Early AI Adoption and Firm Productivity Growth in a Middle-Income Economy

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Abstract

This paper examines the relationship between artificial intelligence (AI) adoption and firm-level productivity growth in a middle-income economy. Combining data on AI use from the 2019 Colombian Enterprise ICT Survey with longitudinal manufacturing data, I estimate productivity growth differentials between adopters and non-adopters while accounting for pre-adoption characteristics and productivity trajectories using entropy balancing. AI adoption is associated with a 16 percent cumulative increase in labor productivity over 2016–2019, equivalent to roughly 5 percent annualized growth. These differentials appear to be driven by higher sales and value added rather than reductions in costs or employment, are similar among in-house and outsourced AI developments, and increase for firms with higher pre-existing technical capabilities. Finally, the analysis points to changes in organizational structure as a potential adjustment margin. AI adoption is associated with a small but significant decline in the share of administrative workers, suggesting a reallocation of tasks away from administrative functions.

Keywords— AI, Labor productivity, Middle-income economies

JEL Codes— O14, D22, D24

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1 Introduction

A growing strand of the economic literature has studied the effects of artificial intelligence (AI) adoption on firm-level productivity, generally documenting substantial heterogeneity in firms' ability to materialize these gains. Due to the availability of granular data on AI adoption, most existing evidence comes from the United States and Europe, while considerably less is known about the productivity implications of AI for firms operating in developing economies.

This paper provides one of the first firm-level estimates of the productivity growth differentials associated with AI in a middle-income economy. I combine detailed information on AI adoption by Colombian manufacturing firms in 2019 with annual manufacturing surveys to examine the relationship between AI and subsequent labor productivity growth. In the absence of data on the exact adoption timing and persistence and following recent literature facing similar challenges in developed economies, I employ conservative assumptions regarding the plausible windows when adoption was likely to take place. Specifically, I compare productivity growth over alternative pre-specified windows and balance firms on pre-treatment characteristics, including prior productivity levels and growth trajectories.

Overall, the paper contributes to the emerging literature on AI and productivity by providing evidence from a developing economy, studying different sources of heterogeneity related to technology implementation and initial capabilities as well as margins of adjustment in the workforce composition. As AI diffusion accelerates globally, understanding these complementarities will be central to assessing its potential for productivity growth in middle- and low-income countries.

The paper is most related to recent work studying the effects of AI adoption on firm productivity dynamics. Existing evidence on the relationship between AI and firm productivity is mixed, with several studies finding that the positive link is largely driven by the self-selection of the most productive firms with pre-existing IT capabilities into AI adoption (Calvino and Fontanelli, 2023; Alekseeva et al., 2021; Calvino and Fontanelli, 2024; Brynjolfsson et al., 2019). To address this issue, authors have mainly relied on balancing techniques (Fontanelli et al., 2025; da Silva Marioni et al., 2024; Siedschlag and Duran, 2025; Calvino and Fontanelli, 2024) and instrumental variables constructed using sectoral adoption or exposure to skills supply (Czarnitzki et al., 2023; Babina et al., 2024; Cette et al., 2022).

In addition to the limited data availability on AI adoption at the firm level, the analysis of

the relationship between AI and productivity in middle and low-income economies is challenged by the lack of longitudinal data allowing to account for pre-adoption firms' characteristics. By combining data from annual manufacturing and innovation surveys with unique firm identifiers, this paper accounts for pre-existing characteristics, including ICT investments, and employs matching techniques to balancing the adopters and non-adopters samples. Additionally, data on AI adoption and firms' employment is sufficiently detailed to study important sources of heterogeneity and mechanism identified in the literature such as larger gains for adopters that can develop their own AI systems in-house (Calvino and Fontanelli, 2024) and changes in workforce composition (Yang, 2022).

More generally, the paper also connects with the literature on the effects of ICT investments in developing economies (Niebel, 2018; Paunov and Rollo, 2016; DeStefano and Timmis, 2024; Dedrick et al., 2013; Aker and Mbiti, 2010; Indjikian and Siegel, 2005). For instance, Commander et al. (2011) finds early evidence of positive ICT (harward) capital and productivity using firm-level data for India and Brazil. More recently, Hjort and Poulsen (2019) show large effects of fast internet on employment in twelve African economies and evidence for increased productivity at the firm-level driving these impacts in Ethiopia.

The results of this paper indicate that AI adoption is associated with a labor productivity (value added per employee) growth differential of approximately 16 percent over the 2014–2019 period relative to non-adopters. This magnitude is economically meaningful, particularly given the still limited diffusion of AI among Colombian manufacturing firms, with an adoption rate of about 7 percent in 2019. Estimates across alternative growth windows are similar in magnitude, a pattern consistent with relatively recent adoption rather than long cumulative exposure. Further analysis suggest that these differentials came from higher sales and value-added rather than reductions in firms' costs or employment. However, I find that AI adoption is linked to a decline in the labor share of administrative workers, suggesting reorganization through partial substitution of administrative tasks.

Finally, the paper explores heterogeneity in implementation strategies and absorptive capacity. Productivity growth differentials are similar among firms that developed AI capabilities in-house compared to those that acquired AI externally. Regarding pre-existing capabilities, the results point to technical skills as a key margin through which firms can leverage AI technologies more effectively.

The rest of the paper is organized as follows. Section II describes the data sources and empirical strategy. Section III presents the results. Section IV concludes.

2 Data and Empirical Strategy

The primary data source is the Annual Manufacturing Survey (EAM) covering manufacturing establishments with ten or more employees prepared by the National Department of Statistics (DANE). EAM contains rich information on employment, wages, gross output, input consumption, value-added, production costs and administrative costs.

Data on AI adoption comes from Enterprise TIC Survey (ENTIC) conducted in 2019 and 2020 as part of the National Policy for Digital Transformation and AI developed by the National Council for Economic and Social Policy (CONPES) in 2019.

To account for initial ICT capabilities, I also combine firm-level information on the amount of investment in ICT from the Technology Development and Innovation Survey (EDIT) 2013-2014. This variable includes investments in hardware, software and information processing services intended to generate or improve products and processes, excluding those related to research and development (R&D).

One of the main empirical challenges is that the ENTIC did not record information on the year of adoption or to what extent adoption was intermittent over time. Following Fontanelli et al. (2025), I address this data limitation by making a conservative assumption on the surge of AI adoption. While the most significant advances in predictive AI were developed in 2011, existing studies using AI-related vacancies in the US and observed adoption in Germany coincide on 2015 as the year of takeoff (Acemoglu et al., 2022). Accordingly, Fontanelli et al. (2025) hypothesize that 2012 is the earliest year of adoption in France.

In this paper, I initially set 2014 as the earliest adoption year given the expected delay in technology transfer from high to medium-income economies. At baseline, I contrast differences in labor productivity at the firm level between 2014 and 2019 to avoid potential contamination from the COVID-19 crisis using the following specification:

$$\Delta \log(Y_{i,\omega}) = \alpha + \beta AI_{i,2019} + \Gamma X_{i,2014} + \delta_j + \epsilon_i, \tag{1}$$

where $\Delta \log(Y_{i,\omega})$ is the labor productivity growth measured as value-added per employee for firm i over the time window ω, $AI_{i,2019}$ is an indicator variable for AI adoption in 2019, $X_{i,2014}$ is a vector of firm base characteristics including employment, labor productivity, and an indicator variable for positive ICT investment in 2014. 2-digit industry fixed effects (δ_j) are included to account for systematic variation in productivity trends across industries.

To assess the sensitivity of the results to alternative assumptions about adoption timing, I contrast the baseline ω = 2019–2014 growth window with a shorter window covering ω = 2019–2016. If AI adoption occurred primarily after 2016, estimates based on the shorter window should capture most of the post-adoption dynamics.

A key identifying assumption to interpret the estimated coefficient β as the average productivity growth differential associated with AI is the absence of differential pre-adoption trends between eventual adopters and non-adopters. If eventual adopters were already on systematically steeper productivity trajectories prior to AI adoption, estimates of β would reflect self-selection of most productive firms.

To strengthen this identifying assumption, I implement entropy balancing to reweight the control group so that it matches adopters on pre-treatment characteristics, including baseline productivity, employment, ICT investment, and productivity growth between 2014 and 2016. By reweighting the control group to match adopters on both baseline levels and pre-2016 productivity growth—including higher-order moments of their distributions—the entropy balancing procedure mitigates concerns that dynamic selection drives the results.

To assess potential mechanisms explaining the productivity differentials associated with AI adoption, I employ the specification in Eq. 1 with the growth in sales, value-added, costs, employment, and workforce composition as outcomes. Additionally, I examine heterogeneity of the relationship between productivity growth differentials and AI adoption by considering in-house vs externally purchased AI solution as separate indicator variables. Following Fontanelli et al. (2025), I apply pairwise matching between each adoption type and the control sample of non-users to ensure comparability across groups.

Finally, I allow the productivity growth differentials associated to AI by estimating specifications that interact the AI adoption indicator with baseline measures of technical human capital (employment share of technologists and technicians) and ICT intensity share.

Table 1 presents summary statistics separately for AI adopters and non-adopters. In line with

the existing literature on high-income economies, Panel A shows that AI adopters are larger and more productive on average at baseline in 2014. In contrast, firms that ended up adopting AI in 2019 were less likely to have initial ICT investments relative to non-adopters. Moreover, AI users' workforce composition exhibits a larger share of technologists and technicians, and a lower share of operative workers. Panel B documents larger labor productivity growth for AI adopters over the period 2019-2016, while there are no statistically significant differences for the 2016-2014 growth window. Lastly, Panel C provides summary statistics for ICT features in 2019. On average, AI adopters are more likely to have a fast internet connection, perform data analytic and have an ICT risk policy, although they are less likely to have in-house ICT departments. This pattern is consistent with the fact that most users relied on outsourcing to adopt AI tools and solutions. Regarding AI application purposes, the majority of firms employed AI on production processes, followed by logistics, administrative tasks, and to a lesser extent, marketing.

Table 1: Summary Statistics

	(1)		(2)		(3)	(4)	
	AI adopters		Non AI Users		(1)-(2)	All	
	Mean	SD	Mean	SD	Diff	Mean	SD
Log productivity	11.34	1.23	10.59	1.04	-0.75***	10.51	1.14
Employees	199.32	253.14	80.66	145.09	-118.66***	76.60	146.50
Log value-added	15.84	1.93	14.23	1.71	-1.61***	13.96	1.94
Log sales	16.73	1.92	15.17	1.67	-1.56***	14.91	1.87
Log total costs	15.50	2.09	13.78	1.87	-1.72***	13.56	2.05
ICT investment dummy	0.69	0.46	0.81	0.39	0.12***	0.82	0.38
Operative labor share	0.56	0.22	0.62	0.22	0.06***	0.61	0.23
Admin. labor share	0.29	0.21	0.29	0.20	-0.00	0.30	0.21
Technical labor share	0.15	0.16	0.09	0.13	-0.05***	0.10	0.14
Δ Log productivity, 2019-2014	0.21	0.88	0.13	0.98	-0.08*	0.14	0.97
Δ Log productivity, 2019-2016	0.15	0.79	0.05	0.94	-0.10**	0.06	0.93
Δ Log productivity, 2016-2014	0.06	0.72	0.08	0.81	0.02	0.04	0.87
Fast internet dummy	0.65	0.48	0.60	0.49	-0.05**	0.61	0.49
Data analytics	0.57	0.50	0.08	0.27	-0.49***	0.12	0.32
ICT risk policy dummy	0.74	0.44	0.31	0.46	-0.43***	0.35	0.48
ICT area dummy	0.21	0.40	0.33	0.47	0.12***	0.32	0.47
AI - in-house	0.45	0.50					
AI - outsourcing	0.76	0.43					
AI - production	0.52	0.50					
AI - admin.	0.43	0.50					
AI - marketing	0.37	0.48					
AI - logistics	0.45	0.50					
Obs.	578		7,053		7,631	9,774	

3 Estimation Results

3.1 Labor Productivity Growth

I start by presenting the results for labor productivity growth over different time windows. All models include 2-digit industry fixed effects and the firm-level set of controls. Panel A of Table 2 reports the OLS estimates for the AI coefficient. The estimate for 2014-2016 suggest that eventual adopters exhibit significantly faster productivity growth in the pre-2016 period when adoption was arguably low, indicating dynamic selection into adoption. The estimate for the full window 2014-2019 in column (2) of 22.8% is approximately twice as large as the one for 2019-2016 in column (3) (11.1%). The model in column (4) re-estimates the shorter window 2016-2019 controlling for pre-2016 productivity growth to partially adjust for the presence of pre-trends, which marginally increases the point estimate to 17.6%. Overall, these results suggest that productivity growth was already accelerated for eventual adopters during a potential very early adoption stage, thus biasing the long-window estimates upwards.

Panel B of Table 2 presents the results after performing the entrophy balancing. Once the control group is reweighted to match adopters on baseline characteristics and pre-treatment growth, these differential pre-trends are no longer statistically significant (columnn 1). After reweighting, productivity differentials are concentrated in the 2016–2019 period and estimated at 16% (columns 2-4).

This estimated cumulative differential over 2016–2019 corresponds to roughly a 5.3% annualized labor productivity growth, which is a sizable magnitude in the context of manufacturing firms in a middle-income economy with early levels of AI adoption.

Table 2: Baseline Estimation Results

	Panel A: OLS			
Outcome:	$\Delta \log(Y_{i,2016-2014})$	$\Delta \log(Y_{i,2014-2019})$	$\Delta \log(Y_{i,2016-2019})$	
	(1)	(2)	(3)	(4)
AI_{2019}	0.119***	0.228***	0.111***	0.176***
	(0.0298)	(0.0414)	(0.0336)	(0.0357)
$\Delta \log(Y_{i,2016-2014})$				-0.547***
				(0.0154)
Obs.	6,899	6,921	6,894	6,894
	Panel B: OLS with entrophy weights			
Outcome:	$\Delta \log(Y_{i,2014-2016})$	$\Delta \log(Y_{i,2014-2019})$	$\Delta \log(Y_{i,2016-2019})$	
	(1)	(2)	(3)	(4)
AI_{2019}	0.001	0.165***	0.164***	0.164***
	(0.0267)	(0.0420)	(0.0309)	(0.0342)
$\Delta \log(Y_{i,2016-2014})$				-0.482***
				(0.0404)
Obs.	6,899	6,894	6,894	6,894

Notes: All specifications include 2-digit industry fixed effects and control for log employment, log labor productivity, and a dummy variable for positive investment in ICT technologies at baseline in 2014. All the specifications in Panel B are estimated using entrophy weights. Standard errors clustered at the 2-digit industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

In the Appendix, I conduct different robustness analyses by considering CEM instead of entrophy balancing and including a wider range of initial firm characteristics as controls including workforce composition, importer status, an indicator of R&D investments, and region (Colombian departments) fixed effects (Table A1). Moreover, I re-estimate the baseline specifications using 2012 instead of 2014 as the base year to account for the possibility of very early AI adoption (Table A2).

3.2 Mechanisms and Workforce Composition

This subsection estimates the baseline specification using different firm performance outcomes in order to examine potential mechanisms behind the AI-related productivity growth differentials. I focus on the shorter window 2016-2019 and present the estimation results for the non-balanced and balanced non-adopters control group. Results in Panel A of Table 3 indicate significant growth differentials in sales and value added of nearly 15% and 8%, respectively (columns 1-4), while there is no evidence of significant growth differentials in firms' costs or number of employees (columns 5-8).

Table 3: Estimation Results: Firm Performance and Employment Composition

	Panel A: Employment, sales, and value-added							
Outcome:	$\Delta \log(Sales_{i,2016-2019})$		$\Delta \log(VA_{i,2016-2019})$		$\Delta \log(Cost_{i,2016-2019})$		$\Delta \log(L_{i,2016-2019})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI_{2019}	0.095**	0.146***	0.051*	0.083**	-0.027	-0.010	-0.019	-0.017
	(0.0350)	(0.0242)	(0.0281)	(0.0318)	(0.0555)	(0.0458)	(0.0259)	(0.0211)
Obs.	6,900	6,899	6,888	6,887	6,895	6,894	6,894	6,894
Entrophy w.	No	Yes	No	Yes	No	Yes	No	Yes
	Panel B: Employment composition							
Outcome:	$\Delta Opera_{i,2016-2019}$		$\Delta Admin_{i,2016-2019}$		$\Delta Techn_{i,2016-2019}$		$\Delta Female_{i,2016-2019}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI_{2019}	0.027	0.026	-0.014**	-0.014**	-0.012	-0.009	-0.009**	-0.009
	(0.0218)	(0.0216)	(0.0063)	(0.0062)	(0.0174)	(0.0155)	(0.0043)	(0.0054)
Obs.	6,894	6,894	6,894	6,894	6,894	6,894	6,894	6,894
Entrophy w.	No	Yes	No	Yes	No	Yes	No	Yes

Notes: All specifications include 2-digit industry fixed effects and control for log employment, log labor productivity, and a dummy variable for positive investment in ICT technologies at baseline in 2014. Standard errors clustered at the industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

In Panel B of Table 3, I look at the differentials in workforce composition across operative and administrative workers and technicians between AI-users and non-users (columns 1-6). All labor shares include both direct and outsourced employment. The estimates suggest a small

but significant decline in the share of administrative workers associated with AI adoption of approximately 1.4 percentage points. By contrast, I find no significant differentials in the share of operative workers (columns 1-2) and technicians (columns 5-6). Additionally, I use information on employment by gender from the AMS surveys and present the results when the outcome variable is the share of female employment in columns (7) and (8). The coefficients are negative but only statistically significant when comparing the unweighted samples.

These results on employment composition contrast with the existing literature on AI occupational exposure that documents higher exposure for high-skilled technical and male jobs (Webb, 2019). Similarly, Yang (2022) finds negative effects of AI technology on the share of labor force with educational qualifications among Taiwanese firms while Albanesi et al. (2025) shows a positive link between these technologies and changes in the female employment share in Europe.

By contrast, the results in this paper suggest that AI adoption is associated with changes in organizational structure, particularly a decline in administrative labor shares, suggesting a potential different adjustment margin through which firms reorganize production. This pattern might be consistent with partial substitution of administrative tasks which may be more salient in the context of middle-income economies where organizational capital is more scarce and less efficient (Bruhn et al., 2010).

3.3 Heterogeneity in AI Implementation and Initial Capabilities

This subsection explores whether the productivity growth differentials associated with AI adoption vary according to implementation strategies and firms' initial capabilities.

Table 4 distinguishes between firms that developed AI solutions in-house and those that adopted AI through outsourcing. Columns (1)–(2) estimate specifications including both adoption types simultaneously, while columns (3)–(6) consider each adoption mode separately. Across specifications, both in-house and outsourced AI adoption are associated with positive and statistically significant productivity growth differentials.

Although the point estimates for in-house adopters are somewhat larger than those for firms relying on external providers, the differences are not always statistically significant. Unlike existing evidence for France by Calvino and Fontanelli (2024) showing that the link between AI and productivity arises for AI developers only, these results suggest that outsourcing also allows

firms to capture sizable benefits.

Table 4: Heterogeneity - AI Implementation

Outcome:	$\Delta \log(Y_{i,2016-2019})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$AI_{2019}^{In-house}$	0.171**	0.172**	0.222***	0.208***		
	(0.0709)	(0.0653)	(0.0745)	(0.0726)		
$AI_{2019}^{Outsourcing}$	0.170***	0.167***			0.201***	0.198***
	(0.0344)	(0.0377)			(0.0391)	(0.0426)
Obs.	6,894	6,894	6,894	6,894	6,894	6,894
Entrophy Weights	No	Yes	No	Yes	No	Yes

Notes: All specifications include 2-digit industry fixed effects and control for log employment, log labor productivity, and a dummy variable for positive investment in ICT technologies at baseline in 2014. Standard errors clustered at the industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

I next examine whether the productivity effects of AI depend on firms' pre-existing capabilities. Table 5 reports the results. Column (1) interacts AI adoption with the baseline share of technical workers, while column (2) considers ICT investment intensity measured as the ratio of ICT investment to sales.

The estimates in column (1) indicate a positive and statistically significant interaction between AI adoption and the initial share of technical employees. The interaction coefficient suggest that as the share of technical workers rises, the implied productivity differential becomes substantially larger.

In contrast, the results in column (2) provide weaker evidence of heterogeneity with respect to ICT intensity. While the interaction between AI adoption and ICT investment over sales is positive, the coefficient is not precisely estimated and not statistically significant. This suggests that, conditional on other firm characteristics and pre-treatment trends, differences in ICT intensity alone do not generate heterogeneous returns to AI adoption.

Overall, in line with evidence for high-income economies (Brynjolfsson et al., 2019), the heterogeneity analysis highlights the importance of complementary capabilities related to human capital in shaping the productivity returns to AI adoption.

Table 5: Heterogeneity - Initial Capabilities

Outcome:	$\Delta \log(Y_{i,2016-2019})$	
	(1)	(2)
AI_{2019}	0.083*	0.157***
	(0.0421)	(0.0348)
$Tech_{i,2011}$	0.240	
	(0.1778)	
$AI_{2019} \times Tech_{i,2011}$	0.521**	
	(0.2280)	
$ICTInv./Sales_{i,2011}$		0.651
		(0.3852)
$AI_{2019} \times ICTInv./Sales_{i,2011}$		-0.219
		(0.3785)
$\Delta \log(Y_{i,2016-2014})$	-0.476***	-0.479***
	(0.0387)	(0.0392)
Obs.	6,894	6,894
Entrophy weights	Yes	Yes

Notes: All specifications include 2-digit industry fixed effects and control for log employment, log labor productivity, and a dummy variable for positive investment in ICT technologies at baseline in 2014. Standard errors clustered at the industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

4 Conclusion

This paper provides new suggestive evidence on the relationship between AI adoption and firm-level productivity growth in a middle-income economy. Using detailed survey information on AI adoption among Colombian manufacturing firms combined with longitudinal administrative data, I document a sizable productivity growth differential associated with AI use. After reweighting firms to account for pre-adoption characteristics and productivity trajectories, AI adoption is associated with a 16 percent cumulative increase in labor productivity over the 2016–2019 period, equivalent to approximately 5 percent annualized growth.

The analysis suggests that these gains are primarily driven by higher sales and value-added rather than cost reductions or employment contractions. At the same time, AI adoption is associated with changes in workforce composition, particularly a decline in the share of administrative workers. This pattern contrasts with some evidence from high-income economies and points to potentially different adjustment margins among developing economies.

The heterogeneity results underscore the role of complementary capabilities. In particular, productivity differentials are stronger among firms with higher pre-existing technical employment shares, consistent with complementarities between AI technologies and absorptive capacity.

Several limitations remain. The absence of precise information on the timing and persistence of adoption prevents a fully dynamic evaluation of treatment effects. While the balancing mitigates concerns about differential pre-trends, the estimates should be interpreted as productivity growth differentials rather than causal treatment effects.

Future research leveraging richer panel data or policy-induced variation in adoption would help further clarify the causal effects and mechanisms. The availability of detailed data sets, such as the ENTIC in Colombia, is crucial to assess the potential gains of AI and other technologies in middle and low-income economies. Expanding future survey waves to include information on the exact timing and persistence of adoption would allow for more precise estimation of the dynamic effects of AI on firm performance.

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Table A1: Robustness Analysis - Additional Controls

Outcome:	$\Delta \log(Y_{i,2016-2019})$				
	(1)	(2)	(3)	(4)	(5)
AI_{2019}	0.093***	0.150***	0.150***	0.150***	0.154***
	(0.0271)	(0.0274)	(0.0275)	(0.0275)	(0.0337)
Obs.	6,815	6,894	6,894	6,894	6,894
Weights	CEM	Entrophy	Entrophy	Entrophy	Entrophy
Controls		+worforce composition	+imported inputs	+R&D investments	+region FE

Notes: All specifications include 2-digit industry fixed effects and control for log employment, log labor productivity, and a dummy variable for positive investment in ICT technologies at baseline in 2014. Standard errors clustered at the industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A2: Robustness Analysis - Alternative Periods

	(1)	(2)
AI_{2019}	0.002	0.278***
	(0.0372)	(0.0445)
Obs.	6,559	6,582
Period	2012-2016	2012-2019
Entrophy weights	Yes	Yes

Notes: All specifications include 2-digit industry fixed effects and control for log employment, log labor productivity, and a dummy variable for positive investment in ICT technologies at baseline in 2012. Standard errors clustered at the industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.