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Portuguese Workforce Exposure to Artificial Intelligence and Automation: An analysis of firm productivity

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AI Declaration

During the preparation of this master's thesis, the author(s) utilized ChatGPT for the following purpose:

1.ChatGPT was used to support code development in Stata, assist in understanding academic literature, and to refine language for improved clarity.

2. After using ChatGPT, the author(s) diligently reviewed and edited the content produced by the tool. We take full responsibility for the final content presented in this thesis.

By signing this declaration, we affirm that the content of this master's thesis reflects our original work, augmented by the responsible use of AI.

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Abstract

Digital technologies have a growing relevance in society; in this context, this dissertation investigates the impact of digitalization technologies, specifically AI and automation, on Portuguese firm productivity, using an employer-employee matched longitudinal dataset and economic and financial data on all private Portuguese firms, from 2017 to 2021.

Digitalization technologies are divided into two categories, comprising its dual effects: destructive digitalization is studied with the exposure metric of Frey and Osborne (2017), which estimates occupations' probability of automation (e.g., replacement of human-performed tasks); transformative digitalization is measured through the exposure metric of Felten et al. (2021), which assesses workforce exposure to AI (e.g., labor-augmenting technologies that enhance worker efficiency). Three distinct measures are used to aggregate occupational exposure at the firm-level: percentage of workers highly exposed to digitalization, average exposure of the workforce to digitalization; and percentage of workers across high, medium, and low digitalization exposure levels. Productivity is assessed with multiple indicators, including Labor Productivity, Turnover per worker, and Total Factor Productivity (use of Ackerberg et al.'s (2015) method to account for endogeneity).

Implementing Fixed Effects methods, we find that high AI exposure is connected to enhanced levels of productivity, indicating that AI mostly likely increases workers' and firms' productivity. On the contrary, workforce exposure to automation seems to marginally decrease productivity; interaction effects further suggest that AI's productivity gains are diminished in firms with higher automation exposure. Our findings highlight the importance of corporate digital integration, also stressing the relevance of high levels of education and digital literacy to grasp productivity effects. This research offers valuable insights for policy makers in Portugal, so that efficient policies can be adopted to maximize digitalization's benefits and boost Portugal's economic growth.

Key words: AI (artificial intelligence); automation; digitalization; workforce exposure; productivity.

Table of contents

Chapter 1. Introduction

1.1 Problem Contextualization

Digital technologies are rapidly evolving, along with their growing relevance in society. The COVID-19 pandemic and arrival of powerful AI technologies like ChatGPT accelerated this process, increasing the reliance on digital tools, notably for remote work, research, and service-related interactions (Ciarli et al., 2021). We are transitioning a technological revolution, driven by AI (artificial intelligence) and automation, which are reshaping labor markets and economic dynamics globally (Nyagadza et al., 2022). Portugal has been partially protected from the effects of technologies due to a delayed technology adoption, linked with an historically low qualified workforce; Portugal occupies an intermediate position in the DESI (Digital Economy and Society Index) (Comissão Europeia, 2022). Yet, digital adoption and skill levels are rising, and hence, so is the impact of digital technologies in Portugal (Casas et al., 2025).

Previous revolutions have proved to affect nearly all aspects of society, delivering enormous wealth and progress, but also undesired disruptions (Acemoglu and Restrepo, 2019; Makridakis, 2017). Likewise, digitalization comprises dual effects: transformative digitalization renders workers more efficient, with labor-augmenting technologies, while destructive digitalization replaces human-performed tasks through automation (Fossen and Sorgner, 2019). Hence, we study the impact of this technological revolution, and more specifically of AI and automation, on firms' productivity.

AI technologies mimic human intelligence, functioning as machines programmed to act and learn like humans. Given that in this study AI exposure is measured by Felten et al. (2021), our classification of AI technologies aligns with theirs; evidence shows that these technologies tend to be labor-friendly (Fossen and Sorgner, 2019). Automation technologies are those taking over tasks formerly carried out by humans, specifically the ones identified as such by Frey and Osborne (2017); these technologies tend to be labor-saving. Certain technologies may be classified simultaneously as AI and automation. We use the concepts of destructive digitalization, labor-saving technologies and automation interchangeably. Similarly, constructive digitalization is connected to labor-augmenting technologies, referred to as AI. Digitalization involves replacing traditional processes with digital technologies;

exposure to digitalization technologies denotes the extent to which jobs or occupations are affected by digital technologies.

The body of literature on digitalization technologies is continuously expanding, with a main focus on labor demand and wage inequality. A major contribution was that of Frey and Osborne (2017), which predicted that 47% of US jobs are at high risk of automation. More optimistic perspectives exist, such as that of Arntz and Gregory (2016), stating that only 9% of US employment is automatable. However, studies on the impact of digitalization technologies on productivity remain limited.

Productivity is a key driver of economic growth, as it determines how efficiently an economy uses its resources (labor, capital and technology) to produce goods and services (Hall et al., 2010). It is a main factor to determine a firms' competitiveness and profitability and so, understanding productivity shifts due to digitalization is important both for firms, in determining their stance in adopting digitalization technologies, for policymakers, to develop policies that promote economic growth and avoid negative externalities, and for society as a whole, as productivity influences job creation, income, innovation and social prosperity.

A selection of studies investigate the connection between digitalization technologies and productivity. Generally, we anticipate a positive association between automation/AI adoption and productivity (Gal et al., 2019; Tschang and Almirall, 2021). Acemoglu and Restrepo (2019) assert that automation increases firms' productivity by reducing costs; Eloundou et al. (2023) predict that 15% of worker tasks in the US would be completed more efficiently with access to AI. However, what has been in fact observed is a decline in productivity growth, which points us towards a productivity paradox. Why is productivity growth not increasing alongside the expansion of digitalization technologies, as expected? Calvino and Fontanelli (2023a) argue that although AI users are generally more productive, this is attributable to the self-selection of highly productive and digital-intensive firms into AI adoption. Agrawal et al. (2019) additionally advert to the dangers of over automation. Unraveling this productivity paradox is one of the primary motivations of this study.

To our knowledge, no prior studies have examined the impact of workforce exposure to AI and automation on firms' productivity, within the Portuguese macroeconomic environment. Existing research focused on the Portuguese context primarily contributes by measuring how the timing of digital adoption influences productivity levels in firms (Cerqueira et al., 2023) and by classifying firms' productivity through a task-based approach (Fonseca et al., 2018). Likewise, studies examining the simultaneous effects of AI and automation remain limited; Fossen and Sorgner (2019) add a valuable input in this domain, by analyzing the transformative and destructive effects of digitalization technologies on occupations in parallel, since they indeed coexist.

This dissertation aims to address the gaps previously outlined, by complementing the literature on the effects of digitalization technologies on firms' productivity, through analyzing both the effects of AI and automation independently and also their combined impact, and by performing the analysis within the Portuguese macroeconomic context. We study how the workforce exposure to AI and automation affects firms' productivity by applying econometric models on a longitudinal employer-employee dataset, built on companies headquartered in Portugal. We assess occupational-level exposures, using the metric of Frey and Osborne (2017) to estimate the automation probability of occupations, and deriving the AI exposures from the metric of Felten et al. (2021). Three distinct measures of digitalization exposure are developed to aggregate occupational exposures at the firm-level. In a first approach we measure the percentage of workers highly exposed to AI and automation. Additionally, we compute workers' average digitalization exposures. Finally, we estimate the percentage of workers with high, medium and low exposures in a firm. The impact of these digitalization exposures on productivity is quantified through two measures of worker productivity (Labor Productivity, Turnover per worker) and three measures of firm productivity (TFP, Turnover and GVA). Our main indicator of digitalization exposure is the percentage of workers highly exposed to AI and automation; for productivity, we rely on Labor Productivity as the primary metric. Worker productivity metrics assess the productivity of workers in a firm, while firm productivity metrics asses the firm's productivity directly.

We find that, on average, high AI exposures are connected to higher levels of productivity, indicating that AI mostly likely increases workers' and firms' productivity. On the contrary, workforce exposure to automation seems to decrease productivity, though its effect is not as clear. All our exposure and productivity metrics support these findings, with the exception of GVA, which reveals opposing results. Some challenges encountered were the difficulty of accurately measuring productivity, the large number of variables in the datasets, and the scarcity of studies focused on the impact of digitalization exposure on productivity. Our findings underscore the importance of AI integration and digital literacy in boosting workers' and firms' performance, while signaling potential drawbacks of automation.

1.2 Dissertation Structure

The dissertation is organized as follows. We discuss the existing literature in Chapter 2, particularly, on the topics of destructive and transformative digitalization, productivity, and their interconnection. Chapter 3 presents the data and variables used, along with descriptive statistics. In Chapter 4 we describe the methodology adopted, detailing the econometric model and framework applied. Chapter 5 presents and discusses the results obtained and finally, Chapter 6 outlines the conclusions of the study, along with its limitations and suggestions for potential policies and future research.

Chapter 2. Literature Review

This chapter analyzes literature on digitalization technologies' impact on firms' productivity. Initially, in Section 2.1, we look into the dual effect of digitalization technologies, differentiating between two categories of technologies: labor-saving and labor-augmenting. In Section 2.2, we examine the concept of productivity and its metrics. Finally, in Section 2.3, we explore the gap between expected and observed productivity, and examine how automation and AI affect firms' productivity. Additionally, we present two hypotheses to be tested.

2.1. Labor-saving and labor-augmenting technologies

Business transformation is happening at a fast rate through digital technologies, which are influencing society's economic and social progress (Brodny and Tutak, 2022). The process of digitalization revolutionizes firms and how jobs and activities operate, conveying a significant adaptation in skills and job roles (Ciarli et al., 2021). Destructive digitalization focuses on the detrimental impact of labor-saving technologies on workers; these technologies replace human work by machines, resulting in job losses and increased inequality (Acemoglu and Restrepo, 2019; Fossen and Sorgner, 2019; Korinek and Stiglitz, 2021). As for transformative digitalization, it addresses the beneficial effects of labor-augmenting technologies on workers, by upgrading their skillsets and rendering them more efficient (Fossen and Sorgner, 2019), hence broadening employment opportunities and potentially reducing inequalities, a possibility termed "Turing Transformation" (Agrawal et al., 2023).

In essence, labor-augmenting technologies increase labor demand by complementing human tasks and thus improving workers' efficiency; labor-saving technologies reduce labor demand by automating, that is replacing, human performed tasks (Kogan et al., 2023; Montobbio et al., 2024; Prytkova et al., 2024). Furthermore, a technology can be both labor-saving and labor-augmenting, representing a duality of destructive and transformative effects.

Various authors adopt different methodologies to distinguish between the two families of technologies, along with measuring its exposure levels. One possible approach might be to use textual analysis of patents. Montobbio et al. (2024), Kogan et al. (2023), Prytkova et al. (2024) and Webb et al. (2020) are some examples who apply this technique. The authors employ natural language processing to compare job descriptions, detailing the tasks performed in each occupation, with patent texts describing the applications of digitalization technologies. They then examine the overlap between job descriptions and patents, to determine which occupations are more exposed to automation. Technologies with a strong overlap can perform many tasks within an occupation and are considered labor-saving. If instead, technologies support tasks conducted in occupations, rendering them easier or more efficient, they are labor-augmenting.

A different methodology is that of Felten et al. (2018, 2021), which develop AI exposure scores to quantify AI's impact on occupations. Felten et al. (2018) rely on patents (and hence, on the available knowledge), using a backward looking measure of AI advances to assess the present impact of AI; Felten et al. (2021) use crowd-sourced predictions concerning whether AI will be capable of executing the tasks within an occupation in the future, to assess AI's forthcoming impact. If the technology can perform a task at the same level or better than humans, it is labor-saving. Otherwise, if it improves the efficiency or speed of the task without eliminating the need for human abilities, it is labor-augmenting.

Frey and Osborne (2017) adopt an alternative methodology to assess the susceptibility of jobs to automation, focusing exclusively on labor-saving technologies. This methodology starts by identifying which tasks can be automated and the barriers to this process; it identifies the abilities of perception and manipulation, along with creative and social intelligence, as the main bottlenecks for automation. After that, it relies on occupational data to understand the nature of work (tasks involved) in various jobs, and then relates task characteristics to automation barriers, to predict the likelihood of each job to be automated, depending on the extent to which its tasks are subject to automation bottlenecks. This methodology thus divides jobs into three categories of automation risk: low probability (0-0.3), jobs which require creative and social skills and are less likely to be automated; medium probability (0.3-0.7), partially automatable jobs but still need human input; and high probability (0.7-1), repetitive jobs, highly susceptible to automation – most workers in transportation, administrative support and production are in this last category. This methodology is based on expert labeling combined with machine learning.

Fossen and Sorgner (2019) explore the impact of digitalization on occupations by analyzing the effect of labor-saving (destructive digitalization) and labor-augmenting technologies (transformative digitalization) simultaneously. Destructive digitalization is measured by the likelihood of automation and computerization, as estimated by Frey and Osborne (2017), while transformative digitalization, based on Felten et al. (2018), is assessed by the way AI changes job tasks without replacing workers. With these measures, Fossen and Sorgner (2019) divide occupations into four categories: Rising Stars, where jobs evolve but are not replaced; Machine Terrain, where jobs content is altered, with the potential of role transition; Human Terrain, where jobs remain stable with minimal digitalization effects; and Collapsing Occupations, where jobs are likely to be substituted by machines, with unchanged job content.

When assessing the potential of digitalization, several levels of analysis can be adopted (e.g., national, regional, firm, occupational, worker). Two main approaches are broadly considered: an occupation-based approach, which studies digitalization at the level of occupations, and a task-based approach, that studies digitalization's potential at the level of specific tasks within occupations (Filippi et al., 2023). Digitalization directly affects tasks and only indirectly influences occupations (Septiandri et al., 2023); its impact depends on the level of routine involved in the tasks of an occupation (Cirillo et al., 2021). It increases the productivity of higher skilled workers by supporting abstract tasks (require creativity and high cognitive capacities) and relieving them from routine tasks (Tschang and Almirall, 2021). On the contrary, it reduces the need for routine-intensive occupations, which are automated. All these factors lead to a skill-premium within firms (Barth et al., 2020; Jaimovich et al., 2012) and to a labor market polarization (Frey and Osborne, 2017; Humlum, 2019).

2.2. Productivity

The shift in labor dynamics has a direct impact on firms' productivity, as worker and machine productivity changes. Productivity is commonly defined as the ratio of output to input (Rogers, 1998) and so, firms' productivity may be characterized as the efficiency of a firm in converting inputs into outputs. Several levels of analysis can be adopted to quantify productivity, namely: firm productivity, relying on metrics such as Turnover, Gross Value Added (GVA) and Total Factor Productivity (TFP). Likewise, worker productivity measures like Labor Productivity and Turnover per worker are also relevant (Cerqueira et al., 2023). Furthermore, while worker productivity metrics allow for easier comparison across firms, as all are based on a single worker's efficiency, firm productivity metrics express productivity conditional on firm's size, rendering the comparison less explicit; nevertheless, these allow to capture the contributions of labor, capital, and other factors.

These measures provide different insights on productivity. Labor Productivity (Value Added per number of workers) and TFP (Total Factor Productivity) emphasize the efficiency with which inputs are used, Turnover (Volume of sales and services provided) and Turnover per worker assess financial output, and GVA (Turnover minus cost of intermediate goods) captures value creation. Turnover metrics might exaggerate the role a firm plays in value creation, when compared to Value Added metrics, since they don't account for the costs of production and sales, unlike Labor Productivity and GVA.

2.3. Digitalization technologies and productivity

Assuming that digitalization increases the productivity of workers (Gal et al., 2019; Tschang and Almirall, 2021), then in a world with an increasing development of digitalization technologies, it would be expected for firms' productivity growth to increase. Nevertheless, what has been in fact observed is a reduction of firms' productivity growth alongside the accelerated digitalization (Corrado et al., 2021), with a small contribution of measured digital capital to productivity growth (Mollins and Taskin, 2023). This event was named the "Productivity Paradox" and is clarified by Brynjolfsson et al. (2017) and Damioli et al. (2021). They point out that even though fast technological change has led to systems surpassing human level performance across numerous areas, productivity growth has in fact been declining, instead of the expected increase. This phenomenon, also named "Solow Paradox", highlights the disconnection between technological progress and measurable productivity gains.

Various justifications have been proposed to account for the contradiction. Damioli et al. (2021) and Gao and Feng (2023) attribute the paradox to implementation lags, that is, the need for a significant period to allow complementary technologies to develop, leading to a delay in productivity gains. Corrado et al. (2021) and Calvino and Fontanelli (2023a) present another hypothesis, explaining the paradox by the J-curve, namely, that digitalization may initially lead to decreases in productivity, due to adaptation challenges, before boosting productivity. Brynjolfsson et al. (2017) propose two additional rationales: either the paradox is a result of an unfounded optimism, or due to redistribution, that is, an unequal distribution of the gains, which encloses an intense competition and subsequent dissipative effects. The "Productivity Paradox" and the subsequent gap between expected and observed productivity raise the question: "What is the impact of the workforce exposure to AI and automation on firms' productivity?". The adoption of digital technologies does not ensure a boost in productivity. Instead, it comes with its challenges (Horvat et al., 2019).

When firms automate operations, they replace labor with capital, such as machines and software (Restrepo, 2024). Automation generates contradicting forces; it replaces tasks previously performed by humans, causing a displacement effect which reduces labor demand; on the other side, it may boost productivity, by utilizing robots capable of task automation. This increase in productivity, named productivity effect, induces the decline of the production costs, which might lead to a decline in prices, in case of highly competitive environments. If the prices decrease, the demand will probably increase, and there might be a need for more labor (Barbieri et al., 2019; Yan Ing and Grossman, 2023).

The reinstatement effect, which counterbalances the displacement effect, is also a result of automation. Labor-saving technologies may cause short-term job displacement, but have the potential to generate opportunities by the development of new tasks and industries (Goldin and Katz, 1998). The creation of new tasks reintroduces labor into a wider variety of activities, which increases labor demand. Therefore, the net effect of automation on workers depends on the balance between the displacement effect and the productivity effect, as well as the reinstatement effect (Acemoglu and Restrepo, 2019), which contributes to contradicting studies regarding the consequences of automation. Agrawal et al. (2023) argue that automation can improve job prospects and broaden opportunities. Conversely, Korinek and Stiglitz (2021) state that these technologies are usually labor-saving, resource-saving and lead to winner-takes-all dynamics. Indeed, the effect of automation is dependent on the tasks that technologies will be able to automate (Restrepo, 2024).

The degree to which digitalization impacts productivity is also dependent on the mix of workers in a firm. A balance between digitalization technologies and human workforce must be kept in order to attain the highest productivity gains, since automation entirely without human labor can be counterproductive. In fact, excessive automation may occur, characterized by organizations not necessarily focused on improving their efficiency, but instead simply aiming to automate as much as possible, ultimately decreasing productivity (Agrawal et al., 2019). Regarding the impact of labor-saving technologies on productivity, we construct the following hypothesis:

Hypothesis 1: Firms with a greater percentage of workers highly exposed to automation will experience an increase in productivity.

From the opposing side, regarding the augmenting side of digitalization, labor-augmenting technologies are generally associated to AI, which is expected to bring positive productivity effects to both workers and firms. Czarnitzki et al. (2023) find that AI increases Labor Productivity in 14.6%. Gao and Feng (2023) additionally reveal that an increase in AI adoption is associated with a growth of TFP for manufacturing firms. Nucci et al. (2023) also compare firms adopting digital technologies with the non-adopters, finding that AI-patenting firms (firms holding exclusive rights over their AI technologies) experience higher productivity levels – TFP increases by 0.97 percentage points. All these studies reinforce the idea that AI increases firm's productivity, which subsequently leads us to further question: "Through which mechanisms does AI bring these positive productivity effects?".

AI is a fusion of software, hardware and databases (Corrado et al., 2021). It integrates existing technologies into automation processes, fosters new innovations and reduces uncertainties through reliable forecasts (Czarnitzki et al., 2023; Damioli et al., 2021). Hence, AI affects productivity at the firms' level by interconnecting organizations, improving information availability and decision making, using predictive analytics and big data and increasing capital efficiency (Makridakis, 2017; Mollins and Taskin, 2023). Moreover, it improves worker's efficiency by complementing their abilities (Fossen and Sorgner, 2019).

Beyond the direct effects of labor-augmenting technologies on workers and firms, their impact is significantly amplified by complementary assets, such as other technological and strategic investments (Lee et al., 2022; Mollins and Taskin, 2023). In fact, new technologies usually start by driving the development of complementary technologies before any attainable effects are observed (Horvat et al., 2019). One clear example is the relationship between AI and innovation. AI breakthroughs enable the emergence of complementary innovations, which amplify firms' productivity (Brynjolfsson et al., 2017; Rammer et al., 2022). Moreover, complementary innovations stimulate firms' growth by boosting product innovation (Babina et al., 2024). Digital technologies also assist firms in keeping ahead of the market and maintaining their competitive advantages, rendering firms more adaptable (Brodny and Tutak, 2022). Furthermore, certain firms' features enhance the effectiveness of digitalization technologies. Cerqueira et al. (2023) assert the importance of timing and good management, highlighting the advantages of being first movers. Nucci et al. (2023) emphasize the advantage of larger and older firms, and those inserted in the service sector. Additionally, skilled labor is a key variable to augment the positive effect of digitalization technologies on firms' productivity (Goldin and Katz, 1998; Mollins and Taskin, 2023). This forms the basis to an additional hypothesis, regarding the impact of labor-augmenting technologies on productivity:

Hypothesis 2: Firms with a greater percentage of workers highly exposed to AI will experience an increase in productivity.

Chapter 3. Data

3.1 Data on workers, firms and exposures

To study the impact of digitalization technologies on firms' productivity, we employ data regarding workers, firms and exposure measures. Worker level data is taken from QP (Quadros de Pessoal), an annual longitudinal dataset linking employer-employee, containing information on all workers in private Portuguese firms with a minimum of one remunerated employee, including information on their gender, age and level of education. Firms' data is retrieved from SCIE (Sistema de Contas Integradas das Empresas), featuring economic and financial attributes of the Portuguese firms, namely their industry, region, tenure, number of employees and economic performance. QP is provided by the Portuguese Ministry of Labor, Solidarity and Social Security and SCIE by Statistics Portugal. The exposure measures are retrieved from the studies of Felten et al. (2021) for transformative digitalization and Frey and Osborne (2017) for destructive digitalization.

The occupational classifications are based on the classification system used in the USA, the SOC (Standard Occupational Classification). To adapt them to the Portuguese labor market, we employ a conversion table linking the SOC to the ISCO-08 (International Standard Classification of Occupations 2008) – a standardized categorization developed by the International Labor Organization and adopted by the European Union. Workers (and their respective occupations) are matched to each firm by a unique firm identifier, and occupations are matched to an exposure level. With this, it is possible to correspond AI and automation exposures to workers, and consequently to the respective firm. The longitudinal dataset ranges from 2017 to 2021, comprising a five-year period. We have a sample of 220 thousand observations, each representing yearly firm and average workers' characteristics, composed of annual averages for 3 million workers across 44 thousand firms – the analysis does not include single-member firms or micro firms (with less than 10 employees).

3.2 Variable Description

Table 1 provides an overview of the variables employed in this study. It presents the dependent variables used to measure productivity; the explanatory variables associated with the three distinct digitalization exposure measures; the inputs of the productivity function; and the control variables.

Table 1: Variable description

Variables	Description	Details
Dependent Variables		
Labor Productivity (LP)	Value Added per Number of workers	Worker productivity
Turnover / Wkr	Turnover per Number of workers	
TFP	Total Factor Productivity	Firm productivity
Turnover	Turnover	
GVA	Gross Value Added	
Explanatory Variables		
% of workers highly exposed to AI	% of worker with AIOE scores above 0	Measure 1
% of workers highly exposed to automation	% of workers with automation probability above 70%	
Average AI exposure	Average AIOE score	Measure 2
Average automation exposure	Avergae automation probability	
% of workers highly exposed to AI_PCTL	% of workers in the 70th-100th percentile of AI exposures	Measure 3
% of workers moderatly exposed to AI_PCTL	% of workers in the 30th–70th percentile of AI exposures	
% of workers with low exposure to AI_PCTL	% of workers in the 0th-30th percentile of AI exposures	
% of workers highly exposed to automation	% of workers with automation probability above 70%	
% of workers moderately exposed to automation	% of workers with automation probability between 30% and 70%	
% of workers with low exposure to automation	% of workers with automation probability below 30%	
Inputs of Productivity Function		
Personnel Expenses	Total wages, social charges, and employee-related expenses	Labor
Intermediate Consumption	Input costs, external services, and additional operating expenses	Intermediate inputs
Fixed Capital Formation	Net acquisition of fixed assets used for production	Capital
Non Current Assets	Fixed assets held for more than one year	
Control Variables		
Large firm	Firms with 250 or more employees	
Medium firm	Firms with 50 to 249 employees	
Small firm	Firms with 10 to 49 employees	
Firm's tenure	Firm's antiquity	
Workers' age	Average workers' age	
Women Majority	Firms with a majority of female workforce	
Majority with higher education	Firms with a majority of higher educated employees	
Industry	Industry the firm operates in (NACE classification)	
Region	Region the firm is inserted in (NUTS II classification)	
Year	Years 2017 to 2021	

Note: All Dependent Variables and Inputs of productivity function are in log form.

3.3 Descriptive Statistics

We conduct descriptive statistics for the main variables in the study, uniquely analyzing the year of 2021, to avoid biased results (caused by possible seasonality, different sample sizes, economic crisis, among others). We use Labor Productivity as the proxy to measure productivity, and the proportion of workers highly exposed to AI and automation as the metrics of digitalization exposure. We define high AI exposure when AIOE (AI Occupational Exposure) — which identifies key AI applications and relates them to the necessary abilities in occupations — is above zero (Felten et al., 2021). High automation exposure is considered to occur when the automation probability of a certain occupation is above 70%, calculated based on the automation bottlenecks (Frey and Osborne, 2017). We also study the control variables, namely firm's size, tenure, industry, region, worker's age, gender and level of education. The columns of AI and automation represent the proportion of workers highly exposed to AI and automation, respectively; the LP column displays Labor Productivity.

Table 2 shows descriptive statistics for gender, firm size and level of education. Concerning gender, only 33% of Portuguese firms have a female majority. We notice that even though firms with women majorities are, on average, more exposed to AI than firms with women minorities, their average Labor Productivity is smaller. This goes against our expectations, since higher AI exposures are usually connected with higher productivity levels (Czarnitzki et al., 2023). Women might be concentrated in inherently less productive industries. Regarding firms' size, firms are divided into small, medium and large according to SME (Small and Medium-sized Enterprises) guidelines on staff headcount – 84% of firms are small. Although there is no notable difference in AI and automation exposure of small and large firms, we observe that large firms are on average more productive than small firms, event also emphasized by Nucci et al. (2023). Furthermore, the Portuguese workforce is relatively uneducated, with only 19% of workers having a higher education and 12% of firms with a majority of higher educated employees (we consider higher education as holding a bachelor's degree or above). We observe that firms with a majority of higher educated employees are, on average, more exposed to AI and less exposed to automation. Additionally, they are more productive. This is in line with the studies of Goldin and Katz (1998) and Mollins and Taskin (2023), who show the importance of skilled labor in enhancing the positive effect of digitalization on firms' productivity.

Table 2: Descriptive statistics for gender, firm size and level of education

Variables	Total	Group (0/1)	AI	Automation	LP
Women majority	0.33	0	0.36	0.58	33,623.2
	(0.47)		(0.30)	(0.30)	(60,172.4)
		1	0.42	0.57	25,831.6
			(0.37)	(0.34)	(43,435.3)
Large firm	0.02	1	0.40	0.54	43,205.1
	(1.50)		(0.34)	(0.32)	(60,442.8)
Medium firm	0.14	1	0.37	0.58	37,915.9
	(0.34)		(0.32)	(0.30)	(81,832.5)
Small firm	0.84	1	0.38	0.57	29,583.0
	(0.37)		(0.33)	(0.31)	(49,341.7)
Majority with higher education	0.12	0	0.31	0.61	27,869.7
	(0.33)		(0.28)	(0.30)	(33,752.3)
		1	0.88	0.30	53,590.6
			(0.20)	(0.28)	(127,220.8)
Observations	44,245				

Notes: Standard deviations in parentheses. The values in the columns of AI and automation represent the proportion of workers highly exposed to AI and automation, respectively. The LP column shows Labor Productivity. Unlike the regressions, which cover 2017 to 2021, here only 2021 is considered, resulting in fewer observations.

Tables A1 and A2 in the Appendix regard firms' industry and region. Table A1 makes a division of firms into 21 industries, according to NACE (Statistical Classification of Economic Activities in the European Community), developed by Eurostat. High-skilled and essential service industries (D, J, M and P) are the most exposed to AI, with an average of over 80% of workers being highly exposed. Low-skilled manufacturing and service industries (C and I) are the most exposed to automation. However, industry exposure to digitalization doesn't seem to be connected with productivity levels, since apart from industry D – very small number of observations – and J, the most productive industries – B, H and L – are not the ones with higher AI exposures. Calvino and Fontanelli (2023a) assert that productivity growth is aggregated in certain sectors, which is also observed here. In Table A2 we see a division of Portugal into 7 regions, according to NUTS (Nomenclature of Territorial Units for Statistics) II, a standardized system for the territorial division of EU countries, developed by Eurostat. We note that Lisbon is simultaneously the most exposed region to AI and the least exposed to automation. It is also the most productive region, as expected.

Tables 3 and 4 categorize firms and the workforce into five groups, based on firm tenure and worker age percentiles, respectively. From Table 3 we observe that, on average, firm productivity increases alongside its tenure (Nucci et al., 2023). In Table 4 we recognize that the percentage of workers highly exposed to AI reduces, on average, with worker age. Despite that, productivity increases with worker age until an average age of 45 (group 4). Older workers might have lower digital literacy, reducing their representation in highly AI-exposed occupations, but might still drive productivity through their experience and accumulated knowledge.

Table 3: Descriptive statistics for firm's tenure

Firm's tenure	**Total**	**Min**	**Max**	**AI**	**Automation**	**LP**
Group 1	4.16	0	7	0.34	0.59	25,592.6
	(2.04)			(0.35)	(0.35)	(72,251.3)
Group 2	10.90	8	14	0.38	0.57	28,655.7
	(2.05)			(0.34)	(0.32)	(53,220.6)
Group 3	18.63	15	22	0.39	0.56	32,431.2
	(2.24)			(0.33)	(0.31)	(51,789.8)
Group 4	27.28	23	32	0.41	0.56	33,729.1
	(2.94)			(0.31)	(0.30)	(42,551.8)
Group 5	45.89	33	523	0.39	0.59	35,155.5
	(17.08)			(0.29)	(0.27)	(50,926.8)
Observations	44,245					

Notes: Standard deviations in parentheses. Groups 1 to 5 represent firm tenure grouped into quintiles (i.e., 5 percentiles). The values in the columns of AI and automation represent the proportion of workers highly exposed to AI and automation, respectively. The LP column shows Labor Productivity. Unlike the regressions, which cover 2017 to 2021, here only 2021 is considered, resulting in fewer observations.

Table 4: Descriptive statistics for worker's age

Worker's age	**Total**	**Min**	**Max**	**AI**	**Automation**	**LP**
Group 1	33.67	19.1	37.11	0.42	0.58	27,776.1
	(2.77)			(0.38)	(0.36)	(36,455.8)
Group 2	39.08	37.11	40.83	0.41	0.58	30,941.5
	(1.06)			(0.34)	(0.31)	(48,928.0)
Group 3	42.31	40.83	43.75	0.37	0.58	32,239.3
	(0.83)			(0.31)	(0.30)	(46,762.1)
Group 4	45.32	43.75	47.01	0.36	0.57	33063.0
	(0.94)			(0.30)	(0.30)	(53,100.4)
Group 5	49.91	47.01	68.00	0.34	0.56	31,092.6
	(2.43)			(0.29)	(0.30)	(81,068.4)
Observations	44,245					

Notes: Standard deviations in parentheses. Groups 1 to 5 represent workers' age grouped into quintiles (i.e., 5 percentiles). The values in the columns of AI and automation represent the proportion of workers highly exposed to AI and automation, respectively. The LP column shows Labor Productivity. The ages of 17 and 68 were attributed to workers in the categories under 17 or above 68, respectively. Unlike the regressions, which cover 2017 to 2021, here only 2021 is considered, resulting in fewer observations.

This analysis facilitates the understanding of firm and worker specific factors that may influence productivity. Larger and older firms with more educated workers, an average worker age up to 45, and fewer women seem to be more productive. Furthermore, industry and region also seem to trigger productivity disparities. The previously mentioned factors, along with year, will act as control variables in the analysis.

To study possible patterns between digitalization and productivity, we adopt two different approaches. Figure 1 shows firms' productivity divided into 4 categories, based on the majority of workers highly exposed to digitalization. We define 2 dummy variables, each taking a value of 1 if the majority of workers are highly exposed to AI or automation, respectively (quadrants I and IV), and 0 otherwise. We observe that high AI exposures are, on average, linked to the highest productivity levels, while high automation exposures are connected to less productive firms – quadrant I (high AI, low automation) contains the most productive firms, and quadrant IV (low AI, high automation) the least productive. This categorization is similar to the one implemented by Fossen and Sorgner (2019), with adaptations made to classify firms instead of occupations, and with a focus on productivity; each quadrant represents the average productivity of firms dependent on their workers' exposure to AI and automation, simultaneously.

AI		
High	I 46,974.72 (106,156.30)	II 41,635.06 (64,360.63)
Low	III 27,861.66 (36,736.62)	IV 24,480.17 (22,915.02)
	Low	High
	Automation	

Figure 1: Descriptive statistics for productivity with low/high AI and automation exposure. Mean of firms' Labor Productivity. Standard deviations in parenthesis

Figure 2 divides firms' productivity into 9 categories, based on whether the majority of workers have high, medium, or low exposure to digitalization. Firms with no exposure level majority are excluded from this analysis – 14.6% of firms for AI levels and 11.6% of firms for automation. Automation exposure levels are categorized according to Frey and Osborne (2017) probabilities of automation; AI exposure levels are divided by percentiles, using the same thresholds as Frey and Osborne (2017): high if above the 70th, medium if between the 70th and 30th, and low if below the 30th. We observe again a positive relation between high AI exposure and firms' productivity – the most productive firms are in the first three quadrants (high AI exposure). Moreover, we see that high automation exposure is never beneficial, as the third column consistently doesn't exhibit the highest productivity – automation entirely without human workforce will be counterproductive (Agrawal et al., 2019). To note that the standard deviations are considerably large, indicating substantial variability in the grouped samples.

AI	Automation: Low	Automation: Medium	Automation: High
High	I 49,247.04 (116,450.80)	II 45,390.34 (131,556.90)	III 45,500.04 (67,104.77)
Medium	IV 23,434.08 (21,435.88)	V 30,224.89 (35,900.53)	VI 26,079.29 (34,599.27)
Low	VII 25,156.66 (15 922.97)	VIII 23,239.30 (23,266.65)	IX 23,380.01 (20,024.07)

Automation

Figure 2: Descriptive statistics for productivity with low, medium and high AI and automation exposures. Mean of firms' Labor Productivity. Standard deviations in parenthesis

From this analysis, we observe that high AI exposure seems to increase firms' productivity, whereas high automation exposure seems to decrease it; we will validate these inferences in Chapter 5.

Chapter 4. Methodology

We study the effect of digitalization technologies on firms' productivity by applying Fixed Effects models. To link digitalization exposures with firms' productivity, we measure the exposure of each occupation (and respective worker) to AI (Felten et al., 2021) and automation (Frey and Osborne, 2017) given the tasks they include.

Felten et al. (2021) link AI applications to occupational abilities through a measure of AI exposure across occupations, AIOE. To develop this measure, they assess how 10 critical AI applications (abstract strategy games, real-time video games, image recognition, visual question answering, image generation, reading comprehension, language modeling, translation, speech recognition and instrumental track recognition) relate to occupational abilities. The exposure is calculated based on the relatedness between AI applications and abilities, weighted by the relevance of these abilities in different occupations – based on 52 O*NET occupational abilities. This measure is standardized to have a mean of 0 and a standard deviation of 1. An AIOE of 0 indicates that an occupation has an average level of AI exposure when compared to other occupations; a positive score reveals that the occupation's AI exposure is higher than the average; and a negative score suggests that the exposure is lower than the average. This measure is expressed by equations 1 and 2.

$$A_{ij} = \sum_{i=1}^{10} x_{ij} \tag{1}$$

$$AIOE_k = \frac{\sum_{j=1}^{52} A_{ij} \times L_{jk} \times I_{jk}}{\sum_{j=1}^{52} L_{jk} \times I_{jk}} \tag{2}$$

Where *i, j* and *k* index the AI application, the occupational ability and the occupation, respectively. A_{ij} represents the ability-level AI exposure, calculated as the sum of the 10 application-ability relatedness scores, x_{ij}. The exposure of an occupation to AI, $AIOE_k$, is obtained by weighting the ability-level AI exposure, A_{ij}, by the ability's prevalence, L_{jk}, and importance, I_{jk}.

Frey and Osborne (2017) employ a Gaussian process classifier – a machine learning model for task classification that relies in probabilistic principles and Bayesian inference (update of predictions based on new data) – to estimate the probability of automation for occupations. They use the O*NET database, which provides detailed descriptions of occupations, including required skills, abilities, and work activities, to extract key job characteristics. The Gaussian process classifier is trained with the O*NET data and experts' assessment on 70 occupations, labeling them as either automatable or non-automatable, and with this, the model assigns an automation probability, between 0 and 1, to each of the 702 occupations, by sorting which occupations are associated with the main bottlenecks of automation. The automation probability function used is shown in equation 3.

$$P(y^* = 1 \mid f^*) = \frac{1}{1 + \exp(-f^*)} \tag{3}$$

Where f^* reflects the automation likelihood of occupations and $P(y^* = 1 \mid f^*)$ converts it into a probability of job automation, between 0 (no automation probability) and 1 (completely automatable). Furthermore, Frey and Osborne (2017) divide occupations into 3 groups, according to their automation probability: low ($P < 0.3$), medium ($0.3 \leq P \leq 0.7$) and high ($P > 0.7$) risk occupations.

Each worker is linked to a certain occupation and so, with the measures of Felten et al. (2021) and Frey and Osborne (2017), we obtain the exposure of workers to AI and automation. To aggregate the digitalization exposure to the firm-level, we employ 3 measures: Measure 1 – percentage of workers highly exposed in a firm; Measure 2 – average exposure of workers in a firm; and Measure 3 – percentage of workers with high, medium and low exposures.

Measure 1 is formed by taking the AIOE exposure scores/automation probability of workers and calculating the percentage of workers in each firm with scores above 0/an automation probability above 70% – measures the *Percentage of workers highly exposed to AI/automation.* Measure 2 is built from computing the average of the AIOE exposure scores/ automation probabilities in each firm – it is a standardized score in the first case and an average probability in the second – an *Average AI exposure* of 0.6 means that the average workers in a firm have an exposure to AI which is moderately above the average of occupations. Measure 3 is an extension of the first measure, but divides the exposure levels into 3 categories; for automation, the metrics are formed in a similar manner: *Percentage of workers highly/moderately/with low exposure to automation* are the percentage of workers in each firm with an automation probability above 70%, between 30% and 70%, and under 30%, respectively. The AI metrics are formed by dividing the standardized AIOE scores into percentiles, according to the same thresholds (30% and 70%) – a *Percentage of workers moderately exposed to AI* of 60 conveys that 60% of the workers in a firm are between the percentiles 30% and 70% of AI exposure. The Average AI exposure is standardized and ranges from -1.95 to 1.45. All other explanatory variables are percentages.

The same firms are followed through a period of 5 years (from 2017 to 2021); thus, we observe the same firms at different points in time. Having a panel dataset allows us to obtain unbiased estimates even when the unobserved time-constant factors are correlated with the explanatory variables. Our dataset is unbalanced, since there are firms that appear/disappear in the time period in analysis, which might lead to selection bias, as productivity shocks drive firm survival; we are overvaluing the surviving firms, since those who dye contribute fewer times.

We apply Fixed Effects methods to estimate the productivity functions, which allow to account for firm-specific characteristics that do not change over time. Fixed Effects are included for region, industry and year, to control broader factors that may affect productivity, and standard errors are clustered at the firm-level, to address correlation with-in firms and heteroskedasticity. Furthermore, we assume strict exogeneity of all the explanatory variables regarding the idiosyncratic error term – that the explanatory variables are not influenced by the error term at any point in time.

Equation 4 below estimates firms' productivity through the following worker productivity metrics: *Turnover per Worker* and *Labor Productivity*. The same equation is also used to estimate firm productivity, through the measures *Turnover* and *Gross Value Added*, though the study will concentrate mostly on worker productivity metrics (firm productivity metrics can be found in Appendix B).

$$Firms'Productivity_{ft} = \rho AI_{ft} + \lambda Automation_{ft} + \theta IP_{ft} + \Upsilon CV_{ft} + \alpha_f + \mathcal{E}_{ft} \quad (4)$$

Where AI_{ft} and $Automation_{ft}$ represent the exposures to AI and automation, respectively, in firm *f* and in year *t* – the coefficients of these variables allow us to test the hypothesis developed in Chapter 2; they are assessed through 3 different metrics, as described above. IP_{ft} is a vector containing the inputs of the productivity function and CV_{ft} a vector including the Control Variables. α_f is the time constant, firm specific error and ε_{ft} the idiosyncratic, time-varying error.

Additionally, we assess firms' productivity through TFP_{ft}, a productivity metric developed by Ackerberg et al. (2015) in which conditional demand functions are implemented, by considering how productivity affects firms' decisions on inputs, which are made at different points in time (staggered timing). TFP is the residual productivity, that is, the output that remains unexplained by the inputs of labor and capital used, and is employed in studies such as Brynjolfsson et al. (2017) and Gao and Feng (2023). It is a firm productivity metric, yet remains relevant to the study since it allows to account for endogeneity, that is, the explanatory variables being correlated with the error term. Ackerberg et al. (2015) methodology is built on the methods of Olley and Pakes (1996) and Levinsohn and Petrin (2003), who address the problem of simultaneity bias, arising from firms choosing their input levels based on expected productivity, and corrects their functional dependence problem (due to labor being fully determined by other inputs), by allowing a more flexible treatment of endogeneity – the assumption that inputs are selected once productivity is fully observed is relaxed. With TFP_{ft}, the strict exogeneity assumption, which implies a one-way causal relationship between dependent and independent variables, is more robust.

Resembling Ackerberg et al.'s (2015) method, we apply a two-stage estimation to assess firms' productivity. In the first stage (equations 5 and 6) we estimate a structural production function using capital as a predetermined state variable, labor as a flexible free variable, and intermediate inputs as a proxy for unobserved productivity. This allows to extract TFP_{ft}, which represents the unobserved productivity, known to firms but not to econometricians, which would lead to bias due to endogeneity, as a result of correlation between inputs and productivity shocks. In the second step, captured by equation 7, we analyze the factors that influence TFP_{ft} (which expresses the efficiency with which inputs are used in the production process), by applying Fixed Effects methods.[1]

$$Firms'Productivity_{ft} = \delta K_{ft} + \varphi L_{ft} + TFP_{ft} + \varepsilon_{ft} \tag{5}$$

[1] The Stata command used to perform this estimation is *acfest*, developed by Manjón and Mañez (2016).

$$\widehat{TFP} = Firms'Productivity_{ft} - (\hat{\delta}K_{ft} + \hat{\varphi}L_{ft}) \quad (6)$$

$$\widehat{TFP} = \rho AI_{ft} + \lambda Automation_{ft} + \theta IP_{ft} + \Upsilon CV_{ft} + \alpha_f + \mathcal{E}_{ft} \quad (7)$$

Where Capital, K_{ft}, is a vector incorporating *Fixed Capital Formation* and *Non-Current Assets*, and Labor, L_{ft}, comprises *Personnel Expenses* (given that worker productivity metrics overlook firm size, a monetary variable was adopted for Labor, instead of number of workers). *Intermediate Consumption* is used as a proxy to control for TFP, since more productive firms typically use more inputs—making it a useful indicator of unobserved productivity.

The methodology adopted in the study is grounded in the research of several other authors. It complements the work of Frey and Osborne (2017) in that it does not only compute the effect of destructive digitalization, but it also studies the effect of constructive digitalization. Its final goal is also broader, since it focuses on the effects on firms rather than on individual occupations. Moreover, it resembles the study of Fonseca et al. (2018) in that it also classifies firms' productivity, likewise employing TFP as a productivity measure. However, Fonseca et al. (2018) categorizes firms based on the type of tasks their workforce performs (abstract, routine or manual) while we classify firms according to the percentage of workers highly exposed to digitalization technologies. Cerqueira et al.'s (2023) study (focused on the effect of the timing of digital adoption) is also relevant, since it employs Fixed Effects estimators, as we do, and uses identical productivity metrics. The productivity function inputs employed were derived from this study.

Chapter 5. Results

In this chapter, we discuss the results obtained from the regressions conducted to address our research question: "What is the impact on firm productivity of workforce exposure to AI and automation?". For this purpose, we analyze three sets of regressions, each incorporating a different metric of AI and automation exposure. In order to clearly identify the impact of each digitalization technology on productivity and avoid multicollinearity, we estimate the individual effect of AI and automation on productivity, in addition to estimating their joint effect and their effect including an interaction term, for each set of regressions. We conduct the analysis with several productivity metrics, to increase the robustness of the results. Namely, we estimate the effect of digitalization technologies on five dependent variables: Labor Productivity, Turnover per Worker (worker productivity metrics), TFP, GVA and Turnover (firm productivity metrics). Only the three first metrics are displayed in the tables of this Chapter.

All models are estimated using Fixed Effects.[2] Coefficient estimates are considered statistically significant at the 10% level (when p-values are below 0.1); none of the control variables included (firm's size, tenure, industry, region, worker's gender and level of education), with the exception of workers' age, are individually statistically significant, due to limited within-firm variation over time. As expected, the inputs of the productivity function, namely Labor, Intermediate inputs and Capital, are positively correlated with productivity. Across all the regressions, we measure the impact of AI and automation exposure on productivity in basis points (e.g., one-hundredth of a percentage point), given the small magnitude of the effect. The variation across the three sets of regressions comes exclusively from the different metrics of AI and automation exposure being computed.

Table 5 presents the first set of regressions, concerning the impact of high workforce exposure to digital technologies on productivity. Regarding AI exposure, we notice that a greater percentage of workers highly exposed to AI has a positive effect on productivity – the AI exposure metric shows positive and highly significant coefficients. This aligns with our expectations, since various authors predict a positive correlation between AI adoption and firm productivity (Lee et al., 2022; Damioli et al., 2021; Czarnitzki et al., 2023), a pattern that

[2] Although random effects were also computed, they are not reported, as the Hausman test indicates strong correlation between individual effects and regressors, favoring Fixed Effects.

is also reflected in Chapter 3 (Descriptive Statistics). In Panel A we observe that a one percentage point increase in the percentage of workers highly exposed to AI leads to an average increase of 0.06 basis points (bps) in Labor Productivity, a boost of 0.32 bps in Turnover per Worker, and a rise of 0.09 bps in TFP, supporting Hypothesis 2 (positive effect of AI on productivity). Moreover, comparing these values with the percentage of workers highly exposed to AI in Panel C (in which the regressions include AI and automation measures simultaneously), we perceive a slight reduction in the coefficients of the latter, indicating that the effect of AI on productivity is partly absorbed by the effect of automation.

Examining the effect of workforce highly exposed to automation on productivity, we observe that the automation coefficient is only statistically significant for TFP, and only when automation is considered independently (Panel B). Moreover, its effect is negative and rather small: a one percentage point increase in the percentage of workers highly exposed to automation causes an average decrease of 0.04 bps in TFP, contradicting hypothesis 1 (positive effect of automation on productivity). These results are in line with the contradicting effects of automation, described by several authors (e.g., Acemoglu and Restrepo, 2019; Restrepo, 2024), who note that automation can have both positive and negative impacts on firm performance; this makes it difficult to observe a pattern connecting automation levels and productivity.

Panel D displays the regressions including an interaction term between AI and automation, which captures the relationship between the two variables (e.g., the conditional effect of AI on productivity, depending on the level of automation). From the negative significant interaction coefficient in the Turnover per worker regression, we infer that the productivity-increasing effect of AI exposure is weaker in workplaces with high automation exposure. This relationship can also be observed in Figure 3, which shows that the marginal effect of AI on Turnover per worker starts at 0.5 bps for an automation level of 0%, and subsequently decreases with the rise in automation exposure. However, the marginal effect never falls below 0 — the effect of AI exposure on productivity is positive, regardless of the level of automation exposure. It is important to note that the percentage of workers exposed to AI and automation is not mutually exclusive; both values can be simultaneously 0% or 100%.

Table 5: Percentage of workers highly exposed to AI and automation, impact on productivity

	(1) LP	(2) Turnover / Wkr	(3) TFP
Panel A: AI			
% of workers highly exposed to AI	0.058***	0.320***	0.090***
	(0.020)	(0.105)	(0.020)
Panel B: Automation			
% of workers highly exposed to automation	-0.026	-0.102	-0.038**
	(0.016)	(0.095)	(0.016)
Panel C: AI & Automation			
% of workers highly exposed to AI	0.055***	0.308***	0.084***
	(0.020)	(0.107)	(0.020)
% of workers highly exposed to automation	-0.018	-0.058	-0.026
	(0.016)	(0.097)	(0.016)
Panel D: Interaction			
% of workers highly exposed to AI	0.073**	0.502***	0.112***
	(0.031)	(0.168)	(0.031)
% of workers highly exposed to automation	-0.005	0.081	-0.006
	(0.022)	(0.134)	(0.022)
% highly exposed to AI x % highly exposed to automation	-0.033	-0.348*	-0.050
	(0.039)	(0.211)	(0.039)
Observations	163,792	163,792	163,792

Notes: Standard errors (clustered at the firm level) in parentheses. Regressions include controls for firm's size, tenure, industry, region, worker's age, gender, level of education and year dummies. The productivitiy functions include inputs for labor, capital and intermediate consumption. All dependent variables and inputs of productivity function are in log form. Values are expressed in basis points (1 basis point = 0.01 percentage point).
* p < 0.10, ** p < 0.05, *** p < 0.01

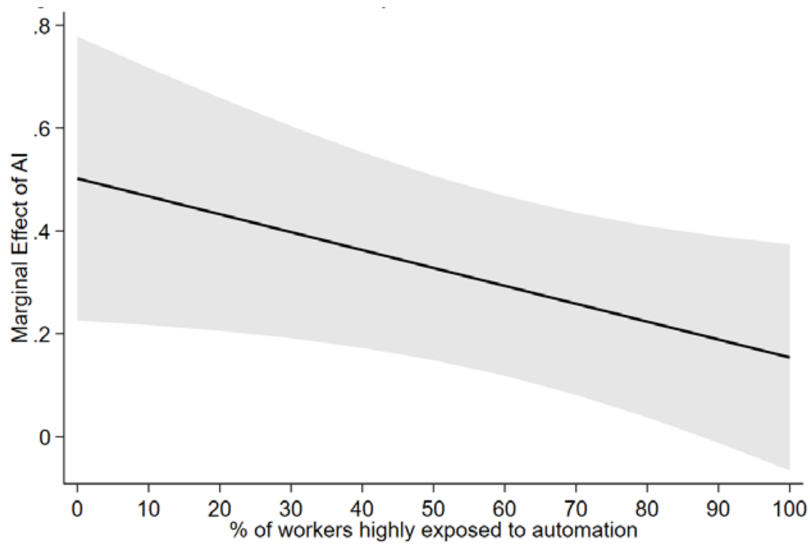

Figure 3: Marginal effect of AI on Turnover per worker (90% confidence interval)

Table 6 display the results of the second set of regressions, illustrating the effect of the average workforce exposure to AI and automation on productivity, and it allows to assess the robustness of the previous results. In panels A and C, we notice that our inferences regarding AI's effect on productivity remain fundamentally the same — AI exposure shows a positive effect on productivity (positive significant coefficients). Concerning automation exposure, illustrated in Panels B and C, it exhibits negative significant coefficients for Labor Productivity and TFP, though the magnitude of these coefficients is small, suggesting that automation exposure seems to be connected with slight reductions in productivity. Our findings align with those of Agrawal et al. (2019), who emphasize the risks of excessive automation, driven by factors such as capital-oriented tax policies and labor market imperfections, potentially leading to inefficiencies. Furthermore, automation is characterized by replacing human labor by machines (Acemoglu and Restrepo, 2019) and so, a potential reason for the challenge in identifying automation's effect on worker productivity might be that with this replacement, worker productivity can no longer be measured — only that of the substituting machines. Observing panels C of Tables 6 and 7, which depict AI and automation simultaneously, we notice that automation is only significant for TFP (firm productivity metric), which might point to the validity of this theory.

Table 6: Average exposure to AI and automation, impact on productivity

	(1) LP	(2) Turnover / Wkr	(3) TFP
	Panel A: AI		
Average AI exposure	0.041*** (0.011)	0.228*** (0.061)	0.059*** (0.011)
	Panel B: Automation		
Average automation exposure	-0.059** (0.028)	-0.258 (0.160)	-0.096*** (0.028)
	Panel C: AI & Automation		
Average AI exposure	0.038*** (0.011)	0.218*** (0.063)	0.053*** (0.011)
Average automation exposure	-0.030 (0.028)	-0.095 (0.166)	-0.056** (0.028)
	Panel D: Interaction		
Average AI exposure	0.056** (0.025)	0.370** (0.149)	0.065** (0.026)
Average automation exposure	-0.026 (0.028)	-0.061 (0.171)	-0.053* (0.028)
AI exposure x Automation exposure	-0.026 (0.035)	-0.231 (0.204)	-0.019 (0.035)
Observations	163,792	163,792	163,792

Notes: Standard errors (clustered at the firm level) in parentheses. Regressions include controls for firm's size, tenure, industry, region, worker's age, gender, level of education and year dummies. The productivitiy functions include inputs for labor, capital and intermediate consumption. All dependent variables and inputs of productivity function are in log form. Values are expressed in basis points (1 basis point = 0.01 percentage point).
* p < 0.10, ** p < 0.05, *** p < 0.01

The third set of regressions, depicted in Table 7, examines the effect of exposure to 3 levels of digitalization technologies: high, medium and low. We observe that the positive significant impact of high AI exposure on firms' productivity persists. Moreover, medium AI exposure also reveals to have a significant positive impact on Turnover per worker, when compared to the base case of low AI exposure. The conclusions regarding the impact of high automation exposure on productivity also remain the same – small negative effect. Medium levels of automation exposure also appear to have a negative impact on productivity.

Table 7: Percentage of workers with high, medium and low exposure to AI and automation, impact on productivity

	(1) LP	(2) Turnover / Wkr	(3) TFP
Panel A: AI			
% of workers highly exposed to AI_PCTL	0.112***	0.517***	0.150***
	(0.027)	(0.137)	(0.026)
% of workers moderatly exposed to AI_PCTL	0.015	0.232**	0.021
	(0.017)	(0.106)	(0.018)
Panel B: Automation			
% of workers highly exposed to automation	-0.069***	-0.257*	-0.112***
	(0.024)	(0.137)	(0.024)
% of workers moderately exposed to automation	-0.067**	-0.238	-0.114***
	(0.027)	(0.153)	(0.026)
Panel C: AI & Automation			
% of workers highly exposed to AI_PCTL	0.099***	0.475***	0.124***
	(0.028)	(0.144)	(0.028)
% of workers moderatly exposed to AI_PCTL	0.013	0.224**	0.016
	(0.018)	(0.106)	(0.018)
% of workers highly exposed to automation	-0.037	-0.121	-0.071***
	(0.025)	(0.145)	(0.025)
% of workers moderately exposed to automation	-0.035	-0.107	-0.074***
	(0.028)	(0.159)	(0.028)
Observations	163,792	163,792	163,792

Notes: Standard errors (clustered at the firm level) in parentheses. Regressions include controls for firm's size, tenure, industry, region, worker's age, gender, level of education and year dummies. The productivitiy functions include inputs for labor, capital and intermediate consumption. All dependent variables and inputs of productivity function are in log form. Values are expressed in basis points (1 basis point = 0.01 percentage point). Low exposure to AI and automation are the base cases.
* p < 0.10, ** p < 0.05, *** p < 0.01

Regarding the firm productivity measures Turnover and GVA, displayed in Tables B1, B2 and B3 in the Appendix, we notice that AI exposure seems to increase Turnover, but to decrease GVA. Furthermore, automation exposure does not seem to have a significant effect on Turnover, but its effect on GVA is positive and significant. Our conclusions regarding digitalization’s effect on productivity persist for Turnover, but the GVA metric appears to contradict the previous findings.

The discrepancy in results between GVA and the remaining productivity metrics could be due to multiple factors. Unlike Turnover, GVA considers the cost of intermediate inputs;

hence, one possible justification for the discrepancy in results may be high implementation costs, since initial inefficiencies can arise as employees and firms adapt to new AI systems (Brynjolfsson et al., 2017). Breakthrough technologies often trigger the creation of complementary assets before their positive effect becomes attainable (Horvat et al., 2019). Differences in measurement levels might also contribute to the divergence in results – AI may support tasks, improving worker productivity, but not necessarily increase firm output, if other inefficiencies exist. Moreover, in the productivity functions we use Personnel Expenses to account for labor, instead of number of workers; hence, if firms increase salaries but reduce the workforce, due to an increase in worker productivity (Tschang and Almirall, 2021) combined with the need for a higher skilled workforce (Goldin and Katz, 1998), the input may remain unchanged while the output decreases, resulting in a lower firm productivity, despite the increase in worker productivity.

When comparing the coefficients obtained in this study (measuring digitalization exposure) with those from analyses of AI adoption (directly measuring firm's use of digitalization technologies), we notice that the magnitude of digitalization's effect is much smaller in our analysis. Table 5 indicates that high AI exposure increases Labor Productivity and TFP in 0.06 and 0.09 basis points, respectively; regarding studies of AI adoption, Czarnitzki et al. (2023) reveal that AI use increases Labor Productivity in 14.6% and Nucci et al. (2023) estimate a 0.97 percentage points increase in TFP (coefficients 3 orders of magnitude larger than ours). It is essential to recognize the differing subjects under analysis between our research (extent to which occupations are affected by digital technologies) and studies of AI adoption (measuring if a firm has implemented at least one AI method in at least one business application area) – it is reasonable to observe weaker effects for workforce exposure to digitalization.

The previous regressions enable us to consistently test the Hypotheses developed in Chapter 2. High automation exposure is negative across all models in which it is significative, except for GVA. Therefore, we likely refute Hypothesis 1, stating that firms with a greater percentage of workers highly exposed to automation will experience an increase in productivity – we anticipate that workforce exposure to automation reduces productivity. On the contrary, the regression results confirm Hypothesis 2 (affirming that firms with a greater percentage of workers highly exposed to AI will experience an increase in productivity), since high AI exposure is positive and highly significant across all models, except for GVA – workforce exposure to AI likely increases productivity.

Digitalization technologies are commonly believed to increase productivity (Gal et al., 2019; Tschang and Almirall, 2021). Thus, regarding our findings, while AI's positive productivity effect was anticipated, the negative effect of automation was unexpected. Indeed, a review of the literature on the topic reveals that perspectives are not straightforward. Czarnitzki et al. (2023) find that AI increases firms' productivity, a conclusion shared by several authors, who identify a significant productivity gap between AI-patenting and non-patenting firms (Damioli et al., 2021), supporting our findings; yet, authors such as Calvino and Fontanelli (2023a) attribute this productivity difference to the self-selection of inherently more productive firms into AI adoption. Regarding automation, the perspectives on its effect also diverge; Humlum (2019) asserts that it positively impacts firm performance, while Foster-McGregor et al. (2021) identify a negative relationship between automation risk and Labor Productivity (highly productive countries concentrate employment in low automation-risk sectors). Agrawal et al. (2019) additionally argue that over automation may ultimately hinder productivity. The contradicting perspectives help to explain our difficulty in finding statistically significant effects of automation. Variations in results across authors may result from differences in the methodologies used to measure digitalization exposure or from variations on the level of analysis adopted (Filippi et al., 2023).

Furthermore, factors such as complementary assets reveal to considerably influence the impact of digitalization technologies (Horvat et al., 2019). Skilled labor is pointed as a crucial component to capture the benefits of digitalization: Goldin and Katz (1998) and Fontanelli et al. (2024) highlight the importance of human capital, mostly ICT engineers, for productivity growth through digitalization technologies. Calvino and Fontanelli (2023b) also note the importance of complementary technologies, such as ERP (Enterprise Resource Planning) and CRM (Customer Relationship Management) in promoting AI use. Additionally, timing and good management (Cerqueira et al., 2023), along with certain firm characteristics – such as being a larger or older firm (Nucci et al., 2023) – also seem to contribute to enhance the positive effects of digitalization.

Chapter 6: Conclusions

This dissertation aimed to clarify the relationship between workforce exposure to digitalization technologies and productivity. We study the impact of workforce exposure to AI and automation on firms' productivity, conditional on several firm and worker characteristics, with the goal of understanding whether these technologies are beneficial for workers' and firms' performance. Informing the Portuguese society on this topic is key, so that the right strategies can be adopted to boost the Portuguese economy and improve firms' competitiveness and profitability, while mitigating the negative effects of digitalization technologies.

We find that firms highly exposed to AI experience positive significant impacts on several productivity metrics. On the contrary, firms highly exposed to automation seem to be connected to lower productivity levels – automation's positive productivity effect is not observed. This indicates that, on average, workforce exposure to AI enhances firms' productivity, while workforce exposure to automation decreases it. We study the impact of digitalization exposure through several approaches: the effect of an increase in the percentage of workers highly exposed; the effect of an increase in the average workforce exposure; and the effect of an increase in the percentage of workers highly, medium and low exposed. The three analyses point to the same conclusions: AI tends to enhance productivity and automation to reduce it, across the full set of productivity metrics used, with the exception of GVA. The results of this study provide a potential justification for the productivity paradox (gap between expected and observed productivity); despite AI's positive contribution to productivity, automation might be generating a contradicting effect, decreasing productivity and ultimately slowing down productivity growth.

Studies on the effect of digitalization technologies on productivity are still scarce and with great limitations, due to the lack of quality data and longevity of these technologies, which results in the absence of a precise and universally accepted definition of AI – one of the limitations of this study. Moreover, we experience the problem of selection bias, since productivity drives firm survival and so, we tend to overvalue the most productive firms; in addition, workers highly exposed to AI often indicate firms' technological excellence, a sign in itself of higher productivity. Concerning the productivity metrics, an additional limitation is that both Turnover and Value Added contain non-positive values, which is an issue when converting the variables into log form. For Turnover, we transform the null values into 1, so that this doesn't pose a problem; for Value Added, no transformations are made, which results in a loss of around 1% of the observations – this is the variable with the smallest number of observations, consequently defining the sample size in the regressions – 163,792 observations. Additional challenges at measuring productivity are the difficulty in accurately quantifying all inputs (like labor and capital) and outputs, and differentiating between productivity shifts due to efficiency improvements or to external factors.

The metrics used to assess digitalization exposure also present certain constraints. Regarding destructive digitalization, we employ the measure of Frey and Osborne (2017) to assess occupations' exposure to automation, which some authors consider to overestimate automation risk – while Frey and Osborne (2017) predict that 47% of jobs in the US will be automatable in a near future, Arntz and Gregory (2016) anticipate an automation of only 9%. With respect to transformative digitalization, we employ the AIOE metric developed by Felten et al. (2021), examining the forthcoming impact of AI, which also has its limitations: when linking AI applications to occupational abilities, it equally weights the 10 AI applications, which is not realistic, since some applications will be more impactful than others; furthermore, AI applications are considered to be independent from each other, which is unlikely (e.g., visual question answering and image recognition). An additional limitation of this study is the lack of control for management or working conditions, despite several studies indicating its significant impact (Cerqueira et al., 2023).

Future research could consider alternative approaches to measuring digitalization exposure, for instance, through textual analysis of patents, as performed by Kogan et al. (2023) and Montobbio et al. (2024). Furthermore, directly assessing firms' use of digitalization technologies, particularly in terms of AI and automation adoption, could bring valuable insights into the topic – this approach was not possible due to the lack of information on firms' integration of digitalization technologies; nevertheless, it would allow to account for additional important factors, such as the impact of the timing of the adoption (Cerqueira et al., 2023) or the variation in effects between owned and leased technologies. In terms of productivity metrics, adapting TFP to measure worker productivity could also be interesting, as this is a comprehensive productivity metric that prevents endogeneity. Furthermore, examining the effect of digitalization technologies on productivity in the medium future and comparing it with the present results might be interesting, particularly considering the theories advocating technologies' retarded effects – Brynjolfsson et al. (2017) and Tschang and Almirall (2021) point out the historical delay in the effects of technologies, which primarily drive the development of complementary technologies before exerting a substantial influence on productivity (Horvat et al., 2019).

Considering the findings of this study, various policies may help to maximize the positive effects of digitalization and increase firms' productivity. Firstly, it is important to create incentives for AI adoption in firms, such as fiscal benefits and subsidies. Furthermore, firms need to be made accountable for improving their exposure to transformative digitalization, by investing in R&D (Research and Development) and supporting workers' formations, as well as being well informed on the trade-offs of digitalization, particularly on which factors enhance its positive effects. Goldin and Katz (1998) and Mollins and Taskin (2023) highlight the importance of skilled labor in grasping positive productivity effects. Policies for increasing workers' digital literacy and to promote higher education are essential, resultant from a growth of the skill-premium within firms (Barth et al., 2020; Jaimovich et al., 2012). Adapting curriculums is also important, so that skill acquisition is aligned with the critical competences for digitalization – abstract tasks; capabilities such as communication, collaboration, and creativity, as well as skills of analysis of diverse types of information, must be cultivated (Casas et al., 2025), so that ultimately worker and firm productivity increases. Finally, it is important to develop policies which distribute the positive effects of transformative digitalization not only to firms, but also to workers; if workers and firms are more efficient, workers' wages and working schedules must reflect this progress.

This dissertation contributes to address the gap in literature on the effects of digitalization technologies on firm productivity. It provides insights into digitalization's effect on firm productivity, which might contribute to accelerating Portugal's economic growth, by driving efficient policies which maximize the benefits of digitalization. We adopt an infrequent approach in the assessment, by measuring workforce exposure to digitalization, instead of AI and automation adoption; our findings underscore the importance of high workforce exposure to AI in boosting workers' and firms' performance, while signaling potential drawbacks of automation – they highlight the importance of digital literacy and corporate digital integration, particularly of AI technologies.

Recognizing the impact of digitalization technologies on productivity raises the question of what its far-reaching consequences will be. Are the possible increases in productivity ultimately likely to deliver positive externalities to society (e.g., will more productive firms invest in greener solutions; will its workers have a better quality of life)?. An adequate digitalization adoption might help to pair Portugal with the other European countries, rendering the Portuguese labor market more competitive. However, issues such as cybersecurity and data confidentiality must not be neglected.

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Appendix

Appendix A - Descriptive statistics for industry and region

Table A1: Descriptive statistics for *industry*

Industry	AI	Automation	LP	N	Designation
A	0.26	0.52	25,467.5	1,250	Agriculture, production animal, hunting, forestry, and
	(0.29)	(0.37)	(32,762.0)		fishing
B	0.20	0.50	43,107.5	190	Extractive industries
	(0.13)	(0.27)	(42,830.1)		
C	0.25	0.70	29,403.5	10,971	Manufacturing industries
	(0.20)	(0.23)	(47,582.2)		
D	0.81	0.35	108,981.1	68	Electricity, gas, steam, hot and cold water, cold air
	(0.26)	(0.29)	(470,406.8)		
E	0.32	0.48	53,971.8	305	Water collection, treatment and distribution,
	(0.20)	(0.26)	(48,432.0)		sanitation, management of waste, and depollution
F	0.24	0.62	25,145.3	5,907	Construction
	(0.20)	(0.28)	(33,350.0)		
G	0.49	0.62	37,350.5	9,424	Wholesale and retail trade; repair of motor vehicles
	(0.30)	(0.25)	(42,655.0)		and motorcycles
H	0.28	0.26	40,738.2	1,912	Transportation and storage
	(0.27)	(0.29)	(86,831.4)		
I	0.15	0.75	17,549.2	4,936	Accommodation and food service activities
	(0.19)	(0.24)	(12,945.6)		
J	0.93	0.25	51,226.3	1,273	Information and communication activities
	(0.17)	(0.29)	(150,146.9)		
L	0.61	0.48	54,329.7	492	Real estate activities
	(0.34)	(0.27)	(146,306.9)		
M	0.85	0.41	38,498.8	2,496	Consulting, scientific, technical, and similar activities
	(0.26)	(0.35)	(42,304.0)		
N	0.43	0.44	29,317.0	1,772	Administrative and support service activities
	(0.39)	(0.36)	(48,600.5)		
P	0.86	0.19	23,025.2	751	Education
	(0.15)	(0.17)	(14,989.2)		
Q	0.52	0.20	26,329.7	1,663	Human health and social support activities
	(0.33)	(0.20)	(28,892.0)		
R	0.50	0.37	28,804.1	397	Artistic, entertainment, sportive, and recreational
	(0.31)	(0.29)	(54,020.7)		activities
S	0.51	0.47	19,835.2	438	Other service activities
	(0.37)	(0.33)	(23,875.6)		
Observations				44,245	

Notes: Standard deviations in parentheses. The values in the columns of AI and automation represent the proportion of workers highly exposed to AI and automation, respectively. The LP column shows Labor Productivity. Unlike the regressions, which cover 2017 to 2021, here only 2021 is considered, resulting in fewer observations.

Table A2: Descriptive statistics for region

Region	AI	Automation	LP	N	Details
11	0.34	0.61	27,185.6	17,448	North
	(0.30)	(0.30)	(38,213.1)		
15	0.33	0.57	27,896.8	2,124	Algarve
	(0.30)	(0.32)	(55,854.4)		
16	0.36	0.58	30,983.8	9,104	Centre
	(0.29)	(0.30)	(33,333.2)		
17	0.49	0.52	37,691.7	11,525	Lisbon
	(0.37)	(0.33)	(83,660.3)		
18	0.33	0.59	29,947.5	2,301	Alentejo
	(0.30)	(0.31)	(41,306.7)		
20	0.31	0.60	25,953.3	833	Azores
	(0.28)	(0.30)	(29,345.9)		
30	0.35	0.60	35,295.9	910	Madeira
	(0.32)	(0.29)	(86,896.5)		
Observations				44,245	

Notes: Standard deviations in parentheses. The values in the columns of AI and automation represent the proportion of workers highly exposed to AI and automation, respectively. The LP column shows Labor Productivity. Unlike the regressions, which cover 2017 to 2021, here only 2021 is considered, resulting in fewer observations.

Appendix B – Results for Turnover and GVA

Table B1: Percentage of workers highly exposed to AI and automation, impact on productivity

	(1) Turnover	(2) GVA
Panel A: AI		
% of workers highly exposed to AI	0.197*	-0.064***
	(0.104)	(0.017)
Panel B: Automation		
% of workers highly exposed to automation	-0.042	0.034***
	(0.095)	(0.013)
Panel C: AI & Automation		
% of workers highly exposed to AI	0.194*	-0.059***
	(0.106)	(0.017)
% of workers highly exposed to automation	-0.014	0.026*
	(0.096)	(0.013)
Panel D: Interaction		
% of workers highly exposed to AI	0.397**	-0.031
	(0.165)	(0.025)
% of workers highly exposed to automation	0.131	0.046**
	(0.133)	(0.018)
% highly exposed to AI x % highly exposed to automation	-0.365*	-0.050
	(0.208)	(0.031)
Observations	163,792	163,792

Notes: Standard errors (clustered at the firm level) in parentheses. Regressions include controls for firm's size, tenure, industry, region, worker's age, gender, level of education and year dummies. The productivitiy functions include inputs for labor, capital and intermediate consumption. All dependent variables and inputs of productivity function are in log form. Values are expressed in basis points (1 basis point = 0.01 percentage point).

* p < 0.10, ** p < 0.05, *** p < 0.01

Table B2: Average exposure to AI and automation, impact on productivity

	(1) Turnover	(2) GVA
Panel A: AI		
Average AI exposure	0.141**	-0.045***
	(0.061)	(0.009)
Panel B: Automation		
Average automation exposure	-0.111	0.088***
	(0.158)	(0.023)
Panel C: AI & Automation		
Average AI exposure	0.141**	-0.039***
	(0.063)	(0.010)
Average automation exposure	-0.006	0.059**
	(0.164)	(0.023)
Panel D: Interaction		
Average AI exposure	0.332**	0.018
	(0.147)	(0.020)
Average automation exposure	0.036	0.071***
	(0.169)	(0.023)
AI exposure x Automation exposure	-0.290	-0.086***
	(0.201)	(0.027)
Observations	163,792	163,792

Notes: Standard errors (clustered at the firm level) in parentheses. Regressions include controls for firm's size, tenure, industry, region, worker's age, gender, level of education and year dummies. The productivitiy functions include inputs for labor, capital and intermediate consumption. All dependent variables and inputs of productivity function are in log form. Values are expressed in basis points (1 basis point = 0.01 percentage point).

* p < 0.10, ** p < 0.05, *** p < 0.01

Table B3: Percentage of workers with high, medium and low exposure to AI and automation, impact on productivity

	(1) Turnover	(2) GVA
	Panel A: AI	
% of workers highly exposed to AI_PCTL	0.334**	-0.071***
	(0.137)	(0.023)
% of workers moderatly exposed to AI_PCTL	0.174	-0.043***
	(0.106)	(0.015)
	Panel B: Automation	
% of workers highly exposed to automation	-0.121	0.066***
	(0.135)	(0.020)
% of workers moderately exposed to automation	-0.122	0.049**
	(0.151)	(0.022)
	Panel C: AI & Automation	
% of workers highly exposed to AI_PCTL	0.322**	-0.054**
	(0.144)	(0.024)
% of workers moderatly exposed to AI_PCTL	0.172	-0.040***
	(0.106)	(0.015)
% of workers highly exposed to automation	-0.032	0.052**
	(0.143)	(0.020)
% of workers moderately exposed to automation	-0.036	0.036
	(0.158)	(0.023)
Observations	163,792	163,792

Notes: Standard errors (clustered at the firm level) in parentheses. Regressions include controls for firm's size, tenure, industry, region, worker's age, gender, level of education and year dummies. The productivitiy functions include inputs for labor, capital and intermediate consumption. All dependent variables and inputs of productivity function are in log form. Values are expressed in basis points (1 basis point = 0.01 percentage point). Low exposure to AI and automation are the base cases.

* p < 0.10, ** p < 0.05, *** p < 0.01

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