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RESEARCH ARTICLE

The complementarity between automation and flexible labour contracts: firm-level evidence from Italy

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Abstract
This study examines the association between firm-level investments in automation technologies and employment outcomes, drawing on a panel dataset of approximately 10,450 Italian firms. We focus on the proliferation of non-standard labour contracts introduced by labour market reforms in the 2000s, which facilitated external labour flexibility. Our findings reveal a positive relationship between automation investments and the adoption of these flexible labour arrangements. Guided by a conceptual framework, we interpret this result as evidence of complementarity between automation technologies – viewed as flexible capital – and non-standard contractual arrangements – viewed as flexible labour. This complementarity is essential for enhancing operational flexibility, a critical driver of firm performance in competitive market environments. From a policy perspective, our analysis highlights the importance of measures that protect labour without undermining the efficiency gains enabled by automation.

Keywords: automation; complementarity; flexible capital; flexible labour; labour contracts

Introduction

The high levels of structural unemployment in Western Europe have traditionally been linked to rigid labour institutions. Consequently, over the past decades, both right- and left-wing governments have introduced a series of policy reforms aimed at increasing labour market flexibility (Eurofound, 2020). For instance, Germany implemented the *Hartz-Konzept* in 2002, while Italy reformed its labour institutions in multiple stages, beginning with the 1997 Treu Law, followed by the 2003 Biagi Reform, and culminating in the so-called 'Jobs Act' in 2014. Spain, which has consistently had the highest structural unemployment rate among major Western European economies, introduced a significant labour reform in 2012 under the Rajoy government. In France, labour market reforms have been particularly contentious, often facing strong public resistance. Nevertheless, the National Assembly passed the *Loi Travail* in 2016.

These market-oriented reforms primarily sought to enhance external labour flexibility by reducing legal and bureaucratic barriers to hiring and firing while expanding non-standard employment forms such as temporary, part-time, and freelance contracts, and temporary work agencies, providing firms with greater flexibility in managing employment levels.

The success of these reforms remains disputed (Kahn, 2012). On the one hand, they seem to have contributed to an increase in employment levels and labour market efficiency (ILO, 2016; Boeri and

Garibaldi, 2019; Rünstler, 2021). On the other hand, flexible labour contracts have been criticized for failing to adequately address labour market segmentation and for exacerbating job insecurity, reducing temporary-to-permanent transitions, lowering wages, and increasing the prevalence of working poor, particularly among young workers (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 the repeal or amendment of the reforms.

Alongside these labour market reforms, recent decades have seen the widespread adoption of automation technologies that expanded the range of tasks, functions, and activities that capital can perform (Frey and Osborne, 2017). Advances in automation have increased capital flexibility by lowering reprogramming costs and enabling machines to execute increasingly complex tasks, including some previously exclusive to human labour. This technological shift has played a crucial role in reshaping labour market dynamics, favouring the hollowing out of middle-skill routine jobs and contributing to labour market polarization (Goos and Manning, 2007; Goos *et al.*, 2009; Autor and Dorn, 2013) not only at an aggregate level, but also within firms, where it has seemingly prompted a division between a core group of protected workers performing key, highly productive tasks and a peripheral group of precarious, easily replaceable workers exposed to demand fluctuations (Cattani *et al.*, 2023).

As such, the labour market dynamics observed in recent years are not solely the result of the aforementioned labour reforms but also of the technological shock brought about by automation. Therefore, analyzing the interplay between these two factors – legal reforms and technological advancements – is essential for designing policies that effectively address both the opportunities and challenges of this evolving landscape.

Within this context, our study examines the relationship between the availability of flexible labour contracts and the adoption of automation technologies at the firm level. At the core of our analysis is the idea that automation and flexible labour are complementary. Complementarity arises when the returns from decisions in one domain (e.g., investing in automation) increase when paired with choices in another domain (e.g., resorting to flexible labour contracts), and vice versa. The notion of complementarity between automation and workforce flexibility is not new. It has been a central theme in discussions on lean production, particularly in studies of the automotive industry during the 1990s. At that time, flexible automation was often associated with high-involvement work practices, such as shop floor teams, problem-solving groups, job rotation, and direct worker responsibility for quality-related tasks (Kochan *et al.*, 1997). Therefore, the focus of that literature was on the complementarity between flexible technology and internal (functional) labour flexibility. In contrast, this paper examines whether a similar complementarity effect applies to external (volume) flexibility, that is the type of labour flexibility best captured by flexible labour contracts (Kalleberg, 2001)

Our empirical analysis, based on a panel of Italian firms, shows that the investment in automation turns out to be robustly associated with an increase in both the number and share of flexible workers within the firm. As thoroughly discussed in the paper, the fact that firms investing in automation are more likely to resort to flexible labour contracts suggests that firms aim to construct a more agile and responsive operational environment. This allows to 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 and the flexibility in the production process enabled by automation technologies.

By highlighting the complementarity between flexible labour and automation technologies, our research contributes to the ongoing debate on labour policies. Over the past two decades, enthusiasm for lighter employment protection legislation – at least in Europe – has waned substantially, with some reforms now under severe scrutiny or being significantly amended (Eichhorst and Marx, 2021). Nevertheless, our analysis suggests that policymakers should carefully consider the complementarity between labour flexibility and automation. Failing to account for this relationship could result in efficiency losses, particularly given the current widespread diffusion of automation technologies. These technologies depend on flexible labour arrangements to fully unlock their potential, as they allow firms to adapt quickly to demand fluctuations and technological requirements. A reduction in labour flexibility today would not only diminish firms' ability to adjust their workforce, but it would also reduce the economic returns on their investment in automation. Thus, it is crucial to devise policies that balance the need for worker protection with maintaining the operational flexibility required to sustain efficiency in this evolving landscape.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 discusses a simple conceptual framework for the complementarity between automation and flexible labour. Section 4 describes the data and empirical strategy. In Section 5, we present the estimates of the relationship between investments in automation and firms' use of flexible labour, as well as other firm-level employment outcomes. Section 6 addresses relevant policy implications, and Section 7 concludes.

Literature review

The economic literature on automation has primarily examined its effects on employment levels and workforce skill composition. By contrast, contractual arrangements and their influence on automation outcomes remain relatively underexplored. This study helps to fill that gap by investigating the complementarity between automation and flexible labour contracts, positioning our analysis within the broader framework of technology-institution complementarity (Pagano and Rowthorn, 1994). Therefore, our approach is aligned with the literature on varieties of capitalism, which examines how institutional differences produce distinct economic equilibria (Aoki, 2001; Hall and Soskice, 2001; Pagano and Vatiero, 2015), and with the literature on institutional complementarities (Pagano and Vatiero, 2015; Cattani *et al.*, 2023).

Our work adds to the expanding literature on automation's impact on firm-level employment from an institutional perspective. Bessen *et al.* (2020), analyzing 36,000 Dutch firms (2000–2016), find that investing in automation boosts long-term growth in both employment and revenue, although it temporarily slows job creation. Dixon *et al.* (2021) show that Canadian firms importing robots (1996–2017) expand non-managerial employment but reduce managerial positions. Turning to Spain, Koch *et al.* (2021) report a roughly 10% rise in firm-level employment following robot adoption, especially among high-skilled workers, while Ballestar *et al.* (2022) highlight the pivotal role of workforce capabilities for successful robotics adoption. In France, Acemoglu *et al.* (2020) document how robot adoption lowers labour shares yet raises productivity, value added, and overall employment – largely at the expense of non-adopting rivals. Finally, Balsmeier and Woerter (2019) examine digitalization in Swiss firms, finding that investments in robots, 3D printing, and related technologies benefit high-skilled labour while negatively affecting low- and medium-skilled employment. By contrast, Bonfiglioli *et al.* (2023) argue that automation (specifically, robot adoption) reduces employment in French manufacturing firms, suggesting that previous positive findings may reflect endogeneity in investment decisions. In another recent working paper, Caselli *et al.* (2024) use an instrumental variable strategy to study how operational and informational digital technologies affect Italian firms, uncovering distinct impacts on labour force structure.

Another closely related strand of literature investigates how employment protection legislation influences innovation. At the aggregate level, Murphy *et al.* (2017), analyzing a panel of OECD countries, find that rigid employment protection laws hinder innovation. Similarly, Traverso *et al.* (2023) report that statutory dismissal protection is negatively linked to robot adoption, suggesting that more flexible labour regulations lower adjustment costs and foster automation. In contrast, Acharya *et al.* (2013; 2014) adopt a hold-up risk perspective, arguing that stringent labour laws can motivate firms and workers to undertake risky, innovation-enhancing activities by safeguarding employees from opportunistic behaviour. Vatiero (2017) likewise highlights how labour law and ownership concentration together shape national innovation trajectories. Building on this perspective, Belloc (2019) uses an instrumental variable approach to establish a causal link between employment protection legislation and innovation.

Firm-level evidence further complements these findings. Belloc *et al.* (2023) show that the presence of employee representation correlates positively with automation adoption, as workers' representative bodies facilitate 'skill-improving' redesigns, an effect reinforced by Berton *et al.* (2024). In a similar vein, Dughera *et al.* (2023) propose a reversed-U relationship between innovation and fixed-term employment, underscoring the importance of human capital 'portability'. Meanwhile, Hoxha and Kleinknecht (2020) document a negative relationship between non-standard employment and product innovation (though not process innovation), as well as a detrimental effect of external labour flexibility on innovation in firms reliant on cumulative knowledge. By contrast, Franco and Landini (2022) highlight that internal flexibility – based on workforce stability and firm-specific human capital – drives innovation. Our research contributes to this literature by offering a new perspective to understand how the adoption of new technologies (i.e., automation) interacts with labour contracts.

Conceptual framework

Our study examines the interplay between investments in automation and flexible labour contracts, focusing on their complementarity. In this section, we begin by defining these two domains and discussing their implications for firm performance, thereby laying the foundation for our analysis. We then explore the nature of this complementarity, examining how they can jointly enhance firms' operational flexibility.

Automation

Acemoglu and Restrepo (2018) define automation as a technology that expands the range of tasks and functions that can be performed by capital. In a similar vein, we conceptualize automation as a set of technologies that increase the flexibility of physical capital and result in an expansion of the spectrum of tasks achievable through capital. Moreover, and this is key to our perspective, automation also enables capital to undertake tasks that were previously unattainable due to their complexity or subtlety and to switch between relatively different tasks at relatively low cost.

Robots represent a paradigmatic example of automation. Prevalent descriptions of robots emphasize their reprogrammable and multipurpose capabilities. 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. In our 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. For example, IoT-enabled devices – physical objects equipped with sensors, software, and other communication technologies – can create a network of interconnected objects that communicate, collect data, and potentially act on it. Whether used alone or in combination with big data technologies, IoT technologies facilitate predictive maintenance, control of manufacturing processes, real-time tracking and inventory management, and other advanced applications (for a review of applications in manufacturing and logistics, see Osterrieder *et al.*, 2020; Zheng *et al.*, 2021; Sahu *et al.*, 2021).

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, contributing 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.

Flexible labour contracts

We operationalize external labour flexibility within the framework of labour contracts. Over the past decades, labour reforms have sought to increase flexibility by expanding the range of employment

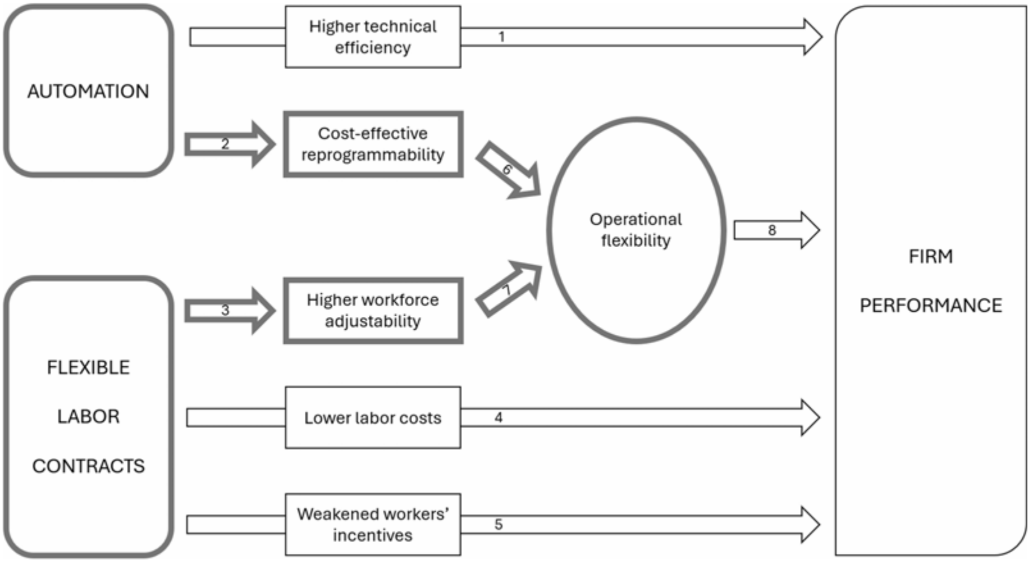

Figure 1. Conceptual framework.

arrangements available to firms. These include temporary contracts, part-time agreements, freelance work, and employment relationships facilitated by temporary work agencies or other multi-party setups. Unlike traditional open-ended contracts, these arrangements have created a new legal framework that has fundamentally reshaped the economic opportunities and incentives for both workers and firms, making external labour flexibility a significantly more viable and cost-effective option.

On the one hand, these new contracts have increased firms' ability to swiftly adjust their workforce in response to market shocks (arrow 3). Firms can therefore resort to these contracts to rapidly increase or decrease the total number of workers employed and quickly reshape the skill mix of the workforce.

On the other hand, while these contracts sometimes provide workers with the flexibility to engage in multiple projects, diversify their skills, and better manage their work-life balance, they have more often been associated with increased job insecurity, diminished worker protections, and reduced bargaining power. This has translated into lower labour costs for firms (arrow 4), but it has also weakened workers' incentives to acquire firm-specific skills (arrow 5). In fact, as discussed in Acharya *et al.* (2013; 2014) and Dughera *et al.* (2022; 2023), workers discount the likelihood of losing their current job by refraining from undertaking firm-specific human capital investments (i.e., acquiring skills that are useful only within their current firm). This reluctance can reduce labour productivity within firms and even hinder innovation.

In the Italian context, various types of flexible employment contracts have been introduced over time. These new non-standard forms of employment include, among others: fixed-term contracts (*contratti a tempo determinato*); freelance work where the worker operates as an independent contractor, providing services on a project-by-project basis (*contratti di collaborazione coordinata e continuativa*); 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*), an arrangement where the employee is called upon to work as needed; and casual work contracts (*contratto di prestazione occasionale*), designed for situations in which the employer requires temporary labour for short-term or sporadic tasks.

Before proceeding with the discussion, it is worth stressing that the use of flexible contracts is associated with external labour flexibility, or the extent to which a firm responds to changes in its labour requirements by means of hiring and firing. It does not capture, however, internal labour flexibility, that is, the extent to which a firm adapts to changing conditions, demand, or challenges reorganizing its existing workforce.

Complementarity

In this paper, we define complementarity as the interaction between different choice variables such that an increase in one variable enhances the returns to increasing the other. In adopting this definition, we follow Roberts (2007, p. 34), who explains that 'the two choice variables are complements when doing (more of) one of them increases the return of doing (more of) the other'. This definition of complementarity is similar, though not identical, to the one adopted by Aoki (2001) and others (cf. Pagano and Vatiero, 2015). In Aoki's framework, complementarity is strategic: two distinct parties make choices in interdependent domains. By contrast, in our setting, decision-making is centralized within a single entity – the firm – which makes choices across two interdependent domains: technology and labour. At the heart of both approaches lies the property of supermodularity, which captures the essence of complementarity, as it implies that as the level of automation of a firm increases, the marginal return of increasing labour flexibility grows; similarly, as the firm's labour flexibility increases, the marginal return to automation also increases.

The Amazon warehouse hiring strategy provides a textbook example of how the optimal level of labour flexibility changes in response to automation investments. Advances in smart shelves, real-time assistance, and augmented reality have reduced training needs and minimized the requirement for firm-specialized skills. Consequently, maintaining a stable, permanent workforce has become more costly, as firms can now better adapt to demand fluctuations by hiring temporary workers when needed. Following warehouse transformations involving robots and AI, Amazon recently launched an online platform to connect temporary labour demand with temporary workers, effectively transitioning warehouse roles into gig work. A similar pattern is observed by Acemoglu and Johnson (2023), who highlight how automation and technological advancements have led customer-facing industries to abandon rigid scheduling structures, such as the traditional 8-to-4 workday. As automation has increased, firms have moved away from rigid contractual employment models towards more flexible work arrangements, including zero-hour contracts and dynamically adjusted schedules, better aligning labour availability with fluctuating demand. In both cases, the key insight is that higher levels of automation raise the marginal returns to labour flexibility. As automation increases, the optimal degree of labour flexibility also rises, particularly through external labour markets for non-firm-specific tasks.

Symmetrically, supermodularity implies that the optimal level of capital flexibility depends on the degree of labour flexibility. If labour is rigid, automation investments are less appealing because the firm cannot easily adjust its workforce to capture efficiency gains. Vice versa, when labour is flexible – whether through internal reassignment or external hiring and firing – the firm can dynamically realign its workforce with production demands, reducing redundancy and maximizing returns from automation. Consider a car manufacturing plant. If labour contracts are rigid – featuring strict employment conditions, fixed job roles, and high severance costs that make layoffs expensive – investing in advanced automation technologies, such as robotic assembly lines, will become less attractive.

It is important to note that the use of flexible labour contracts can occur alongside a deskilling process. However, these represent two distinct levels of analysis, and the relationship among automation, deskilling, and the adoption of flexible labour is not straightforward. For example, while unskilled temporary workers in Amazon warehouses might illustrate how both mechanisms can operate simultaneously when automation increases, the significant deskilling of manual labour observed in Europe and the United States following the introduction of the moving assembly line (a pioneering form of industrial automation) was accompanied by increased job stability. The so-called 'five-dollar workday program', was aimed at retaining blue-collar assembly line operators, and mitigate

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the high and unpredictable impact of workers' turnover on the equipment efficiency. Similarly, also the relationship between modern forms of automation on skill intensity is, at best, mixed (McGuinness *et al.*, 2023).[1]

Operational flexibility

The complementarity between automation and flexible labour is rooted in their shared ability to enhance 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 face strong competition and volatile, unpredictable demand. Hence, to maintain competitiveness, they must be able to adapt their production plans swiftly. This might include frequently updating product characteristics, simultaneously producing multiple product varieties, or even offering a degree of customization to meet customer needs.

The highest level of operational flexibility can be achieved only through a combination of adjustable workforce and reprogrammable machines: on the one hand, automation guarantees capital flexibility for rapidly adjusting and scaling relatively standardized, routine tasks (arrow 6); on the other hand, the availability of flexible labour contracts allows firms to adjust the workforce in all areas where human labour is required (arrow 7).

In summary, while technical efficiency, labour costs, and workers' incentives serve as channels through which automation and flexible labour independently influence firm performance, re-programmability, and workforce adjustability shape firm outcomes indirectly, through their effect on operational flexibility (arrow 8). Thus, the decision to invest in automation is best understood in conjunction with the decision to adopt flexible labour contracts as both contribute to a firm's ability to adjust production efficiently due to the supermodular relationship between automation and labour flexibility.

These considerations underpin our empirical analysis. As discussed by Brynjolfsson and Milgrom (2013), complementarity can be indirectly tested by analyzing the correlation between two practices. If two practices are complementary, they will consistently be adopted (or avoided) together, since market competition tends to eliminate firms employing inefficient combinations. Consequently, a significant correlation between resorting to automation and using flexible workers provides indirect evidence against the null hypothesis of non-complementarity. Referring to Figure 1, the specific components of the conceptual framework tested in our analysis are highlighted with bold grey lines.

Data and methods

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 gathers firm-level data across various domains, including managerial structures, recruitment methods, industrial relations, investments, international trade exposure, technological innovation, and credit access. Data are collected from a random sample of firms.

For the empirical analysis, we leverage a question introduced in the 2018 survey wave, which asked whether, during the 2015–2017 period, the firm had invested in automation technologies. These technologies span a range of solutions, including but not limited to, IoT systems, robotics, 3D printers, automatic machines, as well as intangible assets such as cloud computing, big data analysis, and cybersecurity. As a key treatment variable, we define a dummy variable identifying firms that have invested in certain 'hard' automation technologies, namely: robotics, internet of things (IoT), big data,

[1]Although an exploration of deskilling lies beyond the scope of our analysis, we do not find any significant association between automation investments and firm-level changes in the number and share of highly educated workers.

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and augmented reality. According to this definition, about 1,900 firms (18% of the sample) reported investing in at least one of these technologies. Investments in 'hard' automation technologies likely indicate a deliberate effort to expand automation capabilities, and they can more directly affect work activities by reshaping the distribution of tasks between humans and machines, having significant implications for the labour contractual arrangements firms choose.

In order to investigate the relationship between investment in automation technologies, labour contracts, and other firm-level employment dynamics, we rely on a matched difference-in-differences (matched DiD) approach. The matching procedure, 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 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.

To control for pre-existing business dynamics, we consider the percentage change in employment between 2014 and 2015 (the number of workers in 2014 is a recall datum). We also include dummies to capture whether the firm made any kind of investment in 2014 and whether it introduced process innovations during the preceding three years.

Lastly, to control for relevant firm characteristics, we match on the logarithm of revenue, on firms' sector of activity (14 classes), geographical location of headquarters (5 macro-regions), organizational structure (corporations vs. unlimited liability companies), and international exposure (exporting firms).[2] These variables help control for sectoral, regional, and structural heterogeneities that could confound the analysis.

Starting from the matching variables described above, we estimate the propensity score using a probit model. Matching is then performed on the linearized propensity score (*lps*), its logit transformation. Specifically, we conduct 1:5 nearest neighbor matching with replacement, enforcing a caliper of 0.15 (approximately 15% of the *lps* standard deviation).

When matching is applied to the full sample, no statistically significant differences are found in the average covariate values between treated and matched control firms (the average standardized bias is just 1.2%), and in almost all cases, the variance ratio is close to 1 (see Tables A1 and A2 in the Appendix). The distributions of the *lps* for treated and matched control units are nearly identical (see Appendix Figure A1). Similarly strong post-matching statistics are obtained when analyzing the subset of firms with at least 50 employees in 2015.

Following the identification of the matched control group, we employ weighted[3] OLS regression to estimate different variants of the model specified in the following equation:

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

In this model, the dependent variable y_{it} represents an observed outcome for firm i in period t. As detailed in each table, this can include the log or the share of flexible workers employed by the firm, the log of total employees, as well as the log of workers' turnover, terminations, or new hirings. Flexible workers, in this context, refer to those hired under fixed-term or other non-standard employment contracts introduced – or formalized through clearer legal frameworks – by labour market reforms in the early 2000s. These contracts, discussed in Section 3.2, include fixed-term hires (*contratti a tempo*

[2]All matching covariates are listed in Appendix Tables A1 and A2.

[3]The weights are obtained with the matching procedure.

determinato), on-call workers (*lavoratori a chiamata*), freelancers under coordinated and continuous collaboration (*collaborazioni coordinate e continuative*), and casual workers (*contratto di prestazione occasionale*).

In line with standard DiD terminology, $Treat_i$ identifies firms that invested in automation technologies between the two waves of the survey (2015–2018); $After_t$ is a dummy indicating the period following the investment decision (i.e., 2018); and $Treat_i \times After_t$ is the interaction term. Its coefficient, β_3, captures the ceteris paribus association between investment in automation and the dependent variable (which, under the conditional independence assumption, also corresponds to the average treatment effect on the treated – though this condition is not required for our analysis). $Revenue_{it}$ represents the total revenue reported by the i-th firm at time t; it serves as a key proxy for firm size and financial health, both of which are critical determinants of firms' employment strategies and their ability or willingness to invest in automation technologies; x_{it} is a vector of additional controls, both time-varying and time-invariant. The inclusion of control variables is intended to account for other potential confounding factors, ensuring a more precise estimation. These controls include dummies for the sector of economic activity (14 classes), a dummy for the utilization of employment support programs (short-term layoff benefits and/or redundancy support measures) in the preceding year, a dummy for the presence of trade union representatives within the firm, and a set of dummies for the macro-region where the firm's headquarters is located (5 macro-regions).

It is important to note that, under the conditional independence assumption, β_3 can be interpreted causally. However, this is not central to our analysis, as our main focus is on the association between automation and flexible labour contracts. While the matching procedure accounts for observable characteristics – ensuring comparability between treated and untreated firms – and differencing controls for time-invariant group-specific unobservables and common time-varying shocks, unobserved confounding factors may still remain. Thus, the conditional independence assumption may not fully hold, and our results should be interpreted as indicative of associations (i.e., co-occurrence) rather than causal relationships.

Mediation analysis

Our analysis explores the relationship between automation and the size and structure of firms' labour forces, with a particular focus on flexible work arrangements. We acknowledge, however, that changes in labour force size are likely to correlate, at least in the short term, with changes in labour force structure. As such, variations in the number of flexible workers may not necessarily reflect genuine changes in firms' equilibrium labour force flexibility requirements. Indeed, when a firm reduces labour demand, non-permanent workers are typically the first to lose their jobs. Conversely, if a firm seeks to expand its workforce – for example, because investment in automation increases the productivity of marginal workers – it will likely test new hires using non-permanent contracts.

To address these dynamics and further validate our findings, we perform a mediation analysis as a robustness check. By doing so, we aim to disentangle the direct and indirect channels linking automation investments and workforce flexibility, ensuring that this association, which represents the main result of the analysis, is not solely driven by changes in the overall workforce size.

The structure of the mediation model is based on mediation equation (equation 2) and outcome equation (equation 3).[4] 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 total effect is given by $\mu_3\delta_4 + \delta_3$.

[4]For a diagram of the model, see Appendix Figure A2.

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

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

Here, $log(Emp_{it})$ and $log(FlexEmp_{it})$ are, respectively, the log of the total number of employees and flexible employees of firm i at time t. $Treat_i$ and $After_t$ are defined as in equation 1, while x_{it} is a vector of the usual control variables.[5]

Results

Automation and resort to flexible employment

The relationship between automation and flexible employment is reported 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 labour.

The key finding is the positive association between automation and the number of flexible workers within firms (columns 1–5). Indeed, in a context of a generalized increase in the number of flexible workers (as indicated by the positive and significant coefficient of $After_t$), firms investing in automation experienced an additional rise of approximately nine percentage points. Notably, the estimate obtained using a 'naive estimator' (i.e., without matching or controlling for confounders, as shown 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 50 employees (columns 4–5) do not lead to substantially different results.

When examining the relationship between automation and the share of flexible employees (columns 6–10), we again observe a consistently positive and significant association. This suggests that investments in automation technologies can lead to a restructuring of the labour force towards more flexible contracts. However, the association is significant only at the 10% level, making it somewhat weaker than that obtained using the log of flexible workers as the dependent variable.

In an effort to identify the primary drivers behind our main results, we repeated the analysis by isolating each automation technology. This exercise presented in the Appendix (Table A3) suggests that the positive association between automation and flexible workers is primarily driven by investments in IoT and robotics, which are also the two largest subgroups in our sample (466 and 386 firms, respectively).

Automation and other firm employment dynamics

In this section, we explore the relationship between automation investments and other employment-related outcomes at the firm level. Although not central to the complementarity hypothesis, these variables offer a broader perspective on how automation may influence firms' hiring and firing decisions.

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 turnover (job terminations + hires), both expressed in logs. For labour force size (columns 1–5), we find a significant positive association between automation investments and the total number of workers employed by the firm, with results larger for medium-large firms. In the full sample, the naive estimation of the interaction coefficient (column 1) is about 50% higher than the adjusted estimates in columns (2)–(3). This suggests an upward omitted variable bias. Moreover, neither $\hat{\beta}_1$ nor $\hat{\beta}_2$ are statistically significant. This indicates the absence of significant ex-ante average differences in the number of employees between automating and non-automating firms. In addition, changes in the number of employees between 2015 and 2018 are fully accounted for by our matched DiD setting. Overall, our estimates on the relationship between

[5]Since the Stata command mediate does not allow the use of analytical weights, matching is performed by including the lps among control variables, serving as balancing score. This is a common alternative method for performing matching.

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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*** (0.030)	0.091** (0.039)	0.085** (0.037)	0.123* (0.061)	0.119** (0.058)	0.004 (0.005)	0.011* (0.006)	0.010* (0.006)	0.015* (0.008)	0.015* (0.008)
Automation	0.599*** (0.077)	0.025 (0.039)	0.028 (0.037)	0.057 (0.068)	0.046 (0.060)	−0.006 (0.006)	−0.001 (0.004)	−0.000 (0.004)	0.001 (0.006)	−0.000 (0.006)
After	0.221*** (0.021)	0.213*** (0.031)	0.204*** (0.028)	0.218*** (0.046)	0.180*** (0.042)	0.036*** (0.003)	0.027*** (0.004)	0.026*** (0.004)	0.014*** (0.005)	0.011** (0.005)
Log(Revenue)		0.335*** (0.025)	0.331*** (0.022)	0.163*** (0.037)	0.199*** (0.029)		−0.007*** (0.002)	−0.001 (0.002)	−0.012*** (0.004)	−0.007*** (0.002)
Matching		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Additional controls			Yes		Yes			Yes		Yes
Observations	20,926	10,126	10,126	3,807	3,807	20,926	10,126	10,126	3,807	3,807
R-squared	0.058	0.250	0.305	0.046	0.149	0.009	0.016	0.090	0.020	0.152
Sample	Full	Full	Full	50+ empl.	50+ empl.	Full	Full	Full	50+ empl.	50+ empl.

Notes: The table presents estimates of the association between automation (i.e., robotics, IoT, big data, and augmented reality) and 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 50 employees in 2015. Standard errors are clustered at the level of sector-of-activity*firm-dimension-class: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.

automation and firm-level employment align with existing literature. They lie between the findings of Koch *et al.* (2021) and Acemoglu and Restrepo (2020) – both limited to 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 percentage points, which rises to about 13 percentage points in medium-large firms. The positive effect on turnover suggests that firms may be reorganizing their production, perhaps to better align with new automated processes. 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, recruiting employees with the desired qualifications while simultaneously laying off some of the workers whose roles have become redundant.

Finally, in Table 3, we analyse the relationship between automation, hiring, and terminations, effectively unpacking turnover. For terminations, we find no significant effect of automation, which contrasts sharply with results obtained using the naive estimator. On the other hand, the correlation between automation and hiring is positive: about +11% for the full sample and +17% for medium-large firms only. Also in this case, the naive estimator suggests the presence of an upward self-selection bias.

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 assumption about automation leading to job losses at firm level. This lack of correlation might

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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*** (0.022)	0.055** (0.027)	0.053** (0.024)	0.082*** (0.030)	0.072** (0.027)	0.151*** (0.032)	0.073** (0.033)	0.071** (0.030)	0.138** (0.056)	0.124** (0.053)
Automation	1.085*** (0.154)	0.015 (0.027)	0.017 (0.023)	−0.018 (0.036)	−0.000 (0.036)	0.740*** (0.109)	−0.009 (0.037)	−0.003 (0.033)	−0.055 (0.067)	−0.029 (0.059)
After	0.025** (0.011)	−0.013 (0.016)	0.010 (0.018)	−0.040 (0.032)	−0.018 (0.031)	0.152*** (0.021)	0.169*** (0.024)	0.204*** (0.025)	0.189*** (0.041)	0.229*** (0.036)
Log(Revenue)		0.588*** (0.033)	0.523*** (0.029)	0.296*** (0.041)	0.298*** (0.036)		0.455*** (0.032)	0.433*** (0.028)	0.249*** (0.043)	0.283*** (0.037)
Matching		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Additional controls			Yes		Yes			Yes		Yes
Observations	20,926	10,126	10,126	3,807	3,807	20,907	10,114	10,114	3,807	3,807
R-squared	0.093	0.636	0.705	0.266	0.375	0.055	0.337	0.420	0.020	0.152
Sample	Full	Full	Full	50+ empl.	50+ empl.	Full	Full	Full	50+ empl.	50+ empl.

Notes: The table presents estimates of the association between automation (i.e., robotics, IoT, big data, and augmented reality) and both the (log) absolute number of firm employees and (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 50 employees in 2015. Standard errors are clustered at the level of sector-of-activity*firm-dimension-class: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.

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 suggests that automation might be creating new roles or requiring additional human resources, possibly to manage, maintain, or complement automated processes.

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 relationship is driven by higher hiring rates, which also explain 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 growth in labour's marginal productivity that is due to automation but unrelated to the complementarity between flexible capital and labour. In this case, the firm will hire new workers under flexible contracts, even though the firm plans to make them permanent shortly thereafter.

This interpretation is consistent with the mediation model results. As shown in Table A4 (Appendix), both $\hat{\mu}_3$ and $\hat{\delta}_4$ are positive and significant, indicating a strong indirect effect of automation on flexible workers mediated by total employment (see Table 4). However, the direct effect of automation remains both positive and significant, accounting for nearly two-thirds of the overall relationship.

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Table 3. Automation and employment dynamics II

	Log terminations					Log hiring				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Automation *After	0.098*** (0.029)	0.020 (0.035)	0.020 (0.031)	0.056 (0.064)	0.036 (0.061)	0.169*** (0.029)	0.110*** (0.030)	0.106*** (0.030)	0.171*** (0.047)	0.165*** (0.046)
Automation	0.556*** (0.098)	−0.033 (0.034)	−0.027 (0.030)	−0.065 (0.065)	−0.027 (0.056)	0.620*** (0.086)	0.014 (0.033)	0.019 (0.031)	−0.018 (0.064)	−0.015 (0.061)
After	0.112*** (0.018)	0.146*** (0.025)	0.201*** (0.028)	0.203*** (0.044)	0.288*** (0.046)	0.135*** (0.020)	0.149*** (0.024)	0.140*** (0.022)	0.175*** (0.045)	0.144*** (0.040)
Log(Revenue)		0.374*** (0.031)	0.343*** (0.026)	0.226*** (0.042)	0.248*** (0.035)		0.376*** (0.030)	0.377*** (0.026)	0.242*** (0.041)	0.285*** (0.037)
Matching		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Additional controls			Yes		Yes			Yes		Yes
Observations	20,926	10,126	10,126	3,807	3,807	20,907	10,114	10,114	3,804	3,804
R-squared	0.041	0.281	0.377	0.070	0.223	0.055	0.282	0.348	0.075	0.204
Sample	Full	Full	Full	50+ empl.	50+ empl.	Full	Full	Full	50+ empl.	50+ empl.

Notes: The table presents estimates of the association between automation technologies (i.e., robotics, IoT, big data, and augmented reality) and the logarithm of 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 50 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 4. Automation and flexible workers: mediation analysis

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

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 lps 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: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.

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Intention to invest in automation and firm employment dynamics

To further assess the robustness of our findings, we re-estimate the models by redefining the treatment variable. Drawing on the survey question that asks firms whether they have invested in automation technologies (possible answers: 'Yes', 'No', or 'In the future'), we considered only those firms that have not yet invested but indicated the intention of doing so in the future.

We find that, unlike actual investment, the intention to invest is not significantly associated with any of the labour outcomes considered (see Appendix Table A5). This null finding suggests that simply planning to adopt automation does not lead firms to alter their current employment strategies. First, it helps mitigate concerns that firms might be adjusting their workforce composition in anticipation of future automation. Second, to the extent that intending firms could share unobserved characteristics (e.g., a forward-looking, innovative culture), the absence of any correlation suggests that our identification strategy effectively controls for firm heterogeneity, thus reinforcing the validity of our empirical approach.

Discussion

Over the past three decades, labour market reforms have significantly diversified the types of employment contracts available to firms and workers. Italy provides a clear example of how labour market reforms can deepen the divide between different segments of the workforce, creating a dual labour market. The upper segment consists of permanent workers, particularly those hired before the reforms, who retain strong protections under pre-existing contracts. In contrast, the lower segment comprises highly flexible, low-paid, and non-unionized workers – disproportionately represented by young people, women, and migrants – employed under various non-standard contracts. In this paper, we examine the relationship between investments in automation and firm-level employment outcomes, focusing specifically on the use of flexible employment contracts. Our analysis reveals that firms investing in automation tend to increase the number of workers employed under flexible contracts. Using the framework proposed by Brynjolfsson and Milgrom (2013), we interpret this result as an indirect test of complementarity between automation and flexible labour. While Cattani *et al.* (2023) argue that automation could reduce non-standard contracts by substituting routine tasks, often performed by workers hired under such arrangements, the positive correlation we observe suggests that the substitution effect is offset by other dynamics, such as the complementarity between automation and flexible labour. Therefore, our findings do not contradict theirs; rather, we focus on the net effect, reflecting the coexistence of these opposing mechanisms within firms' labour adjustment strategies.

The key insight of this paper is recognizing the complementarity between automation technologies and flexible labour contracts, an aspect often overlooked in existing research. This interpretation aligns with the findings of Traverso *et al.* (2023), who emphasize the crucial role of flexible labour market legislation in driving automation adoption, particularly in the context of robotics. The early literature's focus on the risks of job substitution associated with automation may have contributed to this neglect. In contrast, the more recent 'task-based approach' highlights that automation replaces specific tasks rather than entire jobs, and these automated tasks often complement those performed by humans (Caselli *et al.*, 2025). To fully exploit this complementarity, human tasks must be performed with comparable flexibility, underscoring the critical role of flexible labour arrangements in maximizing automation's potential.

It follows that, if the complementarity hypothesis holds true, legislative changes that increase firms' costs of rapidly adjusting their workforce will also diminish the returns on investments in automation. Consequently, if policymakers overlook how reduced labour flexibility negatively affects the value of automation investments, reforms intended to limit labour flexibility could have an adverse impact on firm performance. Our results help to reason systematically about policy trade-offs: to mitigate some of the negative effects of labour reforms on workers, future reforms should aim to influence labour costs and workers' incentives without curtailing firms' ability to rapidly adjust their workforce.

Regarding workers' incentives, when they can be easily laid off, workers will largely refrain from investing in firm-specific human capital, as they would become 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, institutional arrangements should promote training programs aimed at developing task and skill-specific human capital (Gibbons and Waldman, 2019). This can be done by increasing the portability of workers' skills (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.

As discussed throughout the paper, our analysis focuses on external labour flexibility that is the flexibility achieved through hiring and firing. However, as mentioned by Signoretti *et al.* (2022), labour flexibility can also be achieved through internal labour 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 labour 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.

From a managerial perspective, automation introduces further complexity, as it should not be seen merely as a tool for labour substitution but as an opportunity to reimagine how tasks are distributed between humans and machines. As Franco and Landini (2022) argue, building an agile organization requires that both labour and capital be managed with comparable levels of flexibility to fully exploit the economic potential of automation. Managers must consider not only the tasks being automated but also the broader workflows that depend on them, ensuring that automation enhances overall operational flexibility. To address this challenge, firms should adopt strategies that harmonize short-term cost efficiencies with sustainable workforce planning. For instance, by enhancing internal flexibility, firms can reduce their reliance on external flexibility. Moreover, hiring practices that combine the use of flexible contracts for immediate needs with clear pathways to stable employment can mitigate risks such as high turnover and skill mismatches.

Conclusions

In this paper, we use a panel of Italian firms to study the association between investment in automation technologies and various firm-level employment outcomes. In particular, we focus on the positive relationship between automation and firms' resort to non-standard, flexible labour contracts, which have been introduced in the legislation with the labour 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 labour, which jointly determine firms' operational flexibility. Finally, we briefly discuss how future labour policies should aim to improve workers' conditions without compromising firms' ability to rapidly adjust their workforce, as this may lead to a reduction in the return on investment in automation.

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Appendix

Appendix material can be accessed at the Authors' webpage or at the following link: https://drive.google.com/file/d/1Ra_K59_BCoywR2BBH4terJ2ABnidZDlh/view?usp = sharing.

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