Artificial Intelligence and Firm-Level Productivity: Early Evidence from a Small Open Economy

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Abstract

Artificial Intelligence (AI) is a modern general-purpose technology (GPT) with the potential to enhance the productivity of firms in every sector of the economy. Notwithstanding the growing interest in AI as a new source of productivity growth, evidence on firm-level productivity gains from using AI is scarce. This paper contributes to filling this evidence gap using firm-level data from Ireland over 2013-2024. By leveraging a Local Projection Difference-in-Differences framework and Propensity Score Matching, we find that, at this early stage, on average, the productivity gains from AI adoption are small, delayed, and short-lived in time. However, the heterogeneity analysis reveals more substantial, immediate, and persistent effects for firms that use AI for specific purposes, particularly in marketing, business administration, and ICT security as well as for those adopting technologies that automate workflows or assist in decision-making, such as robotic process automation (RPA).

1 Introduction

Artificial Intelligence (AI) is a modern general-purpose technology (GPT) with the potential to enhance the productivity of firms in every sector of the economy (Brynjolfsson et al., 2019), maybe the most general of all GPTs so far (National Academies of Sciences and Medicine, 2025). However, the effects of AI on productivity are likely to be delayed in time due to adjustment costs and additional complementary investments in other intangible assets such as skills, in particular new digital skills such as advanced analytics and programming skills, data, software and organisational change (Brynjolfsson et al., 2021). Investment in education and workforce training programmes are key to maximise the potential economic benefits from using AI.

There are several channels through which AI can enhance productivity. First, AI enables firms to put in place new combinations of existing technologies leading to higher productivity (Agrawal et al., 2018). 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 et al., 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).

Notwithstanding the growing interest in AI as a new source of productivity growth, to date there is little evidence on the adoption of AI across firms and on the effects of AI on firm-level productivity due to a lack of data to measure the use of AI. Against this background, this paper contributes to filling this evidence gap by estimating the impacts of AI adoption of labour productivity using firm-level data from Ireland over 2013-2024 and Local Projection Differencein-Differences (LP-DiD) regressions complemented with Propensity Score Matching (PSM) to balance differences between treated and control groups. Compared to the existing literature, we examine the dynamics of the effects over three-year periods after adoption and distinguish between productivity effects across different application purposes and technologies.

Our research results indicate that at this early stage, the average effects of AI adoption are small (around 4%), do not manifest immediately and are short-lived. In particular, the effects are only statistically significant in the second year after adoption and become weak by the third year. In contrast, we find stronger (10 to 11%), immediate, and longer-lasting effects (two years after adoption) for firms using AI for marketing or sales, organisation of business administration processes or management, and ICT security purposes, applying AI more intensively (more than two purposes), and applying technologies that automate workflows or assisting in decision making (software robotic process automation - RPA).

Our paper contributes to a small but growing literature on measuring the adoption of AI and other digital technologies across firms and the relationship between using AI and firm productivity (Babina et al., 2024; da Silva Marioni et al., 2024; Czarnitzki et al., 2023; Damioli et al., 2021; Calvino and Fontanelli, 2023a,b). Most closely related is work by da Silva Marioni et al. (2024) studying the effects of AI adoption measured with patenting across 15 European economies using LP-DiD and PSM methods and a distance to frontier framework. Compared to this paper, we measure AI adoption as reported by the firms and examine heterogeneity across different purposes and technologies. Moreover, to the best of our knowledge, this is the first paper examining the adoption of AI and the relationship between using AI and firm productivity across a representative sample of firms in Ireland. As an advanced small open economy with a sizeable ICT sector, Ireland is an interesting case for this empirical analysis.

The rest of the paper is organised as follows. Section 2 discusses the related literature. Section 3 presents the empirical strategy. Section 4 presents the data and descriptive statistics. Section 5 discusses the estimation results. Finally, Section 6 concludes.

2 Related Literature

Our paper connects to several literature strands. First, we add to the empirical literature 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 (Cardona et al., 2013, for a review of this evidence, see for example). Studies that found a positive significant effect of ICT on productivity include among others: Bertschek and Kaiser (2004); Black and Lynch (2001); Bloom et al. (2012); Brynjolfsson and Hitt (2003, 2000); and O'Mahony and Vecchi (2005). Our paper extends this literature with evidence on the adoption of AI as a new GPT and the effects of its use on firm productivity.

Second, another related literature strand has examined the effects of investment in intangible assets on firm productivity. Di Ubaldo and Siedschlag (2021) employ an augmented dynamic production function empirical approach accounting for path dependency and endogeneity. Using 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, they further estimate 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.

Third, a recent literature has examined the relationship between digitalisation and firm productivity. Cette et al. (2022) find that firms in France that used 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 the period 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. Coyle et 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.

Finally, our paper adds to a small literature examining the relationship between using AI and firm productivity 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 (2023a) 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 the 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.

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. They find that adoption rates of advanced technologies over the analysed period were low, particularly for AI and robotics: 3.2% of firms adopted AI and 2% of firms adopted robotics. Estimates obtained with separate panel regressions for each technology indicate that adoption rates increase with firm size and, apart from 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% relative to 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 (Acemoglu et al., 2022b; Brynjolfsson et al., 2021). An alternative interpretation is related to the difficulty to disentangle the effects of using specific technologies on productivity given that these technologies are often 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%).

Babina et al. (2024) finds 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 led to 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).

3 Empirical Strategy

We employ the Local Projections Difference-in-Differences (LP-DiD) approach to estimate dynamic treatment effects across multiple time horizons following the adoption of AI. This method extends the local projection framework to a DiD setting, allowing for the estimation of dynamic event-study coefficients while omitting units that may still be affected by the treatment in the future. By doing so, the LP-DiD avoids the negative weighting bias commonly associated with traditional two-way fixed-effects estimators (Dube et al., 2025). The baseline specification is:

$$\ln Y_{i,t+h} - \ln Y_{i,t-1} = \beta_h^{LP-DiD} \Delta AI_{i,t} + \Gamma X_{i,t} + \sum_{j=-1}^{1} \theta_j^h \Delta AI_{i,t} \delta_t^h + e_{i,t}^h \tag{1}$$

where $Y_{i,t+h}$ denotes labour productivity of firm i in year t measured as turnover per employee, h represents the time horizon relative to treatment h equal to three years, δ_t^h captures time fixed effects, and $e_{i,t}^h$ is the error term. The treatment variable $\Delta AI_{i,t}$ equals 1 for newly adopters and 0 for "clean controls"—units that have not yet been treated by time $t+h$. Since the model is estimated in first differences, firm time-invariant factors are differenced out (Dube et al., 2025).

The identification of the effect relies on the comparison of treated and control firms' labour productivity relative to their pre-treatment mean value. To construct the control group, we use propensity score matching to predict AI adoption. The probit model is estimated to obtain propensity scores by pooling all firm-level observations pre-2019 and controlling for labour productivity (turnover-per-employee), employment, age, and a set of 2-digit NACE industry dummies. Treated units are matched to their ten nearest neighbors within a caliper set to one-fourth of the standard deviation of the estimated propensity score, following Stuart and Rubin (2008). This matching strategy ensures that treated and control units are balanced on observable pre-treatment characteristics.

The identification relies on two key assumptions: (i) parallel trends, which requires that. in the absence of treatment, treated and control units would have followed similar trajectories; and (ii) no anticipation, which assumes that units do not change behavior in anticipation of receiving the treatment. We aim to minimize the likelihood of pre-treatment trends by comparing firms that have similar observed characteristics pre-2019 and account for anticipation effects using one year leads and lags in the specification ($\sum_{j=-1}^{1} \theta_j^h \Delta AI_{i,t}$).

4 Data and Measurement

4.1 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 Survey on e-commerce and ICT 2013-2024. The survey size is conducted annually by the CSO following the Eurostat[1] guidelines on 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 survey collects information on AI adoption, IoT 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. In the case of AI, data on adoption was collected in 2021, 2023 and 2024. Since the 2020 wave include a question on big data analysis during 2019, we define AI adoption in that year based on the use of machine learning, natural language processing, natural language generation, or speech recognition. The sample for the analysis contains information from 6,850 firms, observed in at least two years.[2]

[1] Eurostat Guidelines for the Survey on E-commerce and ICT are available from the following web link.

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

4.2 Measuring the Adoption of AI across Firms

Artificial Intelligence is defined in the Survey on e-commerce and ICT[3] 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". Having clear definitions of AI technologies in the survey questionnaire alleviates concerns about measurement errors and self-reporting bias. Detailed descriptions of AI technologies are given in Table A1 in the Appendix.

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 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).

4.3 Summary Statistics

Table 1 presents summary statistics for adopters (treated), all non-adopters, and those matched as the control group. On average, AI adopters are larger in terms of number of employees and turnover, are older, and are more likely to adopt other digital technologies (software for sharing electronically information within the enterprise -ERP and CRM, and Internet of Things -IoT) than non-adopters. Regarding purposes, the most common area of application is ICT security, followed by marketing, production, organisation, and logistics. On average, adopters use AI for 2 purposes. The last column of Table 1 also documents that the employment and age are more balanced between AI adopters and the matched control group of non-adopters. Figure 1 further verifies the covariate balance after the PSM by showing that the the density plots of the propensity score for treated and control groups after matching are very similar.

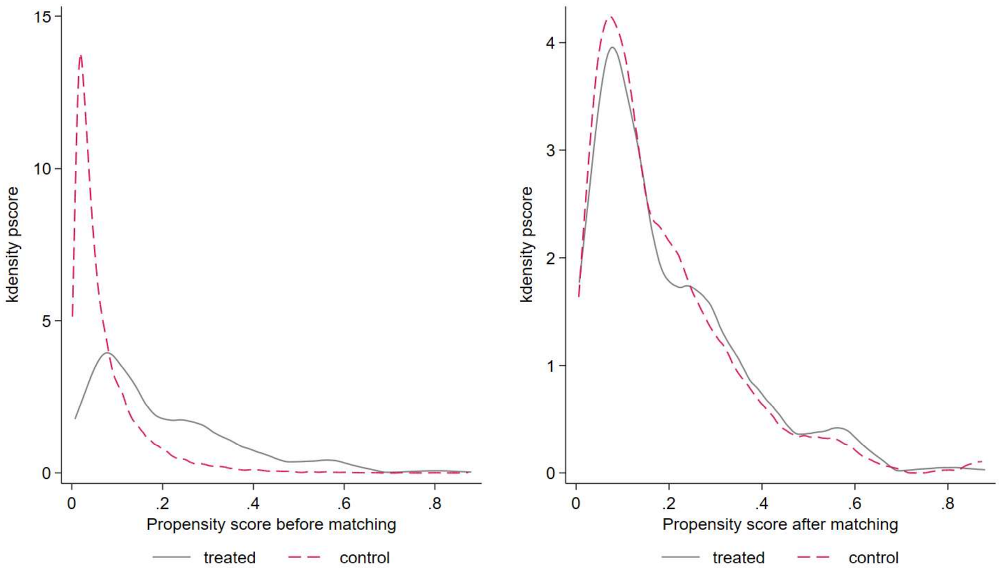
[3] The Survey on E-commerce and ICT 2021 Form is available from the following web link.

Table 1: Summary Statistics, 2013-2024

	All	Adopters	Non-Adopters	Matched
Employees	4.42	22.93	8.88	19.25
Age	10.66	30.56	17.53	20.77
Turnover (mn)	4.42	7.75	3.08	6.80
Other technologies				
Cloud computing	0.36	0.97	0.35	0.29
ERP	0.16	0.70	0.15	0.18
CRM	0.16	0.27	0.16	0.21
IoT	0.23	0.25	0.23	0.48
ICT specialists	0.17	0.53	0.16	0.23
Number of other techn.	0.58	1.93	0.55	0.64
Purposes				
Marketing		0.48		
Production		0.38		
Organisation		0.36		
Logistics		0.31		
ICT security		0.50		
Accounting		0.03		
Research		0.15		
Intensity		2.02		

Notes: All estimates weighted with weights that represent the employment share of each type of firm in the Business Register industry-size bins.
Source: Authors' calculations/estimates based on Research Microdata Files (RMFs) from the Survey on e-commerce and ICT 2013-2024 and Business Register RMFs 2013-2022, provided by the Central Statistics Office (CSO) of Ireland.

Figure 1: Propensity Scores Density Distributions

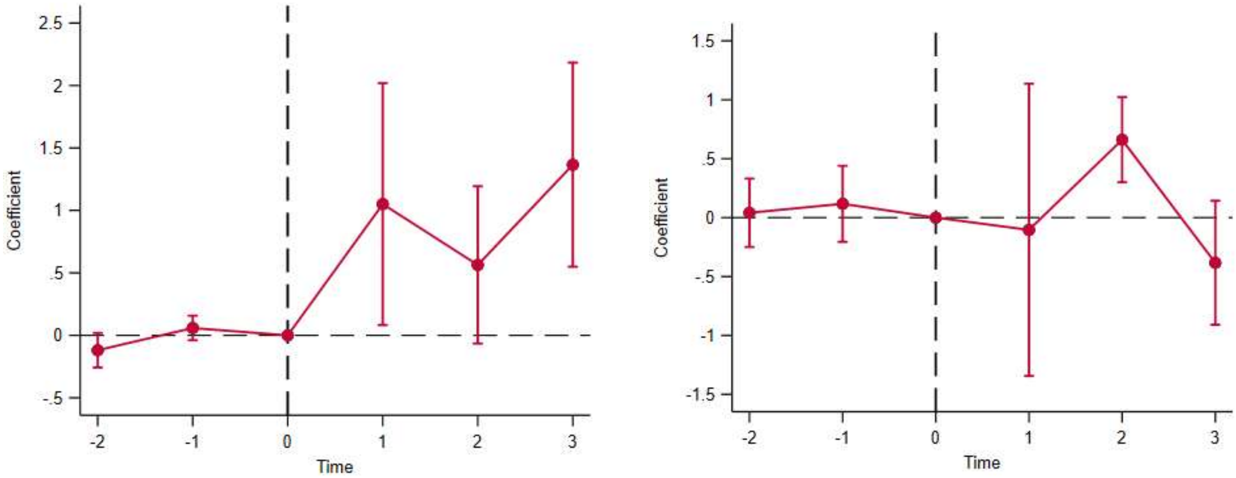


Notes: The graphs plot the distributions of estimated propensity scores for treated and control groups before (left) and after (right) matching.

5 Estimation Results

Figure 2 presents the LP-DiD event study estimates of the effect of AI adoption on labour productivity. We present the baseline results when using all non-adopters as the control group (Panel A), and the matched sample resulting from the PSM (Panel B). We do not find evidence of statistically significant trends pre-treatment. In both cases, the post-pooled coefficient is positive and statistically significant but the dynamics are different. The estimation results for the non-matched control group suggest positive and statistically significant effects that materialise immediately after adoption and tend to increase over time. According to these estimates, the pooled post-treatment effect expressed as relative changes with respect to the mean productivity of the non-adopters is 5.3%. In the case of the matched control group, the point estimate is only statistically significant in the second year after adoption and dissolves thereafter. Benchmarking to the matched control group, the post-pooled estimate is equivalent to 3.7% increase in the mean productivity.

Figure 2: Baseline Estimation Results



Panel A. Control Group: All Non-adopters | Panel B. Control Group: Matched Sample

Notes: LP-DiD event study estimates and 95% confidence intervals for the effect of AI adoption. The control group is all non-adopters in Panel A, and the matched sample resulting from the PSM in Panel B. The pre-treatment pooled coefficients are 0.021 (with a standard deviation of 0.034) in Panel A and 0.021 (0.034) in Panel B. The post- treatment pooled coefficients are 0.637 (0.305) in Panel A and 0.452 (0.218) in Panel B. Standard errors clustered at the firm level.

We now turn to examine the effects for selected AI adoption purposes and technologies by interacting the AI adoption variable with a binary variable that takes the value of 1 if the firm ever used AI for that purpose/technology. One concern is that this interaction would result in a very small treated group when using very specific purposes or technologies suc as accounting or research, so we focus on selected business purposes and technologies for which the treated group is large enough. Table 2 presents the pooled estimation results of this heterogeneity analysis. Columns 1-4 present the estimates of adoption for firms that applied AI for ICT security, marketing, logistics, and organisation purposes, regardless of the technology employed, while Columns 5-6 presents the estimates of AI adoption for firms that used software robotic process automation (RPA), regardless of the application purpose.

We find that AI has the strongest effects when applied to ICT security, marketing, and organisation purposes, as well as when adopting technologies automating different workflows or assisting in decision making -RPA). In contrast, we do not find statistically significant pooled effects when considering logistics as a purpose or deep learning as an adopted technology. The magnitude of the effects is equivalent to 10.6% to 11.2% increase in average productivity relative to the matched control group. For these purposes, the dynamics (not shown in the paper) show that the effects manifest immediately after adoption and are statistically significant up to the second year of adoption.[4] In the Appendix, we also show that these results are robust to using never treated units as controls, letting the adoption to vary over time (non-absorbing treatment), and using an alternative PSM matching with the two nearest neighbours (Figures A3 to A5).

Table 2: Estimation Results - Heterogeneity by Selected Purposes and Technologies

	(1)	(2)	(3)	(4)	(5)	(6)
Pooled pre-treatment	-0.413	0.044	-0.662	-0.086	0.054	0.055
	(0.305)	(0.146)	(0.707)	(0.198)	(0.152)	(0.150)
Pooled post-treatment	1.303***	1.264***	-0.811	1.287***	1.283***	-0.354
	(0.124)	(0.138)	(0.707)	(0.135)	(0.133)	(0.234)
Obs.	7,614	7,623	7,306	7,579	7,538	7,560
Purpose	ICT sec.	Marketing	Logistics	Organisation	Any	Any
Technology	Any	Any	Any	Any	RPA	Deep learning

Notes: *p<0.1, **p<0.05,***p<0.01. Standard errors clustered at the firm level in parentheses.

Source: Authors' calculations/estimates based on Research Microdata Files (RMFs) from the Survey on e-commerce and ICT 2013-2024 and Business Register RMFs 2013-2022, provided by the Central Statistics Office (CSO) of Ireland.

6 Conclusions

This paper provides new evidence on the effect of AI adoption on firm-level productivity using data from Irish enterprises between 2013 and 2024. By leveraging a Local Projection Difference-in-Differences framework and Propensity Score Matching, we estimate dynamic effects of AI adoption

[4]These results can be provided by the authors upon request.

on labour productivity, accounting for observable differences between treated and control firms and addressing potential sources of bias.

Our results suggest that, at this early stage of adoption, on average, the productivity gains from AI adoption are small, delayed, and short-lived in time. However, the heterogeneity analysis reveals more substantial, immediate, and persistent effects for firms that use AI for specific purposes, particularly in marketing, business administration, and ICT security as well as for those adopting technologies that automate workflows or assist in decision-making, such as robotic process automation (RPA). These findings point to increased efficiency and marketing improvements as the main channels through which AI currently boosts productivity growth at the firm level.

This study contributes to a growing body of work quantifying the economic impact of AI at the micro level and offers timely insights for policymakers. While AI is often discussed in terms of transformative potential, our evidence suggests that realising its productivity benefits depends critically on how intensive and where the technology is applied within firms. Further research could shed light on several additional questions, such as the extent to which productivity-enhancing effects from using AI can be isolated from broader returns to the adoption of digital technologies and the role of investment in complementary intangible assets such as computer software, organisational capital, digital skills and training in ICT skills. The results will inform a range of enterprise policies as well as education and training policies and the role they can play in adapting to changing demands for skills formation in the era of AI.

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Appendix

Table A1: Artificial Intelligence Technologies

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

Source: Survey on e-Commerce and ICT 2021 and 2023, Central Statistics Office of Ireland.

Table A2: Definitions of Variables and Data Sources

Variable	Definition	Data Source
User of Artificial Intelligence (AI)	A binary indicator equal to 1 if the firm used at least one AI technology, 0 otherwise.	Survey on e-commerce and ICT 2020-2023, CSO
AI intensity	The ratio between the number of AI purposes reported by a given firm and the total number of AI purposes across business areas	
User of Internet of Things (IoT)	A binary indicator equal to 1 if firm used IoT technologies, 0 otherwise.	
User of cloud computing services	A binary indicator equal to 1 if firm used cloud computing services, 0 otherwise.	
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, 0 otherwise.	
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).	
User of e-commerce	A binary indicator equal to 1 if firm reported sales from e-commerce, 0 otherwise.	
Value added	Turnover without the cost of purchases of goods and services.	
Labour productivity	Value added divided by the number of employees.	
Capital input	Change in total capital assets relative to previous year.	CIP and ASI data, 2019-2022
Wage per employee	Gross earnings (without other labour costs, e.g. employer' social security contributions divided by the number of employees.	
Market share	The ratio of a firm's turnover over the total turnover in its NACE 2-digit sector.	
Sector	Sector of firm's main activity as defined by the Nomenclature of Economic Activities (NACE Rev.2) classification at 2 digits.	
Region.	The location of a firm in the Republic of Ireland as categorised by the Nomenclature of Territorial Units for Statistics at level 3 (NUTS 3).	Business Register, 2020

Table A3: Robustness Analysis - Never Treated Units

	(1)	(2)	(3)	(4)
Pooled pre-treatment	0.002	0.045	-0.083	0.058
	(0.150)	(0.147)	(0.200)	(0.154)
Pooled post-treatment	0.437**	1.263***	1.299***	1.294***
	(0.222)	(0.140)	(0.139)	(0.138)
Obs.	5,556	6,690	6,654	6,515
Purpose	Any	Marketing	Organisation	Any
Technology	Any	Any	Any	RPA

Notes: *p<0.1, **p<0.05,***p<0.01. Standard errors clustered at the firm level in parentheses.

Source: Authors' calculations/estimates based on Research Microdata Files (RMFs) from the Survey on e-commerce and ICT 2013-2024 and Business Register RMFs 2013-2022, provided by the Central Statistics Office (CSO) of Ireland.

Table A4: Robustness Analysis - Non-absorbing Treatment

	(1)	(2)	(3)	(4)
Pooled pre-treatment	-0.005	-0.136	0.075	0.075
	(0.068)	(0.080)	(0.184)	(0.072)
Pooled post-treatment	0.473***	1.272***	1.242***	1.128***
	(0.176)	(0.124)	(0.140)	(0.149)
Obs.	5,556	6,919	6,654	6,890
Purpose	Any	Marketing	Organisation	Any
Technology	Any	Any	Any	RPA

Notes: *p<0.1, **p<0.05,***p<0.01. Standard errors clustered at the firm level in parentheses.

Source: Authors' calculations/estimates based on Research Microdata Files (RMFs) from the Survey on e-commerce and ICT 2013-2024 and Business Register RMFs 2013-2022, provided by the Central Statistics Office (CSO) of Ireland.

Table A5: Robustness Analysis - Alternative PSM

	(1)	(2)	(3)	(4)
Pooled pre-treatment	0.075	0.046	-0.126	0.000
	(0.161)	(0.162)	(0.207)	(0.183)
Pooled post-treatment	0.100	1.213***	1.233***	1.234***
	(0.253)	(0.183)	(0.179)	(0.167)
Obs.	4,194	4,734	6,654	6,890
Purpose	Any	Marketing	Organisation	Any
Technology	Any	Any	Any	RPA

Notes: *p<0.1, **p<0.05,***p<0.01. Standard errors clustered at the firm level in parentheses.

Source: Authors' calculations/estimates based on Research Microdata Files (RMFs) from the Survey on e-commerce and ICT 2013-2024 and Business Register RMFs 2013-2022, provided by the Central Statistics Office (CSO) of Ireland.