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Automation and flexible labor contracts: Firm-level evidence from Italy[*†]

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Abstract

This study examines the association between investments in automation technologies and employment outcomes at the firm level, utilizing a panel dataset of about 10,450 Italian firms. Focusing on the proliferation of non-standard, flexible labor contracts introduced by labor market reforms in the 2000s, we identify a positive relationship between automation investments and the adoption of flexible labor arrangements. With the aid of a conceptual framework, we interpret these findings as evidence of complementarity between flexible capital, represented by automation technologies, and flexible labor, manifested through non-standard contractual arrangements. This complementarity is crucial for enhancing operational flexibility, a critical determinant of firm performance in the modern market environment. However, while this adaptability is beneficial for firms, it raises concerns about job security, the potential for lower wages among workers, and the reduction of workers' incentives to invest in human capital. In terms of policy implications, our analysis underscores the need for measures that safeguard workers' interests without compromising the efficiency gains from automation.

Keywords: Automation; Labor Contracts; Flexible Capital; Flexible Labor.
JEL codes: D20; J30; J41; K31.

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[†] *Massimiliano Vatiero wishes to dedicate this article to the memory of Riccardo Del Punta (Professor of Labor Law at the University of Florence, Italy), who passed away in November 2022. Professor Del Punta – Massimiliano's mentor and friend – believed strongly in the positive contribution of institutional economics to research and reforms of labor law.*

1 Introduction

The high levels of structural unemployment of Western European countries have been traditionally attributed to rigid labor market institutions. Therefore, over the last decades, both right and left wing Western European governments have introduced a series of policy reforms aimed at increasing labor market flexibility (Eurofound, 2020). For example, Germany introduced the *Hartz-Konzept* in 2002, while Italy tried to reform its labor institutions in more steps, starting with the 1997 Treu Law, and following with the 2003 Biagi Reform, and the so-called 'Jobs Act' in 2014. Spain, characterized by the highest structural unemployment rate among major Western European countries, introduced an important reform in 2012, under the Rajoy government. In France, labor market reforms have been a contentious issue, often met with significant public resistance. Despite this, the National Assembly passed the *Loi Travail* in 2016. Overall, these classical market- oriented reforms reduced legal and bureaucratic barriers to employment, hiring, and firing, and introduced or expanded atypical forms of employment. At the core of these reforms was the provision of flexible labor contracts, such as temporary work contracts, part-time work contracts, freelance contracts, temporary work agencies, and other atypical forms of employment. Overall, these flexible labor contracts reduced hiring and firing costs, ultimately giving firms more flexibility as they can more easily adjust their workforce.

The success of these reforms is disputed (Kahn, 2012). On the one hand, net of the effects of the multiple economic crises that have affected Europe, the structural unemployment rate appears to have indeed decreased. According to numerous analyses, in fact, the reforms seem to have contributed to an increase in employment and labor market efficiency (International Labour Organization, 2016; Boeri and Garibaldi, 2019; Rünstler, 2021). On the other hand, flexible labor contracts have been considered by some as not only somewhat inefficient in tackling labor market segmentation, but also responsible for the increase in job insecurity, a decrease in temporary to permanent transition, the reduction of wages, and the creation of working poor, especially among the young (Boeri and Garibaldi, 2007; Barbieri and Cutuli, 2015). Along these lines, critics often argue that while flexibilization may create jobs, these jobs are often of lower quality (Aumond et al., 2022; Giuliani and Madama, 2022). Therefore, in recent years, an increasing number of voices, at least in Europe (Eichhorst and Marx, 2021), have called for either a repeal of or an amendment of the reforms.

Alongside these labor market reforms, the past decades have witnessed the widespread adoption of automation technologies (Frey and Osborne, 2017). This adoption has led to an expansion in the set of tasks, functions, jobs, and activities that capital can perform By enhancing the flexibility of capital, this technological shift has contributed to reshape labor market dynamics (Brynjolfsson and McAfee, 2014; Grigoli et al., 2020). As such, the dynamics observed in labor markets over the last years are not solely the consequence of legal reforms – like the aforementioned changes in labor institutions – but also the result of a technological shock. Therefore, analyzing the interplay between the two is essential for devising policies that address both the opportunities and the challenges presented by this new, evolving landscape.

Within this context, our study focuses on the relationship between flexible labor arrangements and the adoption of automation technologies. At the heart of our analysis is the idea that automation and flexible labor contracts are complementary. Complementarity occurs when the returns deriving from choices in one domain (for our case, the choice of investing in automation) increase as they are complemented by choices in a second domain (the choice of using flexible labor contracts). Our empirical findings, based on a panel of Italian firms, show that the investment in automation turns out to be robustly associated with an increase in the number of flexible workers within the firm. As thoroughly discussed in the paper, the fact that firms investing in automation are more likely to leverage flexible labor arrangements suggests that, by increasingly intertwining technological advancements with flexible employment, firms aim to construct a more agile and responsive operational environment. Such strategy can boost efficiency and adaptability in response to rapidly evolving market conditions. For instance, in the case of demand fluctuations, the firm can react using both the availability of flexible contracts that allow rapid alignment of the workforce with changing scenarios and the flexibility in the production process enabled by automation technologies. Arguably, moreover, the two strategies reinforce each other, with the return associated with each strategy being greater when the other is also concurrently pursued.

By studying the complementarity between flexible labor and automation technologies, our research contributes to the current debate on labor policies. Indeed, after about two decades, the mood towards lighter employment protection legislation, at least in Europe, seems to have changed (Eichhorst and Marx, 2021), and some of the reforms are under severe scrutiny or have been fundamentally amended (e.g., the 2022 reform of Sanchez has largely reversed the 2012 Rajoy reform). However, given the widespread diffusion of automation technologies in current business practices, reforms aimed at reducing labor flexibility may lead to a loss in efficiency that could be substantially higher than anticipated.

While emphasizing that joint access to automation and flexible employment increases the economic value of automation and overall firm adaptability, we also point out that it may have some negative implications for workers and firms. In particular, our discussion revolves around its potential detrimental effects on workers' productivity and firms' competitiveness due to the reduction in incentives to make human capital's specific investments (Acharya et al., 2013; Dughera et al., 2023).

Articulating these concerns, we argue that updating the labor reforms of the last couple of decades should be directed at avoiding the endangerment of quality work while accommodating the need for flexibility and supporting efficiency gains resulting from the complementarity between automation and flexible employment arrangements.

The remainder of the paper is organized as follows. In Section 2, we review the related literature. In Section 3, we outline a simple conceptual framework where we discuss how automation and flexible labor may interact in influencing firm performance. In Section 4, we describe the data and the empirical strategy. The estimates of the relationship between investment in automation and firm resort on flexible labor, and other firm-level employment outcomes, are then presented in Section 5. Section 6 discusses some policy implications. Section 7 concludes.

2 Literature review

Our paper is related to the rapidly expanding body of research literature examining the relationship between automation technologies and employment at the firm level. This literature, has typically focused on the overall employment effect and the skill composition of the workforce, while less attention has been paid to the role of contractual arrangements (for a comprehensive review of the topic, see Mondolo, 2022; Filippi et al., 2023).

Bessen et al. (2020), using an annual survey over the period 2000-2016 covering 36,490 unique Dutch firms, show that firms investing in automation exhibit higher long-term growth in employment and in revenue than non-automating firms. However, they also highlight that employment growth slows in the aftermath of the investment, a result that is consistent with the labor-saving nature of automation. In another empirical work using firm-level data on the purchases of robots imported by Canadian firms from 1996 to 2017, Dixon et al. (2021) show that investments in robotics are associated with increases in non-managerial employment, and with a substantial decline in managerial employment. This suggests that robots displace managerial work, leading, *inter alia*, to an increase in the span of control for supervisors remaining within the organization. Using an annual survey covering around 1,900 Spanish manufacturing firms from 1999 to 2016, with detailed information on robot use in the production process of individual firms, Koch et al. (2021) investigate differences in robot adoption across firms. They find that robots raise firm-level employment by around 10 percent (with positive employment effects especially pronounced among high-skilled workers). Using the same data, Ballestar et al. (2022), study the workforce's characteristics that allow firms to become robotic, analyzing and discussing the optimal combination of technology and human capital's characteristics which is able to boost the transformation process toward automation and robotics.

Acemoglu et al. (2020) study firm-level changes associated with robot adoption using data from France between 2010 and 2015. Consistent with their theoretical expectations, they find that firm-level adoption of robots coincides with declines in labor shares, increases in value-added and productivity, and declines in the share of production workers. Moreover, they show that overall employment increases faster in firms adopting robots at the expenses of non-adopting competitors. In another paper, Balsmeier and Woerter (2019)'s empirical analysis exploits Swiss firm-level data of investment on a list of specific digital technologies, including robots, 3D printing, autonomous vehicles, and the Internet of Things. They find that investment in digitalization is associated with increased employment of high-skilled labor, whereas low- and medium-skilled labor tends to decline or remain unaffected. In contrast, in a recent working paper, Bonfiglioli et al. (2023) find that investment in automation (more precisely, in robots) had a negative impact on the employment of French manufacturing firms, and that the positive association identified by previous studies is likely to be driven by the endogeneity of investment with demand shocks. Finally, in another recent working paper, Caselli et al. (2024) develop an instrumental variable strategy to analyze the impact of operational and information digital technologies on Italian firms, finding a differential impact on the labor force structure.

Another close strand of literature is the one concerning the relationship between employment protection legislation and innovation. At an aggregate level, examining a panel of OECD countries, Murphy et al. (2017) find that rigid employment protection legislation jeopardizes innovation. At the firm level, on the other hand, Belloc et al. (2023) find a positive association between the presence of employee representation and the adoption of automation technologies. They interpret this as evidence that the presence of workers' representative bodies favours the introduction of technologies that are complementary to labor and whose adoption requires a "skill-improving" redesign of the job. Malgarini et al. (2013), examining the Italian case at a firm level, find evidence of a negative effect of the use of temporary contracts on innovative investments before the Great Recession, while finding no evidence of such an effect afterwards. On the same topic, Dughera et al. (2022) develop a theoretical model that highlights the possible complementarities between firms' hiring and innovation strategies, highlighting that without adequate coordination in the managerial structure firms may end up caught in Pareto-inefficient equilibria characterized by high reliance on temporary workers and low innovation. In a follow-up paper, coupling a theoretical model with an empirical analysis, Dughera et al. (2023) further explore the relationship between innovation and fixed-term employment, arguing for a reversed-U relationship between the two, and highlighting the key role of 'portability' of human capital investment.

The relationship between employment protection and automation has also been analyzed in light of the literature on hold-up risk. For instance, Acharya et al. (2013) and Acharya et al. (2014) argued that stringent labor laws can create ex-ante incentives for firms and workers to undertake risky but long-term rewarding activities that spur innovation. This is because workers may be more willing to make efforts to learn and innovate if they know that they will be protected from opportunistic behaviour by the firm. A different view has been presented by Traverso et al. (2023), who find that statutory protection against dismissal is negatively associated with the adoption of robots. They suggest that robot adoption tends to be higher in environments with more flexible labor regulations, indicating that regulatory frameworks that are perceived as more supportive of business – especially those with more flexible labor laws – tend to reduce adjustment costs and, consequently, create more favorable conditions for firms to invest in industrial robots.

3 The complementarity between automation and flexible labor contracts: a conceptual framework

Our study focuses the complementarity between automation and flexible labor. In this section, we begin by defining these two concepts and their consequences on firm performance, thereby setting the foundation for our analysis. Then, we delve into the nature of such complementarity, discussing how they can jointly enhance firms' operational flexibility.

Acemoglu and Restrepo (2018) defined automation as a technology that enlarges the number of tasks and functions that may be performed with capital. In a similar vein, we conceptualize automation as a set of technologies that increases the flexibility of the (physical) capital and that, when implemented, it results in an expansion of the spectrum of tasks achievable through capital. Moreover, and this is key for our perspective, automation also enables capital to switch between relatively different tasks at a relatively low cost. As automation advances, it further broadens the flexibility of capital, enabling it to undertake tasks that were previously unattainable due to their complexity or subtlety, and to be reprogrammed at lower costs.

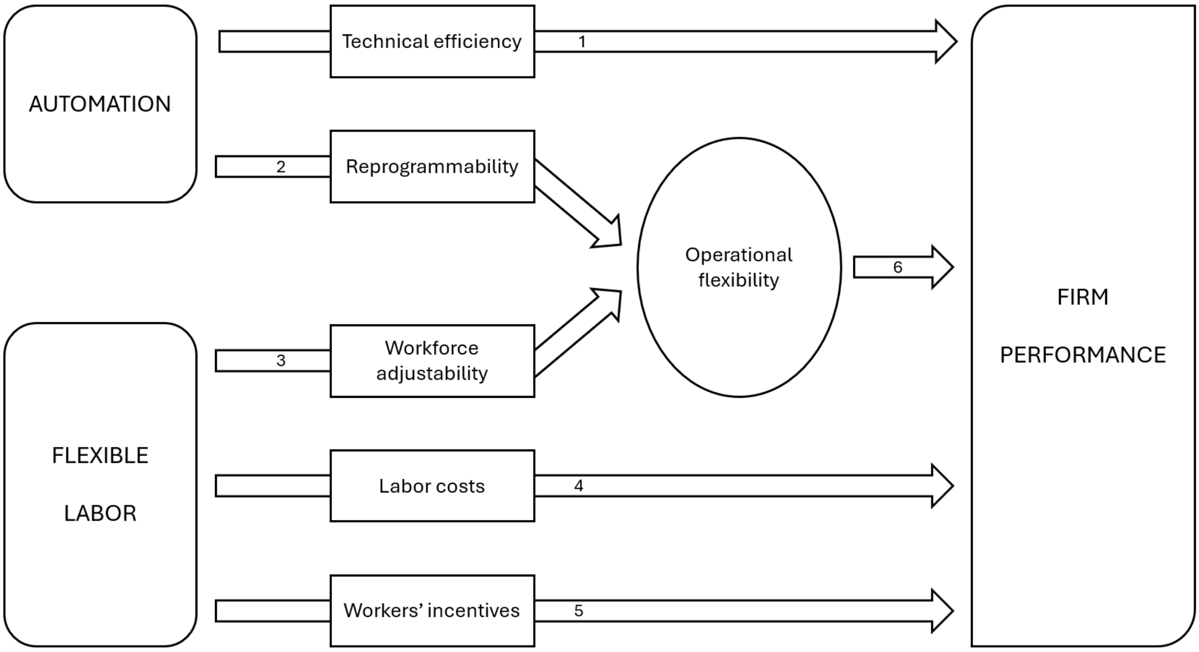
Robots represent a paradigmatic example of automation, epitomizing how it increases the flexibility of physical capital in industrial and service settings. Despite the absence of a singular, formal definition, prevalent descriptions of robots consistently emphasize their reprogrammable and multipurpose capabilities (UNCTAD, 2017; ISO, 2021; IFR, 2023). Such reprogrammability, which enables robots to perform a variety of tasks – switching from one to another – without significant mechanical modifications, represents a key aspect of automation that is fundamental to understand the complementarity between automation technologies and flexible employment.

Automation, however, is not limited to robots and, in this analysis, we also consider technologies such as the internet of things (IoT), big data, and augmented reality. Each of these technologies contributes to the flexibility of capital in distinct ways. IoT connects devices for 'smart' operations, which can be easily reprogrammed. Big data technologies enhance decision-making by collecting an unprecedented amount of data that can be transformed into information through different types of real-time analysis. Augmented reality improves workers' task execution with interactive digital overlays, which can be easily reprogrammed according to the evolving needs of the firm. Similarly to robots, and in line with our theoretical perspective, these technologies exemplify how automation increases the flexibility of capital by broadening the tasks and functions it can perform, and by making capital itself less specific, i.e., allowing for smoother transitions from one task to another.

Hence, to summarize, automation increases capital flexibility along two distinct lines, as represented by arrows 1 and 2 in Figure 1. On one hand, it extends the set of tasks that can be performed by capital, and because certain tasks may be better performed by machines than by human labor, it contributes to increase technical efficiency. On the other hand, due to its reprogrammable features, it enhances the capacity of capital to switch from one application to another at low cost. In other words, it reduces the overall specificity of capital investment.

In the context of labor, we conceptualize flexible labor through the lens of labor contracts. The labor reforms of past decades have broadened the set of employment arrangements available to firms, introducing temporary work contracts, part-time agreements, and freelance contracts, as well as employment relationships mediated by temporary work agencies and other multi-party employment setups. Differing substantially from traditional, open-ended employment contracts, these arrangements led to a new legal framework that substantially reshaped the opportunities and the economic incentives of both workers and firms. On the one hand, these new contracts have increased firms' ability to swiftly adjust their workforce in response to market shocks (arrow 3). Importantly, firms can resort to these contracts not just to rapidly increase or decrease the total number of workers employed, but also to quickly reshape the skill mix of the workforce. On the other hand, while they sometimes offer workers the flexibility to engage in multiple projects, diversify their skills, and better manage their work-life balance, in most of the cases these contracts have been associated with increased job insecurity, diminished workers' protection, and reduced workers' bargaining power. This translated

Figure 1: Conceptual framework



in lower labor costs for firms (arrow 4), but it also affected workers' incentives in acquiring firm-specific skills (arrow 5). In fact, as discussed in Acharya et al. (2013; 2014) and in Dughera et al. (2022; 2023), workers discount the likelihood of loosing their current job by abstaining to undertake firm-specific human capital investments (i.e., acquiring skills that are useful only in the firm they're working in) which may boost labor productivity within the firm, and even foster innovation.

In the Italian context, various types of flexible employment contracts have been introduced over time, substantially expanding the landscape of formal arrangements available to workers and firms. New and atypical forms of employment include, among others: fixed-term contracts (*contratti a tempo determinato*), used to hire workers for a specific, pre-determined period;[1] freelance under coordinated and continuous collaboration contracts (*contratti di collaborazione coordinata e continuativa*), where the worker operates as an independent contractor, providing services on a project-by-project basis; temporary agency work contracts (*contratto di somministrazione di lavoro*), where the worker is employed by a temporary work agency and then supplied to a third company to perform work for a limited period; on-call work (*contratto di lavoro a chiamata / intermittente*), a work arrangement where the employee is called upon to work as needed, often without a fixed schedule or guaranteed hours; and casual work contracts (*contratto di prestazione occasionale*), designed for situations where the employer requires temporary labor for short-term or sporadic tasks.

[1]This type of contract already existed, but reforms simplified its use for firms.

By definition, complementarity involves the interactions among changes in different choice variables. Two choice variables complement each other if an increase in the level of one variable increases the returns to increasing the other one. That is, "the two choice variables are complements when doing (more of) one of them increases the return of doing (more of) the other" (Roberts, 2007, p. 34). In contrast, choice variables are substitutes if choosing (more of) one reduces the attractiveness of choosing (more of) the other.

While there are several reasons why automation and flexible labor can complement each other, they can be typically traced back to their contribute to firms' operational flexibility. Operational flexibility is a firm's ability to promptly adapt its operations and production processes in response to shocks. Operating in an increasingly global market, firms confront a strong competition and a volatile, unpredictable demand. Hence, to maintain competitiveness, they must be able to adapt their production plans swiftly. This might involve frequently updating product characteristics, producing several varieties of the same product simultaneously, or even providing customers with a certain degree of product customization. Moreover, the more frequent the changes in product specifications, the more challenging it becomes to manage shifts in the quantity demanded through fine inventory control alone, as this necessitates rapid and continuous production adjustments. The evolution of the competitive environment, therefore, has made operational flexibility a more critical ingredient of firm success than it was in the past.

While both the resort to flexible labor and the investment in automation technologies can individually enhance firm resilience and adaptability in certain (and, sometimes, overlapping) operational domains, the highest level of operational flexibility – that is strategic to firm performance – can be achieved only with a combination of the two. Indeed, adjustable workforce and reprogrammable machines may even be seen as two components of the same construct, that is, operational flexibility. On the one hand, automation guarantees flexibility for rapidly adjusting and scaling relatively standardized, routinary tasks. On the other hand, the availability of flexible employment arrangements allows firms to adjust the workforce in all the areas when human labor is required. Thus, resorting to either automation or flexible labor alone might be an inefficient way to increase operational flexibility. In formal terms, this might be equivalent to assuming that operational flexibility is a homogeneous function of degree one of reprogrammability and workforce adjustability, which individually exhibit diminishing marginal returns.

In a nutshell, while technical efficiency, labor costs, and workers' incentives represent channels through which automation and flexible labor independently affect firm performance, reprogrammability and workforce adjustability influence firm outcomes only indirectly, through their effect on operational flexibility (arrow 6). Therefore, the choice of investing in automation can be better understood if considered together with the choice of resorting to flexible labor contracts. Since, according to our hypothesis, these two domains of choice complement and reinforce each other, in our empirical analysis we expect to find investments in automation being associated with an increase in the use of flexible forms of labor. Indeed, assuming they start from a state of equilibrium, firms aiming to enhance operational flexibility will typically seek to advance in both domains.

Before proceeding with the discussion of the empirical strategy, it is worth mentioning that while automation represents internal capital flexibility (i.e., capital can perform different tasks within a firm), in the domain of labor, the use of flexible contracts is associated with external flexibility. In fact, it signals the extent to which a firm responds to changes in its labor requirements by means of hiring and firing. It does not capture, however, internal labor flexibility, that is the extent to which a firm adapts to changing conditions, demand, or challenges without resorting to external measures such as layoffs or hiring, but reorganizing its existing workforce.

4 Data and methods

4.1 Main analysis

In this study, we utilize the data from the 2015 and 2018 waves of the *Rilevazione Imprese e Lavoro* (RIL) survey to construct a panel encompassing around 10,450 Italian firms. Conducted by the Italian National Institute for Public Policies Analysis (Inapp), the survey aims to explore the dynamics of labor demand and the core attributes of Italy's productive and entrepreneurial sectors, with a particular focus on the competitive landscape, on organizational changes in the workforce, and on labor market's demand-supply mechanisms. To achieve this, it gathers firm-level data across various domains, including managerial structures, recruitment methods, industrial relations, investments, international trade exposure, technological innovation, and credit access. Data have been collected via computer assisted telephone interviewing, and the sample encompasses a random selection of firms from the active business registries in Italy.

For the empirical analysis, we leverage a question introduced in the 2018 wave of the survey, which asked whether, during the 2015-2017 period, the firm has invested in automation technologies. These technologies encompass a range of solutions, including but not limited to, IoT solutions, robotics, 3D printers, automatic machines, as well as intangible assets such as cloud computing, big data analysis, and cybersecurity. In particular, we define a dummy variable to identify firms that have invested in certain 'hard' automation technologies, namely: robotics, internet of things (IoT), big data, and augmented reality. We differentiate these technologies from other investments in 'soft' automation solutions such as cloud computing, web applications, cybersecurity, and system upgrades. The rationale behind this separation is that investments in 'soft' automation solutions had become relatively commonplace during the second half of the 2010s. Consequently, we posit that such investments may not distinctly reflect a firm's proactive stance or strategic intent to leverage automation for improving operational flexibility.[2] On the contrary, investments in 'hard' automation technologies potentially signal a deliberate organizational endeavor to increase its automation capabilities, which might, in turn, have meaningful implications for the labor contractual arrangements chosen by the firm.

In order to investigate the relationship between of investment in automation technologies, labor contracts and other firm-level employment dynamics, we rely on a matched difference-in-differences (matched DiD) approach. The matching procedure, that can be viewed as a strategic subsampling technique (Imbens and Rubin, 2015), is based on a set of background variables, measured at the beginning of 2015 or earlier, aimed at ensuring a well-balanced comparison between the treated and control groups. Specifically, these variables are chosen to capture the structure of the firm's workforce, the intrinsic characteristics of the firm, and the firm's business dynamics before the investment in automation, thereby mitigating the confounding effect of omitted variables. Indeed, these matching variables aim to capture the firm's propensity towards innovation (and, in particular, the decision to invest in automation technologies), as well as the *ex ante* trajectory of the outcome variables of interest.

To adequately capture the firm's workforce structure, we match on the following variables: the natural logarithm of the number of workers, the proportion of workers holding a university degree, the proportion of blue-collar workers, the proportion of workers hired under flexible contracts, and the proportion of unionized workers. Overall, these variables should provide a relatively detailed picture of the firm's labor force composition just before the investment takes place.

In addressing the firm's business dynamics, we consider the percentage change in employment between 2014 and 2015, represented as a log difference in the number of workers (the number of workers in 2014 is a recall datum). Additionally, we include binary indicators for whether the firm made new investments in 2014 and whether the firm introduced process innovations over the preceding three years.

Lastly, to encapsulate relevant firm characteristics, we match on the natural logarithm of revenue, which serves as a proxy for firm size. We further categorize firms based on their sector of activity (14 classes), geographical location of headquarters (5 macro-regions), organizational structure (distinguishing corporations from unlimited liability companies), and international exposure (identifying exporting firms). These variables are crucial in

[2]Indeed, the majority of firms reported investments in some form of 'soft' automation technology.

controlling for sectoral, regional, and structural heterogeneities that could potentially confound the analysis.

Starting from the matching variables described above, we estimate the propensity score (ps), that is the probability of treatment assignment based on observed covariates, using a probit model. Subsequently, we identify the control group by performing a match on the linearized propensity score (lps), which is the logit transformation of the ps.[3] In particular, we conduct a 1:5 nearest neighbour matching with replacement, enforcing a caliper of 0.15, which is about 15% of the lps standard deviation and falls within the range of optimal caliper widths as suggested by the literature (Austin, 2011). After the matching procedure, we conducted balance checks to ascertain its effectiveness in reducing biases in covariate distributions. When matching is performed on the full sample, no statistically significant differences in the average values of the covariates between the treated and the matched controls are observed (the average standardized bias is just 1.2%) and in almost every case the variance ratio is very close to 1 (for a more detailed comparison of the distribution of the covariates in the treatment and control groups before and after matching, see Tables A1 and A2 in the Appendix). As depicted in Figure 2, the distributions of the lps of treated and control units become virtually identical post-matching. By supporting the balance in observed covariates between the groups and suggesting that the common support condition is satisfied, this further enhances the robustness of the empirical analysis. Equivalent post-matching statistics are obtained from the analysis conducted on the subset of firms with at least 15 employees in 2015.

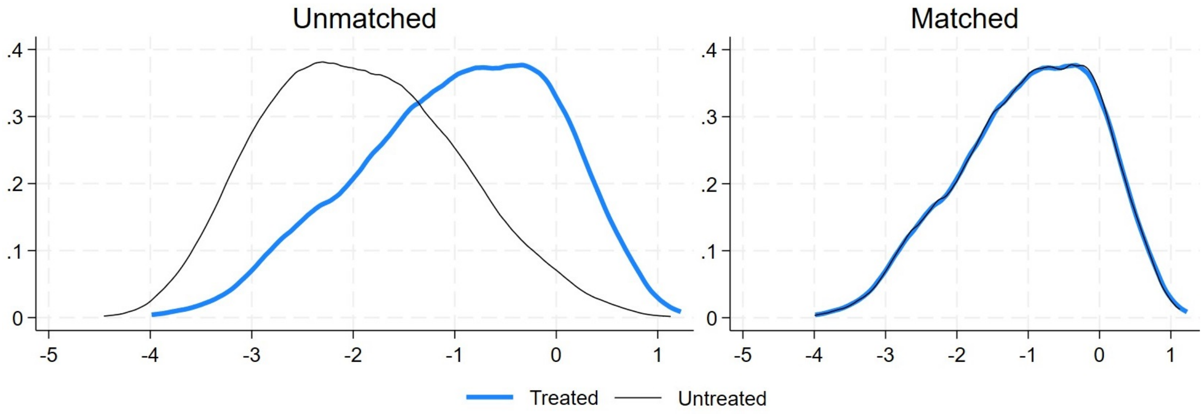
Following the identification of the matched control group, we employ Ordinary Least Squares (OLS) to estimate different variants of the model specified in the following Equation 1. The regression analysis is not conducted on the full sample, but exclusively on the subset of treated firms and their (weighted) matched untreated counterparts.

$$y_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 After_t + \beta_3 (Treat_i \times After_t) + \beta_4 \log(Revenue_{it}) + \gamma' x_{it} + \varepsilon_{it} \quad (1)$$

In this model, the dependent variable y_{it} is an observed outcome of firm i in period t; following the standard DiD terminology, the dummy $Treat_i$ indicates whether the i-th firm is part of the treatment or the matched control group, and $After_t$ is a dummy indicating the post-treatment period (equal to 1 if t=2018). The interaction term, $(Treat_i \times After_t)$, is meant to capture the treatment effect on the treated. Furthermore, $Revenue_{it}$ is the

[3] As discussed, among others, by Imbens and Rubin (2015), this transformation ($lps = \log(ps/1-ps)$) is often preferred in matching estimations as it linearizes the odds of the propensity score, facilitating a more balanced comparison between treated and control units, especially in cases where the propensity score distribution is skewed. Utilizing the lps ensures that the same absolute difference in propensity scores corresponds to the same relative difference in odds, thereby providing a more consistent metric for matching across the range of propensity scores.

Figure 2: Distribution of linearized propensity score



Notes. The figure illustrates the distribution of the linearized propensity score for the groups of treated and untreated firms (full sample) before (upper panel) and after (lower panel) matching.

total revenue reported by the i-th firm at time t, and x_{it} is a vector encompassing both time-varying and time-invariant controls. These controls incorporate dummies for the sector of economic activity the firm is engaged in (14 classes), a dummy indicating the utilization of employment support programs (short-term layoff benefits and/or redundancy support measures) in the preceding year, a dummy marking the presence of trade union representatives within the firm, and a set of dummies indicating the macro-region where the firm headquarter is located (5 macro-regions).

Overall, the inclusion of the control variables is aimed to capture other possible confounding factors, ensuring a more accurate estimation of the treatment effect. On the one hand, revenue is a key proxy for firm size and financial health, both crucial factors in influencing firms' employment strategy and ability/willingness to invest in automation technologies On the other hand, the inclusion of a set of additional controls is aimed at further mitigate the omitted variable concerns. In fact, including sector dummies controls for industry-specific trends and characteristics, which may affect both firms' likelihood to invest in automation and their occupational dynamics, helps mitigate potential confounding effects. Moreover, firms that have resorted to employment support programs may exhibit different financial or operational profiles, which could influence their investment in automation and employment choices. Similarly, trade union representation within a firm may affect labor contract negotiations and other employment-related decisions, as well as firm's decision to invest in automation. Finally, macroregional dummies help to account for geographic variation in economic conditions related to local demand dynamics and local factor endowment, all of which could affect firms' automation investments and employment dynamics. However, it's important to acknowledge that despite our efforts, we cannot guarantee that the Conditional Independence Assumption (CIA) is satisfied. There could still be unobserved confounders affecting both the treatment and the outcome variables. Hence, even if we do our best to control for observable differences, our study design doesn't allow us to clearly establish of causal relationships. Therefore, even though we employ standard DiD terminology, the findings should be interpreted as associations rather than causal relationships, within the constraints of the available data and methodological framework.

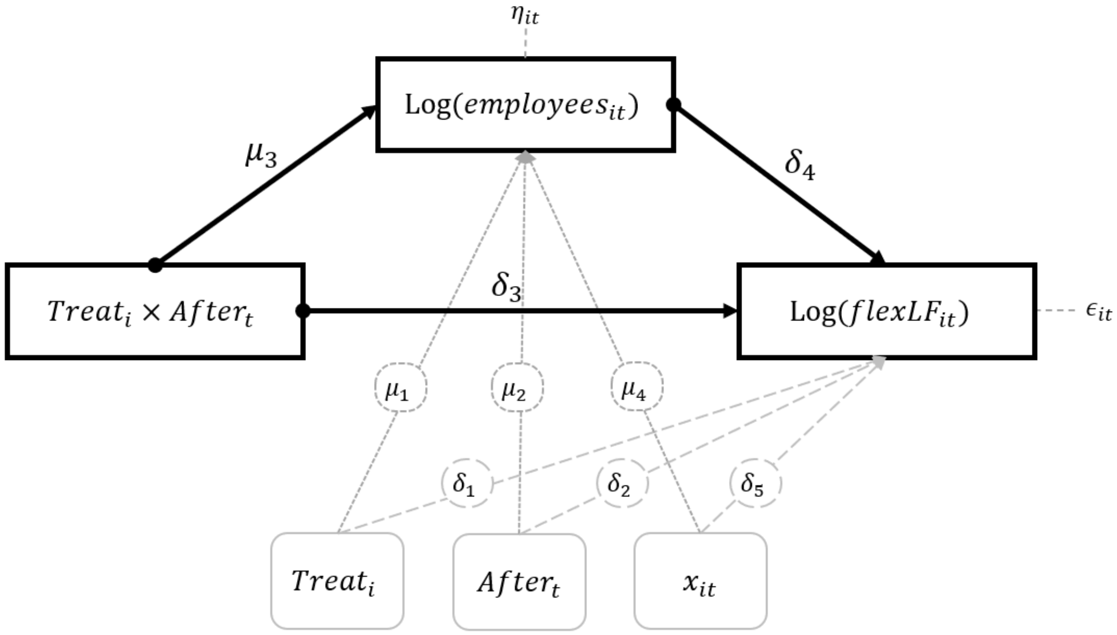
As a dependent variable, we consider a set of outcome variables which includes the logarithm of the number and the share of flexible workers employed by the firm, as well as the logarithm of total firm employees, total new hires, total terminations, and total turnover. Under the umbrella of flexible workers, we include all those workers who have been hired with fixed-term and other non-standard types of employment contracts that have been introduced (or to which the legislator has given a more defined legal framework) with the labor market reforms of the early 2000s. Specifically, these include fixed-term hires (*contratti a tempo determinato*), on-call workers (*lavoratori a chiamata*), freelancers under coordinated and continuous collaboration (*collaborazioni coordinate e continuative*), and casual workers (*contratto di prestazione occasionale*).

4.2 Mediation analysis

In our analysis, the discussion revolves on the relationship between automation and firms' labor force size and structure. We acknowledge, however, that a change in labor force size will likely be correlated, at least in the short term, with the labor force structure, so that changes in the number of flexible workers might not reflect actual changes in the equilibrium labor force flexibility requirements of firms. For example, when a firm reduces labor demand, non-permanent workers will likely be the first to lose their job. On the other hand, if a firm wants to increase its labor force, it will probably test the new hires resorting to non-permanent contracts (this, at least, in countries where labor laws are strict).

We therefore resort to mediation analysis (Hayes, 2017) to assess the extent to which the change in flexible workers associated with investment in automation is due to a genuine shift in firms' workforce flexibility needs. The structure of the mediation model is graphically represented in Figure 3. The adoption of automation ($Treat_i \times After_t$) has a direct influence on the number of flexible workers through channel δ_3. The adoption of automation, however, also influences (through channel μ_3) the number of employees which, acting as mediator, affects the outcome variable through channel δ_4. Other variables in the model are allowed to influence both the mediator and the outcome variable. In this setting, the indirect effect of automation mediated by firm's workforce size is $\mu_3\delta_4$, while the its total effect is given by $\mu_3\delta_4 + \delta_3$. The estimates of the parameters are therefore

Figure 3: Mediation model



obtained estimating a mediation model based on the following mediation equation (Eq. 2) and outcome equation (Eq. 3).

$$\begin{aligned} \log(Emp_{it}) = \mu_0 + \mu_1 Treat_i + \mu_2 After_t + \mu_3 (Treat_i \times After_t) + \\ + \boldsymbol{\mu_4}' x_{it} + \mu_5 lps_i + \eta_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} \log(FlexEmp_{it}) = \delta_0 + \delta_1 Treat_i + \delta_2 After_t + \delta_3 (Treat_i \times After_t) + \\ + \delta_4 \log(Emp_{it}) + \boldsymbol{\delta_5}' x_{it} + \delta_6 lps_i + \epsilon_{it} \end{aligned} \tag{3}$$

where $\log(employees_{it})$ and $\log(FlexEmp_{it})$ are, respectively, the natural log of the total number of employees and of flexible employees of firm i at time t. $Treat_i$ and $After_t$ have been already defined, while x_{it} is a vector of control variables (we test different sets, as specified in regression tables). In this case, to calculate the standard errors for the total effect, matching is performed by including the lps among the control variables, serving as a balancing score.[4] Although this procedure is considered less elegant than weighting, it is widely accepted in the literature as nearly equivalent.

[4]For simplicity, the *lps* has not been explicitly represented in Figure 3.

5 Results

5.1 Automation and resort to flexible employment

The relationship between automation and flexible employment is detailed in Table 1. Overall, in line with our complementarity hypothesis, the empirical results suggest a positive correlation between investment in automation and firms' resorting to flexible labor.

The strongest finding pertains to the effect of automation on the (log) number of flexible workers within the company (columns 1-5). Indeed, in a context of a generalized increase in the number of flexible workers (where the coefficient of $After$ is always positive and significant), in companies that have invested in automation, their number has increased by about 9 additional percentage points. It is worth noting that the estimate obtained with a 'naive estimator' (i.e., the one without performing matching and without including control variables, reported in column 1) is significantly larger (about +40%) than those obtained after matching and controlling for revenue and other potentially relevant confounders. Among these estimates, those focusing only on firms with at least 15 employees (columns 4-5) do not lead to substantially different results.

Regarding the effect of automation on the share of flexible employees (columns 6-10), we find that the coefficient of the interaction term is consistently positive, possibly suggesting that investments in automation technologies can lead to a restructuring of the labor force towards more flexible contracts. However, the results are weaker than those obtained using the log of flexible workers as the dependent variable. In this case, while the point estimate of the interaction coefficient is stable among non-naive models, it is statistically significant (at the 10% level) only for models estimated on the full sample (models 7-8), while it is not when the sample is limited to firms with at least 15 employees in 2015 (models 9-10). On the one hand, this may be due to a scale effect, which could make it harder to detect significant changes in larger firms compared to smaller ones or to the possibility that larger firms have to resort to internal flexibility. In fact, in larger firms, a sizable absolute change in the number of flexible workers might result in only a minor relative change in the ratio of flexible to total workers. Moreover, larger firms have more room for assigning employees to different tasks, resorting to internal flexibility. On the other hand, being a ratio, the dependent variable is potentially subject to double measurement error, both in the numerator and in the denominator. This significantly reduces the statistical power of the regressions (models 9-10 are estimated on 30% fewer observations) and it is likely to introduce attenuation bias.

Overall, the association between investment in automation and the relative increase of flexible worker is also supported by other result presented in the following sections on the paper. Specifically, an analysis comparing the data from columns (1)-(5) in Table 1 with corresponding columns in Table 2 reveals that firms investing in automation exhibit a more than proportional increase in flexible workers relative to total employment.

5.2 Automation and other firm employment dynamics

In this section, we explore the relationship between investment in automation and other outcome variables related to firm-level employment dynamics. Although these outcome variables are not central to the complementarity hypothesis, their examination offers a more comprehensive insight into the hiring and firing decisions of firms associated with investments in automation technologies. Furthermore, some findings suggest that the positive relationship between investment in automation and firms' adoption of flexible work arrangements may be confounded by common HR practices, such as initiating employment with a temporary contract before transitioning to a permanent one, therefore adding empirical support for the mediation analysis.

In Table 2, we explore the correlation between automation and two variables related to employment dynamics at the firm level: the total number of employees and the turnover (job terminations + hires), both expressed in logarithmic terms. Regarding the size of the labor force (columns 1-5), we find that investment in automation is associated with an increase in the total number of workers employed by the firm. Except for the naive estimator (column 1), all models estimate a positive effect of about 5 percentage points. However, this effect is more statistically robust when estimated on the full firm sample. Importantly, the naive estimation of the interaction coefficient, being about 50% higher, may indicate the presence of an upward omitted variable bias, which could affect firm-level studies on automation and employment that do not account for all relevant confounders. In this context, we emphasize that the empirical setting of models (2)-(5) appears to adequately control for firm-level employment dynamics, as neither $\hat{\beta}_1$ nor $\hat{\beta}_2$ are statistically significant. This indicates, on the one hand, the absence of significant ex-ante average difference in the number of employees between automating and non-automating firms and, on the other hand, that all changes in the number of employees between 2015 and 2018 are accounted for by our matched DiD setting. Overall, our estimates on the relation between automation and firm-level employment appear to be in line with literature findings, as they fall between the results of Koch et al. (2021) and Acemoglu and Restrepo (2020) (both of which, however, only focus on manufacturing firms), and those of Bessen et al. (2020).

Analyzing the relationship between automation and employee turnover (columns 6-10), we find that investment in automation appears to be correlated with an increase in employee turnover of about 7-8 percentage points. While the magnitude of the coeffi-

Table 1: Automation and flexible employment

	Log flexible workers					Share of flexible workers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Automation*After	0.124***	0.091**	0.085**	0.093**	0.085**	0.004	0.011*	0.010*	0.009	0.007
	(0.030)	(0.039)	(0.037)	(0.041)	(0.040)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Automation	0.599***	0.025	0.028	0.044	0.048	-0.006	-0.001	-0.000	0.004	0.004
	(0.077)	(0.039)	(0.037)	(0.048)	(0.044)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)
After	0.221***	0.213***	0.204***	0.245***	0.228***	0.036***	0.027***	0.026***	0.022***	0.021***
	(0.021)	(0.031)	(0.028)	(0.031)	(0.030)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Log(Revenue)		0.335***	0.331***	0.277***	0.291***		-0.007***	-0.001	-0.010***	-0.004***
		(0.025)	(0.022)	(0.037)	(0.031)		(0.002)	(0.002)	(0.003)	(0.001)
Matched sample		✓	✓	✓	✓		✓	✓	✓	✓
Additional controls			✓		✓			✓		✓
Observations	20,926	10,126	10,126	7,049	7,049	20,926	10,126	10,126	7,049	7,049
R-squared	0.058	0.250	0.305	0.124	0.200	0.009	0.016	0.090	0.018	0.129
Sample	Full	Full	Full	15+ empl.	15+ empl.	Full	Full	Full	15+ empl.	15+ empl.

Notes. The table presents estimates of the effects of automation (i.e., robotics, IoT, big data, and augmented reality) on both the (log) absolute number and the share of 'flexible' workers within the firm. The matching variables were measured in 2015 and encompass the following: (log) revenue, (log) number of employees, percentage variation in the number of employees over the previous year, share of university-graduated workers, share of blue-collar workers, share of flexible workers, share of unionized workers, sector of activity dummies, location of the headquarters dummies, corporation status dummy, exporter status dummy, new investments in the previous year dummy, and process innovations introduced over the previous three years dummy. Additional controls include a dummy indicating the use of employment support programs in the preceding year, a dummy marking the presence of trade union representatives within the firm, and two sets of dummies controlling for the region where the firm's headquarters is located and for the firm's sector of activity. The results presented in (4)-(5) and (9)-(10) are based on the subsample of firms with at least 15 employees in 2015. Standard errors are clustered at the level of *sector-of-activity*firm-dimension-class*: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

cient remains the same, its statistical significance is lower when the models are estimated on the sample restricted to firms with at least 15 employees. The positive effect on turnover suggests that firms may be reorganizing their production, perhaps to better align with new automated processes. This reorganization could be multifaceted, involving not just a re-evaluation but also a comprehensive restructuring of labor contracts and work arrangements. Such changes are indicative of a strategic adaptation to technological advancements, where firms are not only integrating new technologies into their production processes but also recalibrating the workforce to optimize these technologies' use. For example, if automation require new skill sets, firms might opt to recruit employees with the desired qualifications, and to simultaneously lay off some the workers whose role has become redundant. Notably, this adaptation may extend beyond immediate operational changes, as firms might need to strategically rethink their long-term human resources strategies. Finally, also in in this case, it is worth noting that the naive estimation of $\hat{\beta}_3$ is double compared to that obtained using the other models. This result further highlights the importance of using methodologically rigorous approaches, such as matched Difference-in-Differences (DiD), to more accurately capture the relationship between automation and employment dynamics.

In Table 3, we explore the relationship between automation, hiring, and termination of employment relationships (effectively unpacking turnover). Regarding terminations, we find no effect of automation, which is quite distinct from the results that would be obtained with a naive strategy. On the other hand, the correlation between automation and hiring is positive (around +10/12%), albeit lower than the estimate obtained without employing controls. These results suggest a nuanced understanding of how automation impacts different facets of employment dynamics within firms. The lack of a significant effect on terminations contradicts often held assumptions about automation leading to job losses at firm level. This lack of correlation might suggest that firms are not necessarily replacing existing employees with automated processes, at least not in the short term. Conversely, the positive correlation with hiring rates, although lower than uncontrolled estimates, suggests that automation might be creating new roles or requiring additional human resources, possibly to manage, maintain, or complement automated processes.

5.3 Automation and flexible employment: direct and indirect channels

The empirical findings discussed so far indicate that, at the firm level, investment in automation is associated not only with an increase in flexible workers but also with an increase in the overall number of workers employed. This is driven by an increase in hiring that also explains the rise in turnover. Thus, as mentioned in Section 4.2, the observed increase in flexible workers may simply be a short-term effect of a growth in labor's

Table 2: Automation and employment dynamics I

	Log employees					Log turnover				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Automation*After	0.080***	0.055**	0.053**	0.052	0.055*	0.151***	0.073**	0.071**	0.080*	0.077*
	(0.022)	(0.027)	(0.024)	(0.033)	(0.030)	(0.032)	(0.033)	(0.030)	(0.044)	(0.041)
Automation	1.085***	0.015	0.017	0.010	0.023	0.740***	-0.009	-0.003	0.015	0.032
	(0.154)	(0.027)	(0.023)	(0.028)	(0.029)	(0.109)	(0.037)	(0.033)	(0.044)	(0.038)
After	0.025**	-0.013	0.010	-0.006	0.009	0.152***	0.169***	0.204***	0.225***	0.258***
	(0.011)	(0.016)	(0.018)	(0.025)	(0.025)	(0.021)	(0.024)	(0.025)	(0.030)	(0.030)
Log(Revenue)		0.588***	0.523***	0.452***	0.417***		0.455***	0.433***	0.386***	0.392***
		(0.033)	(0.029)	(0.048)	(0.042)		(0.032)	(0.028)	(0.048)	(0.040)
Matched sample		✓	✓	✓	✓		✓	✓	✓	✓
Additional controls			✓		✓			✓		✓
Observations	20,926	10,126	10,126	7,049	7,049	20,907	10,114	10,114	7,041	7,041
R-squared	0.093	0.636	0.705	0.437	0.541	0.055	0.337	0.420	0.187	0.294
Sample	Full	Full	Full	15+ empl.	15+ empl.	Full	Full	Full	15+ empl.	15+ empl.

Notes. The table presents estimates of the effects of automation (i.e., robotics, IoT, big data, and augmented reality) on both the (log) absolute number firm employees and on (log) firm turnover. The matching variables were measured in 2015 and encompass the following: (log) revenue, (log) number of employees, percentage variation in the number of employees over the previous year, share of university-graduated workers, share of blue-collar workers, share of flexible workers, share of unionized workers, sector of activity dummies, location of the headquarters dummies, corporation status dummy, exporter status dummy, new investments in the previous year dummy, and process innovations introduced over the previous three years dummy. Additional controls include a dummy indicating the use of employment support programs in the preceding year, a dummy marking the presence of trade union representatives within the firm, and two sets of dummies controlling for the region where the firm's headquarters is located and for the firm's sector of activity. The results presented in (4)-(5) and (9)-(10) are based on the subsample of firms with at least 15 employees in 2015. Standard errors are clustered at the level of *sector-of-activity*firm-dimension-class*: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Automation and employment dynamics II

	Log terminations					Log hirings				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Automation*After	0.098***	0.020	0.020	0.034	0.031	0.169***	0.110***	0.106***	0.122***	0.115***
	(0.029)	(0.035)	(0.031)	(0.047)	(0.043)	(0.029)	(0.030)	(0.030)	(0.039)	(0.040)
Automation	0.556***	-0.033	-0.027	-0.015	0.005	0.620***	0.014	0.019	0.036	0.043
	(0.098)	(0.034)	(0.030)	(0.042)	(0.037)	(0.086)	(0.033)	(0.031)	(0.040)	(0.035)
After	0.112***	0.146***	0.201***	0.199***	0.260***	0.135***	0.149***	0.140***	0.189***	0.172***
	(0.018)	(0.025)	(0.028)	(0.031)	(0.034)	(0.020)	(0.024)	(0.022)	(0.029)	(0.027)
Log(Revenue)		0.374***	0.343***	0.339***	0.335***		0.376***	0.377***	0.338***	0.362***
		(0.031)	(0.026)	(0.045)	(0.037)		(0.030)	(0.026)	(0.041)	(0.036)
Matched sample		✓	✓	✓	✓		✓	✓	✓	✓
Additional controls			✓		✓			✓		✓
Observations	20,926	10,126	10,126	7,049	7,049	20,907	10,114	10,114	7,041	7,041
R-squared	0.041	0.281	0.377	0.161	0.283	0.055	0.282	0.348	0.160	0.247
Sample	Full	Full	Full	15+ empl.	15+ empl.	Full	Full	Full	15+ empl.	15+ empl.

Notes. The table presents estimates of the effects of automation (i.e., robotics, IoT, big data, and augmented reality) on both (log) job terminations and hirings. The matching variables were measured in 2015 and encompass the following: (log) revenue, (log) number of employees, percentage variation in the number of employees over the previous year, share of university-graduated workers, share of blue-collar workers, share of flexible workers, share of unionized workers, sector of activity dummies, location of the headquarters dummies, corporation status dummy, exporter status dummy, new investments in the previous year dummy, and process innovations introduced over the previous three years dummy. Additional controls include a dummy indicating the use of employment support programs in the preceding year, a dummy marking the presence of trade union representatives within the firm, and two sets of dummies controlling for the region where the firm's headquarters is located and for the firm's sector of activity. The results presented in (4)-(5) and (9)-(10) are based on the subsample of firms with at least 15 employees in 2015. Standard errors are clustered at the level of *sector-of-activity*firm-dimension-class*: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

marginal productivity that is due to automation but unrelated to the complementarity between flexible capital and labor. In this case, the firm will hire new workers and, as is common in a rigid labor market like the Italian one, new employees will initially be hired under flexible contracts, even though the firm plans to make them permanent shortly thereafter.

This dynamic is consistent with the results of the mediation model. Indeed, as reported in Table A3 (in the Appendix), both $\hat{\mu}_3$ and $\hat{\delta}_4$ are positive and significant, contributing to a positive and robust indirect effect of automation on flexible workers that is mediated by total employment (see Table 4). On the other hand, however, the direct effect of automation remains positive and significant, accounting for almost two-thirds of the overall correlation.

Table 4: Automation and flexible workers: mediation analysis

	(1)	(2)	(3)	(4)
Direct effect	0.0798***	0.0719***	0.0671***	0.0598***
	(0.0259)	(0.0284)	(0.0277)	(0.0268)
Indirect effect	0.0443***	0.0465***	0.0372***	0.0392***
	(0.0117)	(0.0121)	(0.0146)	(0.0123)
Total effect	0.1240***	0.1183***	0.1044***	0.0990***
	(0.0297)	(0.0326)	(0.0313)	(0.0301)
Matching		✓	✓	✓
Log(Revenue)			✓	✓
Additional controls				✓

Notes. The table reports the estimate of the direct effect of investment in automation on (log) flexible workers, as well as its indirect effect, which is mediated by (log) total firm employment. The total effect is the sum of these two. Due to model restrictions, matching is performed by including the linearized propensity score among the control variables in Equations 2 and 3. The table reports full-sample estimates. Standard errors are clustered at the level of *sector-of-activity*firm-dimension-class*: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.4 Intention to invest in automation and firm employment dynamics

To validate the robustness of our main findings, we conduct a secondary analysis wherein the treatment variable is redefined. In this analysis, we exclude all the firms that have already invested in automation and instead consider the intention to invest in automation in the future. This is made possible by the structure of the survey question regarding firm investment in automation technologies, which we also use to define the treatment in the main analysis (the possible answers being "Yes", "No", "In the future"). This approach aims to assess whether the mere intention to automate exerts any significant influence on firm-level labor dynamics.

The results are reported in Table 5. Unlike the significant effects observed with actual investment, the intention to invest in automation is not significantly associated with any of the firm outcomes considered. On the one hand, this result is important as it helps mitigate concerns regarding biases associated with the anticipation effect. Specifically, the anticipation of the benefits (or costs) of future investment in automation may influence current firm decisions (such as hiring), introducing a bias in the estimates. On the other hand, to the extent that the intention to invest in automation may signal unobserved firm characteristics (e.g., a forward-looking, innovative firm culture), a null result suggests that our identification strategy is effective in controlling for firm heterogeneity.

6 Discussion

Over the past three decades, labor market reforms have significantly diversified the employment contracts available to both firms and workers. These non-standard contracts have generally eased labor market rigidities, reducing the costs associated with hiring and firing, thereby contributing to an overall decrease in unemployment rates . However, they have been likely responsible for a reduction of workers' bargaining power, resulting in less job security, lower wages, and a polarization of the labor market. Consequently, recent years have witnessed a mounting pressure for the (re-)introduction of more stringent employment regulations (e.g., see the current debate at the European Parliament, 2023).

In this paper, we explore the correlation between investment in automation and a range of employment outcomes at the firm level. Among other findings, we observe that firms investing in automation also tend to increase the number of workers hired under flexible employment contracts. We argue that this correlation underscores how flexible labor and automation technologies complement each other in enhancing firm operational flexibility, which has increasingly become a key determinant of firm performance in the current market environment.

It is important to highlight that the significance of the complementarity between automation technologies and flexible labor contracts might not have been fully appreciated. This oversight may have been occurred because automation technologies began to proliferate in an environment already characterized by the availability of flexible labor contracts. In other words, it may not have been apparent that the subsequent decades' returns on investment in automation were made possible by a legal framework allowing for a certain degree of labor flexibility. If so, this would in line with the conclusions of

Table 5: Intention to invest in automation and employment dynamics

	Log flexible workers		Share of flexible workers		Log employees		Log turnover		Log terminations		Log hiring	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Future automation*After	0.083	-0.009	-0.006	0.004	0.059	-0.002	0.091	0.027	0.054	-0.048	0.148**	0.131
	(0.054)	(0.094)	(0.009)	(0.013)	(0.039)	(0.050)	(0.058)	(0.084)	(0.050)	(0.071)	(0.056)	(0.087)
Future automation	0.610***	-0.034	-0.002	-0.015	1.026***	-0.022	0.735***	-0.013	0.545***	0.005	0.601***	-0.047
	(0.096)	(0.075)	(0.008)	(0.010)	(0.157)	(0.050)	(0.111)	(0.096)	(0.092)	(0.082)	(0.094)	(0.100)
After	0.241***	0.218***	0.037***	0.023***	0.038***	0.005	0.177***	0.184***	0.128***	0.187***	0.161***	0.113***
	(0.021)	(0.048)	(0.003)	(0.007)	(0.011)	(0.034)	(0.021)	(0.045)	(0.018)	(0.047)	(0.022)	(0.042)
Log(Revenue)		0.296***		-0.003		0.483***		0.391***		0.300***		0.343***
		(0.028)		(0.003)		(0.036)		(0.034)		(0.032)		(0.030)
Matched sample		✓		✓		✓		✓		✓		✓
Additional controls		✓		✓		✓		✓		✓		✓
Observations	20,926	2,428	20,926	2,428	20,926	2,428	20,907	2,425	20,926	2,428	20,907	2,425
R-squared	0.023	0.299	0.009	0.070	0.022	0.674	0.017	0.386	0.012	0.340	0.017	0.326

Notes. The treatment effect is defined as the firm intention to invest in automation in the future. All the firms that actually invested in automation (i.e., the treated firm of the main analysis) have been excluded from the sample. Standard errors are clustered at the level of *sector-of-activity*firm-dimension-class*: *** p<0.01, ** p<0.05, * p<0.1.

Traverso et al. (2023), who argue that a flexible labor market legislation is an important driver of automation (more precisely, of robot adoption). At the same time, the initial focus of the literature on the risks of job substitution associated to automation may have also contributed to such oversight, while the recent 'task-based approach' has emphasized that automation does not replace entire work positions, but only some tasks (which, in turn, are complementary to other tasks performed by humans). To fully exploit complementary, tasks must be carried out with a similar level of flexibility.

At the same time, the initial focus of the literature on the risks of job substitution associated with automation may have also contributed to such oversight, while the recent 'task-based approach' has emphasized that automation does not replace entire work positions but only some tasks, which, in turn, are complementary to other tasks performed by humans (Caselli et al., 2021). To fully exploit complementarity, tasks must be carried out with a similar level of flexibility.

It follows that, if the complementarity hypothesis holds true, changes in employment legislation that increase the costs for firms to promptly adjust their workforce will also diminish the returns on firms' investments in automation. It also follows that, to the extent that the complementarity has been overlooked, such a change will have a greater (negative) impact on firm performance than expected. More precisely, sticking to our conceptual framework, this may occur if legislators do not take into account how workforce adjustability (guaranteed by flexible labor contracts) interacts with the reprogrammability of physical capital (a feature introduced by automation technology) to ensure operational flexibility.

The conceptual framework sketched in Section 3 allows us to briefly touch on a number of topics that may be relevant for policy-making purposes. Indeed, the bottom-line message is that, to mitigate some of the negative effects of labor reforms on workers, future reforms should aim to influence 'labor costs' and 'workers' incentives' without curtailing firms' ability to rapidly adjust their workforce.

A standard policy which primarily operates through the labor costs channel could be the introduction of a minimum wage. As recently pointed out by Caselli et al. (2023), in the case of Italy, such a measure would even increase overall market efficiency. Other measures operating through the same channel include various forms direct support for low-income workers, such as the negative income tax recently discussed for Italy by Bonatti and Traverso (2023) or, more generally, a reduction of payroll taxes (Di Porto et al., 2017).

Regarding workers' incentives, when they can be easily laid off, workers will largely refrain from investing in firm-specific human capital, as they would became vulnerable to firms' hold-up. Dughera et al. (2023) formally outline this trade off. In their model workers' willingness to acquire firm-specific skills decreases with the probability of getting fired and with the degree of specificity of the skills. To mitigate the hold-up problem and incentivize investments in human capital, institutions arrangements should minimise hold-up risk and protect quasi-rents associated with specific investments. This can be achieved by promoting training programs aimed at developing task and skill-specific human capital (Gibbons and Waldman, 2019), by increasing the portability of workers' skills, for example by encouraging skill-based hiring practices (Ward et al., 2023; Sigelman et al., 2024) and by supporting a framework for a national-based skill certification system. Indeed, the development of a standardized skill taxonomy would aid both workers and firms in understanding how certain skills can be transferred between different contexts, across various job roles and industries.

Finally, as clarified at the end of Section 3, our analysis focuses on external labor flexibility, that is the flexibility achieved through hiring and firing. However, as as discussed by Signoretti et al. (2022), labor flexibility can also be achieved through internal flexibility, which consists in the process of reorganizing and adapting the existing workforce to meet the evolving needs of the business. Therefore, introducing policies that encourage such internal flexibility, for example through fiscal incentives and/or by developing a legal framework that better supports the flexible reorganization of the workforce, can contribute tackle the problem of workers' incentives.

7 Conclusions

In this paper, we use a panel of Italian firms to study the association between investment in automation technologies and various of firm-level employment outcomes. In particular, we focus on the positive relationship between automation and firms' resort to non-standard, flexible labor contracts, which have been introduced in the legislation with the labor reforms of the 2000s. By outlining a simple conceptual framework, we interpret this finding as an indication of the complementarity between flexible capital and flexible labor, which jointly determine firms' operational flexibility. Finally, we briefly discuss how future labor policies should aim to improve workers' condition without compromising firms' ability to rapidly adjust their workforce, as this may lead to a reduction in the return on the investment in automation.

References

Acemoglu, D., Lelarge, C., and Restrepo, P. (2020). Competing with robots: Firm-level evidence from France. In *AEA papers and proceedings*, volume 110, pages 383–388.

American Economic Association.

Acemoglu, D. and Restrepo, P. (2018). Artificial intelligence, automation, and work. In *The economics of artificial intelligence: An agenda*, pages 197–236. University of Chicago Press.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6):2188–2244.

Acharya, V. V., Baghai, R. P., and Subramanian, K. V. (2013). Labor laws and innovation. *The Journal of Law and Economics*, 56(4):997–1037.

Acharya, V. V., Baghai, R. P., and Subramanian, K. V. (2014). Wrongful discharge laws and innovation. *The Review of Financial Studies*, 27(1):301–346.

Aumond, R., Tommaso, V. D., and Rünstler, G. (2022). A Narrative Database of Labour Market Reforms in Euro Area Economies. Technical Report No. 2022/2657, ECB Working Paper.

Austin, P. C. (2011). Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharmaceutical Statistics*, 10(2):150–161.

Ballestar, M. T., García-Lazaro, A., Sainz, J., and Sanz, I. (2022). Why is your company not robotic? The technology and human capital needed by firms to become robotic. *Journal of Business Research*, 142:328–343.

Balsmeier, B. and Woerter, M. (2019). Is this time different? how digitalization influences job creation and destruction. *Research Policy*, 48(8):103765.

Barbieri, P. and Cutuli, G. (2015). Employment protection legislation, labour market dualism, and inequality in europe. *European Sociological Review*, 32(4):501–516.

Belloc, F., Burdin, G., and Landini, F. (2023). Advanced Technologies and Worker Voice. *Economica*, 90(357):1–38.

Bessen, J., Goos, M., Salomons, A., and van den Berge, W. (2020). Firm-level automation: Evidence from the Netherlands. In *AEA Papers and Proceedings*, volume 110, pages 389–393, Nashville, TN, USA. American Economic Association.

Boeri, T. and Garibaldi, P. (2007). Two tier reforms of employment protection: A honeymoon effect? *The Economic Journal*, 117(521):F357–F385.

Boeri, T. and Garibaldi, P. (2019). A tale of comprehensive labor market reforms: Evidence from the Italian jobs act. *Labour Economics*.

Bonatti, L. and Traverso, S. (2023). Sussidi ai bassi salari: ragioni e costi di uno strumento di politica economica nel contesto italiano. In Paganetto, L., editor, *Equità e sviluppo. Un programma di legislatura in un mondo in cambiamento*. Eurilink University Press, Rome.

Bonfiglioli, A., Crino', R., Fadinger, H., and Gancia, G. (2023). Robot Imports and Firm-Level Outcomes. Working Papers 528, University of Milano-Bicocca, Department of Economics.

Brynjolfsson, E. and McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Caselli, M., Fourrier-Nicolai, E., Fracasso, A., and Scicchitano, S. (2024). Digital Technologies and Firms' Employment and Training. CESifo Working Paper 11056. CESifo Working Paper No. 11056.

Caselli, M., Fracasso, A., Scicchitano, S., Traverso, S., and Tundis, E. (2021). Stop worrying and love the robot: An activity-based approach to assess the impact of robotization on employment dynamics. GLO Discussion Paper 802.

Caselli, M., Mondolo, J., and Schiavo, S. (2023). Labour market power and the quest for an optimal minimum wage: Evidence from Italy. *Applied Economics*, 55(15):1713–1727.

Di Porto, E., Elia, L., and Tealdi, C. (2017). Informal work in a flexible labour market. *Oxford Economic Papers*, 69(1):143–164.

Dixon, J., Hong, B., and Wu, L. (2021). The robot revolution: Managerial and employment consequences for firms. *Management Science*, 67(9):5586–5605.

Dughera, S., Quatraro, F., Ricci, A., and Vittori, C. (2023). Are temporary hires good or bad for innovation? The Italian evidence. *Economics of Innovation and New Technology*, pages 1–24.

Dughera, S., Quatraro, F., and Vittori, C. (2022). Innovation, on-the-job learning, and labor contracts: an organizational equilibria approach. *Journal of Institutional Economics*, 18(4):605–620.

Eichhorst, W. and Marx, P. (2021). How stable is labour market dualism? Reforms of employment protection in nine European countries. *European Journal of Industrial Relations*, 27(1):93–110.

Eurofound (2020). Labour Market Change: Trends and Policy Approaches Towards Flexibilisation, Challenges and Prospects in the EU Series. Technical report, Publications Office of the European Union Luxembourg.

European Parliament (2023). How the EU Improves Workers' Rights and Working Conditions (Last Update: 03/10/2023). Accessed: 15/04/2024.

Filippi, E., Bannò, M., and Trento, S. (2023). Automation technologies and their impact on employment: A review, synthesis and future research agenda. *Technological Forecasting and Social Change*, 191:122448.

Frey, C. B. and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114:254–280.

Gibbons, R. and Waldman, M. (2019). Task-specific human capital. *American Economic Review. AEA Papers and Proceedings*, 94(2):203–207.

Giuliani, M. and Madama, I. (2022). What if? Using counterfactuals to evaluate the effects of structural labour market reforms: evidence from the Italian Jobs Act. *Policy Studies*, 44:216 – 235.

Grigoli, F., Koczan, Z., and Topalova, P. (2020). Automation and labor force participation in advanced economies: Macro and micro evidence. *European Economic Review*, 126:103443.

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford press.

IFR (2023). *World Robotics 2023 - Industrial Robots*. International Federation of Robotics.

Imbens, G. W. and Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.

International Labour Organization (2016). *Non-standard employment around the world: Understanding challenges, shaping prospects*. ILO, Geneva.

ISO (2021). ISO 8373:2021 Robots and robotic devices. ISO Standard. Available from ISO (https://www.iso.org/standard/75539.html).

Kahn, L. M. (2012). Labor market policy: A comparative view on the costs and benefits of labor market flexibility. *Journal of Policy Analysis and Management*, 31(1):94–110.

Koch, M., Manuylov, I., and Smolka, M. (2021). Robots and Firms. *The Economic Journal*, 131(638):2553–2584.

Malgarini, M., Mancini, M., and Pacelli, L. (2013). Temporary hires and innovative investments. *Applied Economics*, 45(17):2361–2370.

Mondolo, J. (2022). The composite link between technological change and employment: A survey of the literature. *Journal of Economic Surveys*, 36(4):1027–1068.

Murphy, G., Siedschlag, I., and McQuinn, J. (2017). Employment protection and industry innovation. *Industrial and Corporate Change*, 26(3):379–398.

Roberts, J. (2007). *The modern firm: Organizational design for performance and growth.* Oxford University Press.

Rünstler, G. (2021). The macroeconomic impact of euro area labour market reforms: evidence from a narrative panel VAR. Technical Report No. 2021/2592, ECB Working Paper.

Sigelman, M., Fuller, J., and Martin, A. (2024). Skills-Based Hiring: The Long Road from Pronouncements to Practice. Technical report, Burning Glass Institute.

Signoretti, A., Pederiva, L., and Zaninotto, E. (2022). Trading-off flexibility: Contingent workers or human resource practices? A configurational approach. *Human Resource Management Journal*, 32(1):58–75.

Traverso, S., Vatiero, M., and Zaninotto, E. (2023). Robots and labor regulation: a cross-country/cross-industry analysis. *Economics of Innovation and New Technology*, 32(7):977–999.

UNCTAD (2017). Robots, industrialization and inclusive growth. chapter 3 in trade and development report 2017. Technical report, United Nations.

Ward, R., Crick, T., Hanna, P., Hayes, A., Irons, A., Miller, K., Moller, F., Prickett, T., Walters, J., et al. (2023). Using skills profiling to enable badges and micro-credentials to be incorporated into higher education courses. *Journal of Interactive Media in Education*, 2023(1):1–22.

Appendix

Table A1: Balance of matching covariates (part 1)

Variable	Matched	Mean Treat	Mean Control	Stand. bias % bias	Stand. bias % reduc.	t-test (p-value)	Variance Ratio
Log(Employees)		3.8246	2.8302	73.3		0.000	1.17
	✓		3.8093	1.1	98.5	0.756	1.04
Workers w/ univ. degree (sh)		0.13894	0.09581	23.8		0.000	1.05
	✓		0.14632	-4.1	82.9	0.274	0.83
Blue collar workers (sh)		0.55276	0.58459	-9.5		0.001	0.82
	✓		0.53725	4.6	51.3	0.17	0.95
Flexible workers (sh)		0.10188	0.10964	-4.6		0.116	0.67
	✓		0.10278	-0.5	88.5	0.87	0.90
Unionized workers (sh)		0.11465	0.06882	25		0.000	1.21
	✓		0.10981	2.6	89.4	0.465	1.06
Invested in 2014 (dummy)		0.70667	0.43532	57		0.000	
	✓		0.70165	1.1	98.1	0.753	
$\Delta Log(Employees)_{2014-15}$		0.05735	0.02628	10.6		0.000	0.58
	✓		0.06172	-1.5	85.9	0.67	0.57
Process innovation in 2011-14		0.5744	0.28764	60.5		0.000	
	✓		0.5733	0.2	99.6	0.949	
Log(Revenue)		15.751	14.507	67.6		0.000	1.12
	✓		15.751	0	100	0.998	1.05
Is a corporation (dummy)		0.87446	0.73011	36.8		0.000	
	✓		0.87459	0	99.9	0.992	
Exporter (dummy)		0.53031	0.28248	52.1		0.000	
	✓		0.52027	2.1	95.9	0.566	

Notes. The table reports the average values of covariates in the treatment and control groups before and after matching. It also reports the standardized bias, its percentage reduction, and some other statistics that are useful for describing the distribution of the covariates and for assessing the quality of the match.

Table A2: Balance of matching covariates (part 2)

Variable	Matched	Mean Treat	Mean Control	Stand. bias % bias	% reduc.	t-test (p-value)
Region: North-East		0.34109	0.27919	13.4		0
	✓		0.34029	0.2	98.7	0.962
Region: Center		0.17881	0.2075	-7.3		0.009
	✓		0.17979	-0.2	96.6	0.942
Region: South		0.12676	0.17416	-13.3		0
	✓		0.13386	-2	85	0.547
Region: Islands		0.04164	0.06597	-10.8		0
	✓		0.0387	1.3	87.9	0.669
Activity: Food and Tobacco		0.07226	0.05824	5.7		0.033
	✓		0.07055	0.7	87.8	0.849
Activity: Textile, Wood, Media		0.07655	0.08286	-2.3		0.402
	✓		0.0774	-0.3	86.4	0.927
Activity: Chemicals, Siderurgy		0.17453	0.09459	23.6		0
	✓		0.17097	1	95.6	0.788
Activity: Mechanic industry		0.15187	0.06425	28.5		0
	✓		0.15126	0.2	99.3	0.961
Activity: Manufacturing (residual)		0.06797	0.0528	6.4		0.016
	✓		0.06454	1.4	77.4	0.694
Activity: Constructions		0.05695	0.1338	-26.4		0
	✓		0.05756	-0.2	99.2	0.94
Activity: Retail		0.1041	0.14181	-11.5		0
	✓		0.10361	0.1	98.7	0.963
Activity: Transportations		0.03919	0.06225	-10.5		0
	✓		0.03625	1.3	87.3	0.659
Activity: Hotel and resturants		0.02266	0.04565	-12.7		0
	✓		0.02327	-0.3	97.3	0.907
Activity: ITC		0.07838	0.05052	11.4		0
	✓		0.08389	-2.2	80.2	0.564
Activity: Financial services		0.02633	0.03907	-7.2		0.014
	✓		0.02584	0.3	96.2	0.93
Activity: Other services to firms		0.05573	0.07112	-6.3		0.026
	✓		0.05548	0.1	98.4	0.976
Activity: Education and Healthcare		0.03797	0.05409	-7.7		0.008
	✓		0.04495	-3.3	56.7	0.317

Notes. The table reports the average values of covariates in the treatment and control groups before and after matching. It also reports the standardized bias, its percentage reduction, and some other statistics that are useful for describing the distribution of the covariates and for assessing the quality of the match.

Table A3: Mediation analysis: first-stage results

	(1)		(2)		(3)		(4)	
	Log(FlexEmp)	Log(Emp)	Log(FlexEmp)	Log(Emp)	Log(FlexEmp)	Log(Emp)	Log(FlexEmp)	Log(Emp)
Automation*After	0.080***	0.080***	0.072**	0.074***	0.067**	0.057***	0.060**	0.061***
	(0.026)	(0.022)	(0.028)	(0.019)	(0.028)	(0.021)	(0.027)	(0.019)
Automation	-0.002	1.085***	0.026	0.028	0.028	0.015	0.034	0.017
	(0.029)	(0.153)	(0.028)	(0.029)	(0.028)	(0.023)	(0.026)	(0.018)
After	0.208***	0.025**	0.198***	0.026**	0.210***	0.000	0.204***	0.015
	(0.019)	(0.011)	(0.018)	(0.011)	(0.019)	(0.010)	(0.019)	(0.010)
Log(Emp)	0.554***		0.625***		0.650***		0.641***	
	(0.026)		(0.037)		(0.041)		(0.037)	
Log(Revenue)					-0.026**	0.398***	-0.018*	0.300***
					(0.013)	(0.032)	(0.010)	(0.016)
lps			-0.121***	1.018***	-0.115***	0.509***	-0.045**	0.690***
			(0.038)	(0.061)	(0.037)	(0.054)	(0.023)	(0.037)
Additional controls							✓	✓
Observations	20,948	20,948	17,242	17,242	16,561	16,561	16,561	16,561
R-squared	0.4662	0.093	0.454	0.571	0.455	0.722	0.481	0.792

Notes. The table presents the estimates of the models described by Equations 2 and 3, and used to breakdown the direct and indirect effect of automation on flexible workers as presented in Table 4. Standard errors are clustered at the level of *sector-of-activity*firm-dimension-class*: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.