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Navigating the precarious path: Understanding the dualisation of the Italian labour market through the lens of involuntary part-time employment

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ABSTRACT

This article investigates the surge in Involuntary Part-Time (IPT) employment in Italy from 2004 to 2019, exploring its impact on various socio-economic groups and adopting a spatial perspective. The study tests the hypothesis that technological shifts, specifically routine biased technological change (RBTC), and the expansion of household substitution services contribute to IPT growth. There is a widening negative gap in IPT prevalence among marginalized groups - women, young, and less skilled workers. After controlling for sector and occupation, the higher IPT propensity diminishes but remains significant, hinting at persistent discrimination. Additionally, segregation into more exposed occupations and sectors intensifies over time. Leveraging province-level indicators, and using a Partial Adjustment model, there is statistical support for RBTC's correlation with IPT, especially among women. The impact of household substitution services is notably pronounced for women, highlighting sector segregation.

1. Introduction

In the early 2000s, Italy witnessed a significant precariousness in labour, as employers began depending more on temporary and/or part-time workers instead of hiring full-time employees with open-ended contracts. While these work arrangements offer employers a more flexible workforce, they can also lead to increased job insecurity, lower wages, and restricted access to benefits and training for workers (Connolly and Gregory., 2010; Nicolaisen et al., 2019; O'Reilly and Bothfeld, 2002; Scicchitano et al., 2020). The surge in Involuntary Part-Time (IPT) employment is indicative of a broader phenomenon, characterized by the dualisation of the labour market (Barbieri and Cutuli, 2021; Bonacini et al., 2021a; Daniele and Malanima, 2014). This trend signifies a growing divide between "insiders" and "outsiders", where the distinction extends beyond mere employment status (i.e., employed or unemployed) to encompass varying levels of job protection, security, and opportunities among employees (Rueda, 2005).

The existence of a part-time/full-time hourly wage differential has been extensively documented (Aaronson and French, 2004; Fernández-Kranz and Rodriguez-Planas, 2011). The repercussions of part-time employment extend beyond a wage gap, encompassing disadvantages in terms of access to training and opportunities for professional development (Kauhanen and Nätti, 2015). Numerous studies underscore that a considerable proportion of part-time positions offer limited avenues for career advancement and transitioning into full-time roles, often serving as dead-ends or impediments to workers' progress in the labour market (Connolly and Gregory, 2010; O'Reilly and Bothfeld, 2002). Moreover, part-time employment in many European countries can limit access to social security benefits, as eligibility is frequently contingent on meeting minimum work hours and/or maintaining earnings above specified thresholds (Matsaganis et al., 2015). Notably, the dualisation process tends to disproportionately impact already marginalized segments of the labour force, including women, young workers, and non-native workers (Nicolaisen et al., 2019). While existing literature has extensively explored the demographic and business-cycle factors influencing IPT, there is a notable absence of an economic geography perspective. Most

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research has overlooked the spatial dimension, particularly the significant regional disparities within countries. The article aims to fill this gap by describing the impact of IPT on different socio-economic groups and adopting a geographic perspective as its primary objectives.

Other scholars have undertaken a comprehensive exploration of the factors behind the widespread adoption of IPT. Van Doorn and Van Vliet (2022) explore the association between IPT and Routine Biased Technological Change (RBTC). They posit that as technology advances and replaces middle-skill routine jobs, individuals with moderate education find themselves compelled to seek low-skill positions. This dynamic, in turn, enlarges the labour supply, eroding bargaining power within this segment of the job market. Consequently, those reliant on such employment opportunities may find themselves reluctantly accepting part-time positions, despite a preference for full-time engagement. This mechanism aligns with Acemoglu and Restrepo (2022) elucidation of how the repercussions of automation can transcend the directly impacted occupations and sectors, leading to heightened competition for non-automated jobs. A second factor contributing to the rise of IPT is the expansion of household substitution services, encompassing tasks undertaken by households for their own consumption. Examples include cooking, cleaning, childcare, and elderly care. This growth can be attributed to the increasing employment participation of highly skilled women, which expands the demand for such services. Consequently, the second objective of this article is to scrutinise these two sources driving the escalation of IPT.

Employing data from the Italian Labour Force Survey (LFS), this study delves into the escalation of Involuntary Part-Time in Italy from 2004 to 2019. Italy serves as a good case study for investigating IPT dynamics. Over the examined period, the proportion of Italian employees holding part-time contracts surged from 14 % to 21 %.[4] An increase in part-time employment may not inherently be problematic, as it could mirror workers' preferences for more flexible work arrangements. What is noteworthy is that, in this time frame, the non-voluntary share of part-time employment escalated from 39 % to 64 %. Moreover, the percentage of employees engaged in involuntary part-time work more than doubled, rising from 5.4 % to 13.5 %. Notably, the increase in IPT was not uniformly distributed across socio-demographic groups and macro-regions, as detailed in Section 4. This analysis elucidates the groups that witnessed the most pronounced growth in IPT and presents preliminary evidence on the extent of asymmetric growth across various socio-economic traits, such as gender, age, urban-rural status, education level, and geographic origin. This exploration involves an estimation of the influence of local labour market characteristics on the observed patterns.

The article tests the hypothesis from Van Doorn and Van Vliet (2022) regarding the correlation between RBTC and IPT, with a specific focus on the sub-national level and the utilization of refined occupation-specific indicators. Transitioning from a cross-country to a provincial (NUTS3) framework represents a noteworthy enhancement, given the considerable variation in involuntary part-time occurrences within countries, contingent upon regional factors like local industry composition and demographics. This shift is particularly salient in a nation like Italy, which is characterized by low internal migration rates (Bonifazi et al., 2021; Bonifazi et al., 2017), and where a localized focus becomes imperative to identify potential effects arising from heightened competition for non-automated jobs.

Regarding the use of more nuanced indicators, the combination of the INAPP-ISTAT Survey on Italian Occupations (ICP) with the Italian segment of the EU Labour Force Survey facilitates the construction of province-level indicators delineating routine-task specialization based on the occupational composition in each province.[5] An added advantage of leveraging the ICP survey lies in its capacity to capture the distinctive features of Italian jobs. This contrasts with numerous prior studies that relied on the assumption of comparability with US data, wherein O*NET task-content information was matched with European labour market data.

Adding to the literature on IPT, the article aims to unravel the factors behind the unequal growth of IPT among genders and attempts to disentangle the influence of RBTC from the impact of women's increased self-selection into occupations and sectors that predominantly rely on part-time work. Additionally, the work studies the impact of household substitution services on the proliferation of IPT. This entails the creation of an index that captures activities like bars, restaurants, and all services related to private households employing domestic personnel, including caretakers, cleaning personnel, cooks, and babysitters.

Utilising a partial adjustment model, this research provides evidence linking RBTC to an increased prevalence of IPT at the local labour market level. The ramifications of automation extend beyond their impact on (un-)employment rates, encompassing various aspects of job quality. While RBTC does not emerge as the primary catalyst for the heightened growth in IPT among women relative to men, this analysis indicates a more pronounced impact on women resulting from the increased employment share in household substitution services. These findings imply that factors beyond RBTC, including sector segregation, a heightened demand for household-substitution services, and gender norms, may collectively contribute to the high levels of IPT observed among women.

The rest of the article is organised as follows. Section 2 presents a short review of the literature on the determinants of (involuntary) part-time. Section 3 describes the data, while Section 4 presents some stylized facts on IPT in Italy. Section 5 describes this empirical approach and discusses the results of this analysis. Section 6 concludes.

2. Literature review

The literature on involuntary part-time is relatively recent but rapidly expanding. A substantial body of research has explored the worker characteristics associated with a higher likelihood of being employed in Involuntary Part-Time (Busilacchi et al., 2022; Cam, 2012; Denia and Guillo, 2019; Green and Livanos, 2015, 2017; Livanos et al., 2018; Livanos and Tzika, 2022). These studies underscore a key feature of the dualisation process posited by Rueda (2005) - its inclination to impact already marginalized groups. Across these studies, there is consistent documentation of high IPT rates among vulnerable worker categories, notably women, young workers, non-nationals, and those with lower education levels. A few studies also touch on the geographic dimension, revealing higher IPT levels in economically weaker regions, such as Southern regions in Italy (Livanos et al., 2018), South West, Northern Ireland, Wales, and Scotland in the UK (Green and Livanos, 2015), and Western Greece, Attica, Central Macedonia, and the Ionian Islands in Greece (Livanos and Tzika, 2022). Green and Livanos (2017) adopt a cross-country perspective, illustrating higher IPT levels in Southern and Eastern EU countries (Spain, Portugal, and Poland) and lower levels in countries following Anglo-Saxon and Nordic welfare state models.

Another line of literature scrutinises the patterns of transition between employment states and their fluctuations across business cycles. These studies are especially pertinent to the discourse surrounding whether part-time work serves as a stepping stone toward full-time employment or acts as a potential "career trap". Canon et al. (2014) examines changes in transition probabilities to and from involuntary

[4] In the same period, temporary jobs also grew significantly, from 12 % to 17 %, reinforcing the idea that temporary and part-time jobs are the expression of a global phenomenon driving to job insecurity. A similar co-evolution of both dimensions took place at the European level.

[5] See Eichhorst et al. (2015) for a discussion on the importance of moving past national averages when studying non-standard employment in contexts with large occupational heterogeneity.

part-time positions in the aftermath of the Great Recession in the US. They observe that the transitions were primarily linked to shifts in employment composition (full- versus part-time, and voluntary versus involuntary part-time) rather than changes in the distribution of individuals between employment and non- employment. Borowczyk-Martins and Lalé (2020) echoes similar findings, revealing low turnover between involuntary part-time and unemployment. They argue that cyclical fluctuations in involuntary part-time represent a distinct labour-adjustment mechanism, separate from the job creation and destruction influencing cyclical changes in unemployment rates. Intriguingly, they present evidence suggesting that, in the US, the cyclical dynamics of involuntary part-time might be not only a within-employment phenomenon but even a within-employer one.

Insarauto (2021) investigates female vulnerability to involuntary part-time following the Great Recession in Spain. The study concludes that, during the crisis, women were disproportionately affected by the increase in involuntary part-time, and that this was attributable to gender norms in the distribution of family responsibilities, with women working for lower wages than males equivalent and with an economic activity complementary to a family carer role (Pfau-Effinger, 1993, Rubery and Raffety, 2013). Similar findings are reported by Busilacchi et al. (2022) for Italy. This study, more focused on the dualisation process, examines variations in the involuntary component of part-time employment (involuntary part-time over voluntary part-time) rather than overall involuntary part-time levels (involuntary part-time over total employment).

Several studies focus on clarifying structural changes in involuntary part-time shares over time. Valletta et al. (2020) analyse variations in involuntary part-time shares using US state-level panel data for the period 2003–2016. They find that, while the cyclical component fully dissipated between 2010 and 2016, the persistent increase in the involuntary part-time rate during the recovery from the Great Recession was primarily attributable to structural changes in the industry composition of employment. The economic crisis did not affect all workers uniformly but contributed to exacerbating pre-existing gaps.

Only a handful of studies have initiated an exploration into the influence of global mega-trends, including automation, offshorability, and trade. Malo and Cueto (2019) delve into the extent to which automation and offshorability risks intersect with non-standard employment, focusing on Spain. Their findings reveal that, while offshorability risk correlates minimally with non-standard employment, automation risks exert a slightly greater impact on individuals with non-standard work arrangements. However, possessing a higher level of education serves as a mitigating factor for this risk, irrespective of contract type or working hours. Van Doorn and Van Vliet (2022) analyse the connection between lower middle-skill employment, deemed a consequence of RBTC, and involuntary part-time employment across 16 European countries from 1999 to 2010. They identify an association between lower middle-skill employment and a surge in involuntary part-time employment, especially among specific groups such as women and low-skilled workers, who are disproportionately represented in part-time roles.

In response to the economic crisis, many European countries introduced labour market reforms in the 2000s, moving towards more flexible employment contracts (Parello, 2011). Temporary work became not just a short-term response but a strategy influenced by increased competition, organizational changes, and gaps in labor regulation (ILO, 2016). However, some studies emphasize the negative effects of flexible work practices on innovation and productivity (Kleinknecht, 2020). Italy, one of the countries hardest hit by the Great Recession, experienced significant changes in its labour market, including a sharp rise in IPT work, especially in low-wage sectors such as trade and personal services (Busilacchi et al., 2022). Although the overall number of employees recovered post-crisis, the composition of the workforce shifted, with part-time jobs, particularly IPT, becoming more common.

Italy introduced several labour market reforms to increase flexibility, including the Treu Package (Law 196/1997), Biagi Law (Law 30/2003), and Jobs Act (Law 183/2014). These reforms, along with hiring incentives, were implemented to stimulate the labor market and address unemployment. However, discontinuous work patterns became more prevalent, with fixed-term and part-time contracts increasingly used, particularly for younger workers (Filippi et al., 2021). This shift has raised questions about whether the changes are due to structural shifts in the labour market or regulatory changes. The trend towards flexible, short-term employment contracts, encouraged by temporary financial measures, reflects businesses' caution in hiring permanently in an uncertain economic recovery (Berton et al., 2015). In conclusion, while legislative changes have played a key role in shaping the Italian labour market, the growth of temporary and non-standard contracts indicates deeper changes in labour demand. Understanding whether these shifts are driven primarily by structural factors or regulatory changes remains an important area for further research.

In the international literature, following Kalleberg (2003), the study of Van Doorn and Van Vliet (2022) also considers Employment Protection Legislation as a variable in the analysis the findings indicate that it has no significant impact on IPT in the context of automation and routine-intensive job loss. Nonetheless, the authors demonstrate that active labour market policies, including training and job creation programs, can help alleviate these adverse effects by equipping medium-educated workers with the necessary skills to transition into high-skill jobs or by expanding employment opportunities.

3. Data and measures

The empirical analysis uses 103 provinces (equivalent to NUTS3 regions) as substitutes for local labour markets. This approach is widely adopted for studies focusing on Italy, in part because of the limited availability of data at more detailed levels, as evidenced in studies such as Bratti and Conti (2018), Cerciello et al. (2019), and Dotti et al. (2013). The following paragraphs outline the sources and attributes of the data collected on Italian local labour markets.

3.1. IPT and socio-demographic characteristics

The information on involuntary non-standard employment and socio-demographic characteristics at the worker level comes from ISTAT's "*Rilevazione sulle Forze di Lavoro*" (RFL), the Italian section of the EU Labour Force Survey (ISTAT. 2023). The RFL focuses on all individuals residing in households in Italy, with a sample size of approximately 600,000 individuals annually, spread across approximately 1400 Italian municipalities. Conducted every three months, the survey employs a rotation scheme, where samples from different quarters are partially overlapped. This scheme involves including a household in the sample for two consecutive surveys, followed by a two-quarter break before reinserting the household for two more surveys.

The analysis spans from 2004-Q1 to 2019-Q4. ISTAT's labour force survey, initiated in 1959, underwent significant changes over the years. Notably, a profound restructuring occurred in 2004, introducing substantial technical, methodological, and analytical alterations. As a consequence of these changes, it is advisable not to combine data from before and after 2004. Workers employed in involuntary part-time are identified as those with a part-time contract who, when asked about the reason for such an arrangement, respond with "Has not found a full-time job" as opposed to "Does not want a full-time job". Workers employed with a part-time contract who reported either "Other reasons" or "Does not know" have been excluded from the sample.[6] Two sample restrictions are considered: (1) the focus is restricted only to individuals aged 16–64; (2) and solely on employees. Regarding the second restriction, the RFL categorizes employed individuals into three groups: (i) employees, (ii) self-employed, and (iii) independent contractors ("*collaboratori*"). Self-employed individuals are excluded as they, by definition, do not fall under involuntary part-time. Independent contractors are omitted because they are not queried about the voluntariness of their part-time contracts. Employees constitute 71.5 % of total workers in 2004 and 76.3 % in 2019.[7] In addition to the share of involuntary part-time, the RFL is used to compute various control variables. These include: (1) the share of the population aged ≥ 65; (2) the share of the foreign population; (3) the share of the population with a high-school degree; (4) the share of the population with tertiary education; (5) the unemployment rate; (6) the share of working-age women who are employed; (7) the share of employment with short-term contracts. Finally, estimates of province-level value added per worker and annual percentage growth in value added are obtained using ISTAT's online data warehouse.[8]

3.2. Employment share in routine tasks

The information on the task composition and general characteristics of occupations is obtained from the INAPP-ISTAT Survey on Italian Occupations (ICP). The ICP was conducted twice (in 2007 and 2013, we use the latter), with each wave encompassing about 16,000 workers. This ensures representation across sectors, occupations, firm sizes, and macro-regions, providing data at the five-digit CP-2011 classification (covering around 800 occupations). A notable advantage of the ICP is its ability to compute task and skill variables specific to the Italian economy.

A key advantage of the ICP is that it allows to compute task and skill variables that are specific to the Italian economy. The great majority of studies dealing with the task-content of occupations relies on the US Occupational Information Network (O*NET) run by the US Department of Labor. This approach assumes comparability between the US occupational structure, task content, and technology adoption, and the one of other economies, such as the European ones. The ICP stands out as the only European survey replicating the rich and detailed US O*NET structure (Bonacini et al., 2021b). Similar to the US O*NET, occupation-level variables in the ICP are constructed using both survey-based worker-level information and post-survey validation through experts' focus groups. The characteristics of each occupation are captured through a well-structured questionnaire divided into seven sections: knowledge, skills, attitudes, generalized work activities, values, work styles, and working conditions. The survey reports over 400 variables related to skills, attitudes, and tasks.

The construction of various occupation-level indexes derives from the ICP follows Vannutelli et al. (2022), Esposito and Scicchitano (2022), and Cirillo et al. (2021). The main index is the "classic" routine-task index (RTI), closely aligned with the one proposed by Acemoglu and Autor (2011). The index is defined as:

Table 1
Indicators.

Indicator	Source
RTI	Routine task index. Computed as (RC + RM) − NRM − (NRCA + NRCI). Where: RC - Routine cognitive: "Importance of repeating the same tasks"; "Importance of being exact or accurate"; "Structured vs. Unstructured work (reverse)" RM - Routine manual: "Pace determined by speed of equipment"; "Controlling machines and processes"; "Spend time making repetitive motions" NRM - Non-routine manual: "Operating vehicles, mechanized devices, or equipment"; "Spend time using hands to handle, control or feel objects, tools or controls"; "Manual dexterity"; "Spatial orientation" NRCA - Non-routine cognitive - Analytic: "Analysing data/information"; "Thinking creatively"; "Interpreting information for others" NRCI - Non-routine cognitive - Interpersonal: "Establishing and maintaining personal relationships"; "Guiding, directing and motivating subordinates"; "Coaching and developing others"
RTI (augmented)	"Augmented" routine task index. Computed as (RC + RM) − NRM − (NRCA + NRCI + NRMIA). Where: NRMIA - Non-routine manual - interpersonal adaptability (measures "Social Perceptiveness")
RTCI	Routine task index - cognitive. Computed as: RC − NRCA − NRCI
RTMI	Routine task index - manual. Computed as: RM − NRM − NRMIA
% Middle tercile in total employment	Share of employment in middle-wage occupations. To define the terciles, we rank 2-digit occupations based on their average net hourly wage in 2011. We consider "middle-wage" occupations those in the second tercile. Appendix Table A4 reports the list of occupations, average net hourly wage in 2011, and the tercile they belong to.
% Empl. in manufacturing	Share of employment in manufacturing.

Note: all measures are based on INAPP-ISTAT Survey on Italian Occupations (ICP). Sources of the routinization indexes: Acemoglu and Autor (2011) and Carbonero and Scicchitano (2021).

$$
\begin{aligned}
RTI_o = {} & (RC_o + RM_o)_{routine\ component} - (NRM_o)_{non-routine\ manual\ component} \\
& - (NRCA_o + NRCI_o)_{non-routine\ cognitive\ component}
\end{aligned} \tag{1}
$$

The index is calculated for 126 three-digit CP-2011 occupations. The Routine component assesses the extent of task repetitiveness and standardization, as well as the importance of precision and accuracy. It combines the Routine Cognitive (*RC*) indicator, which gauges factors such as task precision and consistency, along with the importance of accuracy, and the Routine Manual (*RM*) indicator, which evaluates the level of repetitiveness and pre-determination in manual operations. The Non-Routine component consists of three terms: Non-Routine Cognitive Analytical (*NRCA*), Non-Routine Cognitive Interpersonal (*NRCI*), and Non-Routine Manual (*NRM*). *NRCA* measures the significance of tasks requiring creative thinking, analysis, and interpretation of data and information. *NRCI* pertains to the importance of social relationships, interaction, managing, and coaching colleagues. *NRM* gauges the level of manual dexterity required for non-routine operations.

An "augmented" version of the *RTI*, aligning more with Autor et al. (2003), introduces a "Non-routine manual: interpersonal adaptability" (*NRMIA*) component. Additionally, two specific routine task indexes are

[6] As argued by a referee, we cannot exclude possible measurement errors of the dependent variable in the survey. For example, involuntary part-time status could be driven by respondents' dissatisfaction with their job status in terms of pay or working conditions. In any case, the survey question is specifically designed to capture whether part-time work is involuntary due to the inability to find full-time employment.

[7] Appendix Table A1 reports the share of workers in each category and their evolution over time.

[8] As information about the nationality of respondents is not available for 2004, we approximate the proportion of foreign individuals in the population during that year by using the proportion from 2005. Value added data are adjusted for inflation using ISTAT's deflator with base 2015.

considered: *RTCI* (Routine task index cognitive) and *RTMI* (Routine task index - manual). Table 1 provides a concise description and source information for all the indexes considered, while Appendix Table A2 outlines the top and bottom five two-digit occupations for each index.

The methodology proposed by Autor and Dorn (2013) defines the share of routine employment in local labour markets, determined by the percentage of local employment in the top tercile of the employment-weighted distribution for each index at the three-digit occupation level. For each index, the specialization of each province *p* at time *t* is computed as:

$$Index_{pt} = \left(\sum_{o} L_{pot} \cdot 1\left[Index_o > Index_o^{66}\right]\right) \cdot \left(L_{pot}\right)^{-1} \tag{2}$$

where L_{pot} is province *p*'s number of workers in occupation *o* at time *t*; $Index_o$ is the index level of each occupation *o*; $Index_o^{66}$is the 66th percentile in the employment-weighted index across all occupations; 1 [·] is an indicator equal to one if the occupation's index value is above $Index_o^{66}$.

To offer a broad understanding of the sectors captured by each index, Appendix Table A3 outlines the top and bottom five sectors based on the employment share in each index (computed using the same approach described in Eq. 2 but using sectors instead of provinces). For comparability with Van Doorn and Van Vliet (2022), the province-level share of employment in middle-wage occupations are also calculated.[9] Finally, to gain a rough estimate of the extent to which observed effects can be attributed to the automation of manual tasks in manufacturing, as opposed to AI automation in services, the province -level shares of employment in manufacturing are computed.

4. The growth of IPT in Italy: stylized facts

Fig. 1 depicts the evolution of part-time employment over time, differentiating between its voluntary and involuntary components. Between 2004 and 2019, the proportion of workers in involuntary part-time contracts nearly tripled. This growth accelerated notably after the 2008 Great Recession, and there has not been a subsequent decline in involuntary part-time (IPT) employment. Importantly, the surge in IPT employment primarily resulted from an increase in the involuntary aspect of part-time work, rather than a rise in the proportion of part-time employees relative to the total workforce. Fig. 2 illustrates the temporal evolution of IPT across various socio-demographic groups. This figure reaffirms that the process of dualisation tends to impact already marginalized groups. In 2004, women, young workers, and less skilled workers had a higher share of IPT, and over time, this gap widened, as the percentage of IPT grew faster for these groups. A notable exception to this dualisation trend is observed in regional variation. Specifically, the North-South gap in terms of the involuntary component of part-time employment has decreased over time. However, this reduction in the gap is not due to a decrease in the percentage of involuntary part-time employment in the South but rather an increase in the same in the North.

Fig. 3 illustrates the change in the share of involuntary part-time (IPT) within one-digit sectors (panel a) and between one-digit sectors (panel b) from 2004 to 2019. The incidence of IPT increased across all sectors during this period, with the most substantial rise observed in the "I. Hotel and catering" sector. In 2019, the "I. Hotel and catering" sector stood out as one of the major contributors to the overall IPT share, constituting approximately 14.8 % - second only to the "G. Retail" sector, which had even higher levels at 15.7 %.

Fig. 4 plots the estimates of a simple linear probability model regressing a binary indicator for IPT on (1) basic socio-demographic characteristics; (2) 12 broad economic activity groups; and (3) 2-digit occupations.[10]

For each of the two time-periods, i.e. 2004 and 2019, we estimate two linear probability models (the unit of observation are workers *i*):

$$IPT_i = \alpha + SocioDem_i + \varepsilon_i \tag{3}$$

$$IPT_i = \alpha + SocioDem_i + Sector_i + Occupation_i + \varepsilon_i \tag{4}$$

The dependent variable IPT_i is a binary indicator, equal to one for involuntary part-time and zero for all other workers. This exercise serves two main purposes. First, it explores which groups became more or less exposed over time - examining, for instance, whether young workers are more exposed at the end of the period compared to the beginning. Second, it observes whether and to what extent the share of "extra-risk" associated with certain groups, attributable to their selection into specific sectors or occupations, varied over time.

In general, the higher propensity towards IPT associated with certain groups (e.g., women and young workers) decreases after controlling for sector and occupation. This implies that higher shares of IPT for these groups are explained, at least in part, by sorting into particular sectors and occupations. However, the estimates remain positive and significant, indicating the presence of some form of "discrimination".

Regarding variation over time, two trends emerge. First, more exposed groups became even more prone to IPT. Second, segregation into more exposed occupations and sectors increases over time. This is evident by comparing the "distance" between the model with only socio-demographics and the one with sector and occupation for 2004 versus 2019.[11]

Fig. 5 plots the correlation between the various $Index_{pt}$ described in Section 3.2 in 2004. This Figure conveys three main messages. Firstly, as expected, RTMI shows a strong correlation with the manufacturing employment share. Secondly, regions with high manufacturing employment differ from those with high employment in household substitution services. This distinction becomes significant when analysing the gender-specific variations in IPT growth, as the decline in manufacturing and the rise in household substitution services impact men and women differently. Household substitution services exhibit a negative correlation with routine indexes, indicating that regions where such services are more prevalent have less employment exposed to routinisation. Finally, Fig. 6 illustrates the negative relationship between RTI and IPT, which is evident both within cross-sections and over

[9] We rank 2-digit occupations based on their average net hourly wage in 2011. We consider "middle-wage" occupations those in the second tercile. Appendix Table A4 reports the list of occupations, average net hourly wage in 2011, and the tercile they belong to.

[10] The socio-demographic characteristic included are: (1) gender; (2) binary indicator for Italian citizenship; (3) age-group ("16–30", "31–44", "45–54", and "55–64"); (4) urban or rural municipality (use the OECD definition of functional urban areas FUA: "No FUA", "FUA", "FUA core"); (5) education ("No high-school", "High-school", and "Tertiary education"); (6) marital and parental status: ("Single without kids", "Couple without kids", "Couple with kids", and "Single with kids"); (7) macro-region ("North-west", "North-East", "Centre", "South and Islands"). As for the economic sector, we include binary indicators for 12 broad economic sectors.

[11] Appendix Figure A1 plots this measure with the relative confidence intervals. To address the potential influence of economic cycles on firms' employment strategies, we reanalysed the data by dividing the study period (2004–2019) into four phases: 2004–2007 (pre-crisis), 2008–2011 (US crisis), 2012–2015 (Eurozone crisis), and 2016–2019 (post-crisis). Results, shown in Appendix Figure A2, indicate that most changes occurred during the first three periods, with stable trends observed post-crisis. This suggests that firms may have used part-time work as a flexible response to economic uncertainty during downturns, returning to more stable patterns as the economy recovered. The relationship between IPT and the reduced transition index aligns with this trend.

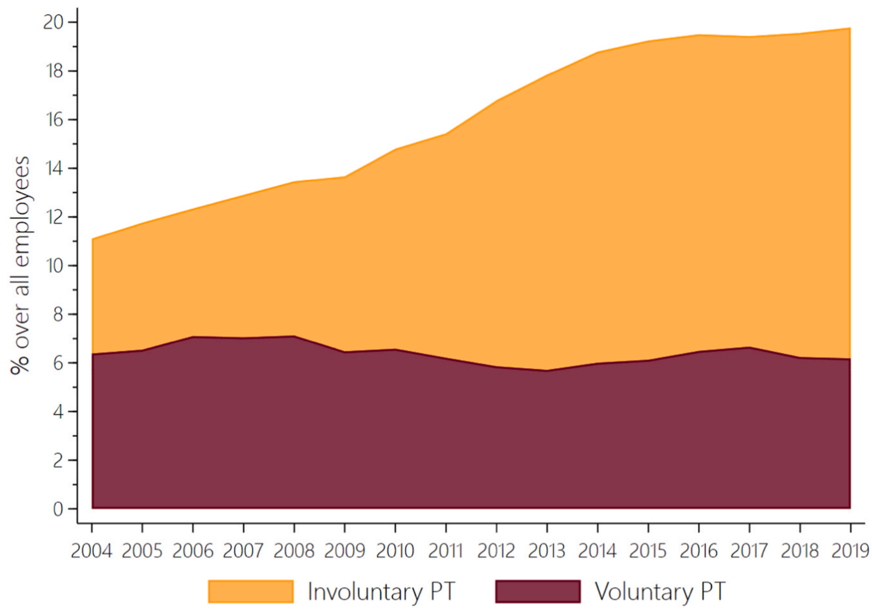

Fig. 1. Share of part time employment 2004–2019.
Source: authors' own calculations. Notes: sample restricted to: (1) individuals aged 16–64; (2) employees (exclude self-employed and independent contractors).

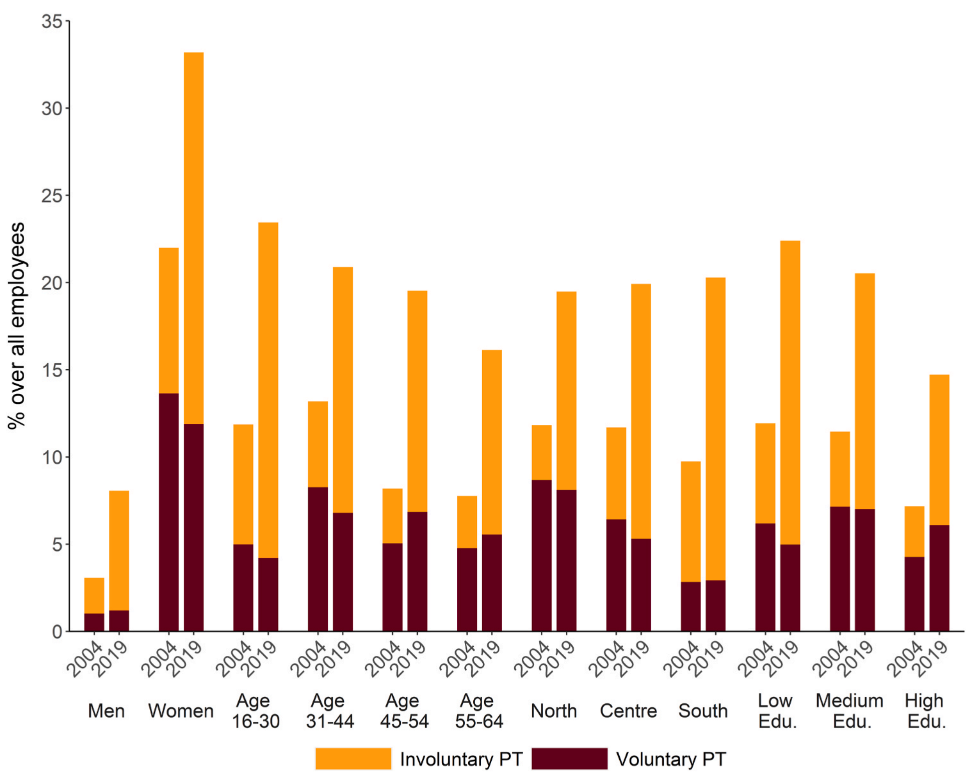

Fig. 2. Variation in share of IPT over time by socio-demographic group.
Source: authors' own calculations. Notes: sample restricted to: (1) individuals aged 16–64; (2) employees (exclude self-employed and independent contractors). "Low Edu." refers to individuals without a high-school degree; "Medium Edu." indicates individuals with a high-school degree; "High Edu." indicates individuals with a tertiary education.

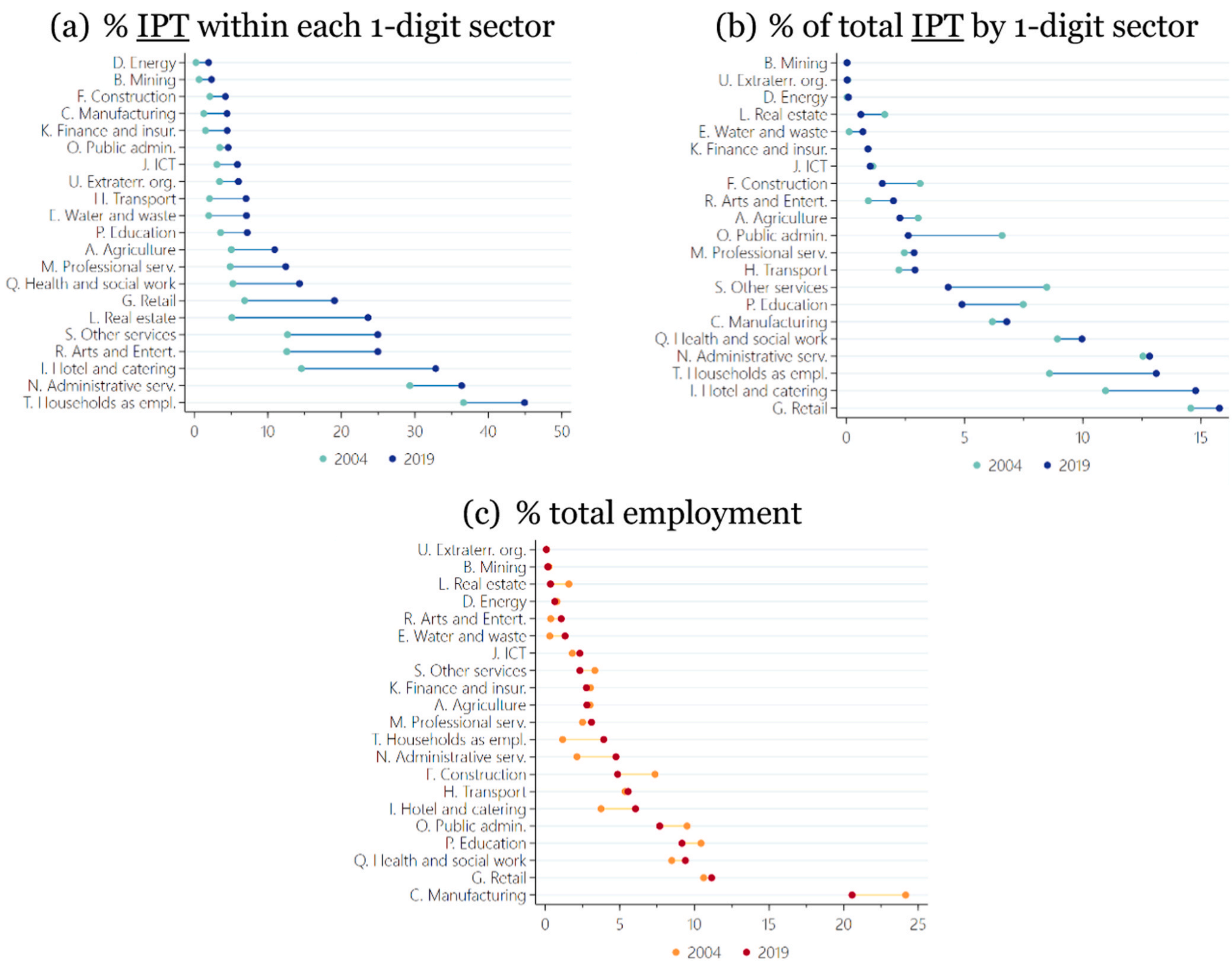

Fig. 3. Variation in share of IPT within and between one-digit sectors.
Source: authors' own calculations. Notes: sample restricted to: (1) individuals aged 16–64; (2) employees (exclude self-employed and independent contractors). Exact shares are reported in Appendix Table A5.

time.[12]

5. Analysis

The empirical approach follows Van Doorn and Van Vliet (2022), a partial adjustment model:

$$\Delta IPT_{p,t} = \alpha + \beta_0\ IPT_{p,t-1} + \beta_1\ Index_{p,t-1} + \beta_1\ X_{p,t-1} + \tau \mathrm{Time} + NUTS1_p + \epsilon_{p,t} \tag{5}$$

where $\Delta IPT_{p,t}$ is the first difference in the share of involuntary part-time in province p at time t, while $IPT_{p,t-1}$ is its lagged level. $Index_{p,t-1}$ is one of the province-level indexes described in Section 3.2 measured at time $t-1$. $X_{p,t-1}$ is a set of province-level controls for: (1) socio-demographic characteristics (share of population aged ≥ 65, share of foreign population, share of population with a high-school degree, share of population with tertiary education); (2) labour market characteristics (share of working-age women who are employed, unemployment rate, and share of employment with short-term contracts); (3) productivity (value added per worker, and annual percentage growth of value added). Appendix Figure A3 reports the correlation among these controls, while Appendix Table A8 reports basic descriptive statistics on all variables used in the regressions. Note the province-level controls from the first and second group are derived from the representative RCFL survey. Finally, *Time* is a linear time trend (as in Van Doorn and Van Vliet, 2022), $NUTS1_p$ is a set of five macro-region (NUTS1) fixed effects, and $\epsilon_{p,t}$ is an error term.[13] Errors terms follow a panel-specific AR(1) autocorrelation structure and assume panel-level heteroskedasticity. The estimation considers 103 provinces and 15 years (2004 is excluded because there is a lack of data for 2003, avoiding the computation of first differences and the lags).

Table 2 reports the estimated β_1, which captures the "short-term" or "transitory" effect of each of our indexes on IPT, while Table 3 reports the long-run multiplier, computed as $\widehat{\beta}_1/-\widehat{\beta}_0$, which captures the permanent effect of our index on IPT in the long run. The results of both

[12] Appendix Table A7 reports the correlations between IPT and our indexes both "raw" and after controlling for year and/or NUTS1 fixed effects. The negative correlations remain relevant even after controlling both for year and NUTS1 regions.

[13] The five macro regions are: (1) North-west, which includes Piemonte, Valle d'Aosta, Lombardia, and Liguria; (2) North-east, which includes Trentino alto Adige, Veneto, Friuli Venezia Giulia, and Emilia Romagna; (3) Centre, which includes Toscana, Umbria, Marche, and Lazio; (4) South, which includes Abruzzo, Molise, Campania, Puglia, Basilicata, and Calabria; (5) Islands, which includes Sicilia and Sardegna.

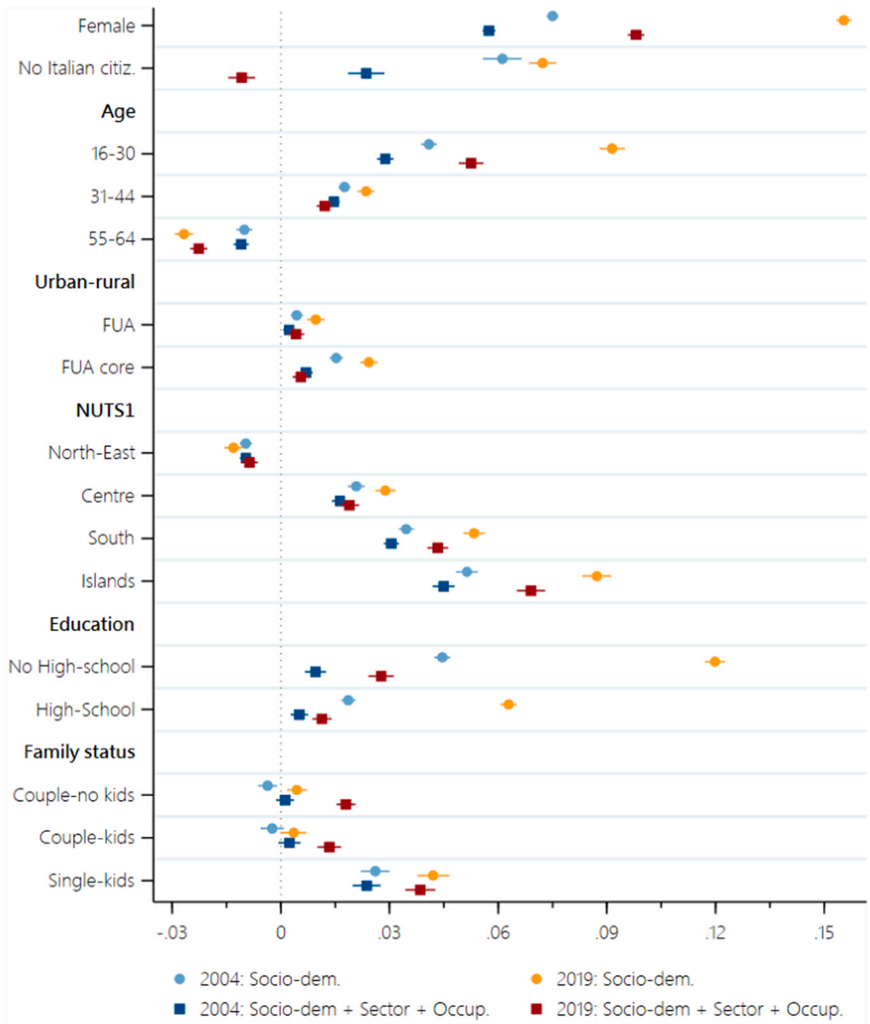

Fig. 4. Determinants of Involuntary part-time.
Source: authors' own calculations. Notes: sample restricted to: (1) individuals aged 16–64; (2) employees (exclude self-employed and independent contractors). To mitigate concerns about small sample sizes, given the large number of sector and occupation fixed effects, the models for 2019 use pooled data from 2017, 2018, and 2019, whereas the models for 2004 draw on data pooled from 2005, 2006, and 2007 (excluding 2004 due to the unavailability of information on respondents' nationality for that year). The base categories for non-binary variables are: "45–54" (Age); "No FUA" (Urban-rural); "North-West" (NUTS1); "Tertiary" (Education); "Single - no kids" (Family Status). Exact estimates are reported in Appendix Table A6. Robust standard errors.

tables support the hypothesis that provinces experiencing a decline in employment in high RTI occupations also experience an increase in involuntary part-time work among low- and middle-skilled workers. This trend holds true regardless of the measure used, whether it is the RTI index, the share of employment in middle-wage occupations, or the employment share in manufacturing. Van Doorn and Van Vliet (2022) describe two mechanisms behind this association: first, medium-educated workers shift into precarious employment being displaced from substituted middle-skill occupations; and second, as low-skill jobs typically require minimal investment in education or training, employers have fewer incentives to offer full-time positions. Notably, the estimates for RTI indexes and the employment share in manufacturing are quite similar, suggesting that the decline in routine occupations can be primarily attributed to the decline in manufacturing, rather than advancements in technologies affecting services. This aligns with the fact that Italy has been slow to adopt new technologies. While the use of industrial robots is widespread in Italian manufacturing, owing to their long-standing presence, it is likely that the adoption of state-of-the-art artificial intelligence AI technologies during the observed time window was modest.[14] Regarding the two sub-components of the RTI, namely RTCI and RTMI, while the former shows slightly larger estimates, there are no statistically significant differences between them.

Interestingly, the association between RTI and IPT appears to be more robust in middle-wage jobs, while the effect on low-wage jobs is negligible. In this regard, the results differ from those of Van Doorn and Van Vliet (2022), as they predict an increase in IPT predominantly in low-paid jobs - a pattern that only emerges in the results when we use the employment share in manufacturing as a measure of routine biased technological change (RBTC).

The analysis in Table 2 is based on workers aged 16–64. While this is the usual age group analysed in studies focusing on the Italian labour market, in the context of involuntary part-time might not be the most appropriate one as part-time workers aged roughly from 16 to 25 might

[14] Following the 2021 report of the International Federation of Robots, Italy is the forth robot adopter in Europe and 11th Worldwide, with about 224 robots per 10.000 manufacturing employees (IFR, 2018)

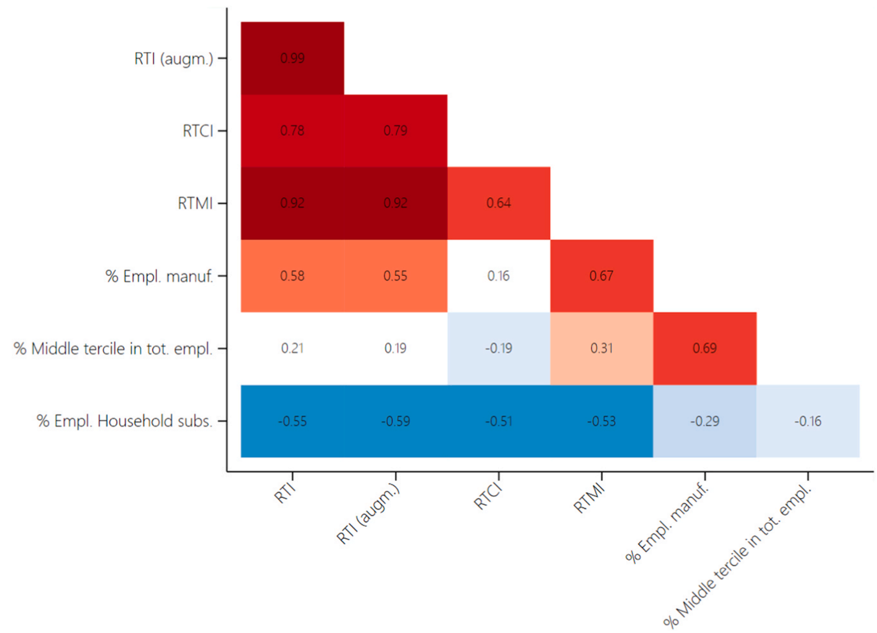

Fig. 5. Correlation of province-level indexes $Index_{pt}$.
Source: Authors' own calculations.

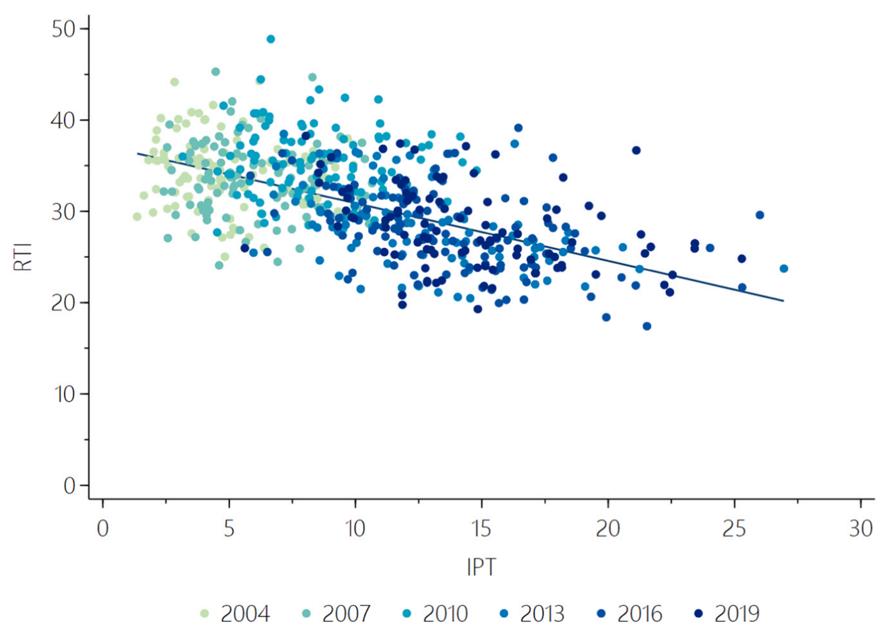

Fig. 6. Variation in RTI and IPT over time.
Source: authors' own calculations. Notes: every dot is a province-year average. Sample restricted to: (1) individuals aged 16–64; (2) employees (exclude self-employed and independent contractors).

be more prone to part-time jobs because of their parallel enrolment in upper secondary or tertiary education. Therefore, Appendix Table A13 replicates the analysis using workers aged 30–64. The results are comparable to the ones of Table 2, suggesting that the inclusion of younger part-time workers is not a source of bias.

Fig. 7 examines the heterogeneous composition of Italy's local labour markets by presenting RTI estimates for provinces in the North, Centre, and South & Islands. Although the negative RTI estimates appear more pronounced in the Southern regions, particularly among workers with a high school diploma, the differences across the three macro-regions are not statistically significant.

Table 4 reports the results by gender, confirming the existence of a relationship between routine biased technological change (RBTC) and involuntary part-time (IPT) for both men and women. To investigate more in detail the higher levels of IPT among women, an additional set of indicators capturing the share of employment in household substitution services was introduced. These services encompass all activities provided by households for their own consumption, such as cooking meals, cleaning, childcare, or elderly care. Specifically, the specification uses a composite indicator, "% Empl. Household subs.", which encompasses employment in the following three NACE Rev.1 sectors: "553. Restaurants", "554. Bars", and "950. Activities of private households employing domestic personnel". Additionally, the estimate includes the employment share of each of these three sectors separately to determine

Table 2
Partial adjustment model.

		Education		Pay tercile	
	All	No HS	HS	Low	Middle
RTI	−0.060***	−0.103***	−0.081***	−0.087***	−0.047***
	(0.010)	(0.019)	(0.013)	(0.020)	(0.012)
	0.21	0.19	0.26	0.20	0.20
RTI (augm.)	−0.061***	−0.104***	−0.080***	−0.085***	−0.047***
	(0.011)	(0.019)	(0.014)	(0.021)	(0.012)
	0.21	0.19	0.26	0.20	0.20
RTCI	−0.069***	−0.117***	−0.085***	−0.102***	−0.051***
	(0.011)	(0.020)	(0.014)	(0.022)	(0.012)
	0.21	0.20	0.26	0.20	0.20
RTMI	−0.056***	−0.086***	−0.076***	−0.083***	−0.044***
	(0.011)	(0.019)	(0.014)	(0.020)	(0.012)
	0.21	0.19	0.26	0.20	0.20
% Middle tercile in tot. empl.	−0.023*	−0.041**	−0.032**	−0.012	−0.029**
	(0.012)	(0.020)	(0.016)	(0.023)	(0.013)
	0.19	0.18	0.25	0.19	0.19
% Empl. manuf.	−0.037***	−0.074***	−0.044***	−0.070***	−0.019***
	(0.007)	(0.012)	(0.009)	(0.013)	(0.007)
	0.21	0.20	0.26	0.21	0.20

Source: authors' own calculations. Notes: each estimate comes from a separate regression including the full battery of controls described in Section 5 (Eq. 5). Appendix Table A15 presents the estimates for the full set of control variables. The dependent variable is the share of involuntary part-time workers IPT by province (2004–2019). We compute the share of IPT: (1) among all employees; (2) among employees without a high- school degree; (3) among employees with a high-school degree; (4) among those in low-paid occupations (bottom tercile); (5) among those in middle paid occupations (middle tercile). Standard errors are reported between parentheses, while the last line of each block reports the R2. We specify errors terms to follow a panel-specific AR(1) autocorrelation structure and assume panel-level heteroskedasticity. Significance levels: * ρ<0.10, ** ρ<0.05, *** ρ<0.01. N=1545 (103 provinces and 15 years).

Table 3
Partial adjustment model - Long run multiplier.

		Education		Pay tercile	
	All	No HS	HS	Low	Middle
RTI	−0.178***	−0.289***	−0.162***	−0.265***	−0.114***
	(0.030)	(0.053)	(0.026)	(0.061)	(0.028)
RTI (augm.)	−0.179***	−0.292***	−0.161***	−0.260***	−0.114***
	(0.031)	(0.054)	(0.027)	(0.062)	(0.029)
RTCI	−0.202***	−0.324***	−0.172***	−0.310***	−0.124***
	(0.032)	(0.054)	(0.027)	(0.065)	(0.029)
RTMI	−0.169***	−0.247***	−0.153***	−0.256***	−0.108***
	(0.032)	(0.055)	(0.027)	(0.061)	(0.029)
% Middle tercile in tot. empl.	−0.072*	−0.121**	−0.069**	−0.038	−0.074**
	(0.038)	(0.060)	(0.033)	(0.074)	(0.033)
% Empl. manuf.	−0.109***	−0.199***	−0.091***	−0.207***	−0.047***
	(0.019)	(0.031)	(0.018)	(0.037)	(0.017)

Source: authors' own calculations. Notes: each estimate comes from a separate regression including the full battery of controls described in Section 5 (Eq. 5). The dependent variable is the share of involuntary part-time workers IPT by province (2004–2019). We compute the share of IPT: (1) among all employees; (2) among employees without a high- school degree; (3) among employees with a high-school degree; (4) among those in low-paid occupations (bottom tercile); (5) among those in middle paid occupations (middle tercile). We specify errors terms to follow a panel-specific AR(1) autocorrelation structure and assume panel-level heteroskedasticity. Standard errors are reported between parentheses. Significance levels: * ρ<0.10, ** ρ<0.05, *** ρ<0.01. N=1545 (103 provinces and 15 years).

which one has a stronger effect. Compared to men, the incidence of involuntary part-time among women is significantly higher in provinces with a greater share of employment in household substitution services. This could be attributed to a combination of factors. One possible explanation is that, with the rise in employment shares among high-skilled women, there is an increased demand for these services, creating more job opportunities in this sector. Additionally, gender norms, defined as the prevailing standards that dictate the anticipated patterns of gender dynamics and the socioeconomic integration of women, may play a role influencing women to be more likely to work in these types of jobs (Pfau-Effinger, 1993).

The occupation classification used in the RFL changed from CP-2001 to CP-2011 starting from the 2011 wave. To exclude the eventuality that the results are driven by the change in the occupation classification, we repeat all the estimations only for the sub-period 2011–2019 (the ICP also uses the CP-2011). The results are reported in Appendix Tables A9 - A12 and are consistent with the ones for the full observation window.

The literature has pointed out that estimates involving technological change may face endogeneity issues. For instance, our routine-task indexes could be correlated with some cyclical unobservable factor that simultaneously influences changes in involuntary part-time (IPT). To address this concern, we adapt the strategy proposed by Autor et al. (2013) to our setup. For each indicator, we compute an instrument *á-la-Bartik* by interacting local sectoral employment shares in 1991 (14 years before the start of the empirical analysis period) with the national index of routine employment share for every sector. To further mitigate endogeneity, we trim the information corresponding to the actual province of interest from the national evolution of the index. The instrument is defined as:

$$\widetilde{Index} = \sum_{s=1}^{S} \frac{L_{s,p,1991}}{L_{p,1991}} \cdot Index_{s,-r,t} \tag{6}$$

where $L_{s,p,1991}$ is the number of workers of sector s in province p in 1991, $L_{p,1991}$ is the total number of workers of province p in 1991, and $Index_{s,-r,}$

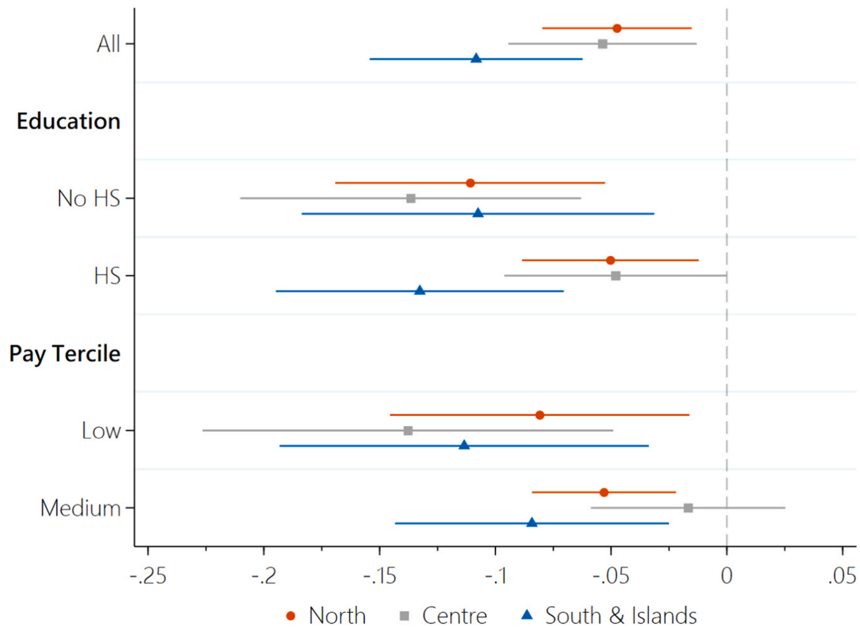

Fig. 7. Analysis by Macroregion (RTI).
Source: authors' own calculations. Notes: each estimate comes from a separate regression including the full battery of controls described in Section 5 (Eq. 5) except for the NUTS1. The dependent variable is the share of involuntary part-time workers IPT by province (2004–2019). We compute the share of IPT: (1) among all employees; (2) among employees without a high- school degree; (3) among employees with a high-school degree; (4) among those in low-paid occupations (bottom tercile); (5) among those in middle paid occupations (middle tercile). We specify errors terms to follow a panel-specific AR(1) autocorrelation structure and assume panel-level heteroskedasticity. Bars represent the 95 % Cis. There are 46 provinces in the North, 21 in the Centre and 36 in the South. The exact estimates are reported in Appendix Table A13.

Table 4
Partial adjustment model - By gender.

	All		No high-school		High-school	
	Men	Women	Men	Women	Men	Women
RTI	−0.052***	−0.075***	−0.056***	−0.109***	−0.084***	−0.082***
	(0.009)	(0.018)	(0.010)	(0.022)	(0.014)	(0.024)
	0.19	0.23	0.18	0.24	0.28	0.27
RTI (augm.)	−0.054***	−0.074***	−0.059***	−0.105***	−0.088***	−0.073***
	(0.009)	(0.018)	(0.010)	(0.022)	(0.014)	(0.025)
	0.19	0.23	0.18	0.24	0.28	0.27
RTCI	−0.056***	−0.078***	−0.060***	−0.112***	−0.076***	−0.091***
	(0.009)	(0.019)	(0.010)	(0.022)	(0.014)	(0.026)
	0.19	0.23	0.18	0.24	0.28	0.27
RTMI	−0.047***	−0.072***	−0.052***	−0.099***	−0.078***	−0.081***
	(0.009)	(0.018)	(0.010)	(0.021)	(0.014)	(0.025)
	0.18	0.23	0.18	0.24	0.27	0.27
% Middle tercile in tot. empl.	−0.028***	−0.007	−0.027**	−0.023	−0.039**	0.002
	(0.010)	(0.020)	(0.011)	(0.024)	(0.016)	(0.028)
	0.17	0.22	0.16	0.23	0.26	0.27
% Empl. manuf.	−0.027***	−0.062***	−0.030***	−0.085***	−0.042***	−0.036**
	(0.005)	(0.012)	(0.006)	(0.014)	(0.008)	(0.016)
	0.18	0.23	0.17	0.24	0.27	0.27
% Empl. Household subs.	0.093***	0.239***	0.095***	0.313***	0.140***	0.217***
	(0.023)	(0.047)	(0.026)	(0.054)	(0.035)	(0.057)
	0.18	0.23	0.17	0.25	0.27	0.28
% Empl. Restaurants	0.119***	0.297***	0.124***	0.305***	0.239***	0.335***
	(0.039)	(0.083)	(0.044)	(0.097)	(0.061)	(0.106)
	0.17	0.22	0.17	0.23	0.27	0.27
% Empl. Bars	0.075	0.421***	0.069	0.479***	0.160	0.228
	(0.066)	(0.133)	(0.073)	(0.154)	(0.101)	(0.168)
	0.17	0.22	0.16	0.23	0.26	0.27
% Empl. Domestic personnel	0.112***	0.185***	0.115***	0.339***	0.116**	0.203**
	(0.036)	(0.070)	(0.041)	(0.081)	(0.056)	(0.087)
	0.17	0.22	0.17	0.24	0.26	0.27

Source: authors' own calculations. Notes: each estimate comes from a separate regression including the full battery of controls described in Section 5 (Eq. 5). The dependent variable is the share of involuntary part-time workers by province: (1) for all women (men); (1) for women (men) without a high-school degree; (3) for women (men) with a high-school degree. Standard errors are reported between parentheses, while the last line of each block reports the R2. We specify errors terms to follow a panel-specific AR(1) autocorrelation structure and assume panel-level heteroskedasticity. Significance levels: * ρ<0.10, ** ρ<0.05, *** ρ<0.01. N=1545 (103 provinces and 15 years).

Table 5
OLS and 2SLS fixed-effects panel data models.

		Education		Pay tercile	
	All	No HS	HS	Low	Middle
OLS					
RTI	−0.083***	−0.126***	−0.087***	−0.133***	−0.067***
	(0.019)	(0.028)	(0.023)	(0.035)	(0.018)
R^2	0.26	0.27	0.33	0.28	0.31
RTI (augm.)	−0.083***	−0.126***	−0.086***	−0.131***	−0.066***
	(0.019)	(0.029)	(0.024)	(0.036)	(0.019)
R^2	0.26	0.27	0.33	0.28	0.31
RTCI	−0.093***	−0.130***	−0.101***	−0.149***	−0.078***
	(0.016)	(0.024)	(0.022)	(0.033)	(0.018)
R^2	0.27	0.27	0.33	0.28	0.32
RTMI	−0.059***	−0.075***	−0.066***	−0.098***	−0.041**
	(0.018)	(0.027)	(0.022)	(0.034)	(0.019)
R^2	0.25	0.26	0.33	0.28	0.31
2SLS					
RTI	−0.162***	−0.203***	−0.208***	−0.298***	−0.122***
	(0.028)	(0.047)	(0.036)	(0.054)	(0.031)
F-Stat.	444.73	464.11	441.29	451.58	458.70
R^2	0.19	0.21	0.26	0.21	0.26
RTI (augm.)	−0.168***	−0.212***	−0.215***	−0.310***	−0.125***
	(0.029)	(0.048)	(0.037)	(0.056)	(0.032)
F-Stat.	433.48	451.05	429.65	439.17	443.00
R^2	0.19	0.21	0.26	0.21	0.26
RTCI	−0.182***	−0.224***	−0.231***	−0.326***	−0.139***
	(0.030)	(0.049)	(0.038)	(0.057)	(0.033)
F-Stat.	478.34	500.75	470.07	484.56	492.63
R^2	0.19	0.21	0.26	0.21	0.26
RTMI	−0.184***	−0.245***	−0.230***	−0.354***	−0.128***
	(0.030)	(0.051)	(0.039)	(0.059)	(0.033)
F-Stat.	416.85	430.57	401.46	416.71	411.28
R^2	0.16	0.19	0.24	0.18	0.24

Source: authors' own calculations. Notes: each estimate comes from a separate regression including the full battery of controls described in Section 5 (Eq. 5), excluding the time-invariant NUTS1 FE. Robust standard errors are reported between parentheses. The dependent variable is the share of involuntary part-time workers IPT by province (2004–2019). We compute the share of IPT: (1) among all employees; (2) among employees without a high-school degree; (3) among employees with a high-school degree; (4) among those in low-paid occupations (bottom tercile); (5) among those in middle paid occupations (middle tercile). Regarding the risk of weak identification, Kleibergen-Paap rk Wald F statistic is reported at the bottom of each estimation block. Significance levels: * ρ<0.10, ** ρ<0.05, *** ρ<0.01. N=1545 (103 provinces and 15 years).

$_t$ is the value of the index in the two-digit sector s at time t, measured using all Italian provinces excluding province p and the other provinces belonging to p's NUTS2 region r. The model is estimated by a 2SLS fixed-effects panel data model with robust standard errors. The model includes all controls present in Eq. 6, excluding the time-invariant NUTS1 indicators. Table 5 reports the results of the IV fixed-effects panel data model. Overall, the results confirm the main trends emerging in Table 2.

6. Conclusion

This article analyses the increase in Involuntary Part-Time (IPT) in Italy from 2004 to 2019 and describes which socio-economic groups experienced the most significant growth in IPT while estimating the impact of local labour market characteristics. The results reveal that the process of dualisation tends to target groups that were already marginalized, with women, young, and less skilled workers experiencing a widening negative gap. The higher propensity towards IPT associated with these groups diminishes after controlling for sector and occupation, though the estimates remain positive and significant, indicating some form of persistent “discrimination”. Furthermore, segregation into more exposed occupations and sectors increases over time. Interestingly, the North-South gap decreased over time, primarily due to the rise in the percentage of involuntary part-time employment in the North. The role of sorting between regions appears to be less significant than at the individual level.

The work examines the hypothesis that, with technology replacing middle-skill routine jobs, medium- educated workers shift towards low-skill positions, diminishing their bargaining power and expanding the labour supply in this segment. Additionally, the article explores another mechanism contributing to the rise in Involuntary Part-Time, especially among women. As high-skilled women increase their employment shares, job opportunities emerge in sectors substituting for household activities, such as restaurants, bars, and domestic services. These new jobs are generally lower-skilled and require increased flexibility, leading to an overall shift in employment towards part-time positions in these sectors. The article uses specific statistical sources for the Italian context to create province-level indicators of routine-task specialization based on the occupational mix in each province. This approach allows to capture the unique characteristics of Italian jobs, contrasting with studies matching O*NET task-content information to European labour market data.

The findings support the hypothesis that provinces experiencing a decline in employment in routine-intensive occupations also witness an increase in involuntary part-time work. This pattern holds true across various measures, including the RTI index, the share of employment in middle-wage occupations, and the employment share in manufacturing. The results by gender report that women are significantly more affected by another factor - namely, the rise in employment share in household substitution services, encompassing bars, restaurants, and all activities involving domestic personnel (e.g., caretakers, cleaning personnel, cooks, and babysitters). This suggests that, beyond RBTC, various other factors such as sector segregation, a surge in demand for household-substitution services, and gender norms may also contribute to explaining higher IPT levels among women. The expansion of the services sector as a whole, and the growth of female participation are also behind the increase in the share of female with non-secured jobs, what contrasts with the limited impact on males,

The results of the research provide important insights for policy makers. The debate on the introduction of a minimum wage in Italy is currently underway. The introduction of a legal minimum wage will undoubtedly have the effect of improving conditions for workers in low paid sectors in Italy, but the minimum wage alone is not sufficient to improve working conditions for the most disadvantaged. This is because firms could respond to the introduction of a legal minimum wage by further reducing the number of hours (formally) worked. It is therefore necessary to think not only about the quantity but also about the quality of work. An integrated industrial and labour policy is needed, with a single strategy to reverse the dualism of the Italian labour market.

Finally, the adoption of a spatial perspective is crucial when examining the labour market. It is implausible to assume that workers displaced from routinised sectors will solely transition to household substitution services. However, there is a redistribution of workers across sectors at the local labour market level, likely influenced by factors such as the bargaining power of workers or societal stereotypes of certain activities, some of which are considered “more acceptable” for women. The result is a further deepening of dualisation in the labour market, with particular intensity for groups that were previously marginalised.

Further research, more focused on a micro scale, would allow to investigate the mechanisms behind the association between routinisation and changes in the demand of household substitution services and the increase in non-voluntary part-time workers.

CRediT authorship contribution statement

Liliana Cuccu: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Sergio Scicchitano:** Conceptualization, Data curation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Vicente Royuela:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests. Liliana Cuccu reports financial support was provided by Spain Ministry of Science and Innovation. Vicente Royuela reports financial support was provided by Spain Ministry of Science and Innovation. The views and opinions expressed in this article are those of the authors and do not necessarily reflect those of INAPP. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.pirs.2024.100061.

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