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"Navigating the Precarious Path: Understanding the Dualisation of the Italian Labour Market through the Lens of Involuntary Part-Time Employment"

Liliana Cuccu, Vicente Royuela and Sergio Scicchitano

UBIREA
Research Institute of Applied Economics

AQR
Regional Quantitative Analysis Research Group

Institut de Recerca en Economia Aplicada Regional i Pública
UNIVERSITAT DE BARCELONA
WEBSITE: www.ub-irea.com • CONTACT: irea@ub.edu

AQR
Grup de Recerca Anàlisi Quantitativa Regional
Regional Quantitative Analysis Research Group
WEBSITE: www.ub.edu/aqr/ • CONTACT: aqr@ub.edu

Universitat de Barcelona
Av. Diagonal, 690 • 08034 Barcelona

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Abstract

This paper 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. Our study tests the hypothesis that technological shifts, specifically routine biased technological change (RBTC), and the expansion of household substitution services contribute to IPT growth. We uncover 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, we find support for RBTC's correlation with IPT, especially among women. The impact of household substitution services is notably pronounced for women, highlighting sector segregation and gender norms' influence.

JEL Classification: J21, J24, O33.

Keywords: Involuntary part-time, Precarisation of labour, Automation.

Liliana Cuccu: University of Barcelona. Email: liliana.cuccu@ub.edu

Vicente Royuela: University of Barcelona.

Sergio Scicchitano: John Cabot University, INAPP National Institute for Public Policy Analysis and Global Labor Organization (GLO).

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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 et al., 2010; Nicolaisen et al., 2019; O'Reilly et al., 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 et al., 2021; Bonacini et al., 2021a; Daniele et al., 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 et al., 2004; Fernández-Kranz et al., 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 et al., 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 et al., 2010; O'Reilly et al., 2002). Moreover, part-time employment in many European countries can curtail 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 research has overlooked the spatial dimension, particularly the significant regional disparities within countries. Our paper 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 et al. (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 et al. (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 our paper is to scrutinise these two sources driving the escalation of IPT.

Employing data from the Italian Labour Force Survey (LFS), our study delves into the escalation of Involuntary Part-Time in Italy from 2004 to 2019. Italy serves as an apt case study for investigating IPT dynamics. Over the examined period, the proportion of Italian employees holding part-time contracts surged from 14% to 21%. 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 surge in IPT was not uniformly distributed across socio-demographic groups and macro-regions, as detailed in Section 4. Our 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.

We test the hypothesis 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, we combine the INAPP-ISTAT Survey on Italian Occupations (ICP) with the Italian segment of the EU Labour Force Survey. This combination facilitates the construction of province-level indicators delineating routine-task specialization based on the occupational composition in each province.[1] 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, we aim to unravel the factors behind the unequal growth of IPT among genders. We attempt 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, we study 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, our 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

[1] 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.

in IPT among women relative to men, our 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 paper 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 our empirical approach and discusses the results of our 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 et al., 2019; Green et al., 2017; Green et al., 2015; Livanos et al., 2018; Livanos et al., 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 et al., 2015), and Western Greece, Attica, Central Macedonia, and the Ionian Islands in Greece (Livanos et al., 2022). Green et al. (2017) adopts 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 scrutinised 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) examined changes in transition probabilities to and from involuntary part-time positions in the aftermath of the Great Recession in the US. They observed 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 et al. (2020) echoed similar findings, revealing low turnover between involuntary part-time and unemployment. They argued 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 presented 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) investigated female vulnerability to involuntary part-time following the Great Recession in Spain. The study concluded 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. Similar findings were reported by Busilacchi et al. (2022) for Italy. This study, more focused on the dualisation process, examined 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 focused on clarifying structural changes in involuntary part-time shares over time. Valletta et al. (2020) analysed variations in involuntary part-time shares using US state-level panel data for the period 2003–2016. They found 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 et al. (2019) delved into the extent to which automation and offshorability risks intersect with non-standard employment, focusing on Spain. Their findings revealed 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 et al. (2022) analysed the connection between lower middle-skill employment, deemed a consequence of Routine-Biased Technological Change (RBTC), and involuntary part-time employment across 16 European countries from 1999 to 2010. They identified 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. Nonetheless, the authors demonstrated 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

We use 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 et al. (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

We gather information on involuntary non-standard employment and socio-demographic characteristics at the worker level 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 1,400 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.

Our 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. To define a worker as employed in involuntary part-time, we identify 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". This choice is among various options, including "Does not want a full-time job", "Other reasons", and "Does not know". We apply two sample restrictions: (1) we include only individuals aged 16-64; (2) we focus solely on employees. Regarding the second restriction, the RFL categorizes employed individuals into three groups: (1) employees, (2) self-employed, and (3) independent contractors ("*collaboratori*"). We exclude self-employed individuals 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 constituted 71.5% of total workers in 2004 and 76.3% in 2019.[2] In addition to the share of involuntary part-time, we use the RFL 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.[3]

3.2 Employment share in routine tasks

We obtain information on the task composition and general characteristics of occupations 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

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

[3]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.

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.

We follow Vannutelli et al. (2022), Esposito et al. (2022), and Cirillo et al. (2021) for constructing various occupation-level indexes derived from the ICP. The main index is the "classic" routine-task index (RTI), closely aligned with the one proposed by Acemoglu et al. (2011). The index is defined as:

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

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.

We also include an "augmented" version of the RTI, aligning more with Autor et al. (2003), by introducing a "Non-routine manual: interpersonal adaptability" (NRMIA) component. Additionally, we examine two specific routine task indexes: 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.

Adopting the methodology proposed by Autor et al. (2013) to define the share of routine employment in local labour markets, we determine 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:

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

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; $1\left[\cdot\right]$ is an indicator equal to one if the occupation's index value is above $Index^{66}$.

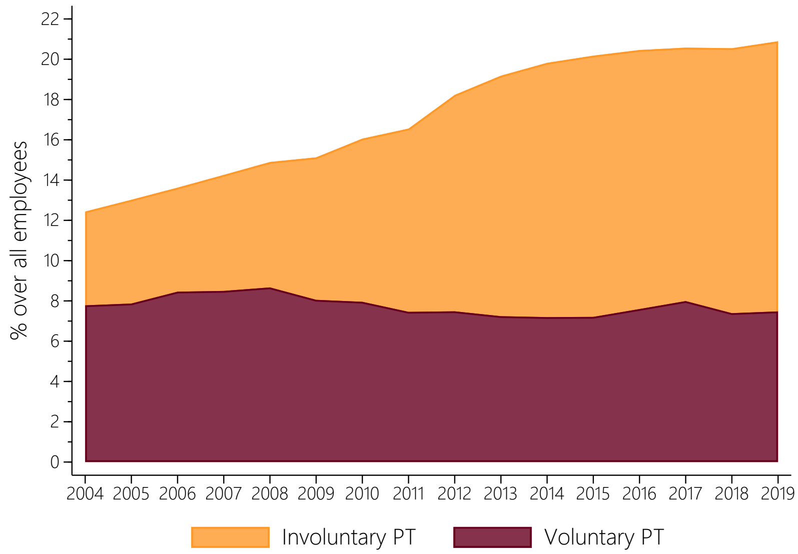
To offer a broad understanding of the sectors captured by each index, Appendix Table A3 outlines the top and bottom five sectors based on the employment share in each index (computed using the same approach described in Equation 2 but using sectors instead of provinces). For comparability with Van Van Doorn et al. (2022), we also calculated the province-level share of employment in middle-wage occupations.[4] 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, we consider the province-level share of employment in manufacturing.

4 The growth of IPT in Italy: Stylized facts

Figure 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. Figure 2 illustrates the temporal evolution of IPT

[4]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.

Figure 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).

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.

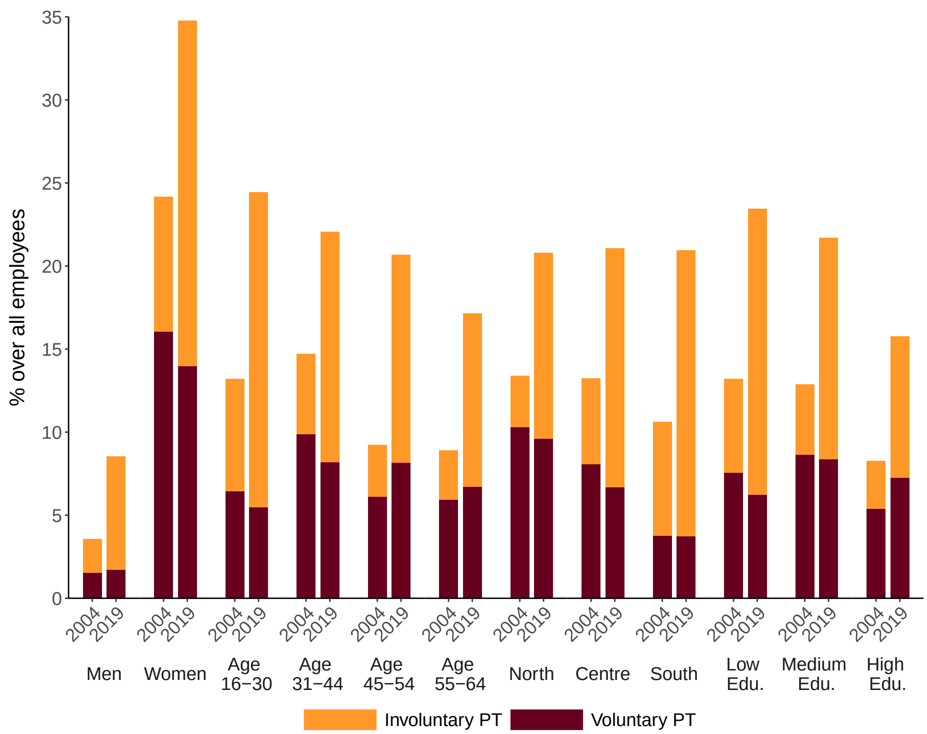
Figure 3 illustrates the change in the share of involuntary part-time (IPT) within one-digit sectors (panel a) and between one-digit sectors (panel b) from 2004 to 2019. The incidence of IPT increased across all sectors during this period, with the most substantial rise observed in the "I. Hotel and 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%.

Table 1: Indicators

Indicator	Description	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"	Acemoglu et al. (2011) and Carbonero et al. (2021)
RTI (augm.)	"Augmented" routine task index. Computed as $(RC + RM) - NRM - (NRCA + NRCI + NRMIA)$. Where: NRMIA - Non-routine manual - interpersonal adaptability (measures "Social Perceptiveness")	Acemoglu et al. (2011) and Carbonero et al. (2021)
RTCI	Routine task index - cognitive. Computed as: $RC - NRCA - NRCI$	Acemoglu et al. (2011) and Carbonero et al. (2021)
RTMI	Routine task index - manual. Computed as: $RM - NRM - NRMIA$	Acemoglu et al. (2011) and Carbonero et al. (2021)
% Middle tercile in tot. empl.	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. manuf.	Share of employment in manufacturing.	

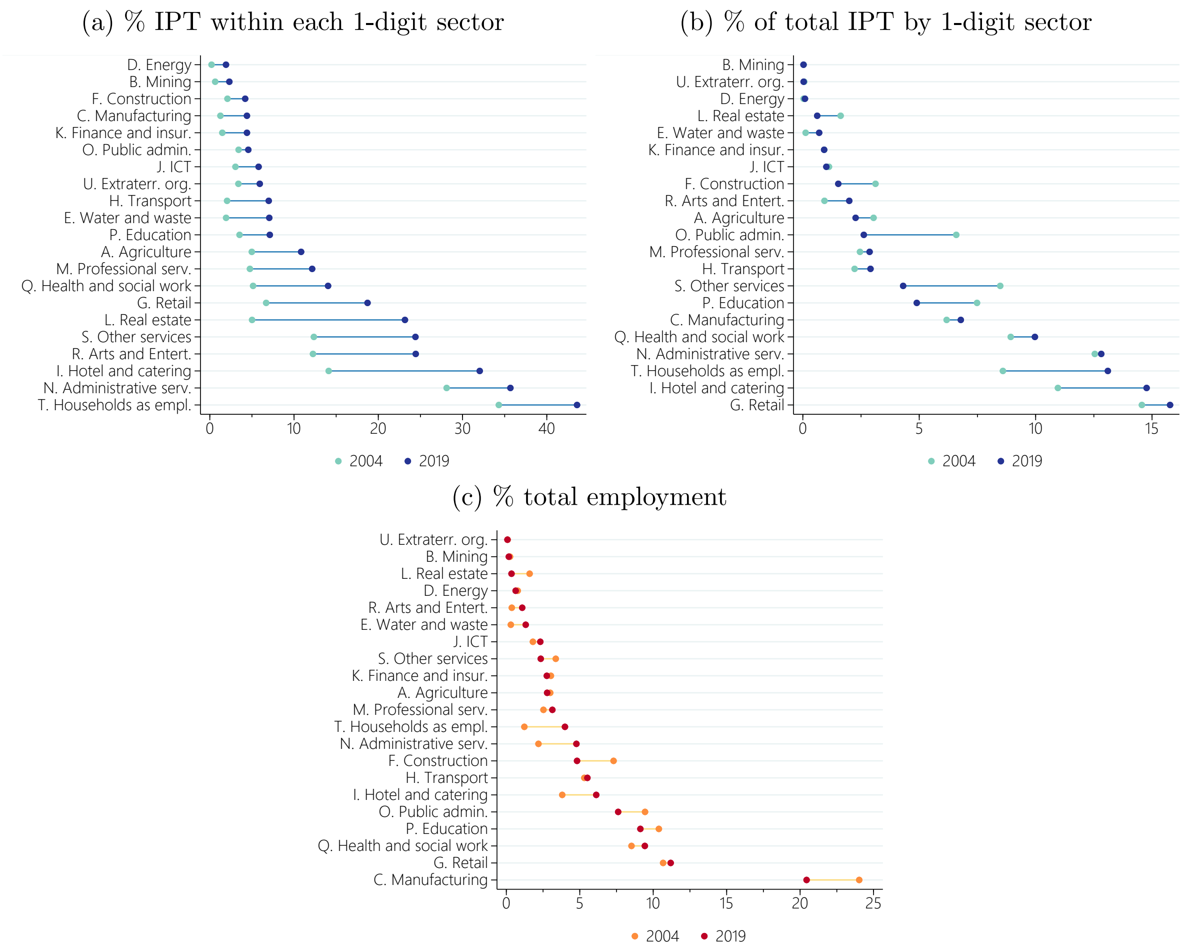
Notes: all measures are based on INAPP-ISTAT Survey on Italian Occupations (ICP).

Figure 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.

Figure 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.

Figure 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.[5] For each of the two time-periods, i.e. 2004 and 2019, we estimate three linear probability models (the unit of observation are workers i):

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

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

$$IPT_i = \alpha + SocioDem_i + Sector_i + Occupation_i + \epsilon_i \tag{5}$$

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.

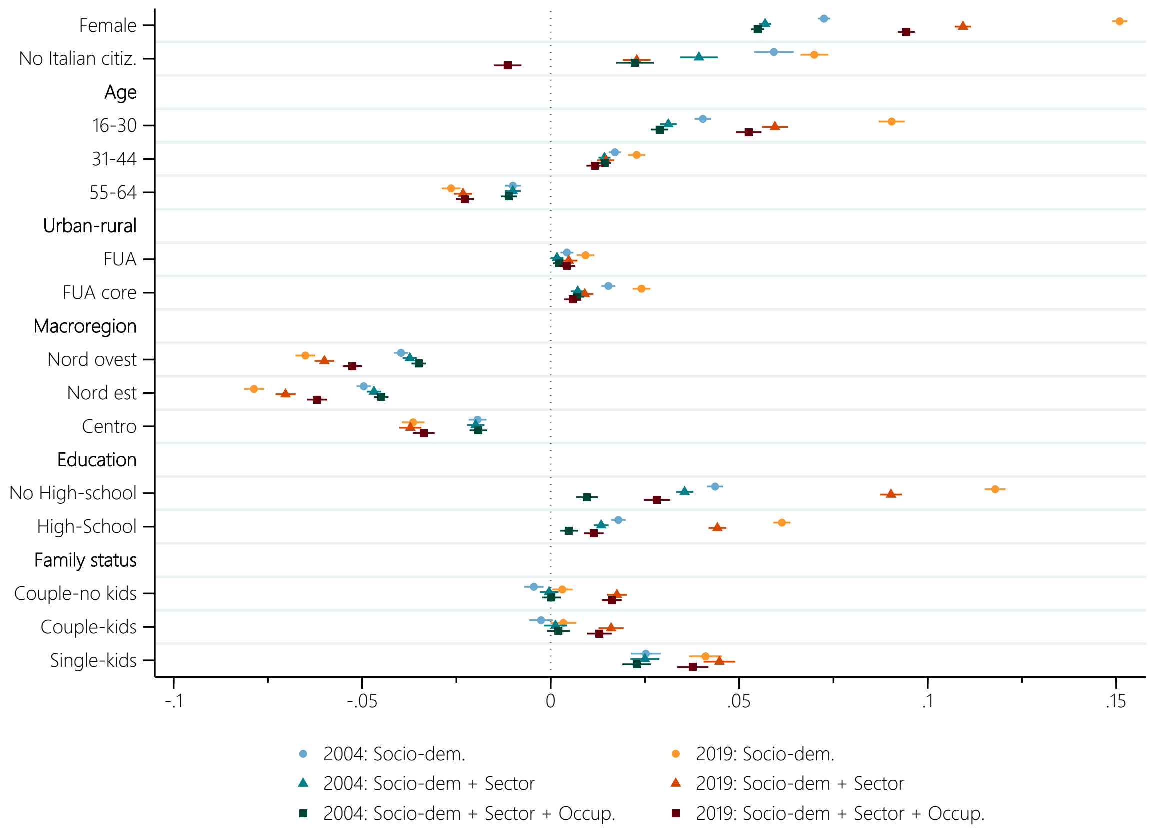
In general, the higher propensity towards IPT associated with certain groups (e.g., women and young workers) decreases after controlling for sector and occupation. This implies that higher shares of IPT for these groups are explained, at least in part, by sorting into particular sectors and occupations. 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.[6]

[5] 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.

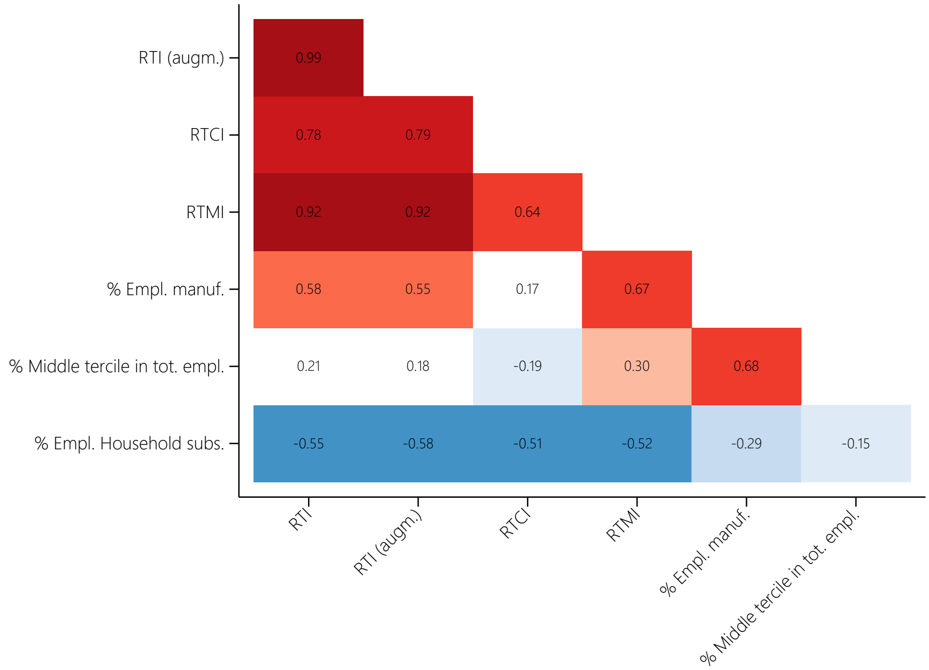
[6] Appendix Figure A1 plots this measure with the relative confidence intervals.

Figure 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). Exact estimates are reported in Appendix Table A6. Robust standard errors.

Figure 5: Correlation of province-level indexes $Index_{pt}$

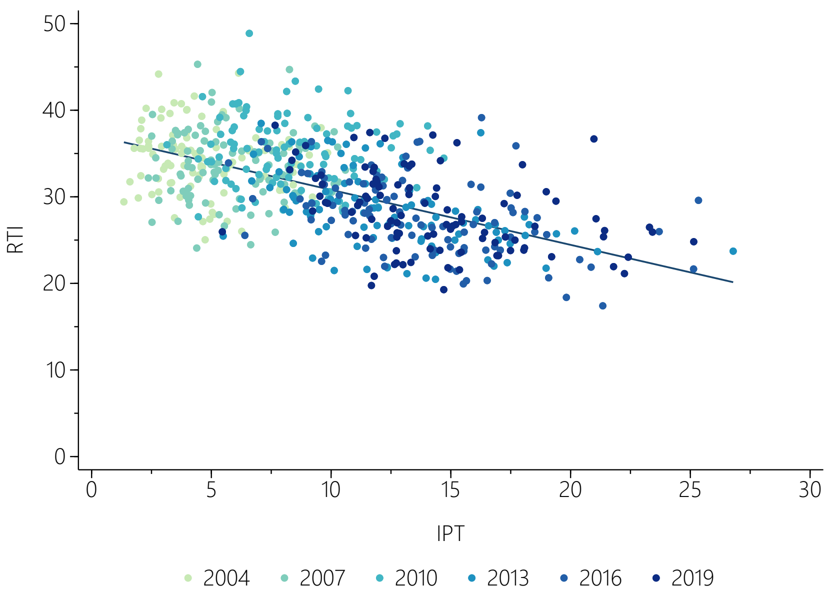


Source: Authors' own calculations.

Figure 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, Figure 6 illustrates the negative relationship between RTI and IPT, which is evident both within cross-sections and over time.[7]

[7]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.

Figure 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).

5 Analysis

We follow the empirical approach of Van Doorn et al. (2022) and estimate the following partial adjustment model

$$\Delta IPT_{p,t} = \alpha + \beta_0 \cdot IPT_{p,t-1} + \beta_1 \cdot Index_{p,t-1} + \beta_2 \cdot X_{p,t-1} + \tau \cdot Time + NUTS1_p + \epsilon_{p,t} \quad (6)$$

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 A2 reports the correlation among these controls, while Appendix Table A8 reports basic descriptive statistics on all variables used in the regressions. Finally, $Time$ is a linear time trend (as in Van Doorn et al., 2022), $NUTS1_p$ is a set of five macro-region (NUTS1) fixed effects, and $\epsilon_{p,t}$ is an error term.[8] We specify errors terms to follow a panel-specific AR(1) autocorrelation structure and assume panel-level heteroskedasticity. We estimate the model for 103 provinces and 15 years (2004 is excluded because we cannot compute the first differences nor the lags, as we lack data for 2003).

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 $\frac{\hat{\beta_1}}{-\hat{\beta_0}}$, which captures the permanent effect of our index on IPT in the long run. The results of both 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

[8] 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.

share in manufacturing. 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 artificial intelligence (AI) technologies. 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 AI technologies during the observed time window was modest.[9]

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, our results differ from those of Van Doorn et al. (2022), as they predict an increase in IPT predominantly in low-paid jobs - a pattern that only emerges in our results when we use the employment share in manufacturing as a measure of routine biased technological change (RBTC).

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, we introduced an additional set of indicators capturing the share of employment in household substitution services. These services encompass all activities provided by households for their own consumption, such as cooking meals, cleaning, childcare, or elderly care. Specifically, we use 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, we include the employment share of each of these three sectors separately to determine 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 may play a role, influencing women to be more likely to work in these types of jobs.

[9]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).

Table 2: Partial adjustment model

	All	Education		Pay tercile	
		No HS	HS	Low	Middle
RTI	-0.058***	-0.099***	-0.080***	-0.080***	-0.046***
	(0.010)	(0.019)	(0.013)	(0.020)	(0.012)
	0.21	0.19	0.27	0.20	0.20
RTI (augm.)	-0.058***	-0.100***	-0.079***	-0.078***	-0.046***
	(0.010)	(0.019)	(0.014)	(0.020)	(0.012)
	0.21	0.19	0.27	0.20	0.20
RTCI	-0.067***	-0.113***	-0.084***	-0.096***	-0.051***
	(0.011)	(0.019)	(0.014)	(0.021)	(0.012)
	0.21	0.20	0.27	0.20	0.20
RTMI	-0.054***	-0.083***	-0.074***	-0.076***	-0.043***
	(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*	-0.040**	-0.034**	-0.012	-0.028**
	(0.012)	(0.020)	(0.016)	(0.023)	(0.013)
	0.19	0.18	0.25	0.19	0.19
% Empl. manuf.	-0.036***	-0.071***	-0.043***	-0.066***	-0.018***
	(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 (Equation 6). 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 R^2. We specify errors terms to follow a panel-specific AR(1) autocorrelation structure and assume panel-level heteroskedasticity. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$. N=1,545 (103 provinces and 15 years).

Table 3: Partial adjustment model - Long run multiplier

		Education		Pay tercile	
	All	No HS	HS	Low	Middle
RTI	-0.172***	-0.277***	-0.159***	-0.246***	-0.113***
	(0.030)	(0.052)	(0.026)	(0.061)	(0.028)
RTI (augm.)	-0.173***	-0.281***	-0.157***	-0.242***	-0.113***
	(0.031)	(0.053)	(0.026)	(0.062)	(0.028)
RTCI	-0.196***	-0.314***	-0.168***	-0.295***	-0.123***
	(0.032)	(0.053)	(0.027)	(0.064)	(0.029)
RTMI	-0.163***	-0.237***	-0.150***	-0.237***	-0.107***
	(0.032)	(0.054)	(0.026)	(0.061)	(0.028)
% Middle tercile in tot. empl.	-0.073*	-0.120**	-0.072**	-0.039	-0.072**
	(0.038)	(0.060)	(0.033)	(0.074)	(0.033)
% Empl. manuf.	-0.106***	-0.192***	-0.089***	-0.196***	-0.046***
	(0.019)	(0.030)	(0.017)	(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 (Equation 6). 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: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$. N=1,545 (103 provinces and 15 years).

The occupation classification used in the RFL changed from CP-2001 to CP-2011 starting from the 2011 wave. To exclude the eventuality that our results are driven by the change in the occupation classification, we repeat all our 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 our 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:

$$\widetilde{Index} = \sum_{s=1}^{s} \frac{L_{s,p,1991}}{L_{p,1991}} \cdot Index_{s,-r,t} \tag{7}$$

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 $Index_{s,-r,t}$ 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. We estimate a 2SLS fixed-effects panel data model with robust standard errors. The model includes all controls present in Equation 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.

Table 4: Partial adjustment model - By gender

	All		No high-school		High-school	
	Men	Women	Men	Women	Men	Women
RTI	-0.052***	-0.070***	-0.057***	-0.102***	-0.085***	-0.078***
	(0.009)	(0.018)	(0.010)	(0.021)	(0.014)	(0.024)
	0.19	0.23	0.18	0.24	0.28	0.27
RTI (augm.)	-0.054***	-0.069***	-0.059***	-0.098***	-0.088***	-0.070***
	(0.009)	(0.018)	(0.010)	(0.022)	(0.014)	(0.024)
	0.19	0.22	0.18	0.24	0.28	0.27
RTCI	-0.057***	-0.073***	-0.061***	-0.104***	-0.077***	-0.085***
	(0.009)	(0.019)	(0.010)	(0.022)	(0.014)	(0.025)
	0.19	0.22	0.18	0.24	0.28	0.27
RTMI	-0.047***	-0.067***	-0.052***	-0.093***	-0.078***	-0.076***
	(0.009)	(0.018)	(0.010)	(0.021)	(0.014)	(0.024)
	0.18	0.22	0.18	0.24	0.28	0.27
% Middle tercile in tot. empl.	-0.028***	-0.007	-0.027**	-0.025	-0.039**	-0.001
	(0.010)	(0.020)	(0.011)	(0.024)	(0.016)	(0.027)
	0.17	0.22	0.17	0.23	0.26	0.27
% Empl. manuf.	-0.027***	-0.058***	-0.030***	-0.080***	-0.042***	-0.034**
	(0.005)	(0.011)	(0.006)	(0.014)	(0.008)	(0.015)
	0.18	0.23	0.17	0.24	0.27	0.27
% Empl. Household subs.	0.096***	0.227***	0.099***	0.297***	0.143***	0.201***
	(0.023)	(0.046)	(0.026)	(0.053)	(0.035)	(0.056)
	0.18	0.23	0.17	0.24	0.27	0.28
% Empl. Restaurants	0.118***	0.277***	0.122***	0.279***	0.238***	0.300***
	(0.039)	(0.081)	(0.044)	(0.096)	(0.061)	(0.103)
	0.17	0.22	0.17	0.23	0.27	0.27
% Empl. Bars	0.081	0.418***	0.072	0.483***	0.169*	0.209
	(0.066)	(0.130)	(0.073)	(0.150)	(0.101)	(0.165)
	0.17	0.22	0.16	0.23	0.26	0.27
% Empl. Domestic personnel	0.116***	0.174**	0.121***	0.320***	0.122**	0.194**
	(0.036)	(0.068)	(0.040)	(0.079)	(0.056)	(0.085)
	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 (Equation 6). 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 R^2. We specify errors terms to follow a panel-specific AR(1) autocorrelation structure and assume panel-level heteroskedasticity. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$. N=1,545 (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	-0.082***	-0.123***	-0.087***	-0.127***	-0.067***
	(0.019)	(0.028)	(0.023)	(0.034)	(0.017)
R^2	0.26	0.27	0.33	0.28	0.31
RTI (augm.)	-0.081***	-0.122***	-0.085***	-0.125***	-0.065***
	(0.019)	(0.028)	(0.024)	(0.035)	(0.018)
R^2	0.26	0.27	0.33	0.28	0.31
RTCI	-0.091***	-0.128***	-0.099***	-0.143***	-0.077***
	(0.016)	(0.024)	(0.022)	(0.033)	(0.018)
R^2	0.27	0.27	0.34	0.28	0.32
RTMI	-0.058***	-0.073***	-0.065***	-0.094***	-0.041**
	(0.018)	(0.027)	(0.022)	(0.034)	(0.019)
R^2	0.25	0.26	0.33	0.27	0.31
			2SLS		
RTI	-0.158***	-0.198***	-0.206***	-0.287***	-0.121***
	(0.028)	(0.047)	(0.036)	(0.053)	(0.031)
F-stat.	442.92	462.62	439.66	449.45	457.88
R^2	0.19	0.21	0.26	0.21	0.26
RTI (augm.)	-0.164***	-0.206***	-0.213***	-0.298***	-0.124***
	(0.029)	(0.048)	(0.037)	(0.055)	(0.032)
F-stat.	432.82	450.71	429.09	438.19	443.31
R^2	0.19	0.21	0.26	0.21	0.26
RTCI	-0.178***	-0.219***	-0.229***	-0.314***	-0.138***
	(0.030)	(0.049)	(0.037)	(0.057)	(0.032)
F-stat.	475.82	498.53	467.44	481.50	491.12
R^2	0.19	0.21	0.26	0.21	0.26
RTMI	-0.180***	-0.239***	-0.229***	-0.341***	-0.127***
	(0.030)	(0.051)	(0.039)	(0.058)	(0.033)
F-stat.	416.45	430.60	401.40	416.27	411.65
R^2	0.16	0.19	0.24	0.18	0.25

Source: authors' own calculations. *Notes:* each estimate comes from a separate regression including the full battery of controls described in Section 5 (Equation 6), 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: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$. N=1,545 (103 provinces and 15 years).

6 Conclusion

In this paper, we analysed the increase in Involuntary Part-Time (IPT) in Italy from 2004 to 2019. We described which socio-economic groups experienced the most significant growth in IPT while estimating the impact of local labour market characteristics. Our 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.

We examined 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, we explored 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. We used 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 allowed us to capture the unique characteristics of Italian jobs, contrasting with studies matching O*NET task-content information to European labour market data.

Our 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. When examining the results by gender, we observed 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 results of our research provide important insights for our 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 poor workers 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, we argue that adopting 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.

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Appendix: Additional Tables and Figures

Table A1: Number of workers by type of employment

Year	Tot. workers	Empl. (%)	Self-empl. (%)	Contract. (%)
2004	259,883	71.51	26.48	2.01
2005	256,183	72.66	25.50	1.84
2006	249,070	72.84	25.17	1.99
2007	244,805	73.20	24.88	1.92
2008	242,900	73.56	24.63	1.81
2009	232,488	73.91	24.50	1.59
2010	230,843	73.84	24.56	1.60
2011	225,378	74.20	24.13	1.67
2012	208,718	74.41	23.82	1.77
2013	206,409	74.43	23.99	1.57
2014	203,719	74.39	24.05	1.56
2015	203,019	74.65	23.87	1.49
2016	200,764	75.22	23.52	1.26
2017	201,866	75.91	23.02	1.06
2018	203,038	76.12	22.92	0.95
2019	201,964	76.26	22.85	0.89

Source: author's own calculations.

Table A2: Indexes by two-digit occupation

	RTI	RTI (augm.)	RTCI	RTMI
11. Members of executive legislative bodies	0.0	0.0	0.0	15.0
12. Entrepreneurs, directors and managers of large companies	15.8	22.4	14.4	39.8
13. Entrepreneurs and managers of small enterprises	32.6	36.2	32.8	39.3
21. Specialists in mathematical, computer, chemical, physical and natural sciences	38.0	49.4	35.5	63.5
22. Engineers, architects and associate professionals	23.5	35.8	26.4	48.9
23. Specialists in the life sciences	43.0	33.5	38.7	23.5
24. Health care specialists	39.8	25.6	42.3	0.0
25. Specialists in humanities, social sciences, arts and management	31.0	34.2	29.0	41.2
26. Education and research specialists	17.1	11.6	23.9	0.5
31. Technical professions in science, engineering and production	40.8	48.1	39.0	54.6
32. Technical professions in the health and life sciences	52.0	38.1	49.8	14.7
33. Technical professions in organisation, administration and financial and business activities	38.0	42.9	37.1	46.6
34.Technical professions in public and personal services	33.6	31.7	36.5	23.2
41. Secretarial and office machinery clerks	48.3	44.8	48.2	32.2
42. Cash handling and customer service clerks	78.8	68.4	71.7	44.3
43. Administrative, accounting and financial management clerks	55.2	59.1	53.5	54.3
44. Clerical staff for the collection, control, storage and delivery of documents	51.8	54.2	49.5	50.5
51. Skilled trades workers	69.3	73.0	72.2	53.6
52. Skilled occupations in accommodation and food service activities	63.1	64.7	63.5	50.0
53. Skilled occupations in health and social services	82.2	64.4	82.3	18.0
54. Skilled occupations in cultural, security and personal services	61.6	50.1	68.4	10.1
61. Craft and related trades workers in mining, construction and building maintenance	74.4	82.0	79.3	61.4
62. Craft and related trades workers and skilled metalworkers and electrical and electronic equipment installers and maintenance workers	68.7	74.3	68.4	62.9
63. Craft and related trade workers in precision mechanics, arts and crafts, printing and related trades	76.1	83.7	70.4	**79.9**
64. Agricultural, forestry, animal husbandry, fishing and hunting craftsmen and craft trade workers	52.0	62.2	57.7	54.3
65. Craft and related trades workers in the food processing, wood, textile and entertainment industries	76.7	79.6	68.7	**73.7**
71. Industrial plant operators	**88.0**	**86.7**	77.9	**73.8**
72. Semi-skilled assemblers of fixed series production machinery and assembly workers	**100.0**	**99.8**	**86.0**	**89.0**
73. Stationary machinery operators in agriculture and the food industry	**96.8**	**100.0**	79.7	**100.0**
74. Drivers of vehicles, mobile machinery and lifting equipment	75.3	81.4	**89.3**	43.3
81. Unskilled trades and service occupations	85.7	**85.0**	**89.6**	50.6
82. Unskilled occupations in domestic, recreational and cultural activities	**92.5**	78.8	**100.0**	19.7
83. Unskilled occupations in agriculture	68.7	74.1	75.4	50.5
84. Unskilled occupations in manufacturing, mining and construction	**87.7**	**92.7**	**94.5**	59.3

Source: author's own calculations. *Notes:* employment-weighted averages of five-digit indexes. Indexes are normalized to be on a 0-100 scale. For each index, values of the top five occupations are marked in bold, while values belonging to the bottom five are underlined.

Table A3: Indexes by one-digit sector

	RTI	RTI (augm.)	RTCI	RTMI
A. Agriculture	6.9		**60.1**	
B. Mining	**66.1**	**66.5**	**65.8**	
C. Manufacturing	**57.1**	**57.6**		**63.5**
D. Energy				
E. Water and waste				
F. Construction	**58.8**	**58.9**	**58.7**	**40.4**
G. Retail				**56.9**
H. Transport				
I. Hotel and catering				
J. ICT	5.1	5.1	3.0	
K. Finance and insur.	1.9	1.9	2.0	
L. Real estate		7.8	7.8	10.6
M. Professional serv.	4.7	4.5	4.0	8.6
N. Administrative serv.	**58.5**	**58.4**	**58.4**	**55.0**
O. Public admin.				
P. Education				1.2
Q. Health and social work				5.0
R. Arts and Entert.	4.8	5.1	4.8	
S. Other services				
T. Households as empl.	**77.3**	**76.8**	**91.4**	**76.2**
U. Extraterr. org.				14.0

Source: author's own calculations. *Notes:* values in bold belong to the the top five, while numbers not in bold refer to the bottom five.

Table A4: Occupations by wage

Occupation	Net hourly wage	Below median	Medium tercile	Bottom tercile
24. Health care specialists	15.76			
11. Members of executive legislative bodies	15.25			
12. Entrepreneurs, directors and managers of large companies	15.20			
26. Education and research specialists	14.45			
13. Entrepreneurs and managers of small enterprises	12.62			
22. Engineers, architects and associate professionals	11.36			
91. Armed forces officers	11.29			
23. Specialists in the life sciences	11.22			
25. Specialists in humanities, social sciences, arts and management	11.21			
21. Specialists in mathematical, computer, chemical, physical and natural sciences	10.70			
92. Sergeants, superintendents and marshals of the armed forces	10.62			
34.Technical professions in public and personal services	9.90			
93. Troops of the armed forces	9.42			
32. Technical professions in the health and life sciences	9.29		✓	
33. Technical professions in organisation, administration and financial and business activities	9.28		✓	
31. Technical professions in science, engineering and production	9.27		✓	
42. Cash handling and customer service clerks	8.36		✓	
44. Clerical staff for the collection, control, storage and delivery of documents	8.31		✓	
41. Secretarial and office machinery clerks	8.12		✓	
43. Administrative, accounting and financial management clerks	8.06	✓	✓	
74. Drivers of vehicles, mobile machinery and lifting equipment	7.88	✓	✓	
71. Industrial plant operators	7.70	✓	✓	
62. Craft and related trades workers and skilled metalworkers and electrical and electronic equipment installers and maintenance workers	7.53	✓	✓	
53. Skilled occupations in health and social services	7.50	✓	✓	
63. Craft and related trade workers in precision mechanics, arts and crafts, printing and related trades	7.33	✓	✓	
72. Semi-skilled assemblers of fixed series production machinery and assembly workers	7.14	✓		✓
54. Skilled occupations in cultural, security and personal services	7.10	✓		✓
73. Stationary machinery operators in agriculture and the food industry	7.09	✓		✓
61. Craft and related trades workers in mining, construction and building maintenance	7.09	✓		✓
51. Skilled trades workers	7.00	✓		✓
81. Unskilled trades and service occupations	6.79	✓		✓
65. Craft and related trades workers in the food processing, wood, textile and entertainment industries	6.74	✓		✓
52. Skilled occupations in accommodation and food service activities	6.71	✓		✓
84. Unskilled occupations in manufacturing, mining and construction	6.61	✓		✓
82. Unskilled occupations in domestic, recreational and cultural activities	6.45	✓		✓
64. Agricultural, forestry, animal husbandry, fishing and hunting craftsmen and craft trade workers	6.42	✓		✓
83. Unskilled occupations in agriculture	5.36	✓		✓

Source: author's own calculations. *Notes:* occupations ranked by their average hourly net wage in 2011.

Table A5: Employment shares by sector and IPT

			Within sector		Between sectors	
	%Empl. 04	Δ Empl.	%IPT 04	Δ IPT	%IPT 04	Δ IPT
C. Manufacturing	24.02	–3.58	1.26	3.15	6.18	0.61
G. Retail	10.67	0.52	6.69	12.03	14.56	1.21
P. Education	10.39	–1.26	3.53	3.59	7.48	–2.59
O. Public admin.	9.44	–1.83	3.42	1.15	6.59	–3.97
Q. Health and social work	8.52	0.91	5.14	8.90	8.93	1.04
F. Construction	7.30	–2.49	2.10	2.11	3.12	–1.60
H. Transport	5.31	0.21	2.05	4.94	2.22	0.68
I. Hotel and catering	3.81	2.31	14.11	17.93	10.96	3.81
S. Other services	3.37	–1.02	12.35	12.06	8.48	–4.17
K. Finance and insur.	3.03	–0.28	1.49	2.93	0.92	–0.00
A. Agriculture	2.99	–0.21	4.99	5.85	3.04	–0.77
M. Professional serv.	2.53	0.61	4.76	7.39	2.46	0.41
N. Administrative serv.	2.19	2.58	28.11	7.57	12.54	0.28
J. ICT	1.81	0.51	3.04	2.75	1.12	–0.11
L. Real estate	1.59	–1.23	5.02	18.14	1.62	–1.01
T. Households as empl.	1.23	2.76	34.31	9.28	8.59	4.51
D. Energy	0.78	–0.14	0.21	1.71	0.03	0.06
R. Arts and Entert.	0.37	0.71	12.25	12.20	0.93	1.06
E. Water and waste	0.31	1.01	1.93	5.13	0.12	0.58
B. Mining	0.25	–0.08	0.64	1.68	0.03	–0.00
U. Extraterr. org.	0.09	–0.01	3.40	2.54	0.06	–0.03
	100				100	

Source: author's own calculations. *Notes:* "%Empl. 04" is each sector's employment share in 2004; "Δ Empl." is the growth in each sector's employment share between 2004 and 2019 (in percentage points); "%IPT 04 (Within)" is the IPT share within each sector in 2004; "Δ IPT (Within)" is the variation in IPT share within each sector between 2004 and 2019; "%IPT 04 (Between)" is each sector's share of total IPT in 2004; "Δ IPT (Between)" is the variation in each sector's share of total IPT between 2004 and 2019. Sample restricted to: (1) individuals aged 16-64; (2) employees (exclude self-employed and independent contractors).

Table A6: Determinants of Involuntary Part-time

	Model 1		Model 2		Model 3	
	2004	2019	2004	2019	2004	2019
Woman	0.073***	0.151***	0.057***	0.109***	0.055***	0.094***
No Italian citiz.	0.059***	0.070***	0.039***	0.023***	0.022***	-0.011***
Age						
16-30	0.040***	0.090***	0.031***	0.059***	0.029***	0.052***
31-44	0.017***	0.023***	0.014***	0.015***	0.014***	0.012***
45-54	0.000	0.000	0.000	0.000	0.000	0.000
55-64	-0.010***	-0.026***	-0.010***	-0.023***	-0.011***	-0.023***
No FUA	0.000	0.000	0.000	0.000	0.000	0.000
Urban-rural						
FUA	0.004***	0.009***	0.002*	0.005***	0.002***	0.004***
FUA core	0.015***	0.024***	0.007***	0.009***	0.007***	0.006***
Macroregion						
Nord ovest	-0.040***	-0.065***	-0.037***	-0.060***	-0.035***	-0.053***
Nord est	-0.050***	-0.079***	-0.047***	-0.070***	-0.045***	-0.062***
Centro	-0.019***	-0.037***	-0.020***	-0.037***	-0.019***	-0.034***
Sud	0.000	0.000	0.000	0.000	0.000	0.000
Education						
No High-school	0.044***	0.118***	0.036***	0.090***	0.010***	0.028***
High-School	0.018***	0.061***	0.013***	0.044***	0.005***	0.011***
Tertiary	0.000	0.000	0.000	0.000	0.000	0.000
Family status						
Single-no kids	0.000	0.000	0.000	0.000	0.000	0.000
Couple-no kids	-0.004***	0.003**	-0.000	0.018***	0.000	0.016***
Couple-kids	-0.003	0.003*	0.001	0.016***	0.002	0.013***
Single-kids	0.025***	0.041***	0.025***	0.045***	0.023***	0.038***
NACE						
A. Agriculture			0.007***	0.027***	0.008**	0.008
B-E. Industry and energy			0.000	0.000	0.000	0.000
F. Construction			0.005***	-0.003**	-0.020***	0.004*
G. Retail			0.037***	0.103***	0.017***	0.044***
H. Transport			0.012***	0.027***	-0.004***	0.008***
I. Hotel and catering			0.106***	0.215***	0.051***	0.113***
J-L. ICT, Finance, Real estate			0.021***	0.025***	0.018***	0.026***
M-N. Professional serv.			0.127***	0.186***	0.103***	0.147***
O. Public administration			0.018***	0.007***	0.019***	-0.002
P. Education			0.009***	0.005***	-0.029***	-0.036***
Q. Health services			0.024***	0.063***	0.033***	0.076***
R-U. Other Services			0.138***	0.234***	0.100***	0.144***
Constant	-0.000	0.003	-0.015***	-0.026***	-0.025***	-0.044***
Occup. 2 dig.	No	No	No	No	Yes	Yes
N	365,907	454,736	365,907	454,736	365,907	454,736
Adj. R-squared	0.04	0.08	0.08	0.13	0.09	0.16

Source: author's own calculations. *Notes:* sample restricted to: (1) individuals aged 16-64; (2) employees (exclude self-employed and independent contractors). To avoid small sample issues, models for 2019 pool observations from 2017, 2018, and 2019, while models for 2004 pool observations from year 2005, 2006, and 2007 (2004 is excluded as information about the nationality of respondents is not available for that year). Robust standard errors. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$.

Table A7: Raw and corrected correlations

	Raw	Time FE	NUTS1 FE	Time and NUTS1 FE
RTI	-0.575	-0.324	-0.560	-0.221
RTI (augm.)	-0.578	-0.298	-0.580	-0.222
RTCI	-0.354	0.008	-0.479	-0.153
RTMI	-0.633	-0.445	-0.589	-0.271
% Middle tercile in tot. empl.	-0.451	-0.593	-0.202	-0.168
% Empl. manuf.	-0.490	-0.635	-0.297	-0.354

Source: author's own calculations. *Notes:* sample restricted to: (1) individuals aged 16-64; (2) employees (exclude self-employed and independent contractors). N=1,545 (103 provinces and 15 years). Column "Raw" reports the raw correlation between the IPT at the province level and each index (pooling all 15 years). Column "Time FE" reports the correlation between the residuals of the regression of IPT on a set of year dummies and the residuals of the same regression for each index. Column "NUTS1 FE" reports the correlation between the residuals of the regression of IPT on a set of NUTS1 dummies and the residuals of the same regression for each index. Column "Time and NUTS1 FE" reports the correlation between the residuals of the regression of IPT on a set of year and NUTS1 dummies and the residuals of the same regression for each index.

Table A8: Descriptive statistics

	Mean	SD	Min	25th	50th	75th	Max
IPT	9.92	4.66	1.35	6.23	9.55	12.90	26.79
IPT - No HS	12.14	6.24	1.43	7.12	11.22	16.27	39.78
IPT - HS	9.63	4.84	1.10	5.70	9.30	12.80	27.57
IPT - Low pay tercile	16.74	7.43	2.20	10.47	16.30	22.29	41.60
IPT - Low pay tercile	5.86	3.97	0.13	3.01	4.92	7.74	25.35
IPT - Men	4.67	3.39	0.00	2.20	3.91	6.30	23.44
IPT - Women	16.37	6.87	2.68	10.97	16.26	21.12	37.82
IPT - Men - No HS	4.89	3.68	0.00	2.27	4.00	6.70	26.23
IPT - Women - No HS	18.80	8.40	2.83	12.11	18.44	24.52	45.57
IPT- Men - HS	4.55	3.56	0.00	1.97	3.75	6.11	23.71
IPT - Women - HS	15.47	7.41	1.78	9.44	14.94	20.32	42.62
RTI	30.85	5.14	17.41	26.94	30.91	34.64	48.88
RTI (augm.)	30.23	5.17	16.29	26.30	30.29	33.99	47.88
RTCI	32.26	4.70	19.89	29.01	31.88	35.23	51.19
RTMI	30.27	5.66	15.20	26.29	30.15	34.49	48.07
% Middle tercile in tot. empl.	38.13	5.89	22.66	33.56	38.37	42.72	54.32
% Manuf. empl.	18.69	9.12	3.06	10.91	17.66	25.45	42.04
% Aged 65+	26.18	4.27	14.79	23.21	25.82	29.14	41.55
% Foreign pop.	5.78	3.79	0.07	2.49	5.09	8.86	16.81
% High-school	40.60	4.72	26.53	37.36	41.05	44.04	52.28
% Tertiary education	12.94	3.64	4.91	10.31	12.59	15.12	28.87
% Unempl.	5.84	2.66	1.27	3.75	5.48	7.42	15.78
% Female empl.	47.33	11.57	20.70	37.20	51.96	56.02	68.74
% Limited time contract	14.91	4.79	5.34	11.35	14.01	17.60	36.33
Value added p.w.	58,757.89	7,372.23	42,925.09	53,048.96	59,065.67	64,023.07	79,877.64
Value added growth (%)	-0.28	3.18	-18.44	-2.00	0.18	1.73	20.51

Source: author's own calculations. *Notes:* sample restricted to: (1) individuals aged 16-64; (2) employees (exclude self-employed and independent contractors). N=1,545 (103 provinces and 15 years).

Table A9: Partial adjustment model - Years 2011-2019

		Education		Pay tercile	
	All	No HS	HS	Low	Middle
RTI	-0.053***	-0.090***	-0.072***	-0.072**	-0.035**
	(0.015)	(0.028)	(0.019)	(0.028)	(0.017)
	0.27	0.23	0.32	0.27	0.25
RTI (augm.)	-0.055***	-0.094***	-0.073***	-0.071**	-0.037**
	(0.015)	(0.028)	(0.019)	(0.028)	(0.017)
	0.27	0.23	0.32	0.27	0.25
RTCI	-0.073***	-0.119***	-0.084***	-0.115***	-0.044**
	(0.015)	(0.029)	(0.020)	(0.029)	(0.018)
	0.28	0.24	0.32	0.28	0.25
RTMI	-0.048***	-0.066**	-0.073***	-0.065**	-0.039**
	(0.014)	(0.028)	(0.019)	(0.026)	(0.017)
	0.27	0.23	0.32	0.27	0.25
% Middle tercile in tot. empl.	-0.026	-0.042	-0.043**	-0.023	-0.019
	(0.016)	(0.029)	(0.021)	(0.030)	(0.018)
	0.26	0.22	0.30	0.27	0.25
% Empl. manuf.	-0.036***	-0.077***	-0.047***	-0.058***	-0.022**
	(0.009)	(0.017)	(0.012)	(0.017)	(0.010)
	0.27	0.24	0.31	0.28	0.25

Source: authors' own calculations. *Notes:* each estimate comes from a separate regression including the full battery of controls described in Section 5 (Equation 6). The dependent variable is the share of involuntary part-time workers IPT by province (2011-2019). 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 workmen; (5) among clerks; (6) among those in low-paid occupations (bottom tercile); (7) among those in middle paid occupations (middle tercile). Standard errors are reported between parentheses, while the last line of each block reports the R^2. We specify errors terms to follow a panel-specific AR(1) autocorrelation structure and assume panel-level heteroskedasticity. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$. N=927 (103 provinces and 9 years).

Table A10: Partial adjustment model - Long run multiplier - Years 2011-2019

		Education		Pay tercile	
	All	No HS	HS	Low	Middle
RTI	-0.147***	-0.256***	-0.134***	-0.208***	-0.074**
	(0.040)	(0.077)	(0.034)	(0.079)	(0.035)
RTI (augm.)	-0.153***	-0.268***	-0.136***	-0.206**	-0.078**
	(0.041)	(0.077)	(0.035)	(0.080)	(0.036)
RTCI	-0.201***	-0.332***	-0.156***	-0.327***	-0.092**
	(0.041)	(0.078)	(0.036)	(0.082)	(0.036)
RTMI	-0.137***	-0.191**	-0.137***	-0.188**	-0.084**
	(0.040)	(0.078)	(0.033)	(0.074)	(0.035)
% Middle tercile in tot. empl.	-0.076	-0.125	-0.085**	-0.069	-0.041
	(0.048)	(0.085)	(0.041)	(0.091)	(0.040)
% Empl. manuf.	-0.101***	-0.208***	-0.089***	-0.163***	-0.047**
	(0.023)	(0.043)	(0.022)	(0.045)	(0.021)

Source: authors' own calculations. *Notes:* each estimate comes from a separate regression including the full battery of controls described in Section 5 (Equation 6). The dependent variable is the share of involuntary part-time workers IPT by province (2011-2019). 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 workmen; (5) among clerks; (6) among those in low-paid occupations (bottom tercile); (7) 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: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$. N=927 (103 provinces and 9 years).

Table A11: Partial adjustment model - By gender - Years 2011-2019

	All		No high-school		High-school	
	Men	Women	Men	Women	Men	Women
RTI	-0.043***	-0.077***	-0.048***	-0.112***	-0.069***	-0.066**
	(0.013)	(0.024)	(0.015)	(0.029)	(0.019)	(0.034)
	0.24	0.28	0.23	0.29	0.32	0.31
RTI (augm.)	-0.049***	-0.074***	-0.054***	-0.105***	-0.079***	-0.054
	(0.014)	(0.024)	(0.016)	(0.030)	(0.020)	(0.034)
	0.24	0.28	0.23	0.29	0.32	0.31
RTCI	-0.051***	-0.095***	-0.054***	-0.130***	-0.056***	-0.081**
	(0.014)	(0.025)	(0.016)	(0.030)	(0.020)	(0.036)
	0.24	0.28	0.23	0.30	0.32	0.31
RTMI	-0.044***	-0.068***	-0.051***	-0.089***	-0.080***	-0.064*
	(0.013)	(0.023)	(0.015)	(0.028)	(0.020)	(0.033)
	0.24	0.28	0.23	0.29	0.32	0.31
% Middle tercile in tot. empl.	-0.032**	-0.000	-0.032**	-0.019	-0.040*	0.017
	(0.014)	(0.027)	(0.016)	(0.033)	(0.020)	(0.038)
	0.23	0.27	0.22	0.28	0.31	0.30
% Empl. manuf.	-0.033***	-0.054***	-0.040***	-0.078***	-0.054***	-0.023
	(0.008)	(0.015)	(0.009)	(0.018)	(0.011)	(0.021)
	0.24	0.28	0.24	0.30	0.32	0.31
% Empl. Household subs.	0.068**	0.193***	0.071**	0.255***	0.102**	0.159**
	(0.031)	(0.055)	(0.035)	(0.064)	(0.045)	(0.071)
	0.23	0.28	0.22	0.29	0.31	0.31
% Empl. Restaurants	0.103**	0.280***	0.116**	0.274**	0.255***	0.294**
	(0.051)	(0.094)	(0.058)	(0.111)	(0.078)	(0.122)
	0.23	0.28	0.22	0.28	0.32	0.31
% Empl. Bars	-0.050	0.386**	-0.098	0.447**	-0.108	0.118
	(0.089)	(0.164)	(0.098)	(0.189)	(0.131)	(0.214)
	0.22	0.27	0.22	0.28	0.31	0.30
% Empl. Domestic personnel	0.084*	0.097	0.094*	0.219**	0.074	0.111
	(0.046)	(0.077)	(0.052)	(0.090)	(0.072)	(0.101)
	0.23	0.27	0.22	0.29	0.31	0.31

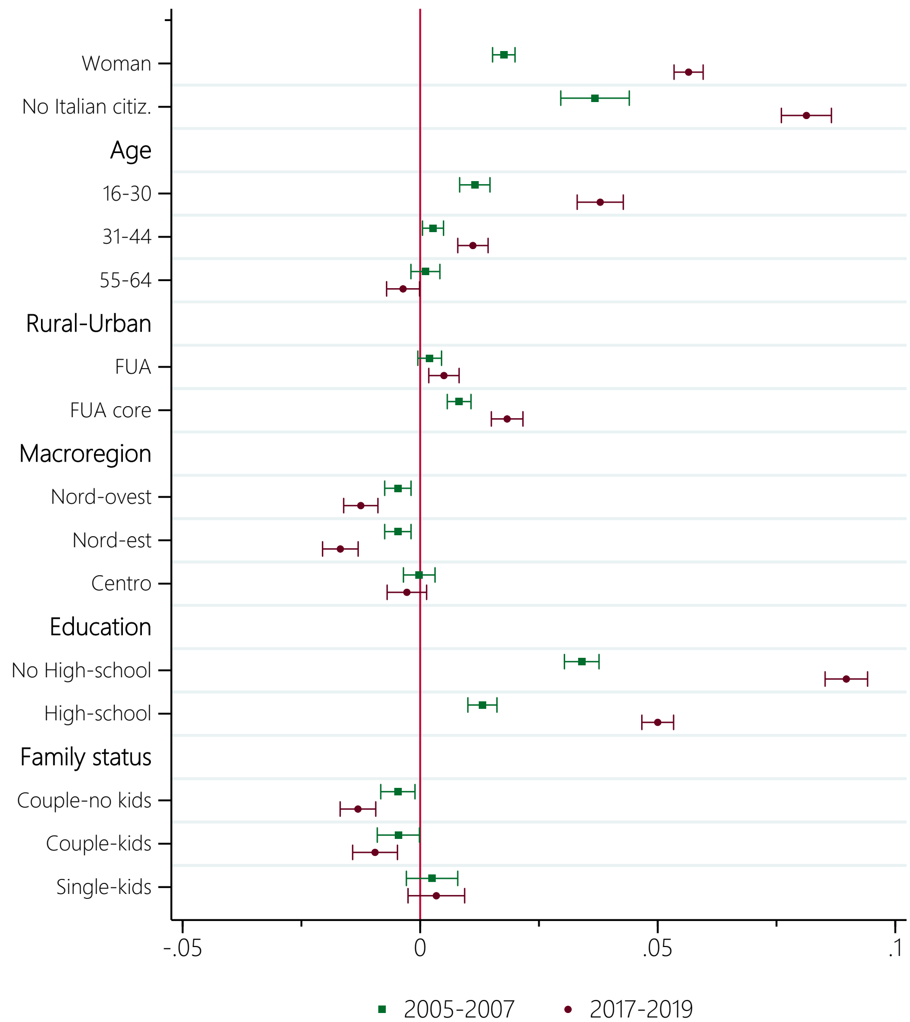
Source: authors' own calculations. *Notes:* each estimate comes from a separate regression including the full battery of controls described in Section 5 (Equation 6). The dependent variable is the share of involuntary part-time workers by province (2011-2019): (1) for all women (men); (1) for women (men) 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 R^2. We specify errors terms to follow a panel-specific AR(1) autocorrelation structure and assume panel-level heteroskedasticity. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$. N=927 (103 provinces and 9 years).

Table A12: OLS and 2SLS fixed-effects panel data models - Years 2011-2019

		Education		Pay tercile	
	All	No HS	HS	Low	Middle
			OLS		
RTI	-0.086***	-0.124***	-0.065**	-0.124***	-0.057**
	(0.024)	(0.040)	(0.032)	(0.045)	(0.025)
R^2	0.38	0.35	0.44	0.37	0.42
RTI (augm.)	-0.090***	-0.122***	-0.068**	-0.125***	-0.059**
	(0.025)	(0.040)	(0.032)	(0.046)	(0.026)
R^2	0.38	0.35	0.44	0.37	0.42
RTCI	-0.086***	-0.106***	-0.075***	-0.114**	-0.071***
	(0.023)	(0.037)	(0.027)	(0.047)	(0.024)
R^2	0.38	0.35	0.44	0.37	0.42
RTMI	-0.071***	-0.076*	-0.066*	-0.124**	-0.027
	(0.026)	(0.038)	(0.035)	(0.052)	(0.026)
R^2	0.37	0.34	0.44	0.37	0.42
			2SLS		
RTI	-0.198***	-0.237***	-0.199***	-0.356***	-0.101***
	(0.034)	(0.058)	(0.042)	(0.067)	(0.038)
F-stat.	255.47	257.40	253.59	255.28	258.18
R^2	0.28	0.26	0.35	0.27	0.34
RTI (augm.)	-0.202***	-0.243***	-0.203***	-0.362***	-0.102***
	(0.035)	(0.059)	(0.043)	(0.068)	(0.038)
F-stat.	262.78	265.49	260.33	262.80	265.60
R^2	0.28	0.26	0.35	0.27	0.34
RTCI	-0.206***	-0.237***	-0.214***	-0.367***	-0.111***
	(0.036)	(0.061)	(0.043)	(0.072)	(0.039)
F-stat.	285.98	287.93	278.75	283.59	285.33
R^2	0.27	0.25	0.35	0.26	0.35
RTMI	-0.201***	-0.253***	-0.200***	-0.384***	-0.084**
	(0.037)	(0.062)	(0.044)	(0.071)	(0.039)
F-stat.	253.24	256.76	249.21	252.92	251.84
R^2	0.26	0.24	0.35	0.26	0.34

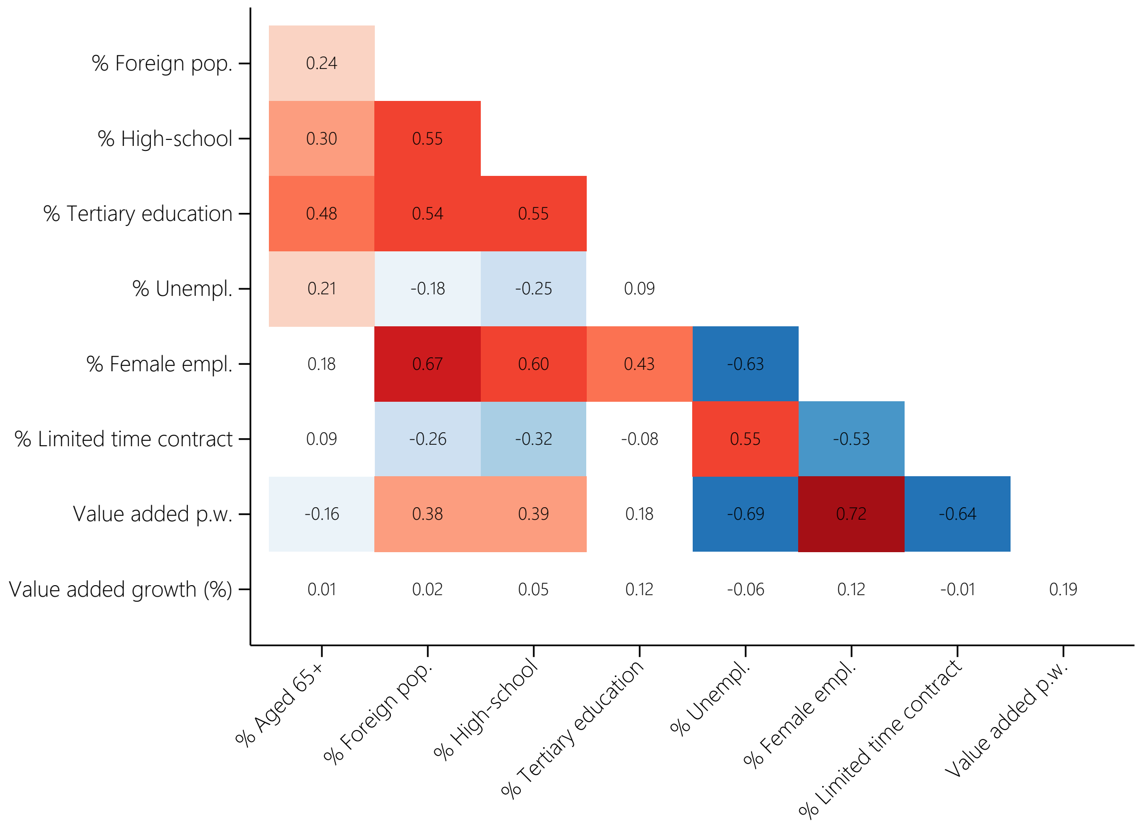
Source: authors' own calculations. *Notes:* each estimate comes from a separate regression including the full battery of controls described in Section 5 (Equation 6), excluding the time-invariant NUTS1 FE. Robust standard errors are reported between parentheses. The dependent variable is the share of involuntary part-time workers IPT by province (2011-2019). 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: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$. N=927 (103 provinces and 9 years).

Figure A1: IPT - Selection into exposed sectors and occupations



Source: author's own calculations. *Notes:* for each of the two time periods considered in Table A6, this plot reports the estimate for Model 1 (base-model with socio-demographic characteristics) minus the one for Model 3 (full model including sector and two-digit occupation.

Figure A2: Correlation of control variables



Source: author's own calculations.

UBIREA

Institut de Recerca en Economia Aplicada Regional i Pública
Research Institute of Applied Economics

WEBSITE: www.ub.edu/irea • **CONTACT:** irea@ub.edu

AQR

Grup de Recerca Anàlisi Quantitativa Regional
Regional Quantitative Analysis Research Group

WEBSITE: www.ub.edu/aqr/ • **CONTACT:** aqr@ub.edu

Universitat de Barcelona
Av. Diagonal, 690 • 08034 Barcelona