INAPP

ISTITUTO NAZIONALE PER L'ANALISI DELLE POLITICHE PUBBLICHE

WORKING PAPER

INAPP WP n. 124

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ISSN 2784-8701

LUGLIO 2024

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LUGLIO 2024

Il working paper è stato realizzato nell'ambito del PTA Inapp 2021-2023, con riferimento alla scheda 'Salari, disuguaglianza e coesione sociale: individui, mercati locali e imprese'.

We thank Silvio Bologna for providing us with valuable insights on the Italian labor market legislation. Usual disclaimer applies.

INAPP – Istituto nazionale per l'analisi delle politiche pubbliche

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ABSTRACT

Automation and young workers' job trajectories: The Italian case

What are the consequences for workers who, over the course of their careers, transition into a new job at a firm that has adopted automation technologies into its production processes? Do their employment prospects increase or decrease? To answer these questions, we examine the job trajectories of a cohort of young workers in Italy by tracking their periods of employment and unemployment. Specifically, we identify whether they were hired by firms that had previously invested in different forms of automation, such as robotics and big data, to assess how exposure to these new types of technologies impact their occupational prospects over time. The empirical analysis is carried out using an employee-employer dataset obtained by merging administrative data on work histories of employees with detailed survey data on firms' characteristics, over the period 2018Q1-2023Q2. Our main findings suggest that having been exposed to automation is positively associated with the probability of staying employed. Additionally, we detect substantial heterogeneities across various dimensions, including firm size, contract types, industrial sectors, and tasks susceptibility to automation. The implications of these results are discussed within the broader context of job resilience and/or the complementary roles of human labor in increasingly automation-integrated environments, by leveraging the post-Covid-19 period in the Italian labor market, following the lifting of firing restrictions.

KEYWORDS: robots, workers, resilience, automation, employment
JEL CODES: D63, E22, E24, J21, J24, O33

Quali sono le conseguenze per i lavoratori che, nel corso della loro carriera, sono occupati in un'impresa che ha adottato tecnologie di automazione nei suoi processi produttivi? Le loro prospettive occupazionali aumentano o diminuiscono? Per rispondere a queste domande, esaminiamo le traiettorie lavorative di una coorte di giovani lavoratori dipendenti in Italia, tracciandone i loro periodi di occupazione e disoccupazione. In particolare, identifichiamo se questi sono stati assunti presso imprese che avevano precedentemente investito in diverse forme di automazione, quali robotica e big data analytics, per valutare come l'esposizione a questi nuovi tipi di tecnologie abbia influenzato le loro prospettive occupazionali a seguito di shock nel mercato del lavoro. L'analisi empirica è condotta utilizzando un dataset employer-employees ottenuto integrando informazioni amministrative sulle storie lavorative dei dipendenti con dati derivanti da un'indagine sulle caratteristiche delle imprese, nel periodo compreso tra il primo trimestre 2018 e il secondo trimestre 2023. I nostri principali risultati suggeriscono che essere stati esposti all'automazione è positivamente associato alla probabilità di rimanere occupati. Inoltre, rileviamo sostanziali eterogeneità rispetto a diverse dimensioni, tra cui la dimensione dell'impresa, la tipologia contrattuale, il settore economico e il grado di esposizione all'automazione della professione svolta. Le implicazioni di tali risultati vengono poi discusse nel contesto più ampio della resilienza lavorativa e/o dei ruoli complementari del lavoro umano in ambienti sempre più integrati con l'automazione, sfruttando il periodo post-Covid-19 nel mercato del lavoro italiano, a seguito della revoca delle restrizioni sui licenziamenti.

PAROLE CHIAVE: *robot, occupazione, resilienza, automazione, lavoratori*

DOI: 10.53223/InappWP_2024-124

Cite as:
Battisti M., Brunetti I., Gravina A.F., Li Donni P. (2024), *Automation and young workers' job trajectories: The Italian case*, Inapp Working Paper n.124, Roma, Inapp

1. Introduction

The advent of automation (in terms of robotics, artificial intelligence and digital technologies) has triggered a profound transformation in the labor market, eliciting widespread concern over the future of employment. This 'fear of automation' is rooted in historical precedents where technological innovations have radically altered job landscapes, often at the expense of traditional roles (e.g., Mokyr *et al.* 2015; Acemoglu and Johnson 2024). Theoretical perspectives on the effects of automation range from optimistic views of enhanced productivity and job creation in new sectors (Nakamura and Zeira 2023), to more pessimistic scenarios where widespread job displacement leads to increased inequality and unemployment (Berg *et al.* 2018; Hémous and Olsen 2022), as well as eroded labor' share (Karabarbounis 2024).

At a general level, Autor (2022) describes how it is easy to forecast which jobs will disappear, but not straightforward to determine which tasks will be necessary in the ongoing process of task substitution (automation replaces humans) and task augmentation (automation and humans complement each other). The latter phenomenon, as suggested by Agrawal *et al.* (2023), in contrast with the traditional view of the automation-skill Tinbergen's race (1974), may reduce inequality – insofar as low-skilled workers may perform at a level closer to that of high-skilled workers.

The first generation of studies, due to the availability of data on robotization, job exposure, patents, and other factors, focused more on the aggregate effects on labor markets (particularly in terms of local labor markets within single countries. See, for instance, Acemoglu and Restrepo 2020; Acemoglu *et al*. 2020; Dauth *et al.* 2021; Koch *et al.* 2021). Differently, recent evidence increasingly points towards the impacts on individual workers (e.g., Acemoglu *et al.* 2023b), as well as the role played by other forms of automation, such as dedicated equipment, cloud computing, and artificial intelligence (see Acemoglu *et al.* 2022). Additionally, the concurrent emergence of international shocks has sparked new attention on the potential role of resilience in automated economic activities and firms, as put forward by Comin *et al.* (2022). Such a role may be amplified or diminished due to the significant heterogeneity in labor market institutions. On one hand, these institutions may reduce cyclicality (Blanchard and Wolfers 2000); on the other hand, they may have feedback effects on technology by driving the adoption of friendly innovations for more protected workers (Alesina *et al.* 2018).

Starting from these considerations, this paper leverages a comprehensive employee-employer panel dataset obtained by merging an administrative dataset on the employees work's histories, deriving from the archive of the Compulsory Communications System, with survey data on firms' characteristics *Rilevazione Imprese e Lavoro* (RIL) conducted by *Istituto nazionale per l'analisi delle politiche pubbliche* (Inapp), and the institutional job market restrictions during the Covid-19 period in Italy to explore the occupational trajectories of a cohort of young workers after the relaxation of these restrictions. This choice serves two main purposes. First, it reduces unobserved heterogeneity among workers, who vary significantly in terms of job safety, education, experience, formal and informal job tenure, and other factors. Second, a growing body of literature over the past two decades has examined the long-term effects on workers exposed to diverse jobs, firms, and conditions early in their careers (see

Wachter 2020, for a review). Our upper age threshold is set at 30 years, which is slightly lower than the standard in the literature, to minimize unobserved effects from other sources[1].

Our focus is on the job dynamics of individuals who worked in firms that adopted automation technologies in their production processes, compared to those who did not, before the lock-down and related institutional shocks. This approach allows us to directly track the impact of specific investments in automation either within the job-firm match, or later, when workers change or lose their occupations. As such, the primary objective of this study is to investigate the extent to which exposure to robotization influences employment probabilities over time.

In particular, our study expands upon the emerging lines of research introduced by Acemoglu *et al.* (2023b), Comin *et al.* (2022) and Acemoglu *et al.* (2022), as we focus on worker-level outcomes by assessing how different automation technologies influence the adaptability of workers in terms of employment probabilities. Moreover, the institutional setting surrounding our investigation allows us to examine whether, and to what extent, firm resilience during economic shocks can extend to workers, adding a new dimension to the understanding of how pre-existing technological investments impacts labor markets.

The key results of the analysis highlight that the probability of being employed is positively associated with exposure to automation. The magnitude of this effect is non-negligible, with an estimated increase in employment probability ranging from approximately 8% to 10%, depending on the specific measure of automation considered. Despite these findings may be influenced by several confounding factors, we are able to control for individual employee characteristics, such as education, gender and nationality, type of job contracts, and account for different firm's characteristics, including firm size (particularly relevant in Italy due to the threshold firing system), economic sector, and others.

The remainder of the paper is structured as follows: section 2 discusses the previous literature in the area to delineate the novelty of this contribution. Section 3 illustrates the data, by describing the cohort of workers we follow, the details of their exposure to automation, other relevant variables, as well as a set of descriptive evidence. Section 4 outlines the institutional setting, the Covid-19 policy responses, a timeline of events, and the overall study framework. Section 5 describes the empirical strategy adopted and presents the benchmark results. Section 6 considers the role of labor market institutions and deals with a series of heterogeneity tests. Finally, section 7 concludes.

2. Overview of related literature

The macroeconomic (and social) consequences of automation are substantial. Grossman and Oberfield (2022) considers factor-biased technical change, primarily due to automation exposure, as one of the most relevant explanations for the long-run trend of decreasing labor share. Relatedly, the theoretical analysis by Caunedo *et al.* (2023) demonstrates that capital-embodied technical change may account for almost 90% of labor reallocation.

[1] See, for example, the pioneering work of Wachter and Bender (2006) (35 years) and the recent study by Arellano-Bover (2022) (34 years) using German data.

Unsurprisingly, with increased data availability, a significant body of literature has emerged to assess the microeconomic effects of automation, particularly robotization. However, the empirical evidence on the impact of robots on the labor market has been mixed. In fact, several contributions indicate significant job losses in highly automated industries (Acemoglu and Restrepo 2020), while others suggest a net increase in employment due to compensatory job creation in other sectors (e.g., Aghion *et al.* 2020; Dauth *et al.* 2021)[2].

The first generation of studies focused on specific measures of exposure and their effects on local labor markets or firm/industry dynamics. By and large, these analyses point out that while automation can lead to job displacement in sectors with high automation intensity, it also results in productivity gains and job creation in other sectors, often due to shifts in economic activity and firm expansion. For instance, Acemoglu and Restrepo (2019b) examined the impacts of automation on employment across U.S. regions, finding significant job displacement in highly automated industries but also noting regional variations in employment outcomes. Dauth *et al.* (2021) focused on Germany, discovering that while robotization reduced manufacturing jobs, it also spurred employment growth in other sectors, such as services. Similarly, Aghion *et al.* (2020) analyzed the French manufacturing sector, revealing that automation led to productivity gains and higher firm growth, which could offset job losses. Benmelech and Zator (2022) extended this analysis to multiple countries, showing that automation's impact on employment varies depending on market structures and competitive pressures.

The second generation of contributions began assessing the impacts on individual workers using general or derived measures of exposure, such as the vulnerability of occupations to automation. Typically, this new line of research finds that while automation displaces certain job types, it can also lead to new opportunities for unskilled workers, highlighting a more nuanced impact on individual employment trajectories. For example, Bachmann *et al.* (2024) used worker-level data across 16 European countries, finding that robot exposure generally improved occupational stability by reducing job separations, though the effects varied significantly depending on initial labor costs and worker age. Similarly, Czaller *et al.* (2021) explored the impact of automation on different types of job tasks, showing that routine tasks are more likely to be automated, but workers in these roles often transition to new employment opportunities, particularly if they receive training and support.

A third area of research underscores the importance of technological investments for maintaining firm performance and resilience in the face of disruptions. On these points, recent contributions by Comin *et al.* (2022) and Copestake *et al.* (2024) examine the role of pre-existing technological sophistication and digitalization in enhancing firm resilience during economic shocks. These studies find that firms with higher levels of technological readiness and digital adoption are better able to withstand and recover from adverse economic events, such as the Covid-19 pandemic. Recently, a new line works expands beyond robotics, by considering the impact of various automation technologies. These studies highlight the significant role of dedicated equipment, specialized software, AI, and cloud computing in driving firm productivity and altering labor market dynamics. According to Acemoglu *et al.* (2022), firms adopting these advanced technologies exhibit higher labor productivity, with increases of up to 11.4%, and face greater demand for skilled labor, while Acemoglu *et al.* (2023a) further document that

[2] For recent surveys, see Yan and Grossman (2023) and Restrepo (2023).

the adoption of these technologies remains concentrated in larger firms, thus affecting a substantial share of the workforce, especially in sectors like manufacturing.

Collectively, this growing literature fills a gap by evaluating the role of automation in influencing labor market performance during and after economic shocks. While traditional approaches have emphasized how restrictive assumptions may hinder post-shock recovery (as highlighted in the classical contribution by Blanchard and Wolfers 2000), this new body of work implicitly acknowledges the complementarity between labor and automation – a factor not explicitly dealt with in earlier empirical studies. In this regard, Italy presents an interesting case study due to its long-standing tradition of dual firing legislation based on firm size thresholds (see, for instance, Messina and Vallanti 2007)[3].

Finally, this work is related to the literature on the effects of initial labor market conditions for young workers. While this literature predominantly focuses on the long-term impacts on earnings throughout an individual's career, Wachter (2020) highlights at least two relevant stylized facts pertinent to our design: i) the effects of adverse initial conditions on the employment of young workers persist at least for 4 years, ii) there are extended complementary impacts on health, and crime, which manifest in the middle stages of workers' careers. However, enforcement mechanisms might exacerbate the situation. As pointed out by Oreopoulos *et al.* (2012), a tight labor market coupled with job losses can compel workers to accept less desirable positions, leading to a downgrade in skills through reduced opportunities for experience and on-the-job learning. Therefore, understanding whether the short-term effects of automation are negative or positive is crucial, especially in a context where a firing freeze is relaxed.

Despite the considerable number of studies on automation over the past decade at different layers of aggregation (see Montobbio *et al.* 2023, for a recent review), evidence at the worker-level remains quite scarce. To the best of our knowledge, a remarkable exception and the closest contribution to ours is that of Acemoglu *et al.* (2023b), which represents the first study to investigate the effects of robot adoption on firms and workers in the Netherlands using administrative data spanning the years 2009-2020. Their main findings indicate that robotization leads to increased productivity and value added for adopting firms, while competitors face negative impacts. At the worker level, the impact of robot adoption is positive (negative) on hourly wage (hours worked), but not statistically significant on the probability of being employed – attributing the latter result to the rigidities of the Dutch labor market. By contrast, workers engaged in routine, replaceable tasks or with low education experience reduced earnings and lower employment probabilities, whereas those not directly displaced by robots benefit from higher productivity and wage increases.

This influential contribution paves the way for necessary research on the role of institutions and other forms of automation. Our work follows this line of inquiry by examining the unique setting of delayed post-shock labor market adaptations due to the government-imposed ban on dismissals during the Covid-19 pandemic until the summer of 2021. In addition, we consider other forms of automation (see

[3] While dual labor markets are often conceived along the lines of formal and informal segments, as discussed in seminal works such as Bulow and Summers (1986), or in terms of permanent and temporary workers, as examined by Bentolila and Saint-Paul (1992), Italy presents a unique case. The country has a historically significant firing threshold established in the 1960s, which creates a notable discontinuity for firms between 10 and 20 employees. This peculiarity has been explored in studies by Boeri and Garibaldi (2019) and Sestito and Viviano (2018).

section 3) and, at the same time, we exploit the discontinuity in firing legislation affecting workers exposed to investment in automation. As far as we can ascertain, this is the first study that explicitly tackles these aspects.

3. Data, variables and descriptive analysis

The empirical analysis is carried out on a comprehensive employee-employer dataset, encompassing a large cohort of young workers, obtained by linking an administrative data source on job flows to a survey on firms' characteristics. The first source is the archive of the Compulsory Communications System (*Sistema delle Comunicazioni Obbligatorie*, COB hereafter) provided by the Ministry of Labor and Social Policies, which records from 2008 information on each working relationship that started, changed or ended for firing, dismissal, retirement, or transformation (e.g., from a fixed-term to an open-ended contract) for all individuals working in Italy as employees[4]. The COB dataset contains detailed information on age, gender, the type of contract (part-time or full-time, temporary or permanent), occupation (5-digit), educational attainment, the sector of activity, and the geographical localization of the work arrangement. From this archive, we use a representative sample obtained by drawing data from four birth dates for each month, for a total of 48 birth dates per year.

The second source of data is the *Rilevazione Imprese e Lavoro* (RIL hereafter) survey conducted by Inapp in 2018 that covers about 30,000 firms operating in the non-agricultural private sector. The survey collects a rich set of information about management and workforce characteristics, firms' productive specialization and competitive strategies, human resource management and labour relations, and public policies.

What is noteworthy for our purposes is that the RIL-2018 survey includes detailed questions related to the firms' investments, between 2015 and 2017 (as such, well before the onset of the Covid-19 pandemic) in several automation areas: robotics, big data analytics, internet of things (IoT), and augmented reality (AR)[5].

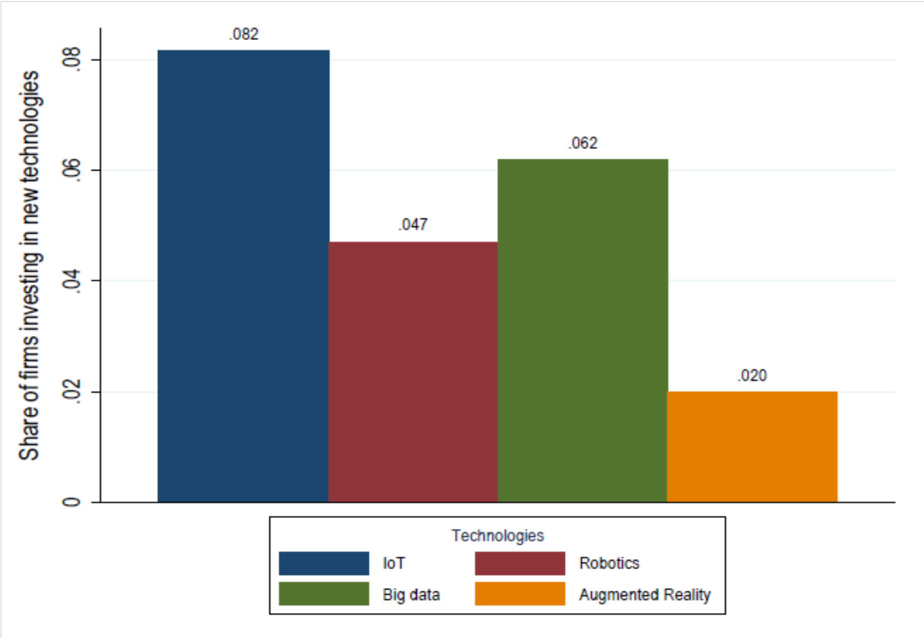
Italy is a leading country in the adoption of industrial robots, consistently ranking high in both global and European statistics. In fact, according to Müller (2023), in 2022, Italy recorded 219 robots per 10,000 employees (the so-called *robot density*) in the manufacturing sector, significantly above the global average of 151. Historically, Italy has maintained a strong presence in robot adoption, often ranking just behind Germany in Europe. While the availability of International Federation of Robotics data has facilitated a wide range of studies in the empirical literature, beginning with the pioneering

[4] Italian firms are legally required to report every hiring, termination, transformation, and extension of employment contracts to the Ministry of Labour and Social Policies. These communications must be submitted through the Compulsory Communications online system.

[5] These categories fall within the taxonomy proposed by Acemoglu *et al.* (2022), representing 3 out of the 5 automation technologies listed (i.e., robotics, dedicated equipment, and cloud-based computing systems and applications). We chose not to use the artificial intelligence data, included in the RIL-2022 survey, to avoid reverse causality driven by automation as a reaction to Covid-19 shocks. For comparative purposes, figure A.2 in the appendix, based on the entire sample of surveyed firms between the two waves of RIL 2018 and 2022, highlight a certain degree of stability in these investments, with the share of firms adopting robotics being approximately twice that of the Dutch firms reported in Acemoglu *et al.* (2023b) (2.2% vs. 1.1%), and only slightly higher compared to the firms surveyed in the US (see Acemoglu *et al.* 2022).

works of Graetz and Michaels (2018) and Acemoglu and Restrepo (2020), the RIL survey provides a more comprehensive look at investments in further forms of automation. As shown in figure 1, our dataset reveals that while 4.7% of firms invested in robots during the 2015-2017 period, 8.2% of firms invested in IoT, 6.2% in big data, and 2.0% in AR.

Figure 1. Investment in new technologies



Source: Author's calculation based on RIL-2018 survey data

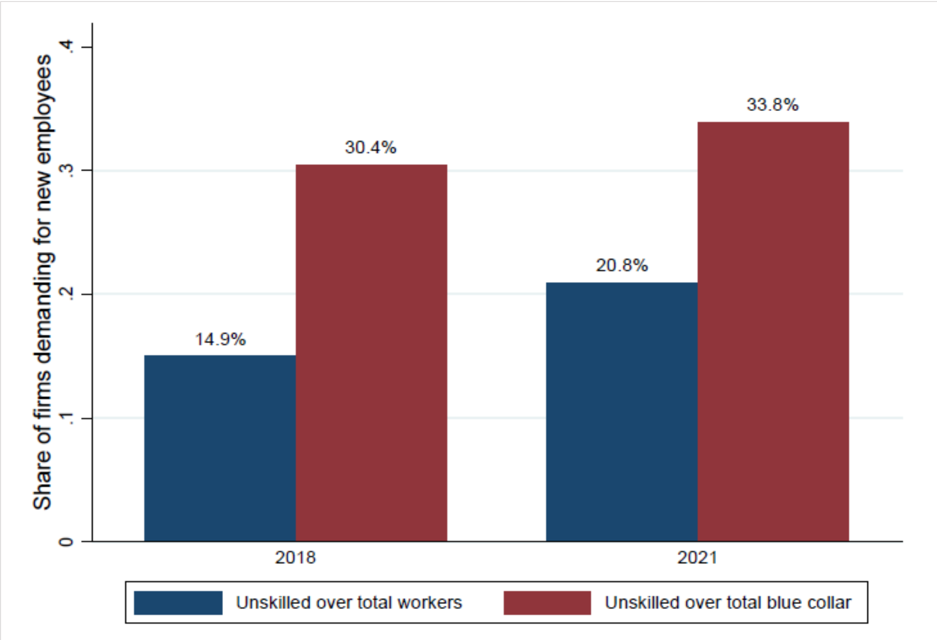
Based on the firm-level investment data, we construct several measures of automation exposure for individual workers, which represent our independent variables of interest. Specifically, we determine whether a worker has been employed by a firm that reported investments in automation during the 2015-2017 period. Next, this information is used to create a dummy variable – as illustrated in table 1, referred to as EXP_A – which takes the value 0 if, in a given quarter (t), the worker (i) is either unemployed ($E_{i,t}$ = 0) or employed ($E_{i,t}$ = 1) as employee in a firm that did not invest in automation (cases A and C, respectively). Conversely, it assumes the value 1 starting from the quarter in which the worker is employed by a firm that invested in automation, regardless of the worker's employment status until the end of the period under investigation (cases B and D, respectively).

Table 1. Employment and automation exposure combinations

Employment status	**Type of firm**	
	No automation	**Automation**
$E_{i,t}$ = 0	A: EXP_A = 0	B: EXP_A = 1
$E_{i,t}$ = 1	C: EXP_A = 0	D: EXP_A = 1

An additional aspect of firms' search for complementarity between automation and workers is illustrated in figure 2 below. Indeed, the RIL survey includes a specific question on the job profiles the firm is looking for with one category focusing on unskilled workers for the *management and control of industrial* *machines and automated or robotic plants*. Figure 2 shows that the share of firms demanding for unskilled blue-collar tends to increase from approximately 15% to 21% between the 2018 and 2022 surveys. This trend further underscores the importance of investigating whether exposure to automation enhances the adaptability of certain workers to operate effectively in an automated environment.

Figure 2. Shares of firms demanding new employees by job profiles



Source: Author's calculation based on RIL 2018 and 2022 surveys data

The empirical analysis is conducted on a quarterly basis, from the beginning of 2018 to mid-2023. As for sample selection, we consider all contractual arrangements involving employees, with the exception of the armed forces, aged between 15 and 30. Since our main focus is to analyze relevant shifts in job trajectories, we remove all contracts with a duration below 90 days. The employees' age restriction minimizes concerns due to experience, seniority (either in institutional terms or within firms), and other characteristics that could introduce significant hidden differences.

After imposing these criteria, we track 67,709 workers quarterly – accounting for a total of 1,489,816 observations – by cross-referencing their employment transitions within 10,902 firms – a subset resulting from the merging process between the COB dataset and the RIL-2018 survey.

From the COB dataset, we collect a series of information on worker-level characteristics, including gender; nationality[6]; education level (i.e., primary, secondary, post secondary, and tertiary school), and macro-region of residence (i.e., North, Centre, South and Island). Table 2 reports worker-level descriptive statistics. Likewise, a further large set of firm-level control variables are gathered from RIL. This includes: firm's size, firm's age (i.e., the number of years of activity), the sector of activity, the (log of) sales per capita, and the characteristics of workforce: the shares of workers with different levels of education (i.e., college, graduate and elementary school) and occupation (i.e., manager and executive;

[6] Specifically, it is a dummy variable equal to 1 if the worker is not of Italian nationality, and 0 otherwise.

white collars; blue collars), and the share of employees with temporary contract. Moreover, we include other managerial's characteristics: the share of firms according to three age-groups of management (under 39, between 40-59, and over 60), and the share of firms with family ownership. Descriptive statistics for the firm-level dimension are presented in table 3.

Table 2. Worker-level summary statistics (*percentage values*)

	OBS	Mean	Std. dev.
Female	67,709	0.40	0.49
No Italian citizenship	67,709	0.12	0.32
Primary school	67,703	0.27	0,45
Secondary school	67,703	0.47	0.50
Post secondary school	67,703	0.19	0.40
Tertiary school	67,703	0.02	0.15
North	67,709	0.61	0.49
Centre	67,709	0.17	0.37
South and Island	67,709	0.22	0.41

Note: all observations are weigthed.
Source: Authors' calculations based on COB-RIL 2018 dataset

Table 3. Firm-level summary statistics

	OBS	Mean	Std. dev.
Firm's size	10,902	38.70	281.29
Firm's age	10,902	20.00	15.41
Share of executive	10,902	0.04	0.35
Share of white collar	10,902	0.35	0.37
Share of blue collar	10,902	0.61	0.28
Share of temporary employees	10,902	0.24	0.28
Share of college employees	10,902	0.13	0.24
Share of graduate employees	10,902	0.51	0.35
Share of employees with elementary school	10,902	0.35	0.35
Share of firms with manager>=60y	10,775	0.38	0.48
Share of firms with manager 40-59y	10,775	0.24	0.43
Share of firms with manager<=39y	10,775	0.09	0.27
Share of firms with family ownership	10,902	0.88	0.33
Log(sales per capita)	9,989	11.63	1.40
Mining and quarrying	10,902	0.01	0.10
Food and tobacco products	10,902	0.03	0.17
Textiles	10,902	0.04	0.19
Chemicals and chemical products	10,902	0.08	0.27
Machinery and equipment	10,902	0.06	0.23
Other manufacturing	10,902	0.04	0.18
Construction	10,902	0.13	0.34
Wholesale and retail trade	10,902	0.17	0.38
Transportation and storage	10,902	0.03	0.18
Accommodation and food service activities	10,905	0.19	0.39
Information and communication	10,902	0.04	0.21
Financial and insurance activities	10,902	0.01	0.09
Other service activities	10,902	0.11	0.32
Education and health services	10,902	0.07	0.25

Note: all observations are weigthed.
Source: Authors' calculations based on COB-RIL 2018 dataset

4. Institutional setting, Covid-19 arrangements and study design

Historically, Italy has been one of the most restrictive OECD countries in terms of the possibility to fire workers, as first reported by Lazear (1990). The first regulation of dismissals in Italy was Law n. 604 of 1966, which required employers to either reinstate workers or pay severance in cases of unfair dismissal. The amount of severance depended on the worker's tenure and the size of the firm. This threshold was later set at 15 employees by Law n. 300/1970 (Statute of the Workers)[7]. Despite revisions introduced by the so-called *Jobs Act* of 2015, a higher level of protection still applies to employees in firms with more than 15 workers (see, for instance, the ruling of the Italian Constitutional Court n. 44/2024). This creates a significant disparity in job security between employees of firms with more than 15 employees and those with fewer (see, for example, Kugler and Pica 2008; Boeri and Garibaldi 2019). Another notable characteristic is the pronounced difference in protection between permanent and temporary workers (Boeri and Garibaldi 2007; Daruich *et al.* 2023). The combination of these factors results in a fragmented Italian labor market, with highly protected segments and highly flexible ones.

The Italian experience during the Covid-19 pandemic is emblematic in highlighting government interventions to maintain economic stability and protect workers. When Covid-19 made its significant onset in Italy, the entire country entered a full lockdown. The government initially identified essential sectors that would continue operations, including agriculture, certain manufacturing, energy and water supply, transport and logistics, ICT, banking and insurance, public administration, education, healthcare, and some service activities (Italian Prime Minister 2020). Non-essential sectors, such as most manufacturing, wholesale and retail trade, hotels, restaurants, bars, entertainment, and sports activities, were completely shut down (Casarico and Lattanzio 2022). In response to the economic shock, the government introduced two significant labor market policies in March 2020. First, a Covid-19 furlough scheme, which extended wage subsidies to all firms, regardless of size, allowing them to reduce labor costs by cutting work hours. Second, with the goal of preventing firms from firing workers and thus preserving employment, a large ban on layoffs was adopted. These measures were extended through subsequent decrees and remained in place until the summer of 2021. The government's decisions, while initially based on the concept of cruciality, also had significant intersectoral impacts, affecting both open and closed sectors due to economic linkages (Caracciolo *et al.* 2020).

To contextualize this narrative in our specific framework, Figures 3 and 4 delineate, through two timelines of events, hypothetical trajectories of the labor market for the cohort of workers included in our sample, starting with normal periods of job entry and exit (the blue and red curves). The three-year period between 2015 and 2017 corresponds to the time window during which firms surveyed by RIL-2018 reported having adopted some form of automation in their production process. Starting from 2018Q1, we track the workers who transitioned to RIL firms, which could have been either exposed or not exposed to automation (i.e., EXP_A = 1 and EXP_A = 0, respectively). In 2020Q2, Italy entered a lockdown due to the Covid-19 pandemic and, until the end of 2021Q2, a layoff freeze was in place

[7] In particular, according to *article 18* of the labor code, firms with more than 15 employees are subject to the so-called *tutela reale*, requiring the reinstatement of unjustly dismissed workers along with compensation for lost wages. In contrast, firms with 15 or fewer employees fall under *tutela obbligatoria*, where they are only required to provide a severance payment ranging from 2.5 to 6 months of salary.

(depicted by the dashed vertical lines). Subsequently, the firing restrictions were lifted and, from that point on, two extremely different outcomes (and a spectrum of intermediate situations) might have emerged, as a result of the outlined institutional context, for the two groups of exposed and non-exposed workers.

In particular, the exposure to automation could have resulted in higher job resilience and/or complementarity for these workers, as delineated in the figure 3, or it could have led to increased fragility, with lower or more uncertain occupational patterns, as described in figure 4.

Figure 3. Automation and workers: resilience/complementarity scenario

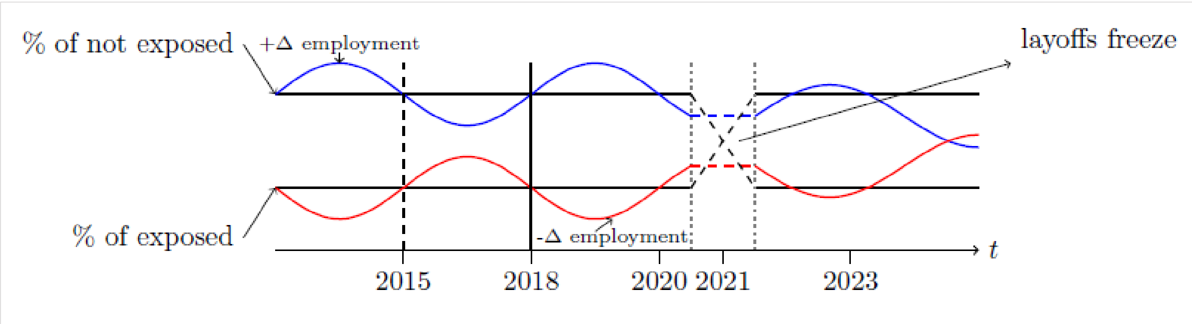
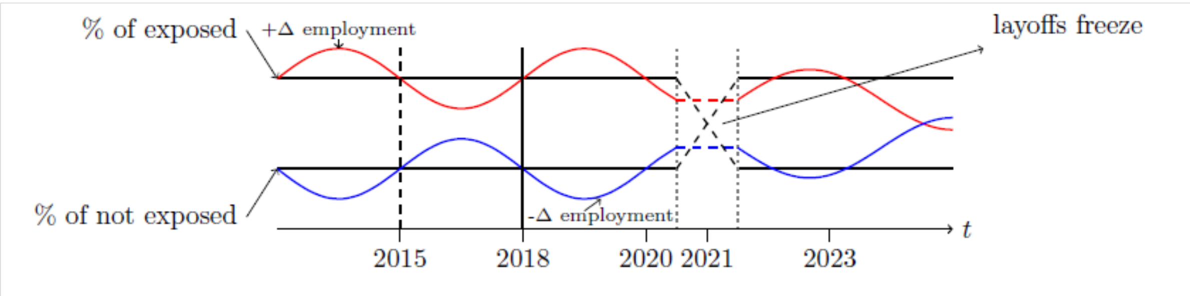


Figure 4. Automation and workers: substitutability scenario

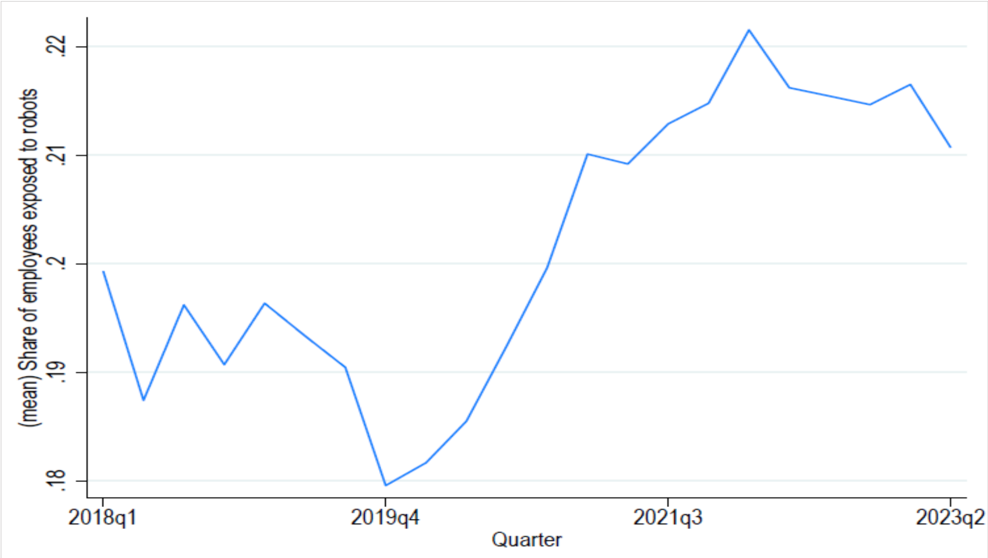


Referring back to the variable construction from the previous section, the share of workers exposed to robots turns out to be increasing over time, as highlighted by figure 5 below[8].

However, this pattern, indicating a relative change of nearly 20%, from 0.18 to 0.22 over two years, may be significantly influenced by firm selection (Jovanovic 1982), which is often linked to firm size. For instance, Acemoglu *et al.* (2023b) used data from firms with more than 50 employees because smaller firms are less likely to adopt automation. In contrast, our sample does not have this limitation, with the average firm size being around 39 employees (see table 3). In section 6, we attempt to disentangle the effects of automation adoption by using the size threshold of 15 employees, which corresponds to different firing regulations – thus taking into account the role of institutions.

[8] Similar trends are observed for the measures of exposure to AR, big data, and IoT, as illustrated in figure A.1 of the appendix.

Figure 5. Evolution of the share of employees exposed to robot



Source: Author's calculation based on COB-RIL merged dataset

5. Empirical strategy and benchmark results

To disentangle state dependence from unobserved heterogeneity, a standard strategy is to exploit the panel structure of the data regressing the dependent variable on its lagged value (to model state dependence) and including subject-specific parameters (to model unobserved heterogeneity) that can be treated as random or fixed (Hsiao 2014). This is generally done by using a *dynamic logit model*.

Let E_{it} indicate a dummy variable value 1 if worker *i* is employed (as employee) at occasion *t* and 0 otherwise. In this specific case t is measured by quarter. The dynamic random effects logit model can then be expressed as follow:

$$E_{it} = 1\{\alpha_i \beta E_{it-1} + \gamma EXP_{A_{it}} + \delta \mathbf{W}_i' + \zeta \mathbf{F}_i' + \sum_{q=2}^{T} \tau_q \eta_q + \epsilon_{it} > 0\}, \quad (1)$$

where α_i are the individual random intercepts assumed to be distributed as a normal N(0, σ^2), ε is a type I extreme value. EXP_A represents, depending on the estimated specification, our measure of exposure to automation, with A = {*robots*; *IoT*; *big data*; *AR*}, and γ being our coefficient of interest. **W** and **F** denote, respectively, vectors of worker and firm characteristics – outlined in section 3 – while η_t indicates quarterly dummies.

Table 4 presents the estimated results of the random effect dynamic logit models based on equation (1). In particular, we report the marginal effects measuring the probability of retaining employment, conditional on having been exposed to various forms of automation technologies. We begin by estimating a baseline model without controls, gradually including quarterly fixed effects, worker- and firm-level characteristics in the estimated specifications[9]. By and large, our findings largely indicate

[9] Detailed estimates, including various sets of controls for automation technologies other than robots, are available upon request.

that the exposure to automation technologies (EXP_A) has a positive and strongly statistically significant impact on employment probability. In particular, once the various levels of controls are included in the models, as in the case of robots (panel a)), the EXP_A associated coefficients remain consistently stable across the estimates and the corresponding type of automation technology. These range from 8.3% (in the case of AR, panel d)) to 9.8% (for big data, panel c) of table 4).

Table 4. Exposure to automation: marginal effects

	Dependent variable: employed							
	a) Robots				**b) IoT**	**c) Big data**	**d) AR**	**e) AL1**
EXP_A	0.120*** (0.001)	0.095*** (0.001)	0.095*** (0.001)	0.094*** (0.001)	0.089*** (0.001)	0.098*** (0.001)	0.083*** (0.001)	0.178*** (0.001)
Lagged dep. var. (t-1)	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects		✓	✓	✓	✓	✓	✓	✓
Worker-level controls			✓	✓	✓	✓	✓	✓
Firm-level controls				✓	✓	✓	✓	✓
Number of workers	67,504	67,504	67,498	60,751	60,751	60,751	60,751	60,751
Number of observations	1,417,538	1,417,538	1,417,412	1,417,412	1,417,412	1,417,412	1,417,412	1,275,731

Note: the table reports the marginal effects of random effect dynamic logit estimates on the probability of being employed when exposed to automation technologies. Worker-level controls include gender, nationality, education level, and macro-region of residence. Firm-level controls encompass firm size and age, sector of activity, (log of) sales per capita, share of workers with different levels of education and occupation, share of employees with temporary contract, managerial's characteristics, and the share of firms with family ownership. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors reported in parentheses.
Source: Authors' calculations based on COB-RIL 2018 merged dataset

In light these outcomes, one might wonder whether the very similar values obtained for the marginal effects are driven by the fact that firms, having the means and resources at their disposal, decided to invest in more than one form of automation. To demonstrate that this is not the case, we take advantage of additional information from the RIL survey, specifically whether a firm has invested in at least one of these technologies (*AL1*). By recalibrating our measure of exposure to account for this possibility, our estimates reveal that when a firm adopts such an investment strategy, the probability of exposed workers remaining employed doubles, reaching 17.8%, as shown in panel e) of table 4. This result suggests that the positive employment effects observed – in panels a)-d) – are not merely due to firms with ample resources investing in multiple forms of automation simultaneously. Rather, it indicates that even a single investment in automation significantly enhances occupational prospects for workers.

Moreover, a puzzling question that might arise is: Could the obtained results be (at least) partially explained by the fact that *healthy* firms, capable of making general investments, particularly in areas other than automation, might themselves positively influence workers' probabilities of staying employed? To control for this specific aspect, we extend our full model specification by introducing an additional measure of exposure to non-automation investments, EXP_{NA}, relying on a question from the RIL survey in which firms were asked if they had made investments in 2017. Therefore, if the role of automation in influencing the probability of workers remaining employed operates through an independent channel, then controlling for EXP_{NA} should not significantly diminish its magnitude. The results of these estimations are reported in table B.1 of the appendix. For each type of automation technologies, what we find is that not only does the estimated marginal effect remain strongly positive and statistically significant, but its magnitude more than doubles. This outcome suggests that healthier firms, capable of making broader, non-automation investments contribute significantly to improving the employment prospects of workers. The synergy between various types of investments, such as in workforce training, infrastructure, and business processes, can lead to more stable and productive work environments, thereby enhancing the positive impact of automation.

Overall, our benchmark estimates indicate that exposure to automation technologies has a significant positive impact on employment probabilities[10]. One plausible interpretation for this result lies in the concept of worker upskilling. Exposure to advanced technologies, such as robotics, may necessitate and facilitate significant skill upgrades among workers, thereby increasing their adaptability and value in the labor market (Autor 2015). Furthermore, industries that embrace robotics tend to experience enhanced growth rates, potentially generating new employment opportunities even as they transform the nature of existing jobs (Bessen 2019).

In addition to upskilling, the resilience of firms adopting automation technologies can provide another layer of explanation, especially if such adaptability can extend to workers. In fact, firms with more flexible production lines, which often include robotic systems, dedicated equipment and digital technologies, might be better equipped to adapt to the rapid shifts in demand during the Covid-19 pandemic without resorting to large-scale layoffs. The ability to manage their workforce effectively during such crises potentially minimized the need for layoffs due to workforce shortages or safety regulations. These firms' strategic workforce planning and investment in automation could enable them to weather the economic downturn more robustly compared to less innovative competitors. Consequently, the resilience underscores the complementary role of automation in stabilizing employment during periods of economic uncertainty.

Moreover, the productivity improvements within firms that invest in automation can contribute significantly to the positive employment outcomes observed. For example, robot adoption can lead to substantial productivity enhancements, potentially resulting in business growth and an increased demand for labor (Graetz and Michaels 2018).

6. Digging deeper: labor market institutions, workers' susceptibility to automation, and heterogeneity

In this section, we explore the potential multifaceted impacts of automation on employment probabilities by examining various dimensions of labor market institutions and sectoral heterogeneity. Specifically, we investigate how factors such as firm size, job contract types (subsection 6.1), and worker qualifications (subsection 6.2) interact with automation investments to influence occupational

[10] Potential issues of endogenous initial conditions could arise in our sample, which might bias the estimation results. To address this concern, we also estimate equation (1) relying on the procedure developed by Stewart (2007) for the Heckman's estimator, which explicitly models the dynamics in of unemployment condition on the initial state (Heckman 1981). The results obtained are comparable to those from the benchmark model. For instance, in the case of exposure to robots, we find a marginal effect of approximately 8.8%, only slightly lower than that observed in panel a) of table 4.

prospects. Additionally, we analyze the sector-specific effects of automation technologies on employment, highlighting the varying impacts across different industrial contexts (subsection 6.3).

6.1 Automation and labor market institutions: firm size and job contract types

Although the previous section highlighted a positive impact of automation exposure on employment retention, this effect may partly result from restrictive firing legislation that prevents workers from being laid off. For instance, if the firms investing in automation are also those legally restricted from firing employees, the observed positive effect on job retention might be more attributable to regulatory constraints than to any complementarity between acquired skills and automation investments.

Italy is an interesting case study due to its traditional employment protection legislation, which provides significantly different levels of protection for workers employed in firms with more than 15 employees compared to those in smaller firms. Specifically, this legislation almost mandates the reintegration of employees into firms with more than 15 workers for individual terminations, whereas firms with 15 or fewer employees typically provide severance pay.

As such, this threshold can create significant differences in job security and influence firms' employment practices and growth strategies (see, for instance, Schivardi and Torrini 2008; Poschke 2009). Typically, as pointed out by Acemoglu *et al.* (2023b), larger firms are more likely to invest in automation. However, our sample shows that small firms also engage in this behavior, albeit to a lesser extent. In fact, as illustrated in figure A.3 in the appendix, larger firms report higher shares of investments in automation (ranging from approximately 3.2% in AR to 12% in IoT, panel b), but those with up to 15 employees have also adopted automation technologies in their production processes. Specifically, 6.1% of these smaller firms have invested in IoT, 2.3% in robotics, 4% in big data, and 1.3% in AR (panel b) of figure A.3). This allows us to apply the specification of equation 1 below and above the 15 employees threshold for all types of automation investments, with the corresponding results reported in table 5. As expected, these largely indicate that for all sources of automation, the effect of exposure is more pronounced in larger firms (bottom panel) compared to smaller ones (top panel), with differences ranging from 1.3% to 4.1% (i.e., in the case of robots and big data, columns (1) and (3), respectively). The exposure to investments in robots, one of the less diffuse forms of investment automation in our sample, appears to be the most homogeneous treatment by firm size (we will return to structural differences among automation types by examining sectoral heterogeneity in subsection 6.3). The top panel reflects an increase in the probability of job retention that is less constrained by firing procedures. Therefore, the range of 6-8% can be considered a lower bound with respect to the results uncovered in the previous section.

Beyond the firing threshold, another crucial dimension of labor institutions worth exploring is the type of job contract. Labor stock adaptation can also occur through variations in job contracts. For instance, a large firm with rigid firing procedures might opt for a higher proportion of temporary workers to maintain a buffer of flexible labor that can be adjusted in response to cyclical economic shocks. In this respect, while employment protection for workers with permanent contracts in Italy is relatively high, the same does not hold for their temporary counterparts. According to OECD (2020), in 2018, the year we start tracking workers in our sample, the strictness of employment protection against dismissals for regular contracts in Italy was 2.56, compared to an OECD average of 2.06. By contrast, for fixed-term contracts, the indicator was 1.63, slightly below the OECD average of 1.70. This discrepancy in job security might be reflected in varying impacts of automation investments on workers, depending on their job type contract.

Table 5. Exposure to automation and firm size: Marginal effects

Dependent variable: employed				
Firm size ≤ 15 employees				
	Robots (1)	**IoT (2)**	**Big data (3)**	**AR (4)**
EXP_A	0.081*** (0.001)	0.061*** (0.005)	0.061*** (0.005)	0.058*** (0.009)
Full set of controls	✓	✓	✓	✓
Number of workers	3,295	3,295	3,295	3,295
Number of observations	69,195	69,195	69,195	69,195
Firm size > 15 employees				
	Robots (5)	**IoT (6)**	**Big data (7)**	**AR (8)**
EXP_A	0.094*** (0.001)	0.090*** (0.003)	0.102*** (0.001)	0.083*** (0.001)
Full set of controls	✓	✓	✓	✓
Number of workers	57,456	57,456	57,456	57,456
Number of observations	1,206,536	1,206,536	1,206,536	1,206,536

Note: the table reports the marginal effects of random effect dynamic logit estimates on the probability of being employed when exposed to automation technologies. Lagged-dependent variable, time fixed effects, worker- and firm-level controls are included in all estimates. * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors reported in parentheses.
Source: Authors' calculations based on COB-RIL 2018 merged dataset

To examine this aspect in the empirical analysis, we compare worked employed with temporary, permanent, and *other* type of contracts[11]. Our hypothesis is that in the context of stringent firing rules, permanent (and *other*) workers are less likely to be affected by changes, as they tend to be more integral to the new production processes. As such, we expect that the probability of remaining employed is higher for these (exposed) workers.

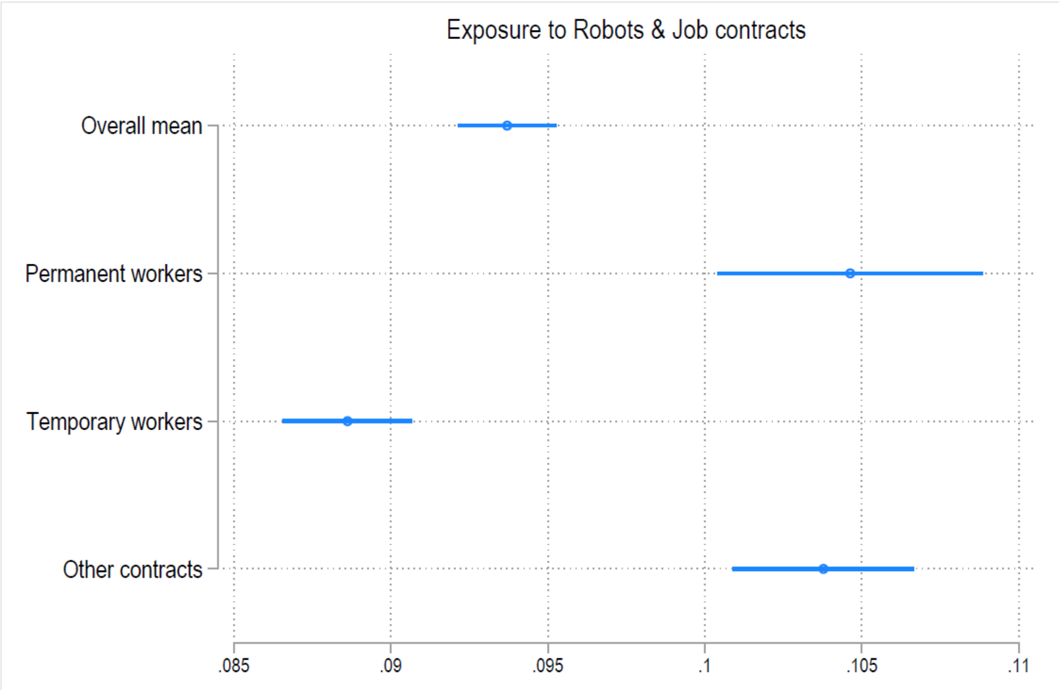
Figure 6 illustrates that temporary workers, when exposed to robots, experience a relatively lower probability of maintaining employment, approximately one fifth lower compared to permanent (and *other*) workers[12]. This finding is consistent with the hypothesis that permanent workers, due to

[11] The *other* category of employment contracts includes: apprenticeship, temporary agency, training, platform and parasubordinate contracts. According to the Italian labor law, apprenticeship (*apprendistato*) contract is a permanent contract regulated by Legislative Decree n. 81/2015 aimed at vocational training and youth employment. In particular, this contract involves on-the-job training with classroom-based learning, and it is designed to facilitate the transition from school to work. Additionally, the contract provides a structured path for skill development, typically for workers between the ages of 15 and 29, and includes protections and obligations for both the employer and the apprentice.

[12] As we find substantially similar results for other forms of automation, these have been excluded from the text for readability purposes but are available upon request.

stringent firing rules, are less likely to be affected by changes in the production process and are more critical to the new automation-driven workflows. The overall picture indicates that the positive effects of automation, such as the complementarity and upskilling of workers, are less pronounced for those in less secure job positions. This is particularly evident due to the variations in firing legislation by firm size and type of contract[13]. Similar results are observed for other forms of exposure to automation technologies, reinforcing the view that job security significantly influences the benefits workers derive from automation. These additional outcomes are reported in figure A.4 of the appendix.

Figure 6. Automation and employment: differences by job/contract stability



Source: Author's calculation based on COB-RIL merged dataset

6.2 *Exposure and vulnerability of workers' qualifications*

One dimension worth exploring based on our results is the distinctiveness of each job in terms of its task content of production (Acemoglu and Restrepo 2019b). Extensive literature on routine-biased technical change elucidates that automation and other advanced technologies are particularly effective at replacing jobs involving routine tasks, whether manual or cognitive. A modern approach to this issue begins with examining the role of computer capital in performing routine cognitive and manual tasks, as analyzed by Autor *et al.* (2003). The theoretical framework by Acemoglu and Autor (2011) further emphasizes how technological progress reshapes labor market demand based on the routinability of tasks. Numerous studies, including those investigating the impact of ICT by Michaels *et*

[13] If we combine these two dimensions, the spread becomes slightly bigger, with a difference between 3 and 4% for each contract type compared to the same contracts in firms with more than 15 employees. Detailed results are available upon request.

al. (2014), and robots by Dauth *et al.* (2021), support this theoretical perspective across various forms of capital.

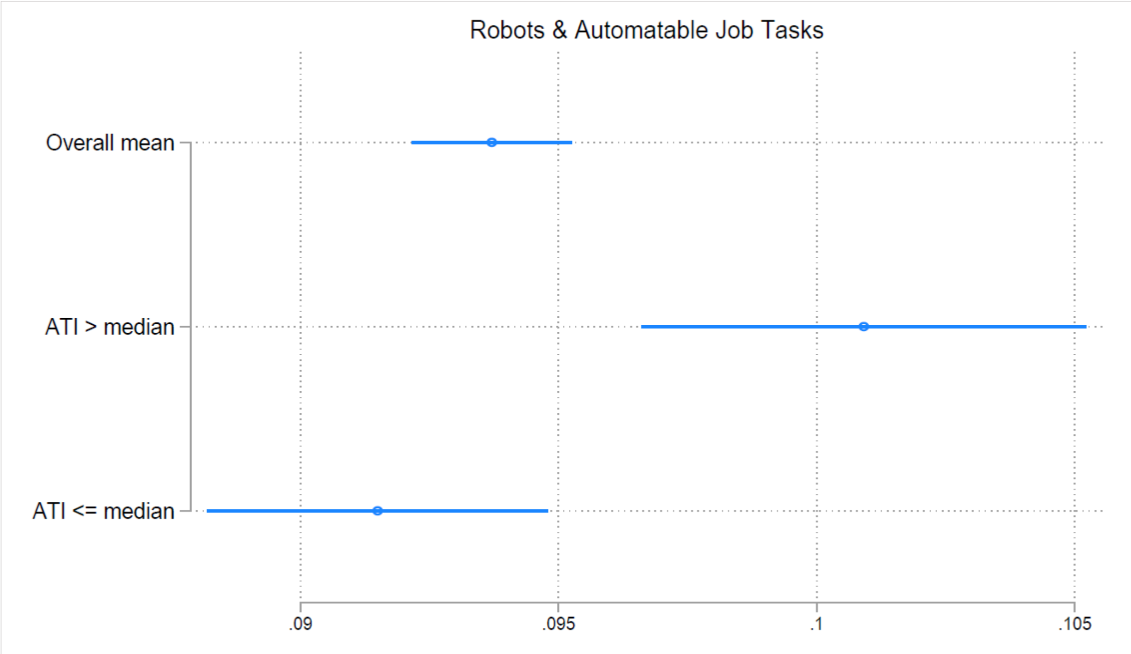
This evolving understanding has underscored the importance of assessing the replaceability of tasks across different worker qualifications, a concept initially explored in the seminal work by Frey and Osborne (2017). In order to characterize the Italian occupations to their intensity of automation tasks, we use the *Indagine Campionaria delle Professioni* (ICP) provided by Inapp. The ICP survey is the Italian equivalent of the U.S. O*NET with the advantage that job task variables are specific to the national labor market accounting, thus, for the structure of the industrial relations characterizing the Italian economy. The ICP survey was last run in 2013 and involves 16,000 workers recording detailed information on all the 5-digit occupations in the Italian labor market.

To obtain a measure of automation task intensity (ATI) for each 5-digit occuaptions, as first step, we average and standardized the workers' responses to the following ICP question: How automated is your job (related to automatic processes)? Subsequently, we compute a categorical indicator that assigns a value of 1 (0) to occupations with an ATI measure above (below) the 50th percentile (i.e., the median) of the ATI distribution. In this way, we are able to categorize occupation into *high* and *low* levels of susceptibility to automation.

Figure 7 displays the results of this further exercise in the case of robots[14]. Contrary to expectations, we find that workers with higher levels of automatable tasks benefit more from exposure to automation. This outcome is roughly 10% greater compared to jobs with automatable tasks below the median. While this finding might seem *prima facie* counterintuitive, it can be explained by several factors. For instance, according to Restrepo (2023), young workers can exhibit a higher ability to reallocate and, as a result, mitigate the adverse impacts of automation. Moreover, firms investing in automation often also invest in reskilling programs to help workers adapt to new technologies. This might ensure that workers with automatable tasks are transitioned into roles that involve supervising and managing automated systems, enhancing their employment security (Autor 2015; OECD 2023). As shown in section 3, the relative demand for unskilled workers has increased in the Italian labor market. This might suggest that automation can create new low-skilled jobs that support the functioning of automated systems, providing more opportunities for these workers (Acemoglu and Restrepo 2019a). Such an eventuality is also consistent with what emerges from figure A.5 in the appendix, which documents that approximately 90% of workers with the qualification Plant and Machine Operators, and Assemblers were hired – by firms in the RIL survey – despite their tasks being highly susceptible to automation (i.e., unskilled blue collars with ATI above than median). Conversely, workers with less automatable tasks may be involved in more traditional roles that do not integrate well with new technologies. In addition to this, the skill mismatch and misallocation that (historically) characterize the Italian labor market (see, for instance, Manacorda and Petrongolo 2006; Boeri *et al.* 2021) can contribute to a reduction of their value to firms focusing on technological advancement.

[14] Similar patterns are observed for the other automation technologies. Therefore, the corresponding results are excluded from the main text, but are available from the Authors upon request.

Figure 7. Automation and employment: differences by task content of automatable qualifications



Source: Author's calculation based on COB-RIL merged dataset

6.3 Sectoral heterogeneity analysis

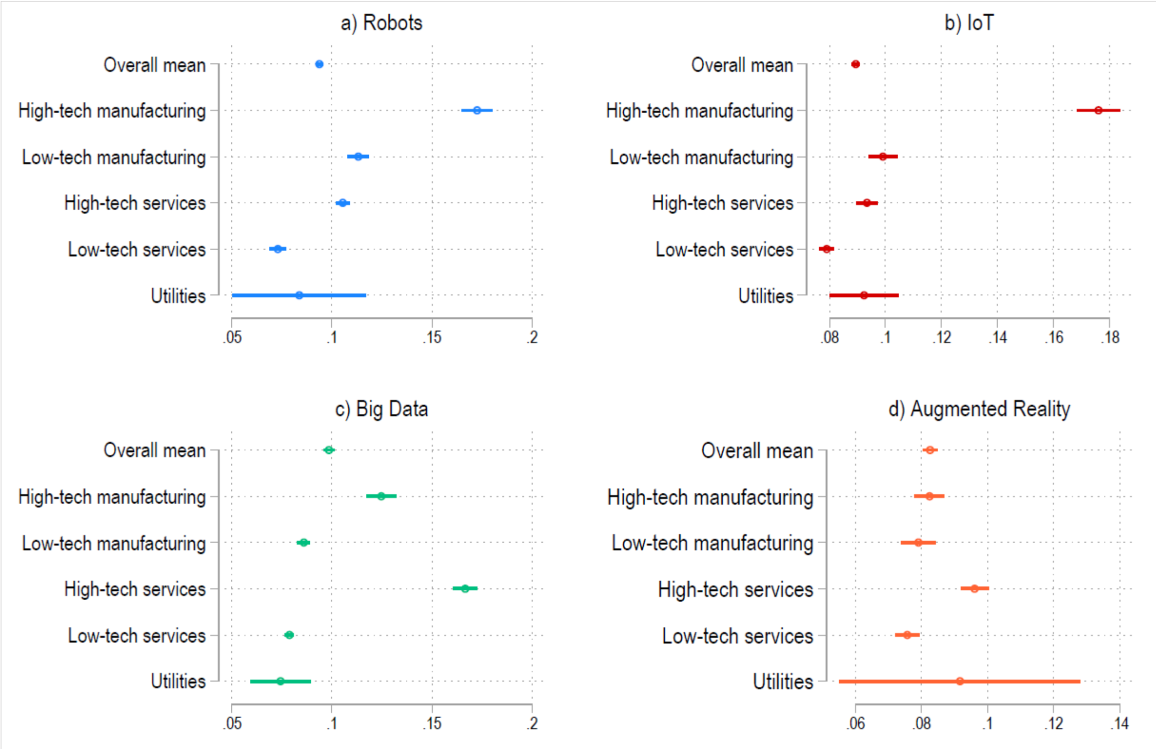
In this subsection, we investigate the potential heterogeneous effects of various forms of automation on the probability of being employed, conditional on workers employed at firms operating in specific economic sectors. As such, this analysis allows us to explore whether the impact of automation technologies differs significantly depending on the industrial context in which workers are employed. In particular, we use five sectoral groups according to their technological content: high-medium- and medium-low-tech manufacturing groups; Knowledge-Intensive sector (KIS) and Low-Knowledge-Intensive sector (LKIS) for the high- and low-tech services; and the Utilities sector group[15].

For each of these macro-sectors, we estimate the full model specification of equation (1) to capture the nuanced impacts of automation technologies within different industrial contexts. The results of such exercises are displayed in figure 8[16].

[15] High- and medium-tech manufacturing include Pharmaceuticals and manufacture of computer; Electronic and optical products; Electrical equipment; Machinery and equipment; Motor vehicles, trailers and semitrailers; Chemicals and chemical products, and the other Transport equipment. Medium-low-tech manufacturing is composed by manufacturing of Food, beverages and tobacco; Textile, apparel, leather, footwear and related products; Mining and heavy industry; other Manufacturing, and Construction. The identification of the KIS and LKIS sectors is based on the NACE Rev2 at the two-digit level and follows Eurostat standards: Knowledge-intensive services (KIS).

[16] Detailed estimates are available upon request.

Figure 8. Automation and employment: sectoral heterogeneity analysis



Source: Author's calculation based on COB-RIL merged dataset

Figure 8 reveals notable differences in the marginal effects of automation technologies on employment retention probabilities across sectors. For instance, as expected, workers operating in high-tech manufacturing significantly increase the probability of staying employed when exposed to robots and IoT (panel a) and b) of figure 8, respectively), reaching a peak of approximately 17%, compared to the overall mean of 9-9.5%. Similarly, big data, in panel c) of figure 8, as a software-based technology, correlates with higher employment retention probabilities in high-tech manufacturing and service sectors. In contrast, our heterogeneity analysis for AR, as shown in panel d), does not indicate considerable deviations from the overall mean, implying a more uniform effect across different sectors.

By and large, these findings highlight the importance of considering sector-specific dynamics when assessing the impact of automation on labor market outcomes, suggesting that these technologies can provide substantial benefits for workers operating in sectors that are more technologically advanced.

7. Conclusions

The impact of automation on labor market outcomes has been extensively studied, yet a general consensus on its net effects remains elusive. Numerous studies have highlighted both positive and negative consequences, with some emphasizing the potential for job displacement and increased inequality, while others point to enhanced productivity and the creation of new employment opportunities. In this context, our study adds to this growing body of literature by examining the specific case of young workers and how their employment trajectories are influenced by automation technologies – specifically robotics, internet of things, big data, and augmented reality. To achieve this, we use a comprehensive employee-employer dataset spanning from 2018Q1 to 2023Q2, relying on administrative information retrieved from COB and the RIL-2018 survey on firms' characteristics, and investigate whether the exposure to different types of automation technologies influences the probability of being employed over time.

Our empirical analysis reveals a positive association between exposure to automation technologies and the probability of remaining employed. Specifically, workers exposed to robotization experienced a significant increase in their employment probability, estimated at approximately 10%. The same applies for the other automation technologies, with estimated probabilities varying only slightly. As such, our findings suggest that automation investments by firms can enhance job stability for their employees. Furthermore, working in automated environments can provide workers with the right set of skills to be complementary to these technologies and/or make them specialized in higher productivity tasks. The presence of a short run complementary effects among automation and labor is very relevant, in the view of the literature on long run consequences of early stages of employment, that highlights how fundamental is this period along the full career.

Results also highlight the importance of the industrial sector in which the firm operates, as well as the firm size and the type of contract (i.e., temporary vs permanent) in moderating or amplifying the effects of automation. Firms with different sizes and belonging to high-tech sectors exhibit varying capacities to integrate automation technologies, which in turn influences the employment outcomes of their workers. The institutional setting in Italy, characterized by a dual firing legislation based on firm size thresholds, further amplifies these differences. In the same vain, the ability of firms to adjust the workforce, especially in response to potential economic shocks, by employing temporary rather than permanent employees, results in a significant discrepancy in the likelihood of remaining employed for these two categories of workers. Ultimately, as expected, workers whose tasks are more susceptible to automation are negatively impacted in their probability of remaining employed.

Overall, our findings contribute to the broader and ongoing debate on automation and employment by providing evidence that these new technologies can enhance job resilience, particularly in the context of economic shocks such as the Covid-19 pandemic. The estimated positive association with employment probability suggests that automation can play a complementary role to human labor, potentially reducing the adverse effects of economic disruptions on employment. This may reinforce young workers perspectives with skill upgrading and job experience acquisition with positive long run effects. However, the study also calls for a nuanced understanding of automation's impact, considering sectoral, firm size, and institutional variations. Policymakers should consider these factors when designing interventions to mitigate the potential negative effects of automation on certain segments of the workforce. Future research should explore the long-term effects of automation on employment across different industries and regions. Additionally, examining the role of complementary skills and training programs in enhancing the adaptability of workers to automated environments could provide valuable insights for policymakers and educators.

In conclusion, while automation poses remarkable challenges to traditional employment structures, it also offers opportunities for enhancing job stability and resilience. By understanding and addressing the factors that influence these outcomes, we can better navigate the transition towards an increasingly automated future.

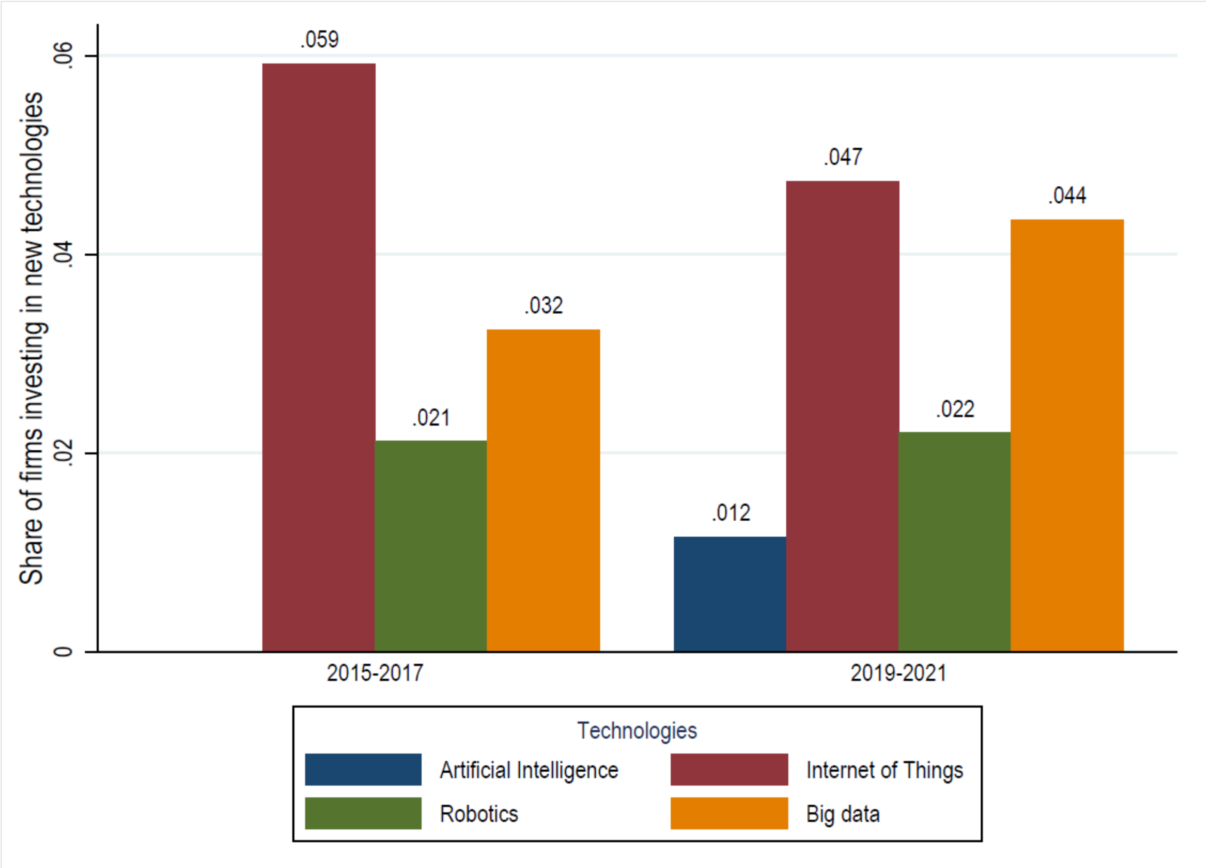
Appendix

A Additional figures and descriptive statistics figure

Figure A.1 Evolution of the shares of employees exposed to other automation technologies

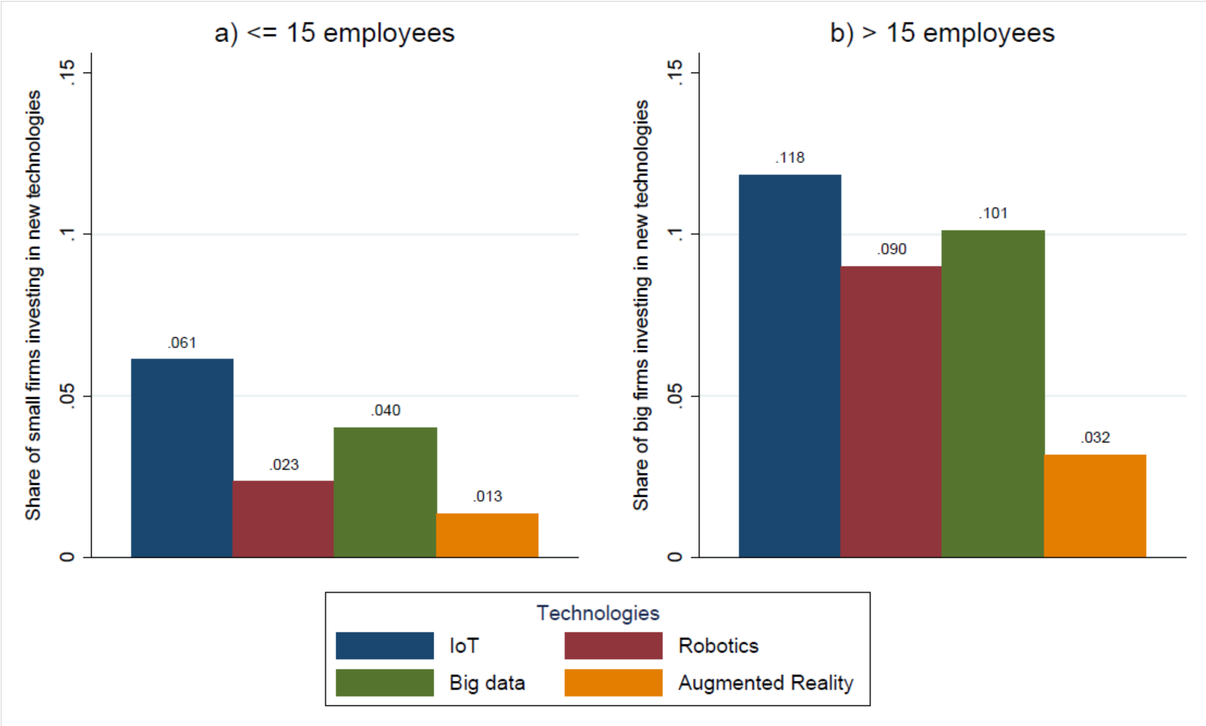
Source: Author's calculation based on COB-RIL merged dataset

Figure A.2 Share of firms investing in automation technologies: 2015-2017 and 2019-2021



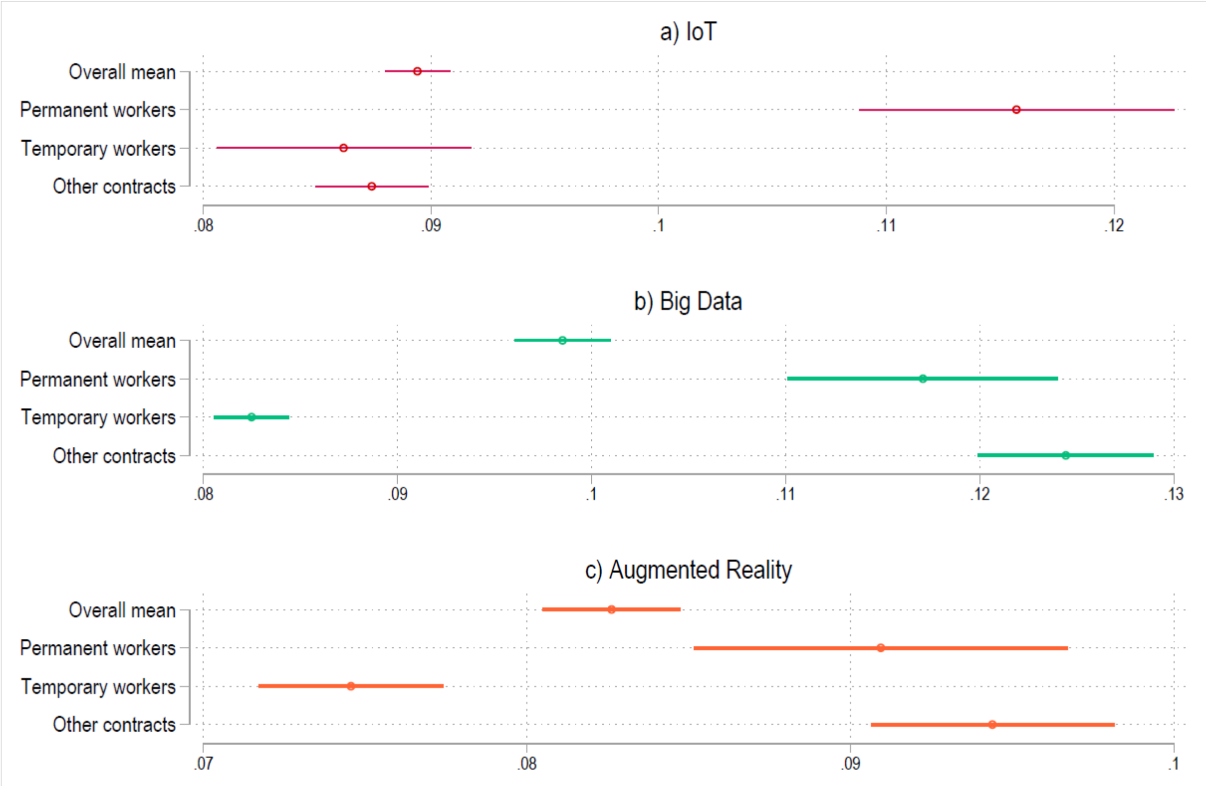
Source: Author's calculation based on RIL 2018 and 2022 surveys data

Figure A.3 Share of firms below and above the threshold of 15 employees investing in automation technologies



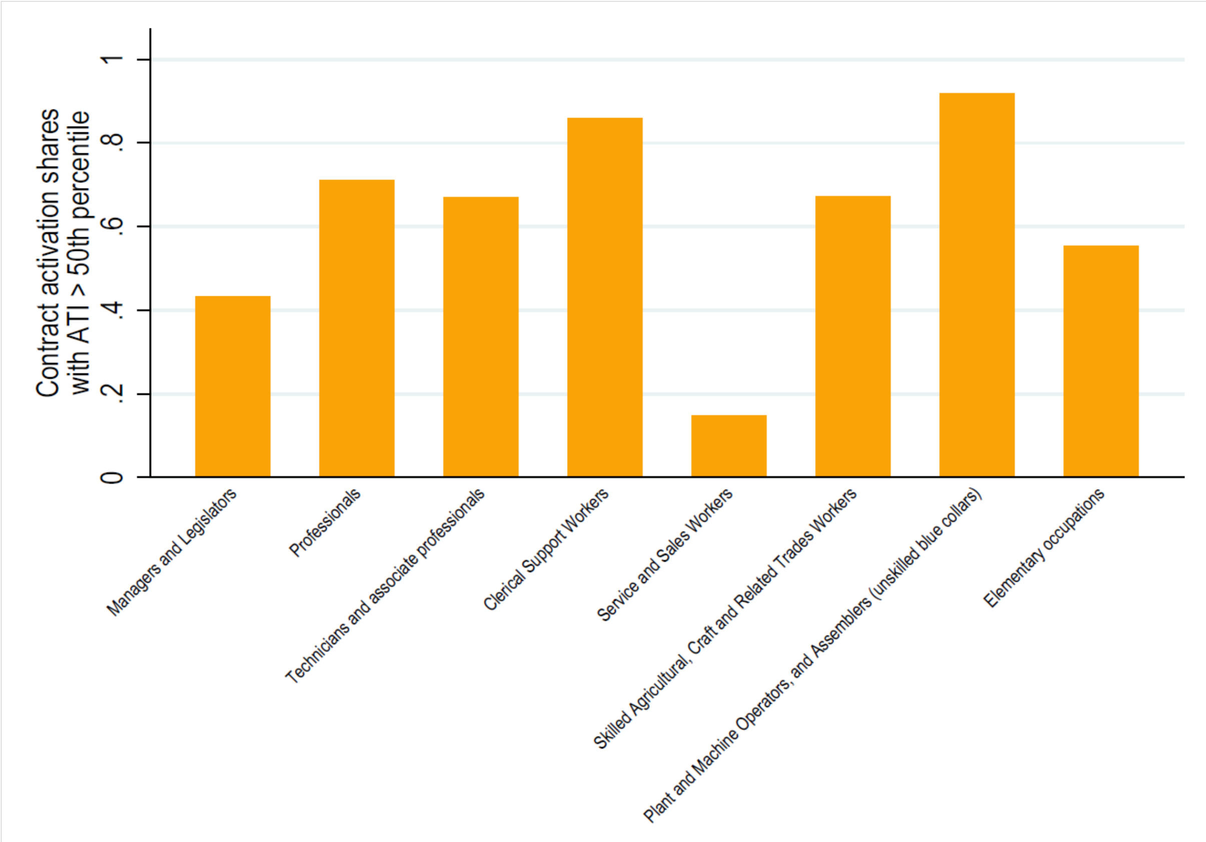
Source: Author's calculation based on COB-RIL merged dataset

Figure A.4 Automation and employment: differences by job/contract stability



Source: Author's calculation based on COB-RIL merged dataset

Figure A.5 Distribution of contract activation shares by occupational macrocategory with ATI > median



Source: Author's calculation based on COB-RIL merged dataset

B Supplementary results

Table B.1 Marginal effects of exposure to automation, controlling for non-automation investments

	Dependent variable: employed			
	a) Robots	**b) IoT**	**c) Big data**	**d) AR**
EXP_A	0.222*** (0.001)	0.229*** (0.001)	0.249*** (0.001)	0.173*** (0.002)
EXP_NA	✓	✓	✓	✓
Full set of controls	✓	✓	✓	✓
Number of workers	60,751	60,751	60,751	60,751
Number of observations	1,275,731	1,275,731	1,275,731	1,275,731

Note: the table reports the marginal effects of random effect dynamic logit estimates on the probability of being employed when exposed to automation technologies. Exposure to nonautomation investments, *EXP_NA* indicates whether workers are exposed to investments made by firms in 2017 in areas other than automation technologies. Lagged-dependent variable, time fixed effects, worker- and firm-level controls are included in all estimates. * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors reported in parentheses.
Source: Authors' calculations based on COB-RIL 2018 merged dataset

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