age | | |
| 6-9 years | -0.051 | -0.028 |
| 10 to 14 years | -0.056 | -0.039 |
| 15-19 years | -0.053 | -0.033 |
| >20 years | -0.041 | -0.029 |
| Industry market share | 0.003*** | 0.002** |
| User of cloud computing services | | 0.050*** |
| User of ERP and CRM software | | 0.033*** |
| User of IoT | | 0.024* |
| User of e-commerce | | 0.015 |
| N | 1,344 | 1,344 |
| Pseudo $R^2$ | 0.201 | 0.290 |
| Region FE | Yes | Yes |
| Industry FE | Yes | Yes |

Note: The figures shown in the table are marginal effects obtained with probit models. The dependent variable is 1 if a given firm reported used AI in 2021 and 0 otherwise. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

*Source*: Authors' calculations based on microdata from the E-commerce and ICT Survey 2021 provided by the Central Statistics Office, Ireland.

## 4 AI Usage and Firm Productivity

### 4.1 Empirical Strategy

To estimate the relationship between using AI and firm productivity, we employ a production function approach linking inputs to outputs. More specifically we follow Brynjolfsson et al. (2017) and Czarnitzki et al. (2023) and estimate an augmented a Cobb-Douglas production function with AI as an input. In this set up, AI is considered an intangible asset that can be accumulated and depreciated and contributes to firm output. The output of a given firm i at time t, $Y_{it}$ is then a function of its total factor productivity ($A_{it}$) , labour input ($L_{it}$), capital input ($K_{it}$), and AI ($AI_{it}$):

$$Y_{it} = f(A_{it},\ L_{it}, K_{it}, AI_{it}) \tag{2}$$

Assuming a Cobb-Douglas functional form for the production function, the four-input functional form is as follows:

$$Y_{it} = \ A_{it} L_{it}^{\alpha_l} K_{it}^{\alpha_k} AI_{it}^{\alpha_{ai}} \tag{3}$$

$\alpha_l, \alpha_k, \alpha_{ai}$ are unknown parameters to be estimated. $Y_{it}$ is value added in a given firm *i* at time *t*. We use the following variables to proxy the four factor inputs:

- Labour input: the average number of employees at the end of the year;

- Capital input: change in capital assets in year *t* relative to previous year;

- AI: *AI user* is a categorical variable equal to 1 if the firm reported using AI and 0 otherwise; *AI intensity* is measured as the ration between the number of AI purposes reported by the firm and the total possible AI purposes (7).

The detailed definitions of the variables used in the empirical analysis are available in Table A1 in the Appendix.

### 4.2 Identification Strategy

To separate the effect of AI on productivity from other firm-specific factors affecting total factor productivity (TFP), we control for firm skills, age, ownership, market share within industry, as well as unobserved industry and region-specific effects. The empirical model is specified as follows:

$$lnVA_{itjr} = lnA_{itjr} + \alpha_l lnL_{itjr} + \alpha_k lnK_{itjr} + \alpha_{ai} lnAI_{itjr} + \beta X_{itjr} + \varepsilon_{itjr} \tag{4}$$

Another econometric issue is the potential endogeneity of AI given that the decision to use AI might not be random. For example, Figure 3 shows that the AI adoption rates are highest for firms in the top productivity percentile. Additional sources of endogeneity are omitted variable bias and measurement error given the subjective nature of the responses to the ICT survey. To account for potential endogeneity of AI, we instrument AI (AI use and AI intensity) with leave-one-firm out industry usage of AI (AI intensity). This peer-effect variable has been used as instrument in other papers (see for example Cette et al. 2021; Siedschlag and Yan 2021). While the industry usage of AI (intensity of AI) is likely to be correlated with AI usage (AI intensity) of a given firm, it is not correlated with unobserved productivity shocks at firm-level.

### 4.3 Estimation Results

Table 3 shows the estimated effects of AI use on firm productivity using the production function model specified by Eq. (4). The results shown in columns 1-4 are obtained with an OLS regression model, while those shown in columns 5-8 are results from the second - stage of an IV regression.

**Table 3: Estimated effects of AI use on firm productivity, results of OLS and IV regressions**

| | OLS Estimates | | | | IV Estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| AI user | 0.317* | 0.150 | | | 0.385*** | 0.105 | | |
| AI intensity | | | 1.936* | 1.382* | | | 2.008*** | 1.051* |
| Log Employment | 1.043*** | 0.406*** | 1.030*** | 0.402*** | 1.041*** | 0.405*** | 1.030*** | 0.402*** |
| log K | 0.037 | 0.420 | 0.036 | 0.042 | 0.036 | 0.042 | 0.036 | 0.042 |
| log Wages | | 0.521*** | | 0.514*** | | 0.524*** | | 0.518*** |
| Log Age | | 0.121 | | 0.126 | | 0.118 | | 0.123 |
| Foreign-owned | | 0.302* | | 0.314* | | 0.299* | | 0.309* |
| Market share | | 0.066*** | | 0.064*** | | 0066*** | | 0.065*** |
| N | 547 | 543 | 547 | 543 | 545 | 541 | 545 | 541 |
| R2 | 0.5819 | 0.6834 | 0.5848 | 0.6856 | 0.575 | 0.6781 | 0.578 | 0.6802 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Region FE | No | Yes | No | Yes | No | Yes | No | Yes |
| F test, F (1,474) | | | | | 67.058*** | | 27.548*** | |

Notes. Estimates are obtained with weighted regressions. The dependent variable is log value added. In the IV regressions, AI usage (AI intensity) is instrumented with the leave-one –out industry averages of AI usage (AI intensity). *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. The values of the F test in the IV regressions are larger than 10 and are statistically significant at 1% indicating that the instruments used for AI are valid.

*Source*: Authors' estimates using the following linked RMFs: ICT 2021, CIP 2020, ASI 2020, Business Register 2020 available from the Central Statistics Office, Ireland.

The estimates reported in column 1 indicate that using AI is associated with higher firm productivity over and above labour and capital inputs. On average, firms using AI generate value added higher by 31.7% compared with non-users of AI. This effect is statistically significant at 10%. The relationship between using AI and firm productivity appears weaker (it is not statistically significant) when conditioned on additional factors controlling for skills (proxied with wages), age, foreign ownership and within industry market share. Accounting for potential endogeneity of AI usage, the estimates obtained with an IV regression are consistent with the OLS estimates. However, the effect of AI usage on firm productivity is larger, 38.5% and stronger (it is statistically significant at 1%). When additional covariates are added, the effect of AI usage is positive but no longer statistically significant.

In contrast, the estimated effect of AI intensity usage on productivity is positive and significant across all regression models. Columns 3 and 4 show the OLS estimates and columns 7-8 show the IV estimates. Looking first at the OLS estimates, the results reported in column 3 indicate that on average, over and above capital and labour inputs, a higher intensity of AI usage is positively associated with firm productivity. The effect of AI intensity on productivity remains positive and statistically significant (albeit at 10% only) when additional covariates are controlled for. Taken into account the value of AI intensity for a firm which uses AI for one purpose (0.143 corresponding to AI used for one business area out of seven business areas), the coefficients for AI intensity reported in columns 3 and 4 suggest that an additional AI intensity unit is associated with a higher value added by 27.7% and 19.7%, respectively. The IV estimates for AI intensity shown in columns 7 and 8 are positive and statistically significant, indicating that firms using AI more intensively have a higher productivity. The estimated effect of AI intensity reported in column 7 implies that on average, an additional AI purpose is associated with the value added higher by 28.7% over and above the effects of capital and labour inputs. The estimated coefficient for AI intensity reported in column 8 implies that on average, firms using AI for an additional purpose generate value added higher by 15%, over and above other factors that influence productivity.

Looking at the estimates for other covariates, these are consistent and appear robust across all regressions. The effect of labour input on productivity is positive and statistically significant at 1% while the effect of capital input is positive but not statistically significant in all regressions. One possible explanation is that, given that we use investment in capital rather than capital stocks, the results might reflect the collapse in investment in capital during the lockdown in 2020. As expected, the estimated effects of skills (proxied with wages) on firm productivity are positive and statistically significant at 1%. Also, consistent with previous evidence, foreign-owned firms and firms with a higher within industry market share are more productive (Di Ubaldo and Siedschlag 2021).

## 5 Conclusions

This paper examines the adoption of AI and the relationship between using AI and firm productivity. The analysis uses four merged firm-level data from Ireland over 2020-2021. The key findings of this analysis are as follows.

AI adoption is not yet widely spread (only 7% of firms report using AI in 2021) and it is uneven across groups of firms. AI usage rates increase with firm size and firm productivity and decrease with firm age. These findings are consistent with existing evidence from other countries (see for example, Calvino and Fontanelli 2023 – evidence from 11 advanced economies; Acemoglu et al. 2022a; and McElheran 2023 for the US; Czarnitzki et al. 2023 for Germany). Estimation results obtained with probit regressions indicate that the propensity to adopt artificial intelligence technologies is positively associated with firm size, within industry market share and the adoption of other digital technologies.

On average, using AI is positively associated with firm productivity over and above capital and labour inputs and controlling for unobserved industry and region-specific effects. On average, the value added generated by firms using AI is higher by 37.1% compared with the value added generated by firms which do not use AI. The effect of using AI on productivity is smaller and the relationship is weaker when conditioned on other covariates that influence firm productivity including skills, age, foreign ownership, and within industry market share. The estimated effect of using AI on productivity obtained with a 2SLS IV regression to account for potential endogeneity of AI is larger, 38.5% and statistically significant at 1%. However, when additional covariates are added, the effect of using AI on firm productivity is smaller and it is not statistically significant. Accounting for potential endogeneity of AI usage, the estimates obtained with an IV regression are consistent with the OLS estimates. However, the estimated effect of AI usage on firm productivity obtained with an IV regression is larger, 38.5% and stronger (it is statistically significant at 1%). When additional covariates are added in the IV regression, the effect of AI usage is positive but no longer statistically significant.

In contrast, the estimated effect of AI intensity usage on productivity is positive and significant across all regression models suggesting that on average, *ceteris paribus*, firms using AI more intensively are more productive.

Our analysis is limited in a number of ways due to data availability. First, given the cross-section nature of the data on the use of AI and other digital technologies, it is not feasible to employ panel data techniques to identify the causal contribution of AI on productivity. Second, the time of the adoption of AI is not known which implies that examining the impact of time lags between adopting AI and enhanced productivity as suggested by Brynjolfsson et al. (2019) is not feasible at this stage. As pointed out by other authors (Acemoglu et al. 2022; Czarnitzki 2023; McElheran 2023) time-series data from follow-on collection of data on the use of AI and other technologies would allow to better explain the variation in adoption rates across firms and identify the causal contribution of AI and other digital technologies on firm performance.

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## Appendix

### Table A1. Definitions of Variables and Data Sources

| Variable | Definition | Data Source |
|---|---|---|
| **Usage of Digital technologies** | | |
| *Advanced digital technologies* | | |
| User of Artificial Intelligence (AI) | A binary indicator equal to 1 if the firm used at least one artificial intelligence technology, 0 otherwise | E-commerce and ICT Survey 2021, CSO |
| User of Internet of Things (IoT) | A binary indicator equal to 1 if firm used Internet of Things technologies | E-commerce and ICT Survey 2021, CSO |
| *Digital tools* | | |
| User of cloud computing services | A binary indicator equal to 1 if firm used cloud computing services | E-commerce and ICT Survey 2021, CSO |
| User of software for sharing of information electronically within firm (SoI) | A binary indicator equal to 1 if firm used software for sharing information electronically within the firm | E-commerce and ICT Survey 2021, CSO |
| Number of digital technologies | A continuous variable ranging from 0 to 4, equal to the number of digital technologies or digital tools used by a given firm (AI, IoT, cloud computing services, SoI) | E-commerce and ICT Survey 2021, CSO |
| User of digital technologies | A binary indicator equal to 1 if firm used at least one digital technology/tool – AI, IoT, cloud computing, SoI | E-commerce and ICT Survey 2021, CSO |
| **Firm characteristics** | | |
| ***Internal factors/firm characteristics*** | | |
| Firm size | The annual average number of persons engaged reported by a firm | CIP and ASI data, 2020 |
| Firm age | The number of years a firm has been active since it was first registered in the Business Register | Business Register 2020 |
| Wage per employee | Gross earnings (without other labour costs, e.g. employer' social security contributions divided by the number of employees | CIP and ASI data, 2020 |
| Ultra-fast internet connection | A binary indicator equal to 1 if firm reports that the maximum contracted download speed of the fastest fixed line internet connection is at least 100 megabits per second | E-commerce and ICT Survey 2021, CSO |
| Investment in tangible assets | Additions to capital tangible fixed assets | CIP and ASI data, 2020 |
| Investment in intangible assets | Additions to capital intangible fixed assets (R&D, computer software, copyrights, patents, intellectual property, other intangible fixed assets) | CIP and ASI data, 2020 |
| Labour productivity | Value added divided by the number of employees. | CIP and ASI data, 2020 |
| **External factors** | | |

| | | |
|---|---|---|
| Market share | The ratio of a firm's turnover over the total turnover in its NACE 2-digit sector. | CIP and ASI data, 2020 |
| Sector | Sector of firm's main activity as defined by the Nomenclature of Economic Activities (NACE Rev.2) classification, 2 digit. | CIP and ASI data, 2020 |
| Region | Regional location of firm in the Republic of Ireland as categorised by the Nomenclature of Territorial Units for Statistics (NUTS 3) | Business Register, 2020 |