

A Service of

ZBW

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

Tiedtke, Julian

Conference Paper Unveiling the Job-Creating and Destroying Effects of Automation through the Lense of Heterogeneity

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2024: Upcoming Labor Market Challenges

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Tiedtke, Julian (2024) : Unveiling the Job-Creating and Destroying Effects of Automation through the Lense of Heterogeneity, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2024: Upcoming Labor Market Challenges, ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at: https://hdl.handle.net/10419/302375

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



WWW.ECONSTOR.EU

Unveiling the Job-Creating and Destroying Effects of Automation through the Lens of Heterogeneity

Julian Tiedtke¹

PhD Student, Institute of Economics, Scuola Superiore Sant'Anna di Pisa

February 27, 2024

Abstract

In this paper we study the impact of investment in automation-related goods on firm- and worker-level outcomes in Portuguese manufacturing over the period 2004-2021. For this purpose, we combine linked employer-employee data and firm balance sheet data with automation-related imports from trade transaction data. We estimate the effects on adopters' outcomes within a difference-in differences design exploiting import lumpiness in product categories linked to automation and AI technologies. We contribute to this emerging literature in three ways: First, we confirm several of the firm-and industry-level. Second, we investigate heterogeneous effects across different type of workers by looking at the impact on employment shares. Third, we study heterogeneous effects across different type of firms considering firm size and firm age. We find a positive average effect on the adopters' employment, valueadded and the labor share, whereas mean hourly wages decline two years after the automation event. Investigating differences in the treatment effect across different group of workers, we find that the employment share of low-educated workers, bluecollar workers and routine-intensive workers increases. Crucially, the employment effect is heterogeneous across firms: a positive scale effect is predominant among small firms, whereas a negative displacement effect is predominant larger firms. In addition, we detect positive employment effects among young firms, but not for old firms. Finally, we find that the positive effects for low-educated, routine-manual and blue-collar workers are driven by the employment increases in small firms. In contrast, in larger firms automation favors high-educated workers at cost of middle-educated workers. Our results emphasize that heterogeneity and the socioeconomic context matter.

1 Introduction

Does automation steal our jobs? Automation is defined as a technology that can perform a task without human intervention (Nof, 2009) and therefore may replace workers in some or all of their tasks. Recent advances in robots and Artificial Intelligence (AI) and their rapid diffusion raised again concerns about the potential adverse effects of automation on employment and inequality (Ford, 2015; Eurobarometer, 2017; Pew, 2017; Arntz et al., 2022). Such concerns have been further fueled by a number of speculative studies predicting striking job losses in occupations that are susceptible to automation (Arntz et al., 2017; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018). It comes unsurprising that the question about how automation affect the organisation of work, tasks and industries receives enormous attention both among researchers and the general public.

From a theoretical point of view, the effects of the adoption of automation technology on employment are ambiguous as both job creating and destroying mechanisms may be at work. In the task-based model (Acemoglu and Restrepo, 2019, 2022; Restrepo, 2023), automation displaces increasingly workers performing routine-intensive tasks. These are in particular clerical or production jobs with routine tasks that are easier to codify and automate (Autor et al., 2003). However, this initial displacement effect may be counteracted by cost-saving gains and by the creation of new tasks leading firms to expand their production scale and increase their demand of labor. These compensation effects are likely to work in favor of workers performing non-automated tasks. Moreover, when adopters increase their productivity and gain market shares this occurs at costs of non-adopting competitors that experience productivity and employment losses (business stealing effects).¹ Finally, as firms exhibit heterogeneous adoption patterns of new emergent technologies (Dosi and Nelson, 2010), and the diffusion of those technologies takes time, the sectoral and the economy-wide effects of labor-saving technologies are the consequences, at each point in time, of the interaction between adopting and non-adopting firms.

A rapidly emerging empirical literature investigating the impact of recent waves of automation technology offers mixed evidence. Most studies are based on country and industry-level data, which come across positive, negative and zero employment effects for more exposed industries and regions (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Gentili et al., 2020; Dauth et al., 2021; Dottori, 2021). A growing literature that has turned to firm-level data tends to find that following an automation event firms increase their employment (Acemoglu et al., 2020; Dixon et al., 2021; Domini et al., 2021; Koch et al., 2021), whereas non-adopting competitors experience employment losses (Acemoglu et al., 2020, 2023; Koch et al., 2021). However, some studies find as well negative employment effects (Bessen et al., 2020, 2023; Bonfiglioli et al., 2020). Finally, studies considering heterogeneous effects across different groups of workers remain inconclusive as they provide several conflicting results: For French data, Acemoglu et al. (2020) find declines in the share of production workers, Aghion et al. (2021) find positive employment effects for unskilled production workers, whereas Domini et al. (2021) find no significant changes in the composition of the workforce considering among others production workers

¹Note that a further compensation force is the Schumpeterian mechanism of new product introduction, as shown in Dosi et al. (2021). However, given the structure of the Portuguese economy this effect is in our case neglectable. For a more thorough discussion of the theoretical literature and other potential mechanisms see Staccioli and Virgillito (2021); Aghion (2021); Corrocher et al. (2023)

and routine-intensive workers. Using both Dutch data, Acemoglu et al. (2023) find negative employment and wage effects for routine production workers and for low educated workers, while Bessen et al. (2023)'s results indicate adverse effects for middle-educated workers. To take stock, we are far from a consensus about the impact of automation at the industry, firm and worker-level.

Against this backdrop, we provide novel empirical evidence for Portugal. Importantly, we emphasize the role of heterogeneity that is crucial to understand and unveil the various job-creating and destroying effects that are at work. More specifically, we study the effects of adoption of automation-technology at the firm-level. For this purpose, we construct a panel for manufacturing firms spanning the period 2004-2021 combining linked employer-employee data with firm balance sheet data and trade transaction data. To proxy investments in automation technology we rely on the frequently used import-based approach (e.g. Acemoglu et al., 2020; Dixon et al., 2021; Domini et al., 2021) exploiting granular product-level information of traded goods. We identify automation events leveraging the lumpy nature of investments in automation technology. Our identification strategy is based on the variation in timing of adopting firms as well as on the comparison between adopting and non-adopting firms employing a staggered difference-in-difference model. To account for the by now well-documented problems related to the presence of heterogeneous effects (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021), we rely on the estimation method recently provided by Callaway and Sant'Anna (2021) that is more robust in such empirical settings. This approach allows us to examine the before-and-after effects of an automation spike in Portuguese manufacturing firms.

We contribute to this emerging literature in three ways: First, we confirm several of the firm-and industry-level findings for Portugal. We find that firms increase their employment following an automaton event. Moreover, we find positive effects for valueadded and the labor share, whereas mean hourly wages decline. Second, the richness of our data allows us to investigate heterogeneous effects across different type of workers.² More precisely, we explore the evolution of employment shares around automation events with respect to the educational level, the task-intensity, macro-occupation groups and by the type of the contract. Our results suggest, in strong contrast to the task-based model, that automation increase the employment share of low-educated workers, routine-manual workers and blue-collar workers. In addition, we find that automation favors permanent contracts.

Finally, we explore the effect of automation technology through the lens of heterogeneity across firms. Specifically, we consider smaller vs. larger firms and young vs. older firms. Our main contribution is that we detect that the employment effect at the firm-level differs: Smaller firms increase in employment following an automation event, whereas larger adopters experience declines. While we find positive employment effects

²Note that most previous studies lack the access to detailed information of the occupational group (e.g. Koch et al., 2021; Bessen et al., 2023)

across young firms, but not for older firms. Importantly, we find that the positive effects for low-educated, routine-manual and blue-collar workers are driven by the employment increases in small firms. In contrast, in larger firms automation favors high-educated workers at cost of middle-educated workers. However, for large firms we cannot find any changes in the composition of the workforce w.r.t. to task groups and macro-occupation groups. Finally, we find that both in small and large firms fixed-term contracts decline.

Our results show that the average employment effect of adopting firms hides heterogeneous dynamics in particular between smaller and larger firms. Importantly, this drives how automation affects different groups of workers. To take stock, our results do not reconcile with the clear predictions of the task-based framework. Instead, they emphasize the importance of the socioeconomic context. Crucially, our results have important implication for labor policy and so-called national Industry 4.0 strategies. For example, as the Industry 4.0 strategy of Portugal targets in particular small- and medium-sized enterprises, while other strategies favor large firms.

This paper continues as follows. In Section 2 we present our data and descriptive statistics on the characteristics of automation investments and differences between adopting and non-adopting firms. In section 3 we discuss our empirical model as well as our results from the event study. Section 4 concludes.

2 Data and Descriptive Statistics

The empirical analysis in this paper combines and examines several administrative data sources provided by the Portuguese National Statistics Institute (INE). We combine linked employer-employee data with firm balance sheet data and automation-related imports from trade transaction data using the unique firm identifier. Our final panel covers a broader definition of the manufacturing sector of continental Portugal spanning the period 2004-2021. In this section we provide a brief description of each data source, their integration into a unique firm-level panel and the main variables of interest, while we give further details about its treatment in the Appendix A.

2.1 Data sources

Linked employer-employee data. The *Quadros de Pessoal* (QP), administered by the Ministry of Employment of Portugal, draws on a compulsory annual census of all private firms in Portugal that employ at least one dependent worker and is conducted since 1985.³ Currently, the full sample includes about 350,000 firms and 3 million employees in each year. Each firm is required by law to report information on it' characteristics, for each of its plants, and for each of its workers at the end of the census reference month

³Note that in the census public administration and non-market services are excluded. QP has been widely used by, amongst others, Blanchard and Portugal (2001), Cabral and Mata (2003) and Card et al. (2015, 2018).

October of each year. Entering the database each firm and each worker are assigned a unique, time-invariant identifying number making it possible to track firms and workers over time.⁴ Variables available in the data set include among other the firm's location, industry, date of creation, employment, sales, ownership and legal basis. At the worker-level, the data covers information on worker's demographic characteristic (date of birth, gender, education and so forth) and job characteristics (occupation group, wage, hours worked, type of contract, and so forth).

Balance Sheet data. The next set of data to be used is the *Sistema de Contas Integrado da Empresa* (SCIE) available since 2004. It is a yearly census of firms collected by INE with the main objective to characterize the economic and financial performance of companies.⁵ The data covers all firms (companies, individual entrepreneurs, and selfemployed) pertaining to the non-financial business sector that carry out an activity producing goods or services during the year.⁶ The large number of variables include among other firm's industry classification (5-digit CAE Rev.3), births and deaths of companies as well as accounting statements, e.g. value added, sales and the wage bill.⁷

Trade transaction-level data. The third data source is the *Comércio Internacional*, which records individual trade transactions (imports and exports) on a monthly basis for firms that are located in Portugal. The information are collected separately for EU partner countries and non-EU partners. Information on extra-EU transactions are collected by customs declarations, which cover the universe of external trade transactions ("Extra-stat"). Since 1993, following the creation of the Single European Market, information on intra-EU transactions has come from the Intrastat system. It is a survey that must be answered by firms whose value of intra-EU trade transactions exceeds a legally binding threshold that has changed over time. For example in 2015 the Portuguese thresholds were set at 250,000 Euro and 350,000 Euro for exports and imports, respectively. Throughout the sample period, the thresholds were set to ensure that the survey overall includes at least 97 percent of intra-EU exports and 93 percent of intra-EU imports each year.⁸ For each transaction the database reports among other trade value (in euros), trading partner

⁴The purpose of this survey is to verify if firms are complying with labor law. Since employers are the one reporting the data, variables such as wages and worker qualifications are less prone to measurement error. The unique worker identifier is based on the worker's social security number. In addition, the Ministry of Employment implements several checks to certify the quality of the data. Overall this implies a high degree of coverage and reliability.

⁵The information gathered in this dataset is the result of a process of integrating information on companies, initially from the Annual Business Survey (IEH) and later from administrative information from the protocol signed with the Tax and Customs Authority

⁶Accordingly, financial and insurance companies are excluded, as are entities that are not marketoriented, namely central and local public administration units and various associative activities.

⁷All the data is subjected to comparisons between year n and year n-1, paying special attention to possible deaths and births of companies, as well as changes in activity, region, levels of staff employed, turnover and legal form. Whenever necessary, companies are contacted to provide additional clarifications, which may or may not lead to occasional corrections, in order to guarantee the statistical quality of the information to be made available.

⁸Note that this data is the country's official information source on imports and exports used for official trade statistics.

country and an 8-digit Combined Nomenclature (CN) product code, an extension of the 6-digit international Harmonized System (HS) trade classification. We use CI to identify importing firms and their imports of automation-related goods based on the 6-digit HS code.

2.2 Sample Selection

We combine firm-level workforce information from QP with firm's accounting information from SCIE and trade information from CI using the unique, time-invariant firm identifier. We keep only firm observations that appear both in the QP and SCIE data sources. The integration of our three sources restrict the analysis to the period 2004-2021. We assign each firm a permanent 2-digit sector based on the most frequent occurrence, since firms industry code may vary across years. We consider in our analysis firms based in continental Portugal and active in manufacturing. Yet we consider a broader definition including manufacturing, mining, energy, water and waste and transportation and storage identified as those who reported main activity codes belonging to division 10-33, 5-9, 35-39, 49-53 of the CAE Rev.3, respectively. We exclude individual entrepreneurs and self-employment enterprises. Considering workers, we restrict the analysis to dependent workers aged between 18 and 65 years old (working-age population). Observations with unreasonable values (e.g. non-positive turnover or gross value added, non-complete basic remuneration, etc.) were discarded. Since our measure of the adoption of automation technology is based on imported product categories, we focus in most of our exercises only on firms that import. In the following we distinguish between the full sample of firms and the importer sample, which includes firms that import at least once over the observed period 2004-2021. All monetary values are being deflated using the Consumer Price Index from INE.

2.3 Automation imports

Data on the adoption of automation technologies at the firm level is rare.⁹ Alternatively, we rely on firm-level information on the value of yearly imports of automation technology from the *Comércio Internacional* (CI) dataset to construct our proxy for the adoption of automation technology. This import-based approach to proxy the adoption of automation technology has been frequently used in the literature (e.g., Acemoglu et al., 2020, 2023; Dixon et al., 2021; Domini et al., 2021, 2022; Humlum, 2019).

More specifically, we identify at the firm-level import goods that embed automationand AI-related technologies based on their 6-digit Harmonized System (HS) product code. Automation-related imports are identified following the taxonomy presented by Acemoglu and Restrepo (2021) partitioning all HS codes referring to capital goods (di-

⁹Currently, such data is available among very few countries, e.g. Germany (Deng et al., 2021), Spain (Koch et al., 2021) and a cross-sectional dataset for the United States (Acemoglu et al., 2022).

visions, 82,94,85,87,90) into several categories of automated and non-automated goods. This includes industrial robots, automatically controlled machines, numerically-controlled machines, automatic welding machines and other. We follow the extensions by Domini et al. (2021, 2022) including 3-D printers (Abeliansky et al., 2020) and imports that relate to AI, namely automatic data processing machines and electronic calculating machines. For a more detailed description see table 2.

Since innovative activity and the exports of capital goods are highly concentrated in a handful of industrialized countries, the diffusion of technological advances takes usually place via trade (Eaton and Kortum, 2001). Andreoni et al. (2023) demonstrate that European countries, with the exception of Germany, have a neglectable role in the export of automation- and AI related capital goods in the global trade network. Therefore, our import-based measure should be a reliable indicator of investments in automation in Portugal. Nevertheless, it has some potential limitations that shall be discussed. First, firms might be wrongly labeled as non-adopters, because firms might purchase automation technologies domestically rather than abroad. However, given the production structure of the Portuguese economy, this is not very likely. Juchniewicz and Łada (2020) show that the Portuguese high-tech sector is significantly delayed and not very competitive in comparison to other European countries. Based on patent data Cséfalvay and Gkotsis (2022) do not find any domestic suppliers of industrial robots in Portugal. However, to reduce the probability to incorrectly label firms as non-adopters, we restrict our empirical analysis to importing firms. Additionally, we further decrease the likelihood when we repeat our baseline estimation including only adopters, i.e. firms that buy automationrelated goods from abroad at least once, and considering only the adoption of industrial robots. Second, firms might resort to an intermediary to purchase goods abroad (Blum et al., 2010; Bernard et al., 2010; Ahn et al., 2011), but they are much less likely to do so for more complex goods (Bernard et al., 2015), involving higher relation specificity such as the ones we are focusing on here. Third, firms might be wrongly classified as adopting firms because they may resell them in the domestic or international markets. However, our analysis does not include retailers and intermediaries. Furthermore, manufacturing firms are known to engage in the (re)export of goods that they do not produce, so-called Carry Along Trade (CAT) (Bernard et al., 2019). Therefore, we run some robustness checks in which we exclude re-exporting firms.

2.4 Automation spikes

Figure 1 displays a steady increase both in the cumulative value of imports and in the share of firms importing automation technology over the period 2004-2021. Although only a small fraction of firms imports automation technology (13% in 2021), they account for a large share of employment that increases over time (from around 45% in 2004 to 53% in 2021). Among firms that import at least once over the observed period, the share of



Figure (1) Evolution of Automation imports in Portugal (2004-2020)

Notes: Figure 1 displays the cumulative value of automation-related imports, the share of firms that already imported automation technology, the employment share of firms that import automation at some point over the period 2004-2021. Red graphs are based on the full sample of firms and black graphs considering solely importers.

adopters is substantially higher (around 41% in 2021) representing an employment share of 71%. Consequently, automating firms represent a highly significant part of modern Portuguese manufacturing despite the small share of adopters. Looking at the distribution of automation-related imports, figure 2a and figure 2b indicate a high degree of heterogeneity across and within industries (2-digit).¹⁰ The right panel shows that the total stock of automation imports concentrates in few industries, e.g. Transport equipment and metal products account alone for almost 50% of all imports. The left panel illustrates that adoption rates differ strongly between industries. Moreover, overall within industries automation remains rare as most firms do not import automation technologies. Importantly, figure 2 depicts that robots represent only a small share of automation processes. This emphasizes the need to consider broader measures of automation technology rather than focusing solely on robots.

As already shown in Bessen et al. (2020, 2023) and Domini et al. (2021, 2022), automationand AI-related imports display the typical spiky behaviour of an investment variable (Asphjell et al., 2014; Letterie et al., 2004; Grazzi et al., 2016). This means that, such imports are rare (i) across and (ii) between firms as well that (iii) a spike represents a very high share of total investment within firms. We demonstrate that this holds as well for Por-

¹⁰Note that there are positive imports of automation technologies across all industries.



Figure (2) Diffusion of Automation-related Imports across Industry

Notes: Panel 2a shows the share of firms that imported once automation technologies by industry. Panel 2b shows the cumulative value of automation-related imports by industry. Both figures are based on the full sample of firms displaying the year 2021.

tuguese firms in manufacturing: First, only around 13% of Portuguese manufacturing firms import automation- and AI-related goods. Second, figure 3a demonstrates that such imports are rare within firms. Among firms who import automation technology, around 35% does it only once, and the frequency decreases smoothly with higher values, except for a small group of firms who import automated goods in all years. Finally, figure 3b shows that a the firm's largest episode represents on average more than 75% of total automation imports, whereas the median represents more than 80% of total automation investment. The shares of lower ranks then rapidly decrease in value.

These statistical properties of automation-related imports, allow us to detect distinct automation events. In line with the previous literature (Domini et al., 2021, 2022; Bisio et al., 2023), we define the largest event for each firm as an automation/AI spike, because of the very skewed nature of this variable within firms. Figure 8 illustrates the evolution of automation imports around our definition of an automation events. Showing a clear one-period increase in automation imports in the year of adoption, the graph gives confidence in our definition.

2.5 Descriptive Statistics

Table 4 provides information on the characteristics between adopting and non-adopting firms. The comparison shows that adopting firms are distinctly different from nonadopting firms: they are on average larger, more productive, pay higher, whereas the



Figure (3) Spikeness of automation imports

Notes: Panel 3a shows the shares of the number of years in which firms import automation technology among firms that import automation-related goods at least once. Panel 3b ranks the mean and median of firms' shares of each year's imports (out of all years) from the largest to smallest.

labor share is substantially lower. Nevertheless, note that 70% of the adopting firms are small-sized. Moreover, adopters are more likely to export, to be in multinational ownership and to be older. Moreover, these differences are less pronounced if we make the comparison with non-adopting importers, even though they remain substantial. Crucially, figure 4 illustrates that differences between adopting and non-adopting firms are already *ex ante* present. Over time adopting firms appear to experience larger growth rates in terms of employment and gross value added. For average hourly wages the graph is less clear, even though it appears to be that the distributions become more similar over time. Moreover, the labor share is growing for both adopting and non-adopting firms over the observed period.

Considering differences in the workforce composition table 5 shows that in adopting firms the share of routine-intensive, low-educated and blue-collar workers tends to be less. Interestingly, 9c depicts that the evolution of the employment shares for these groups of workers between adopting and non-adopting firms is practically identical suggesting that these differences might not be driven by automation. Looking on the type of contract, 5 depicts that there appear to be no significant differences between adopting and nonadopting firms. However, figure 9d illustrates that even though both adopters and nonadopters make more and more use of fixed-term contracts over time, there is an increasingly growing edge between them. This is surprising since one might expect that the adoption of automation technology would pronounce such differences. Looking on the employment shares by the type of contract, we see that both firms make increasingly use of fixed-term contracts over the observed period, whereas non-adopters use these increasingly more than adopters. Interestingly, even though automating firms pay higher wages, almost across all groups of workers, wage trends are in favor of workers in non-automating firms.



Figure (4) Before-After Comparison of the Distribution for Key Variables

Notes: Figure 4 shows the the distribution of four key outcome variables between adopters (red) and non-adopters (black). The solid lines show the empirical probability density function of the first year a firm is in the panel and the dashed line of the last year. The figures are based on the importer sample.

3 The effect of automation events

As discussed in Section 2.4, automation investments have the statistical property to occur in spikes. We exploit this characteristic by investigating the evolution of employment and other firm-level variables around automation spikes by employing a diff-in-diff model. Recent research has shown several problems with the commonly used TWFE estimator in cases of staggered treatment timing and presence of heterogeneity of the treatment effect over time (Meer and West, 2016; Goodman-Bacon, 2021; Athey and Imbens, 2022). Intuitively, the TWFE has been shown to be a weighted average of all possible two-bytwo diff-in-diff estimates that are produced by comparing outcomes of a group of units whose treatment status changes between two time periods to a groups of units whose treatment status does not change. This includes comparisons with units that are never treated and not yet treated ("good comparisons") but as well with units that already have been treated ("bad comparisons"). Since the timing of adoption of automation technology is heterogeneous across industries and firms and the effect of automation is likely heterogeneous, we apply the estimator proposed by Callaway and Sant'Anna (2021) that is more robust in such empirical settings. The methodology is based on a two-step procedure that first involves the estimation of so-called group-time average treatment effects and then aggregates these into parameters of interest such as an overall ATT or into an event study.

More precisely, we estimate

$$ATT(g,t) = E[Y_{i,t} - Y_{i,g-1}|G_i = g] - E[Y_{i,t} - Y_{i,g-1}|G_i = G_{comp}]$$
(1)

where $\operatorname{ATT}(g, t)$ gives the average treatment effect at time t for the cohort that adopts in year $g.^{11}$ $Y_{i,t}$ is the dependent variable of interest at time t for firm i, G_i is an indicator variable with value in the year of adoption of firm i and G_{comp} gives the most general set of comparisons for an adopter at time g, i.e. all firms that never adopt or have not yet adopted at time t, formally $G_{\text{comp}} = \{g'|g' > t\}.^{12}$ Then, we compute the event-study parameter via a weighted average of the treatment effect l periods after the adoption across different adopting cohorts,

$$\hat{ATT}_{l} = \sum_{g} w_{g} ATT(g, g+l)$$
⁽²⁾

where the weights w_g are chosen to account for the relative frequency of each cohort into the adopter's population. We cluster standard errors at the firm-level and provide

 $^{^{11}{\}rm For}$ example, ATT(2015, 2017 would be the average treatment effect in 2015 for firms that adopt automation technology in 2017.

¹²Note that the methods does not impose any restrictions on treatment effect heterogeneity and involves only "good comparisons".

95% bootstrap confidence intervals.

We rely on two main assumptions to identify the average treatment effect on the treated (ATT) of the adoption of automation technology: (1) parallel trends and (2) no anticipation.

Parallel Trends. The parallel trends assumption requires that the average outcome among the treatment and control group would have followed parallel trends in the absence of treatment. This is an unobservable counterfactual, but can assess its validity by evaluating trends prior to adoption. To increase confidence, we impose parallel trends only conditional on covariates relying on the doubly-robust (DR) estimation procedures (Sant'Anna and Zhao, 2020; Callaway and Sant'Anna, 2021).¹³ The appealing advantage of DR estimators is that they remain consistent as long as either the outcome regression is correctly specified or the model for the propensity score, but not necessarily both. We consider three different control groups: i) importers that never adopt, ii) all importers, i.e. those who never adopt and that have not yet adopted and iii) not-yet adopters only. As we move from the former to the latter the confidence that we are comparing firms on similar trends increases. However, in the latter case the sample size decreases substantially such that our estimates are less efficient. Finally, we will run a battery of robustness checks and sensitivity analysis.

No anticipation. No anticipation requires that firms do not anticipate the automation event, i.e. adoption in time t does not has an effect on the observed variable prior the adoption. This assumption cannot be verified. However, we run a series of robustness checks to detect potential anticipation behaviours by changing the horizons of the estimations of pre-spike and post-spike variables.

3.1 Results

In this section we investigate the effect of the adoption of automation on employment and other firm-level outcomes, on the composition of workers and heterogeneous employment effects across different groups of firms. Results are shown in figure 5. For employment, we find a clear increasing trend following an automation spike: four years after the spike, firms are, on average, around 10% larger in terms of employment. The results confirm the positive relationship between automation and the average employment at the firm-level (Acemoglu et al., 2020; Dixon et al., 2021; Domini et al., 2021). Similarly, we find a growth in productivity after an automation spike. Looking at the evolution of the labor share around the automation event, our results suggest that the labor share increases. This is in contrast to the literature that usually finds a negative effect (Acemoglu et al., 2020). However, this may be explained by the results that employment increases more strongly than gross value added. Finally, we find some evidence that mean hourly wages decrease

¹³In our benchmark exercise we control for the baseline values of the log of labor productivity, firm age and export status.

following an automation event. However, when we consider adopters only as our control group, this effect vanishes.



Figure (5) Event Study: Effect of Automation on Firm-level Outcomes

Notes: All automating firms that exist in all years $\tau = \{-4, ..., 4\}$. Whiskers reflect 95% confidence intervals.

Next, we investigate heterogeneity across different groups of workers by looking on employment shares in figure 6). First, we consider differences across different educational levels. We find a positive effect on the share of low-educated workers, whereas we observe a decline in the share of middle-educated workers. In contrast, we do not find an effect on high-educated workers. Looking at task-groups, we find a clear increase in the share of routine-manual tasks and decline in non-routine cognitive tasks. However, the standard errors are very large and only weakly significant. Similarly, we find a positive effect on blue-collar workers. Finally, we find that automation favors permanent contracts. Our results are difficult to interpret and need further explorations.





(c) Employment shares by macro-occupational groups

- Manage

Event time

STEM professiona

-0.02

Blue-collar

- Other Professionals

-



0 1 Event time

🔶 Fixed-term Contract 🝝 Permanent Contract

Notes: All automating firms that exist in all years $\tau = \{-4, ..., 4\}$. Whiskers reflect 95% confidence intervals.

Other non-professionals

3.2 Heterogeneity across different group of firms

The previous analysis has focused on average effects across firms and finds that following an automation event firms increase their employment. In this section, we investigate the effect of automation technology through the lens of heterogeneity. More precisely, based on the firm's initial value, i.e. the first year in the dataset, we divide firms into two categories: we consider (i) smaller (1-49) and larger companies (>49 employees) as well as (ii) young (1-10) and old (> 10 years) firms. Results are presented in figure 7 and table 1. Our results show that the average treatment effect on the treated hides substantial heterogeneity across different group of firms. Looking on the firm size, we show that only small firms grow in employment following an automation event, whereas large firms experience a decline. As small firms represent 70% of adopting firms, the average across all potential group-time differences in differences results in a positive effect. However, the employment share of large firms is substantially larger. Hence, this probably results in a total negative employment effect across adopting firms, as more workers loose their jobs through the net job-destroying effect in large firms, than workers are being newly employed through the job-creating effects in small firms.

Crucially, table 1 shows that these heterogeneity in the effect of automation has important implication for workers. We find that in small firms automation favors low-educated workers, routine-manual and blue-collar workers. In contrast, in large firms the employment share increases for high educated workers at the costs of middle educated workers. However, we cannot find any changes in the composition of the workforce considering task groups and macro-occupation groups.

Considering the initial firm age, we find positive employment effects only among young firms, whereas we zero effects for old firms. Automation in young firms favors low-educated, routine-manual and blue-collar workers, which is similar to the results in small firms. Finally, in old firms we cannot find any effect on the employment share w.r.t. education, task-group and macro-occupational group.



Figure (7) Event Study: Heterogeneous effects across different group of firms

Notes: All automating firms that exist in all years $\tau = \{-4, ..., 4\}$. Whiskers reflect 95% confidence intervals.

Table (1) Event Study: Heterogeneous Effects across Firms and Workers, 200
--

	Smaller	Firms	Larger	Firms	Young	Firms	Old H	rirms
Employment share	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
by education								
Low Education	0.0231^{***}	(0.0038)	-0.003	(0.0054)	0.0235^{***}	(0.0057)	-0.0029	(0.0038)
Middle Education	-0.0137^{***}	(0.0032)	-0.0051^{*}	(0.0036)	-0.0146^{***}	(0.0048)	0.001	(0.0031)
High Education	-0.0093**	(0.0028)	0.0082^{**}	(0.0041)	-0.009**	(0.0042)	0.0021	(0.0027)
by task group	0.010.1***	(0,00,10)		(0.00, -0)		(0,0000)		(0.0071)
Routine-manual	0.0194***	(0.0048)	-0.0058	(0.0073)	0.0254^{***}	(0.0062)	-0.0023	(0.0051)
Routine cognitive	-0.0015	(0.0016)	0.0008	(0.0022)	-0.0034	(0.0023)	0.0014	(0.0015)
Non-routine manual	-0.0036^{*}	(0.0018)	-0.0009	(0.0021)	-0.0044	(0.0023)	-0.0024	(0.0018)
Non-routine cognitive	-0.015***	(0.0046)	0.0053	(0.0065)	-0.0179***	(0.0064)	0.002	(0.0046)
by macro-occupation								
Manager	-0.0028	(0.002)	0.0024	(0.0016)	-0.0027	(0.003)	0.0007	(0.0019)
STEM	-0.0068**	(0.0029)	-0.0018	(0.0031)	-0.0052	(0.0041)	-0.0021	(0.0027)
Other Professionals	-0.0053**	(0.0025)	0.0054	(0.0034)	-0.0065	(0.0036)	-0.0005	(0.0022)
Blue-collar	0.0189^{***}	(0.005)	-0.0091	(0.0075)	0.0258^{***}	(0.007)	-0.0017	(0.0051)
Other non-professionals	-0.0045	(0.0044)	0.0029	(0.0064)	-0.0116^{*}	(0.0059)	0.0027	(0.0044)
by contract								
Permanent Contract	0.0528^{***}	(0.0057)	0.0214^{***}	(0.0069)	0.0526^{***}	(0.0076)	0.0267^{***}	(0.0052)
Fixed-term Contract	-0.0485***	(0.0049)	-0.0220***	(0.0068))	-0.0503***	(0.0074)	-0.0273***	(0.005)

Notes: All automating firms that exist in all years $\tau = \{-4, ..., 4\}$.

4 Conclusion

Despite the rapidly diffusion of automation technologies in most industrialized countries and a rapidly emerging empirical literature, there is still much controversy about the effects of automation on employment. Most previous work finds positive employment effects following the adoption of automation technology. However, evidence is concentrated among few countries and the understanding whether different groups of workers are affected differently remains limited.

In this paper we study the effect of the adoption of automation on Portuguese firms in manufacturing. We use Portuguese linked employer-employee data in combination with balance sheet data and automation-related imports from customs data. We exploit the lumpiness of investment in automation by employing a staggered diff-in-diff model. Our preliminary results show that firms increase their employment and productivity following an automation event. We find evidence that this coincides with an increase in the employment share of low educated workers at the cost of middle educated workers. Moreover, there is weak evidence that automation may favor blue-collar workers and routine-manual workers or at least that they are not affected. This does not reconcile with the clear predictions of the task-based model. Moreover, we find that the positive employment effects favor permanent contracts.

Our main contribution is that we explore heterogeneous effects across different group of firms. We find that only smaller firms increase their employment following an automation event, whereas larger firms experience employment losses. This has important implications for the aggregate level, since larger firms represent a larger share of employment this may suggest that overall more workers loose their jobs in large firms than get a job in small firms. Moreover, we find that automation favors low-educated workers, routine-manual and blue-collar workers in small firms, whereas in large the employment share increases for high educated workers at the costs of middle educated workers. To take stock, our results do not reconcile with the clear predictions of the task-based framework. Instead, they emphasize the importance of the socioeconomic context. Crucially, our results have important implication for labor policy and so-called national Industry 4.0 strategies. For example, as the Industry 4.0 strategy of Portugal targets in particular small- and mediumsized enterprises, while other strategies favor large firms.

References

- Abeliansky, Ana Lucia, Inmaculada Martínez-Zarzoso, and Klaus Prettner (2020) "3D printing, international trade, and FDI," *Economic Modelling*, 85, 288–306, https://doi. org/10.1016/j.econmod.2019.10.014.
- Acemoglu, Daron, Gary Anderson, David Beede et al. (2022) "Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey," Working Papers 22-12, Center for Economic Studies, U.S. Census Bureau, https://ideas.repec.org/ p/cen/wpaper/22-12.html.
- Acemoglu, Daron, Hans R. A Koster, and Ceren Ozgen (2023) "Robots and Workers: Evidence from the Netherlands," Working Paper 31009, National Bureau of Economic Research, http://www.nber.org/papers/w31009.
- Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo (2020) "Competing with Robots: Firm-Level Evidence from France," AEA Papers and Proceedings, 110, 383–88, 10. 1257/pandp.20201003.
- Acemoglu, Daron and Pascual Restrepo (2018) "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment," *American Economic Review*, 108 (6), 1488–1542, 10.1257/aer.20160696.

(2019) "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives*, 33 (2), 3–30, 10.1257/jep.33.2.3.

(2020) "Robots and Jobs: Evidence from US Labor Markets," Journal of Political Economy, 128 (6), 2188 – 2244, https://doi.org/10.1086/705716.

(2021) "Demographics and Automation," *The Review of Economic Studies*, 89 (1), 1–44, 10.1093/restud/rdab031.

- (2022) "Tasks, Automation, and the Rise in U.S. Wage Inequality," *Econometrica*, 90 (5), 1973–2016, https://doi.org/10.3982/ECTA19815.
- Aghion, Philippe (2021) "The Direct and Indirect Effects of Automation on Employment : A Survey of the Recent Literature," https://api.semanticscholar.org/CorpusID: 235592731.
- Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel (2021) "What Are the Labor and Product Market Effects of Automation?: New Evidence from France," working paper, https://www.dropbox.com/s/tssm9mupvzwr8kw/aabj_automation_ dec2021.pdf?dl=0.

- Ahn, JaeBin, Amit K. Khandelwal, and Shang-Jin Wei (2011) "The role of intermediaries in facilitating trade," *Journal of International Economics*, 84 (1), 73–85, https://doi. org/10.1016/j.jinteco.2010.12.003.
- Andreoni, Antonio, Guendalina Anzolin, Mateus Labrunje, and Danilo Spinola (2023)
 "Unveiling Structure and Dynamics of Global Digital Production Technology Networks: A new digital technology classification and network analysis based on trade data," Working Papers 261, Department of Economics, SOAS University of London, UK, https://EconPapers.repec.org/RePEc:soa:wpaper:261.
- Arntz, Melanie, Sebastian Blesse, and Philipp Doerrenberg (2022) "The end of work is near, isn't it? Survey evidence on automation angst," ZEW Discussion Papers 22-036, ZEW - Leibniz Centre for European Economic Research, https://dx.doi.org/10.2139/ ssrn.4247981.
- Arntz, Melanie, Terry Gregory, and Ulrich Zierahn (2017) "Revisiting the risk of automation," *Economics Letters*, 159, 157–160, https://doi.org/10.1016/j.econlet.2017.07.001.
- Asphjell, Magne K., Wilko Letterie, Øivind A. Nilsen, and Gerard A. Pfann (2014) "Sequentiality Versus Simultaneity: Interrelated Factor Demand," *The Review of Economics and Statistics*, 96 (5), 986–998, 10.1162/REST_a_00411.
- Athey, Susan and Guido W. Imbens (2022) "Design-based analysis in Difference-In-Differences settings with staggered adoption," *Journal of Econometrics*, 226 (1), 62–79, https://doi.org/10.1016/j.jeconom.2020.10.012, Annals Issue in Honor of Gary Chamberlain.
- Autor, David H., Frank Levy, and Richard J. Murnane (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration*," *The Quarterly Journal of Economics*, 118 (4), 1279–1333, 10.1162/003355303322552801.
- Barth, Erling, Marianne Roed, Pal Schone, and Janis Umblijs (2020) "How Robots Change Within-Firm Wage Inequality," IZA Discussion Papers 13605, Institute of Labor Economics (IZA), https://ideas.repec.org/p/iza/izadps/dp13605.html.
- Bernard, Andrew B, Emily J Blanchard, Ilke Van Beveren, and Hylke Vandenbussche (2019) "Carry-Along Trade," *The Review of Economic Studies*, 86 (2), 526–563, 10. 1093/restud/rdy006.
- Bernard, Andrew B., Marco Grazzi, and Chiara Tomasi (2015) "Intermediaries in International Trade: Products and Destinations," *The Review of Economics and Statistics*, 97 (4), 916–920, 10.1162/REST_a_00495.

- Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott (2010) "Wholesalers and Retailers in US Trade," *American Economic Review*, 100 (2), 408–13, 10.1257/aer.100.2.408.
- Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge (2020) "Firm-Level Automation: Evidence from the Netherlands," AEA Papers and Proceedings, 110, 389–93, 10.1257/pandp.20201004.
- (2023) "What Happens to Workers at Firms that Automate?," The Review of Economics and Statistics, 1–45, 10.1162/rest_a_01284.
- Bisio, Laura, Angelo Cuzzola, Marco Grazzi, and Daniele Moschella (2023) "The Dynamics of Automation Adoption: Firm-Level Heterogeneity and Aggregate Employment Effects," 10.2139/ssrn.4575897.
- Blanchard, Olivier and Pedro Portugal (2001) "What Hides Behind an Unemployment Rate: Comparing Portuguese and U.S. Labor Markets," *American Economic Review*, 91 (1), 187–207, 10.1257/aer.91.1.187.
- Blum, Bernardo S., Sebastian Claro, and Ignatius Horstmann (2010) "Facts and Figures on Intermediated Trade," American Economic Review, 100 (2), 419–23, 10.1257/aer. 100.2.419.
- Bonfiglioli, Alessandra, Rosario Crinò, Harald Fadinger, and Gino Gancia (2020) "Robot Imports and Firm-Level Outcomes," Technical report, CRC TR 224 Discussion Paper Series.
- Cabral, Luís M B and José Mata (2003) "On the Evolution of the Firm Size Distribution: Facts and Theory," American Economic Review, 93 (4), 1075–1090, 10.1257/000282803769206205.
- Caliendo, Lorenzo, Giordano Mion, Luca David Opromolla, and Esteban Rossi-Hansberg (2020) "Productivity and Organization in Portuguese Firms," *Journal of Political Econ*omy, 128 (11), 4211–4257, 10.1086/710533.
- Callaway, Brantly and Pedro H.C. Sant'Anna (2021) "Difference-in-Differences with multiple time periods," *Journal of Econometrics*, 225 (2), 200–230, https://doi.org/10. 1016/j.jeconom.2020.12.001, Themed Issue: Treatment Effect 1.
- Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline (2018) "Firms and Labor Market Inequality: Evidence and Some Theory," *Journal of Labor Economics*, 36 (S1), S13–S70, 10.1086/694153.
- Card, David, Ana Rute Cardoso, and Patrick Kline (2015) "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women *," *The Quarterly Journal of Economics*, 131 (2), 633–686, 10.1093/qje/qjv038.

- de Chaisemartin, Clément and Xavier D'Haultfœuille (2020) "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," American Economic Review, 110 (9), 2964–96, 10.1257/aer.20181169.
- Corrocher, Nicoletta, Daniele Moschella, J. Staccioli, and Marco Vivarelli (2023) "Innovation and the labor market," MERIT Working Papers 2023-021, United Nations University - Maastricht Economic and Social Research Institute on Innovation and Technology (MERIT), https://ideas.repec.org/p/unm/unumer/2023021.html.
- Cortes, Guido Matias, Ana Oliveira, and Anna Salomons (2021) "Do technological advances reduce the gender wage gap?," Oxford Review of Economic Policy, 36 (4), 903– 924, 10.1093/oxrep/graa051.
- Cséfalvay, Zoltán and Petros Gkotsis (2022) "Robotisation race in Europe: the robotisation chain approach," *Economics of Innovation and New Technology*, 31 (8), 693–710, 10.1080/10438599.2020.1849968.
- Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner (2021) "The Adjustment of Labor Markets to Robots," *Journal of the European Economic Association*, 19 (6), 3104–3153, https://doi.org/10.1093/jeea/jvab012.
- Deng, Liuchun, Verena Plümpe, and Jens Stegmaier (2021) "Robot adoption at German plants," IWH Discussion Papers 19/2020, Halle Institute for Economic Research (IWH), https://ideas.repec.org/p/zbw/iwhdps/192020.html.
- Dixon, Jay, Bryan Hong, and Lynn Wu (2021) "The Robot Revolution: Managerial and Employment Consequences for Firms," *Management Science*, 69 (9), https://doi. org/10.1287/mnsc.2020.3812.
- Domini, Giacomo, Marco Grazzi, Daniele Moschella, and Tania Treibich (2021) "Threats and opportunities in the digital era: Automation spikes and employment dynamics," *Research Policy*, 50 (7), 104137, https://doi.org/10.1016/j.respol.2020.104137.
- (2022) "For whom the bell tolls: The firm-level effects of automation on wage and gender inequality," *Research Policy* (7), 104533, https://doi.org/10.1016/j.respol. 2022.104533.
- Dosi, G., M. Piva, M.E. Virgillito, and M. Vivarelli (2021) "Embodied and disembodied technological change: The sectoral patterns of job-creation and job-destruction," *Research Policy*, 50 (4), 104199, https://doi.org/10.1016/j.respol.2021.104199.
- Dosi, Giovanni and Richard R. Nelson (2010) "Chapter 3 Technical Change and Industrial Dynamics as Evolutionary Processes," in Hall, Bronwyn H. and Nathan Rosenberg eds. *Handbook of The Economics of Innovation, Vol. 1*, 1 of Handbook of the Economics of Innovation, 51–127: North-Holland, https://doi.org/10.1016/S0169-7218(10)01003-8.

- Dottori, Davide (2021) "Robots and employment: evidence from Italy," *Economia Politica*, 38, 10.1007/s40888-021-00223-x.
- Eaton, Jonathan and Samuel Kortum (2001) "Trade in capital goods," *European Economic Review*, 45 (7), 1195–1235, https://doi.org/10.1016/S0014-2921(00)00103-3, International Seminar On Macroeconomics.
- Eurobarometer (2017) "Attitudes Towards the Impact of Digitisation and Automation on Daily Life.," Technical report, European Commission, https://europa.eu/ eurobarometer/surveys/detail/2160.
- Ford, M. (2015) *Rise of the Robots: Technology and the Threat of a Jobless Future*: Basic Books.
- Frey, Carl Benedikt and Michael A. Osborne (2017) "The future of employment: How susceptible are jobs to computerisation?" *Technological Forecasting and Social Change*, 114, 254–280, https://doi.org/10.1016/j.techfore.2016.08.019.
- Gentili, Andrea, Fabiano Compagnucci, Mauro Gallegati, and Enzo Valentini (2020) "Are machines stealing our jobs?," *Cambridge Journal of Regions, Economy and Society*, 13 (1), 153–173, 10.1093/cjres/rsz025.
- Goodman-Bacon, Andrew (2021) "Difference-in-differences with variation in treatment timing," Journal of Econometrics, 225 (2), 254–277, https://doi.org/10.1016/j.jeconom. 2021.03.014, Themed Issue: Treatment Effect 1.
- Graetz, Georg and Guy Michaels (2018) "Robots at Work," The Review of Economics and Statistics, 100 (5), 753-768, https://doi.org/10.1162/rest_a_00754.
- Grazzi, Marco, Nadia Jacoby, and Tania Treibich (2016) "Dynamics of investment and firm performance: comparative evidence from manufacturing industries," *Empirical Economics*, 51 (1), 125–179, 10.1007/s00181-015-0991-2.
- Humlum, Anders (2019) "Robot Adoption and Labor Market Dynamics."
- Juchniewicz, Małgorzata and Magdalena Łada (2020) "Diversification of the competitive position of the advanced technology sector in EU," *International Journal of Management* and Economics, 56 (1), 31–41, doi:10.2478/ijme-2020-0006.
- Koch, Michael, Ilya Manuylov, and Marcel Smolka (2021) "Robots and Firms," The Economic Journal, 131 (638), 2553–2584, 10.1093/ej/ueab009.
- Letterie, Wilko A., Gerard A. Pfann, and J.Michael Polder (2004) "Factor adjustment spikes and interrelation: an empirical investigation," *Economics Letters*, 85 (2), 145– 150, https://doi.org/10.1016/j.econlet.2004.03.017.

- Meer, Jonathan and Jeremy West (2016) "Effects of the Minimum Wage on Employment Dynamics," *The Journal of Human Resources*, 51 (2), 500–522, http://www.jstor.org/stable/24736030.
- Nedelkoska, Ljubica and Glenda Quintini (2018) "Automation, skills use and training," (202), https://doi.org/https://doi.org/10.1787/2e2f4eea-en.
- Nof, Shimon Y. (2009) Automation: What It Means to Us Around the World, 13–52, Berlin, Heidelberg: Springer Berlin Heidelberg, 10.1007/978-3-540-78831-7_3.
- Pew (2017) "Automation in Everyday Life," Technical report, Pew Research Center, https://www.pewresearch.org/internet/2017/10/04/ automation-in-everyday-life/.
- Restrepo, Pascual (2023) "Automation: Theory, Evidence, and Outlook," Working Paper 31910, National Bureau of Economic Research, 10.3386/w31910.
- Sant'Anna, Pedro H.C. and Jun Zhao (2020) "Doubly robust difference-in-differences estimators," *Journal of Econometrics*, 219 (1), 101–122, https://doi.org/10.1016/j.jeconom.2020.06.003.
- Staccioli, Jacopo and Maria Enrica Virgillito (2021) The Present, Past, and Future of Labor-Saving Technologies, 1–16, Cham: Springer International Publishing, 10.1007/ 978-3-319-57365-6_229-1.

A Additional information

A.1 Data Procedures and Variable Construction

We start with the matched employer-employee data set (QP), which includes 5,570,419 firm and 50,960,574 worker observations for the period 2004-2021. We first merge firm and worker data for each year and we then apply for each year the following cleaning procedure: (i) we drop a minority of worker observations with an invalid social security number, i.e., if the worker id has less than 6 digits or more than 10 digits. (ii) For workers with multiple jobs within the same year, we keep his or her highest paying job with the highest hours worked (since most likely, this is his or her primary job)¹⁴. We keep (iii) dependent workers (iv) between 18 and 65 (working-age population). We drop worker-year pairs (v) without complete basic remuneration, (vi) whenever the sum of weekly normal and overtime hours is below 25 and above 80 and (vii) their regular earnings are less than 80 percent of the minimum wage. (viii) Based on the resulting sample, we trim worker-year pairs whose monthly total wage is outside the top 0.5 percentile. Gross monthly earnings from dependent work are obtained by the sum of the five types of pay available in the data (base wages, tenure-related payments, overtime pay, subsidies). We construct hourly total wages by dividing individuals' total monthly remuneration by total monthly hours worked. The data is then appended to construct our linked employer-employee panel data. After this procedure we have 4,187,954 firm-year observations and 35,889,005 worker-year observations. Finally, as the Portuguese classification of occupations (corresponding to the European ISCO classification) has been revised in 2010, we establish a data-driven one-to-one mapping. To do this, we use the following criterion: if the majority of workers in occupation A in 2010 (CPP/2010) have occupation B in 2009 (CNP/1994), then we map occupation A into occupation B.

We then turn to the balance sheet data (SCIE) and recover information on firm's 5-digit industry classification (CAE Rev.3, based on NACE-Rev. 2 Statistical classification of economic activities in the European Community), gross value added at market prices, total sales, wage bill, investment in tangible assets, investment in computer programs (software) and expenses for worker training. We discard observations that have unreasonable values, i.e. non-positive turnover or gross value added.

The customs data records individual trade transactions on a monthly basis. We collapse these transactions to the firm, product, year level and retrieve information on total yearly imports and exports of automation-and AI-related capital goods as described in section 2 and table 2. We then compute total imports and exports aggregating the data at the firm-year level.

Finally, we merge the the matched employer-employee data QP with the balance sheet data SCIE using the unique, time-invariant identifier based on the firm's social security

¹⁴Note that others (e.g. Caliendo et al., 2020) drop workers with multiple jobs in the same year.

number. We keep only firm observations that appear in both data sources. Then we add firm-year trade information from the CI dataset. We assign each firm a permanent 2-digit sector based on the most frequent occurrence, since firms industry code may vary across years, e.g. due to misreporting. We restrict the sample to firms located in mainland Portugal (omitting those in the Azores and Madeira islands) and active in the manufacturing sector. Yet we use a broader definition including manufacturing, mining, energy, water and waste and transportation and storage, identified as those who reported main activity codes belonging to division 10-33, 5-9, 35-39 and 49-53 of the CAE Rev. 3, respectively. The size of our final sample is now 634,983 firm-year observations and 10,646,981 workeryear observations. Since our measure of the adoption of automation technology is based on imported product categories, we consider for most of our exercises only firms that import at least once over the period 2004-2021 (importer sample). This reduces the sample to 192,035 firm-year observations. All monetary values in the paper are quoted in year 2012 Euros, deflated using the Consumer Price Index from INE.

Worker Heterogeneity. To investigate heterogeneous effects across different groups of workers we consider employment shares and average hourly wages for the following categories: First, we classify occupation codes into broad task groups, i.e. non-routine cognitive, routine cognitive, routine manual and non-routine manual, following the work by Cortes et al. (2021). Second, We define five macro-occupation groups: managers , STEM professionals, other professionals, blue-collar workers and other non-professionals. Third, we distinguish workers by their educational level defined as low, middle and higheducated workers. Finally, we distinguish workers on whether their contract is permanent or fixed. For the description of the codification of the occupation codes see table ??.

Firm Heterogeneity. To investigate heterogeneity across firms we consider four key variables that we define as follows: we distinguish firms by (i) their firm size considering small-sized firms (1-49 employees), middle-sized firms (50-249 employees) and large-sized firms (≥ 250 employees), (ii) by their firm age, i.e. young firms (*leq* 10 years) and old firms (≥ 10 years), by their export status, i.e. do they export or not, and by whether the ownership is domestic (foreign capital share ; 10%) or multinational (foreign capital share *geq* 10%.

A.1.1 Identification of automation- and AI-related goods

Table 2 presents the product codes that we use to identify automation- and AI-related imports following the previous work by Acemoglu and Restrepo (2018) and Domini et al. (2021, 2022).

Label	HS codes (6-digits)
Automation	
1. Industrial robots	847950
2. Dedicated Machinery	847989
3. Automatic machine tools	845600- 846699 , 846820 - 846899 , 851511 - 851519
(inc. numerically controlled machines)	
4. Automatic welding machines	851521, 851531, 851580, 851590
5. Weaving and knitting machines	844600-844699 and $844700-844799$
6. Other textile dedicated machinery	844400-844590
7. Automatic conveyors	842831-842839
8. Automatic regulating instruments	903200-903299
9. 3D-printers	847780
Artificial Intelligence (AI)	
10. Automatic data processing machines	847141-847150, 847321, 847330
11. Electronic calculating machines	847010-847029

Table (2) HS product codes referring to automation- and AI-related capital goods

A.2 Occupational groups

Table ((3)	Classifications	of	Occupational	codes

Broad Task Group (Cortes et al., 2021)	Occupational classification coding, CNP94 (3-digits)
Non-routine cognitive	112-131, 211-247,311-315,321-515
Routine cognitive	521-523
Routine manual	711-745,811-834,916-933
Non-routine manual	516,911-915
Macro-Occupation Groups	Occupational classification coding, CNP94 (2-digits) $$
Macro-Occupation Groups Managers	Occupational classification coding, CNP94 (2-digits) 11-13
Macro-Occupation Groups Managers STEM professionals	Occupational classification coding, CNP94 (2-digits) 11-13 21,31
Macro-Occupation Groups Managers STEM professionals Other professionals	Occupational classification coding, CNP94 (2-digits) 11-13 21,31 22-24,32-34
Macro-Occupation Groups Managers STEM professionals Other professionals Blue-collar workers	Occupational classification coding, CNP94 (2-digits) 11-13 21,31 22-24,32-34 71-83
Macro-Occupation Groups Managers STEM professionals Other professionals Blue-collar workers Other non-professionals	Occupational classification coding, CNP94 (2-digits) 11-13 21,31 22-24,32-34 71-83 41-42,51-52,61-62,91-93

Notes: i) We map detailed occupation codes to broad task groups following previous work by Cortes et al. (2021). ii) We classify occupation codes into five macro groups similar to Barth et al. (2020).

A.3 Appendix Tables and Figures

Panel A: Automating Firms	Ν	Mean	St. Dev.	Pc25	Median	Pc75
Gross value added (in 1000 \textcircled{C})	77,133	445,002.9	2,864,856.0	$35,\!536.8$	93, 131.5	$252,\!255.8$
Labor Productivity	77,133	4,315.5	82,093.3	1,255.0	1,773.0	2,608.3
Number of workers	$77,\!133$	70.4	240.8	10	25	61
Hours worked	77,133	$12,\!232.1$	40,872.1	1,730	4,325	$10,\!602$
Number of Establishments	77,133	1.7	13.5	1	1	1
Labor Share	$73,\!539$	0.5	0.2	0.4	0.5	0.6
Mean hourly wage	$77,\!133$	6.7	2.8	4.9	6.1	7.7
Wage bill (in 1000 \textcircled{C})	$77,\!133$	$166,\!845.1$	$818,\!424.8$	$18,\!587.5$	$47,\!458.3$	$122,\!897.4$
Export Status	$77,\!133$	0.7	0.5	0	1	1
Small-sized Firms (in %)	$77,\!133$	0.7	0.5	0	1	1
Middle-sized Firms (in %)	$77,\!133$	0.2	0.4	0	0	0
Large-sized Firms (in %)	$77,\!133$	0.1	0.2	0	0	0
Firm Age	$77,\!115$	23.5	17.4	11	20	31
Young Firms (in %)	$77,\!115$	0.2	0.4	0	0	0
Multinational (in %)	77,133	0.1	0.3	0	0	0
Panel B: Non-Automating Importers	(1)	(2)	(3)	(4)	(5)	(6)
Gross value added (in 1000 \textcircled{C})	114,902	80,188.0	336,636.3	$12,\!495.3$	29,208.5	$68,\!615.6$
Labor Productivity	$114,\!902$	2,529.7	20,284.8	922.7	1,365.8	2,078.0
Number of workers	$114,\!902$	21.0	50.4	4	10	23
Hours worked	$114,\!902$	$3,\!653.8$	$9,\!103.1$	692	1,730	3,971.8
Number of Establishments	$114,\!902$	1.2	1.6	1	1	1
Labor Share	106,069	0.6	0.2	0.4	0.6	0.7
Mean hourly wage	$114,\!902$	5.6	2.6	4.0	4.9	6.4
Wage bill (in 1000 $\textcircled{\bullet})$	$114,\!902$	$37,\!514.9$	$121,\!661.1$	$7,\!281.3$	$16,\!539.9$	$37,\!838.0$
Export Status	$114,\!902$	0.4	0.5	0	0	1
Small-sized Firms (in %)	$114,\!902$	0.9	0.3	1	1	1
Middle-sized Firms (in $\%$)	$114,\!902$	0.1	0.3	0	0	0
Large-sized Firms (in $\%$)	$114,\!902$	0.004	0.1	0	0	0
Firm Age	$114,\!853$	19.2	15.1	8	16	26
Young Firms (in %)	$114,\!853$	0.3	0.5	0	0	1
Multinational (in %)	114,902	0.04	0.2	0	0	0
Panel C: All Non-Automating Firms	(1)	(2)	(3)	(4)	(5)	(6)
Gross value added (in 1000 $\textcircled{C})$	557,850	30,520.6	$176,\!569.3$	4,021.2	9,343.3	$22,\!505.9$
Labor Productivity	$557,\!850$	$1,\!800.7$	$17,\!398.7$	706.1	1,086.3	$1,\!699.8$
Number of workers	$557,\!850$	9.3	27.0	2	4	9
Hours worked	$557,\!850$	$1,\!622.0$	4,837.6	346	692	1,557
Number of Establishments	$557,\!850$	1.1	1.1	1	1	1
Labor Share	$494,\!692$	0.6	0.2	0.5	0.6	0.7
Mean hourly wage	$557,\!850$	4.9	2.2	3.5	4.3	5.5
Wage bill (in 1000 $\textcircled{\epsilon}$)	$557,\!850$	$15,\!622.5$	66,141.1	$2,\!644.3$	$5,\!834.5$	$13,\!550.6$
Export Status	$557,\!850$	0.1	0.3	0	0	0
Small-sized Firms (in $\%$)	$557,\!850$	1.0	0.2	1	1	1
Middle-sized Firms (in $\%$)	$557,\!850$	0.02	0.2	0	0	0
Large-sized Firms (in $\%$)	$557,\!850$	0.001	0.03	0	0	0
Firm Age	$557,\!563$	15.6	13.7	5	12	21
Young Firms (in %)	$557,\!563$	0.4	0.5	0	0	1
Multinational (in %)	557,850	0.01	0.1	0	0	0

Table (4) Summary statistics firm characteristics, 2004-2021

Notes: Panel A reports summary statistics for automating firms. Panel B reports summary statistics for non-adopters that import at least once over the observed period. Panel C reports summary statistics for all non-adopting firms (including importers).

Panel A: Automating Firms	Ν	Mean	St. Dev.	Pc25	Median	Pc75
by task group (in %)						
Routine manual	$77,\!133$	0.607	0.278	0.493	0.668	0.800
Routine cognitive	77,133	0.021	0.073	0.000	0.000	0.000
Non-routine manual	$77,\!133$	0.029	0.094	0.000	0.000	0.018
Non-routine cognitive	77,133	0.341	0.260	0.167	0.277	0.444
by macro-occupation groups (in %)						
Managers	$77,\!133$	0.044	0.097	0.000	0.011	0.052
STEM professionals	$77,\!133$	0.098	0.161	0.000	0.038	0.12
Other Professionals	$77,\!133$	0.067	0.120	0.000	0.030	0.08
Blue-collar	$77,\!133$	0.540	0.292	0.333	0.600	0.760
Other non-professionals	$77,\!133$	0.251	0.239	0.083	0.178	0.348
by educational group (in %)						
Low-educated	$77,\!133$	0.628	0.256	0.500	0.667	0.818
Middle-educated	$77,\!133$	0.240	0.193	0.105	0.203	0.333
High-educated	$77,\!133$	0.131	0.162	0.004	0.091	0.173
by type of contract (in %)						
Permanent	$77,\!133$	0.768	0.249	0.667	0.840	0.971
Fixed	77,133	0.207	0.233	0.009	0.135	0.308
Panel B: Non-Automating Importers	(1)	(2)	(3)	(4)	(5)	(6)
	(-)	(-)	(9)	(*)	(~)	(9)
by task group (in %)	114 009	በ ፍንን	0.352	0.490	0 799	0 000
Routine manual	114,902 114,002	0.022	0.555	0.429	0.725	0.000
Non routing manual	114,902 114,002	0.025	0.096	0.000	0.000	0.000
Non-routine manual	114,902 114,002	0.030	0.110	0.000	0.000	0.000
has mean commution and $(in \mathcal{X})$	114,902	0.312	0.311	0.077	0.212	0.400
Managere	114 002	0.052	0 199	0.000	0.000	0.048
STEM professionals	114,902 114,002	0.052	0.133	0.000	0.000	0.040
Other Professionals	114,902 114,002	0.040	0.155	0.000	0.000	0.020
Plue coller	114,902 114,002	0.005	0.152	0.000	0.000	0.004
Other non professionals	114,902 114,002	0.300	0.340	0.275	0.007	0.001
by educational arrows $(in \ \%)$	114,902	0.271	0.295	0.000	0.107	0.414
Low educated	114 002	0 703	0.200	0 556	0 783	0.035
Middle advested	114,902 114,002	0.703	0.290	0.000	0.765	0.95
High advested	114,902 114,002	0.200	0.235 0.179	0.000	0.145	0.300
has tame of contract (in %)	114,902	0.091	0.172	0.000	0.000	0.111
Permanent	114 002	0.760	0.286	0.626	0.877	1.000
Fired	114,902 114,002	0.709	0.260	0.030	0.011	1.000
r ixeu	114,902	0.201	0.207	0.000	0.090	0.550
Panel C: All Non-Automating Firms	(1)	(2)	(3)	(4)	(5)	(6)
By task group (in %)						
Routine manual	$557,\!850$	0.693	0.357	0.500	0.833	1.000
Routine cognitive	$557,\!850$	0.018	0.097	0.000	0.000	0.000
Non-routine manual	$557,\!850$	0.035	0.137	0.000	0.000	0.000
Non-routine cognitive	$557,\!850$	0.248	0.328	0.000	0.111	0.375
by macro-occupation groups (in $\%$)						
Managers	$557,\!850$	0.068	0.194	0.000	0.000	0.000
STEM professionals	$557,\!850$	0.023	0.107	0.000	0.000	0.000
Other Professionals	$557,\!850$	0.036	0.135	0.000	0.000	0.000
Blue-collar	$557,\!850$	0.657	0.371	0.400	0.786	1.000
Other non-professionals	$557,\!850$	0.215	0.310	0.000	0.000	0.333
by educational group (in %)						
Low-educated	$557,\!850$	0.794	0.295	0.667	0.955	1.000
Middle-educated	$557,\!850$	0.160	0.258	0.000	0.000	0.250
High-educated	557,850	0.046	0.143	0.000	0.000	0.000
by type of contract (in %)	30					
	FF7 0F0	0 700	0.991	0.619	1 000	1 00(
Permanent	557,850	0.769	0.551	0.012	1.000	1.000

Table (5) Summary statistics workforce composition, 2004-2021

Notes: Panel A reports summary statistics for automating firms. Panel B reports summary statistics for non-adopters that import at least once over the observed period. Panel C reports summary statistics for all non-adopting firms (including importers). For further information on the classifi-



Figure (8) Imports around automation event

Notes: Figure 8 shows the evolution of automation import shares (of the sum of total automation imports) around automation events. Note that automation events are defined as the largest event for each firm.



Figure (9) Evolution of employment shares between different groups of workers

Notes: In figure 9 we compare differences between automating and non-automating firms plotting trends of employment shares, total hours worked and mean hourly. In panel we 9c-10c we consider differences by educational group, in panel 9a-10a by task group, in panel 10b-10c by occupational group and in panel 9d-?? by permanent vs. fixed-term contract.



Figure (10) Evolution of wages between different groups of workers

Notes: In figure 9 we compare differences between automating and non-automating firms plotting trends of employment shares, total hours worked and mean hourly. In panel we 9c-10c we consider differences by educational group, in panel 9a-10a by task group, in panel 10b-10c by occupational group and in panel 9d-?? by permanent vs. fixed-term contract.