UNIVERSITAT DE BARCELONA

Struggling Workers in a Changing World: Three Essays on Labour Economics and Political Economy

Liliana Cuccu

PhD in Economics

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Contents

1 Introduction

Fast technological change and rampant globalisation are causing profound transformations in the labour markets around the world. These global megatrends modified the way businesses operate, the distribution of income, and the very nature of work. This brought about a range of new challenges for workers, particularly those at the lower end of the wage distribution.

The introduction of technologies like industrial robots, artificial intelligence, and information and communication technologies are enabling firms to automate a growing number of tasks, replacing workers with advanced technological tools. Indeed, one of the most pressing questions in the automation literature over the last years has been whether or not machines will lead to a future of mass unemployment. The public debate was especially triggered by Frey and Osborne (2017), who estimated that about 47% of total US employment is at high risk of automation over the next one or two decades. However, these estimations have been met with some scepticism. For instance, Arntz et al. (2016) estimated that "only" 9% of jobs across the OECD are potentially automatable. Despite these varying estimates, the prospect of a substantial share of jobs disappearing in the near future presents a significant challenge to the stability of our societies.

Negative effects of automation on labour are not at all circumscribed to the automated occupations or sectors. In fact, one of the main mechanisms through which automation extends beyond the affected sectors is the ripple effect, which arises when automation-displaced workers compete for non-automated tasks, thereby pushing down wages in less-automated occupations and sectors (Acemoglu and Restrepo, 2022). In addition to the risk of job loss, technological advancements have far-reaching consequences in terms of redistribution. The wave of job automation starting at the end of the 20th century with the introduction of computers and industrial robots has had a disproportionate impact on workers with lower or intermediate skill sets. This is because these workers' jobs are characterised by a high share of repetitive and routine tasks, which are easier to automate. On the contrary, the roles of high-skilled workers are less threatened or even complemented by these new technologies, resulting in a rise in demand for their skills and higher wages (Autor and Dorn, 2013; Blanas et al., 2019). Consequently, routine-biased technological change (RBTC) has been deemed responsible for an increasing polarization in the labour market, as jobs in the middle of the wage and skill spectrum have been progressively disappearing (Autor et al., 2003; Goos et al., 2009).

Although restraining automation in an attempt to safeguard employment can result in lost opportunities for growth, decreased competitiveness, and a failure to keep up with international rivals (Aghion et al., 2020; Humlum, 2019; Mitchell and Brynjolfsson, 2017), the absence of suitable policies to assist those adversely affected by disruptive innovations can lead to higher unemployment rates, social exclusion, and widening income gap between winners and losers of technological change (Acemoglu and Restrepo, 2020; Anelli et al., 2021b). This dissertation is composed by three independent yet complementary chapters that offer empirical evidence of how technological advancements can adversely affect workers. Particular emphasis is placed on identifying the groups that are most vulnerable to the negative effects of disruptive innovations. This is because recognizing the "losers" and understanding the various channels through which they are impacted is essential for designing effective policies. The dissertation also highlights that ignoring workers' grievances can have significant implications for society at large, as economic dissatisfaction and the perception of institutional neglect among certain social groups can fuel the rise of populist and far-right movements (Kurer, 2020; Lee et al., 2018; Los et al., 2017).

Chapter 2 of the dissertation challenges the concept of "reallocation" as a solution to automation-induced displacement. Concerns over the potential negative effects of automation on middle- and low-skilled workers are often countered with the argument that displaced workers are "simply" reallocated to other tasks, occupations, or sectors and not permanently excluded from the production process (Nakamura and Zeira, 2018). While it is true that manufacturing job losses have been offset by service sector job gains in some cases (Dauth et al., 2021; Mann and Püttmann, 2021), looking at (aggregate) employment levels alone can mask the adverse effects of displacement on worker welfare, as service sector jobs may offer lower pay and less employment security (Korchowiec, 2019). Starting from these considerations, the chapter contributes to the literature on automation by shedding some light on two aspects which are often neglected by studies on the topic. The first question addressed concerns the quality of the reallocation process in the short- and medium-term for displaced workers. In particular, the study investigates whether automation-exposed displaced workers get reallocated to jobs of lower *quality* compared to workers dismissed from less exposed sectors. Several dimensions of job quality are explored: earnings, job qualification level, employment security (permanent or temporary contract), and type of employment ("regular" or through a temporary employment agency). Going beyond employment levels and aggregate wages to considering other aspects of job quality, especially those related to employment security, is crucial in capturing not only workers' material well-being, but also factors that can trigger feelings of economic insecurity and status decline, which are strong predictors of social and political discontent (Gingrich, 2019; Kurer, 2020). The second contribution of this investigation is the discussion of the effectiveness of job reallocation to a different sector or local labour market as an adjustment mechanism after displacement from increasingly automation-exposed sectors. The standard economic theory predicts that workers displaced from automation-intensive areas will move to better performing labour markets, and those struggling to find a new occupation in the same sector will relocate to a less exposed sector. However, the outcome of sectoral and regional reallocation is not obvious, particularly if there are substantial reallocation frictions between sectors (Lee and Wolpin, 2006) or the difficulty in finding a new job is due to a shift of labour demand towards workers with higher or new skills (Humlum, 2019; Koch et al., 2021).

These questions are addressed using an administrative longitudinal panel covering a large sample of Spanish workers from 2001 to 2017 (*Muestra continua de vidas laborales*, MCVL) and extracting a measure of automation exposure from the International Federation of Robots dataset (IFR), which reports the stock of robots by country, industry, and year. As the adoption of robots is not an exogenous random shock, the analysis is based on an instrumental variable approach (IV) similar to the one used in Autor et al. (2013b), Acemoglu and Restrepo (2020), and Dauth et al. (2021): industry level robot adoption in Spain is instrumented with robot installations across industries in other European countries. What emerges from the analysis is that exposed middle- and low-skilled workers are more likely than non-exposed workers to remain unemployed six months after displacement. Among those who find a new occupation, an additional robot per 1,000 workers increases the probability of being re-employed in a lower-paying job by about two percentage points for middle- and low-skilled workers, with significantly higher penalties for those who relocate to a different sector. Moreover, these workers tend to face a qualification downgrading in the new job and are more likely to be re-employed through temporary employment agencies. High-skilled workers are less negatively affected by exposure, although they can also incur a penalty when changing sectors. The findings presented in this chapter suggest that active labour market policies, such as retraining, might be necessary to help automation-displaced workers transition to a new job of similar quality as their previous one.

Chapter 3 investigates the relationship between routine-biased technological change (RBTC) and the increase in Involuntary Part-Time (IPT). Specifically, the study tests the hypothesis put forward by Van Doorn and Van Vliet (2022) that, as technology advances and replaces middle-skill routine jobs, medium-educated workers are compelled to seek non-automated low-skill jobs. This, in turn, leads to an expansion of the labour supply for low-skill jobs and subsequently decreases the bargaining power of workers. As a result, individuals who depend on such jobs are forced to accept part-time positions, even if they would prefer to work more hours. In this sense, automation can contribute to a broader process of labour market dualisation (Rueda, 2005), characterized by a growing divide between "insiders" and "outsiders", which extends beyond the traditional employed versus unemployed dichotomy to include employees with varying levels of protection, security, and opportunities.

This chapter's contribution to the literature on IPT is twofold. Firstly, it adopts an economic geography perspective, which has been overlooked in previous research that has mostly focused on demographic and business-cycle factors while neglecting the spatial aspect, particularly the disparities within regions of a country. Chapter 3 addresses this gap by examining the impact of local labour market characteristics on IPT growth in Italian provinces (NUTS3), specifically testing the hypothesis on the link between routine-biased technological change and IPT at the sub-national level using refined occupation-specific indicators. Furthermore, this chapter aims at disentangling the extent to which the differential growth of involuntary part-time work between genders can be attributed to the RBTC theory, as opposed to the increasing propensity of women to select occupations and sectors that rely more extensively on part-time employment. With the increase of high-skilled women employment shares, job opportunities arose in sectors that substitute for household activities, such as restaurants, bars, and domestic services. These jobs are typically low-skilled and require a higher degree of flexibility, resulting in a shift towards part-time employment in these sectors on an aggregate level.

With regards to the empirical approach, the study examines the effect of local specialization in routine tasks on the increase of involuntary part-time work across 103 provinces in Italy between the years 2004 and 2019. During this period, the proportion of Italian employees working part-time rose substantially, increasing from 13.8% to 21.2%. Moreover, the non-voluntary component of part-time work saw a significant surge, rising from 39.1% to 63.6%. The analysis draws on the combination of the INAPP-ISTAT Survey on Italian Occupations (ICP) with the Italian section of the EU labour force survey to build province-level indicators of routine-task specialisation based on the occupational mix in each province. A key advantage of using the ICP survey is its ability to reflect the unique characteristics of Italian jobs, in contrast to prior studies that relied on US data and matched O*NET task-content information to European labour market data. The econometric analysis employs a partial adjustment model, which is well-suited for investigating the dynamics of labour market variables that exhibit gradual or sluggish adjustment over time. Furthermore, endogeneity concerns are addressed by an IV fixed-effects panel data model with an instrument *á-la-Bartik*.

The study provides evidence that RBTC is correlated with a higher incidence of IPT in Italian local labour markets, indicating that automation's impact goes beyond affecting unemployment rates and can impact job quality in other ways. Although the study confirms the association between RBTC and IPT for both genders, the results suggest that the stronger growth of IPT among women cannot be solely attributed to RBTC. Instead, Chapter 3's analysis indicates that low-skilled women are disproportionately affected by the expansion of employment in "household substitution" services compared to men. This suggests that, in addition to RBTC, various other factors such as sector segregation, a surge in household-substitution services demand, and gender norms, may also be playing a role in explaining higher IPT levels among women.

Chapter 4 takes a step ahead and examines the potential outcomes that may arise when individuals who consider themselves disadvantaged by technological advancements and globalisation perceive that their social and economic concerns are not adequately being addressed by relevant institutions. Over the past two decades, the Italian logistics industry has experienced rapid growth due to fast development in information and communication systems, the fall in transportation costs, the reduction trade barriers, and the outsourcing of transport and logistics activities in manufacturing (Bonacich and Wilson, 2008; Mariotti, 2015; Vahrenkamp, 2010). Among the many consequences of the so-called "logistic revolution" there has been a tendency of logistics facilities, such as warehouses, cross-dock facilities, intermodal terminals, to move away from congested urban areas and be closer to highways (Bowen, 2008; Woudsma et al., 2008). This led to a proliferation of large logistic hubs, which customarily provide low-paying jobs and precarious employment contracts, into mostly rural towns and villages. Chapter 4 exploits this process to explore the relationship between technology-driven socio-economic changes and political discontent. The construction of large logistic hubs has a strong economic and social impact on local communities, especially when it comes to rural areas. In this sense, the rapid and sizeable expansion of logistics provides a good setting to investigate the connection between socio-economic grievances and support for the populist radical right, as the construction of a new hub works as a sort of exogenous shock. The Italian logistics industry is characterized by a heavy reliance on low-paying and precarious contracts, it employs a large number of foreign workers, and is dominated by multinational corporations. The construction of large logistic hubs can therefore increase the feeling of economic insecurity and trigger cultural backlash against foreign workers and large corporations. (Perceived) socio-economic insecurity can erode trust in traditional political parties and institutions, leading to increased support for populist factions (Akkerman et al., 2017; Boeri et al., 2021; Guiso et al., 2017; Ziller and Schübel, 2015). Indeed, populist parties have been successful in capturing public frustration by tapping into social anxiety and blaming traditional parties for failing to protect ordinary working people from the challenges of the modern world (Frank, 2007; Gaffney, 2020; Gidron and Hall, 2017; Hertz, 2021; Hochschild, 2018; Norris and Inglehart, 2019).

Through an IV and a DiD approach, Chapter 4 provides evidence of a causal relationship between the establishment of new logistics hubs and the rise in the vote share of *Lega*, an Italian populist radical-right party. This relationship might be driven by different mechanisms: an increase in the feeling of economic insecurity, a surge in the anti-immigration sentiment, the hostility towards foreign multinationals. These potential channels are investigated through an event study. Overall, the event study reveals no significant evidence of a large increase of economic insecurity in the affected municipalities, at least in the short run. In fact, the employment share increases and there are no sizeable negative effects neither on total income nor on labour income. On the other hand, there is a significant increase in population, which seems not to be exclusively driven by Italian citizens, providing some support in favour of the second channel. The evidence provided in Chapter 4 calls for a more thorough evaluation of the costs and benefits from hosting a logistic hub, as for many municipalities the expected benefits might be outweighed by negative effects. Local administrators are attracted by the promise of an increase of the overall employment, large investments, positive effects for the other firms in the area, and increase in land prices. However, once the hub is built, the reality they have to face might be different, paving the way for social discontent, which, among other ways, is expressed through an increase in support for populist radical-right parties.

2 Just Reallocated? Robots, Displacement, and Job Quality[1]

2.1 Introduction

Policy makers and economists have long worried about the detrimental effects of technological change on labour markets.[2] While any job loss can be associated with worse job prospects, workers dismissed due to automation and technological change may face additional problems when it comes to reallocation. In this study we analyse whether workers displaced from sectors with an increasing density of robots face a differential penalty when finding a new job, both in terms of salary and other qualitative aspects of the new contract.

Whether in the form of industrial robots or artificial intelligence, technological progress allows firms to automate an increasing number of tasks, replacing workers with advanced technological tools. Following the terminology of Acemoglu and Restrepo (2019), automation results in declining employment (displacement effect), which can be compensated, or even more than compensated, by a higher demand for labour in non-automated tasks (productivity effect), and by the creation of completely new tasks in which labour has a comparative advantage (reinstatement effect). Thus, although some workers may be expelled from the labour market, others can be re-employed in non-automated tasks. While it is well documented that workers who lose their job due to plant closures or mass layoffs suffer significant and enduring employment and wage losses (Couch and Placzek, 2010; Huttunen et al., 2018), less is known about the effect of job loss due to the introduction of robots. Several studies, such as Acemoglu and Restrepo (2020) and Dauth et al. (2021), focused on the overall adjustment of the (local) labour markets. Our work proposes an alternative perspective, investigating the reallocation process following the introduction of robots and focusing on the *quality* of the new jobs found by displaced workers.

In addition to the potential for job destruction and workers' reallocation, a peculiar characteristic of the automation process is its redistributional imprint. The bulk of employment and wage losses are suffered by middle- and low-skilled workers, while the roles typically covered by the high-skilled are complemented

[1]Paper co-authored with Vicente Royuela.

[2]For example, Pratt (2015) warns about a possible "Cambrian explosion" for robotics, which, by taking place at a much larger scale and within a shorter time than previous waves of new technologies, has the potential to displace a larger proportion of the workforce. Similarly, Frey and Osborne (2017) estimate that about 47% of total US employment is at high risk of automation over the next one or two decades.

by new technologies. Therefore, high-skilled workers enjoy higher wages and increased demand (Autor and Dorn, 2013; Blanas et al., 2019). Furthermore, although technological progress results not only in the automation of human labour, but also in the creation of completely new tasks and occupations, these new roles are mostly performed by high-skilled workers (Arntz et al., 2020; Moll et al., 2022). Concerns over potential negative effects on middle- and low-skilled workers are often dismissed with the claim that displaced workers are not permanently excluded from the production process, as they are "just" reallocated to other tasks, occupations, or sectors (Nakamura and Zeira, 2018). Indeed, several studies showed that declining manufacturing employment is compensated, or even more than compensated, by service sector job growth (Dauth et al., 2021; Mann and Püttmann, 2021). When focusing on pure employment levels alone, this might seem a reassuring outcome. However, the same does not hold from a welfare-oriented perspective, as service sector jobs may offer lower pay and less employment security (Korchowiec, 2019). On top of exacerbating inequality among skill groups, automation shocks have the potential to widen regional divergence through the geographic mismatch in job creation and job destruction: while most jobs are destroyed in production-intensive manufacturing hubs, new jobs are created in service-intensive cities and regions, that benefit from robot-induced lower production costs (Acemoglu and Restrepo, 2020).

While curbing automation in an effort to protect employment can lead to missed growth opportunities, crippled competitiveness, and inability to pace with international competitors (Aghion et al., 2020; Humlum, 2019; Mitchell and Brynjolfsson, 2017), failure to complement automation with adequate policies addressing the needs of the "losers" can result in a number of individual and social problems. Several studies documented the impact of job loss on mortality (Browning and Heinesen, 2012; Sullivan and von Wachter, 2009), depression (Riumallo-Herl et al., 2014), cardiovascular health (Noelke and Avendano, 2015), life satisfaction (Aghion et al., 2016), and fertility (Huttunen and Kellokumpu, 2016). Although only some categories of workers are directly affected by automation shocks, the expectation of a reduced income and fewer job prospects generates a feeling of uncertainty that can spread to the whole community (Florida, 2017; Moretti, 2012). As became clear with Brexit in the UK and Trump's victory in the US, perceived economic decline, feelings of abandonment from institutions, and mounting discontent concentrated within specific social groups or regions can have far-reaching consequences for the whole society, as they facilitate the rise of populist and far-right forces

(Kurer, 2020; Lee et al., 2018; Los et al., 2017; McCann, 2018). Given the strong spatial dimension of automation (Autor et al., 2013a; Leigh and Kraft, 2018), industrial robots can be deemed a factor contributing to the emergence of a geography of discontent (Dijkstra et al., 2020) and triggering the so-called "revenge of places that don't matter" (Rodríguez-Pose, 2018). Indeed, there is empirical evidence of the relationship between industrial robots and unhappiness (Hinks, 2021), decreased relative marriage-market value of men (Anelli et al., 2021b), and populist or far-right voting (Anelli et al., 2021a; Caselli et al., 2020b; Frey et al., 2018; Milner, 2021; Petrova et al., 2021).

Empirical evidence is essential to create a system that exploits the full potential of new technologies while protecting the most vulnerable workers and regions with adequate policies. Due to the lack of suitable workers' microdata, most studies evaluating the effect of technological change on labour market outcomes rely on aggregated measures, either at the country, region, industry, or even firm level. However, this approach may provide biased results, as automation changes the composition of employed workers (Grigoli et al., 2020). Besides, the negative effects for specific groups of workers may be overlooked, leading to inappropriate policy responses (Beraja and Zorzi, 2021; Kurer and Gallego, 2019; Raj and Seamans, 2019). This study contributes to bridging these gaps by shedding light on two aspects that are often neglected in studies on automation. The first is the *quality* of the reallocation outcome in the short- and medium-term for *displaced* workers, i.e., workers who are dismissed by their employers.[3] Workers employed in sectors with a high density of industrial robots can be displaced for two reasons. They may be employed in firms that adopt robots, replacing production workers with a more highly skilled labour force (Bonfiglioli et al., 2020; Humlum, 2019; Koch et al., 2021). Alternatively, they may work in non-adopting firms that cannot compete with the increase in productivity of robot-adopting competitors and are eventually crowded out of the market (Acemoglu et al., 2020; Koch et al., 2021). While much attention has been devoted to whether workers displaced by robots are re-employed or not, little has been said about the quality of new job matches. Therefore, the first question we address is:

Q1: Do automation-exposed displaced workers get reallocated to jobs of lower quality compared to workers dismissed from less exposed sectors?

[3]The rich dataset we employ allows us to see the reason for termination for each work spell. We focus on terminations coded as "*54 - Baja no voluntaria*" ("54 - Non-voluntary leave").

While other studies, such as Dauth et al. (2021) and Dottori (2021), address this question by looking at employment and earnings prospects over the long run, we explore several dimensions of job quality: earnings, qualification level, employment security (permanent or temporary contract), and type of employment ("regular" or through a temporary employment agency). Considering other aspects of job quality, especially those related to employment security, is important in capturing not only workers' material well-being, but also factors that can trigger feelings of economic insecurity and status decline, which are strong predictors of social and political discontent (Gingrich, 2019; Kurer, 2020).

The second contribution of this investigation is our discussion regarding the effectiveness of job reallocation to a different sector or local labour market as an adjustment mechanism after displacement from increasingly automation-exposed sectors. Many factors can hurt a worker's re-employment prospects, such as a shift of labour demand towards workers with higher or new skills (Humlum, 2019; Koch et al., 2021), a geographic mismatch between automation-induced job destruction and creation (Acemoglu and Restrepo, 2020), and reallocation frictions between sectors (Lee and Wolpin, 2006). Acemoglu and Restrepo (2020) show that, due to trade links, the negative employment effect in robot-intensive US commuting zones has been at least partly compensated by employment and wage expansion in other areas that could benefit from robot-induced lower production costs. Standard economic theory would expect dismissed workers from automation intensive areas to migrate to better performing labour markets. Indeed, vigorous labour mobility in response to regional utility differentials is a widespread assumption in regional and urban economics (Kline and Moretti, 2014; Rodríguez-Pose, 2018). Similarly, displaced workers struggling to find a new occupation in the same sector are expected to relocate to a sector with less exposure to industrial robots, assuming that new jobs are created there through either the productivity or the reinstatement effect. However, the outcome of sectoral and regional reallocation is not obvious. On one hand, relocating might provide access to better opportunities and higher wages. On the other hand, if worse outcomes are due to the shift of manufacturing labour demand towards a more highly skilled workforce or to the impossibility of transferring sector-specific skills to new occupations, the benefits of relocation might be meagre. Hence, the second question we address is:

Q2: Is reallocation to a different sector or local labour market an effective adjustment mechanism for automation-exposed displaced workers? Do exposed *workers who relocate achieve better conditions in their new jobs compared to those who do not relocate?*

It is important to remark that, while relocation is an endogenous response to the automation shock, assessing whether there are significant differences between the stayers and the leavers provides us valuable hints about possible mechanisms driving the results for the first research question.

This study focuses on the Spanish case for several reasons. First, due to the existence of a detailed dataset on changes in individual workers' labour market status, we are able to follow variations after any job reallocation. Second, Spain is among the developed countries with the highest robot density (IFR, 2018b). Analysing data from the *Encuesta Sobre Estrategias Empresariales* (ESEE), Koch et al. (2021) reported that about 40% of manufacturing workers were employed in firms adopting robots in 2014, with the share being above 70% when considering only large firms (those with more than 200 employees) and around 35% when looking at small firms (those with up to 200 employees). While not a leading country like Germany (investigated in Dauth et al., 2021), Spain is close to the average in Europe in terms of installed robots (IFR, 2018b). Hence, an analysis of the Spanish case may provide new knowledge that can be translated to a wider list of countries. Third, although there is some evidence that automation has negatively affected some categories of Spanish workers (Koch et al., 2021), little is known about whether or how they were reabsorbed by the economic system. Finally, although Spain is a low mobility country, Spanish workers are sensitive to economic factors when it comes to internal migration choices (Melguizo and Royuela, 2020). Therefore, it is an interesting setting in which to investigate whether internal migration has also played a role in alleviating the adverse effects of automation on workers.

What emerges from our empirical analysis is a non-negligible negative impact for middle- and low-skilled workers in sectors exposed to automation. Six months after displacement, these workers are still more likely to be unemployed and have a higher probability of experiencing a fragmented work-life, with multiple contracts and fewer days worked. Among those who find a new occupation, workers displaced from sectors with an increasing density of industrial robots have a higher probability of being re-employed in jobs offering lower pay. The pay differential might be explained by the fact that exposed workers are more likely to end up in jobs requiring lower qualifications. Furthermore, they have a higher probability of being re-employed by temporary employment agencies. Relocation to different sectors or local labour markets does not offer any sort of advantage; if anything, those who switch sectors have an even higher probability of getting a lower paid job.

Some categories of middle- and low-skilled workers who stay employed in sectors and regions more exposed to robots seem to enjoy some of the benefits of automation. In particular, those with a permanent contract in their previous job are less likely to switch to a temporary contract. Few of the negative effects for less skilled workers are short-term, most of them persist for up to 36 months. In general, high-skilled workers are less negatively affected by exposure, although they also incur a penalty when changing sectors.

Our results suggest that active labour market policies, such as retraining, might be necessary to help automation-displaced workers transition to a new job of similar quality. We suggest policies aimed at turning "losers" into "winners" rather than pure compensatory policies, as automation threatens both the material well-being and social status of exposed workers.

The paper is structured as follows. Section 2.2 presents a short literature review, Section 2.3 describes the data, and Section 2.4 discusses our empirical approach. Section 2.5 presents the results, while Section 2.6 and Section 2.7 introduce and discuss the heterogeneity analysis and robustness checks, respectively. Finally, Section 2.8 concludes.

2.2 Literature Review

Any restructuring of firms and labour markets generally involves benefits for many, but significant losses for those who are displaced. As highlighted above, there is a long list of personal and social drawbacks associated with job loss. When looking at labour market outcomes, evidence for the US shows that job displacement has detrimental long-term effects on earnings (Couch and Placzek, 2010; Jacobson et al., 1993; Ruhm, 1991; Stevens, 1997), while evidence for Europe is less conclusive. Gregory and Jukes (2001) and Huttunen et al. (2011) find negligible effects, whereas other researchers, such as Eliason and Storrie (2006), detect significant negative effects for both employment and earnings.

Automation-induced restructuring has the potential to generate many job losses, but it can also create new job opportunities thank to an increase in overall productivity. Although task-based models (Acemoglu and Restrepo, 2019; Acemoglu and Restrepo, 2020; Nakamura and Zeira, 2018) offer a handy conceptual framework for studying the relationship between technological change, employment, and wages, the net effect of automation on these outcomes ultimately remains an empirical question. This is because, as theorized by these same models, the final outcome depends on the equilibrium among a number of forces, such as displacement, productivity, reinstatement, and composition effects (Acemoglu and Restrepo, 2019; Acemoglu and Restrepo, 2020). Furthermore, automation's impact is mediated by a series of context-specific factors, including local labour market institutions (Dauth et al., 2021), workforce age structure (Humlum, 2019), off-shoring intensity (Bonfiglioli et al., 2021), the share of replaceable tasks (Bonfiglioli et al., 2020), and the degree of exposure to international competition (Aghion et al., 2020). Therefore, it is perhaps unsurprising that even when focusing on a specific subset of automation technology, i.e., industrial robots, empirical evidence of its effect on employment is heterogeneous.

In general, cross-industry studies did not detect a net negative impact of automation on employment. Graetz and Michaels (2018) see no effect at all, while Klenert et al. (2023) and Aghion et al. (2020) even estimate a positive impact.[4] However, the industry-level approach might be too narrow, as greater use of robots in an industry can benefit the rest of the economy through lower prices and increased productivity, thereby expanding employment in other industries. To take these spillovers into account, other studies have analysed the effect of robot adoption at the (local) labour market level. Acemoglu and Restrepo (2020) document a strongly negative effect of robots on net employment in the US, showing that employment expansion in less automated commuting zones is not enough to compensate for the large displacement effect in robot-adopting areas.[5] Bonfiglioli et al. (2021) confirm these results using a more detailed dataset on robots and factoring in the role of off-shoring. What emerges from their analysis is that automation has contributed to the re-shoring of economic activity in the US, which mitigates but does not fully compensate for the large displacement effect caused by robots. On the contrary, Dauth et al. (2021) find no effect on total employment at the local level in Germany, as employment

[4]Note that Klenert et al. (2023) use a simple OLS, which might be confounded by positive demand effects influencing both employment and robot adoption.

[5]Leigh et al. (2020) also analysed the US, finding a positive effect of robot adoption on local employment levels. The discrepancy between these results may be explained by several factors. First, Leigh et al. (2020) rely on a simple OLS rather than using IV techniques to purge demand and other confounding shocks. Second, instead of adopting commuting zones as labour market boundaries, they focus on US census-defined core-based statistical areas, which are less representative of actual labour markets. Third, they analyse the post-recession period (2010-2016), while Acemoglu and Restrepo (2020) cover the pre-recession period (1990-2007).

expansion in services has been sufficient to offset the displacement effect in manufacturing. Dottori (2021) reaches similar conclusions for the Italian case.

The majority of firm-level studies find a positive relationship between robot adoption and employment (Acemoglu et al., 2020; Aghion et al., 2020; Dixon et al., 2021).[6] Furthermore, robot adoption seems to be followed by sizeable increases in productivity (Acemoglu et al., 2020; Aghion et al., 2020; Bonfiglioli et al., 2020), which is consistent with employment expansion for adopters generally coming at the expense of non-adopters (Acemoglu et al., 2020; Koch et al., 2021). Interestingly, even within adopting firms the advantages of automation are not passed to all workers equally. Humlum (2019) finds that adopters layoff production workers to hire more skilled workers. Similarly, Acemoglu et al. (2020) and Bonfiglioli et al. (2020) identify a labour demand shift towards a more skilled labour force. On the contrary, Aghion et al. (2020) and Koch et al. (2021) document an increase in employment for low-skilled workers as well, even if it is not as pronounced as the increase for more highly skilled workers. In terms of wages, Aghion et al. (2020) find no effect, while Koch et al. (2021) detect a decline in labour share, and Humlum (2019) estimates an increase in wages for highly-skilled workers but a decline for production workers.

Evidence regarding the effect of robots and automation on individual workers' outcomes is much less abundant. In general, despite the lively debate over the impact of robots on net employment, there seems to be some consensus that at least some displaced workers get reallocated to other occupations, firms, or sectors (Dauth et al., 2021; Mann and Püttmann, 2021). Yet, only a very limited number of studies addresses the fact that these jobs might be of lower quality, offering lower pay and worse employment security. Korchowiec (2019) investigates the impact of industrial robots on occupational mobility in the US and finds that exposed workers are more likely to switch occupations and the probability of switching is greater at the bottom of the wage distribution. Cortes (2016) finds evidence of selection in the ability of workers to switch out of routine jobs, with low-skilled workers being more likely to move to lower-paying, non-routine manual occupations.[7] Bessen et al. (2020) estimate the impact of firm level automation on workers outcomes using a difference-

[6] A notable exception is represented by Bonfiglioli et al. (2020) who find that, although demand shocks result in a spurious positive correlation between robot imports and employment, robot adoption is followed by a decrease in demand for low-skilled labour force, as the demand shifts towards highly skilled professions.

[7] Workers employed in routine jobs are generally considered the most exposed to automation shocks, as their tasks can be easily automated (Autor and Dorn, 2013).

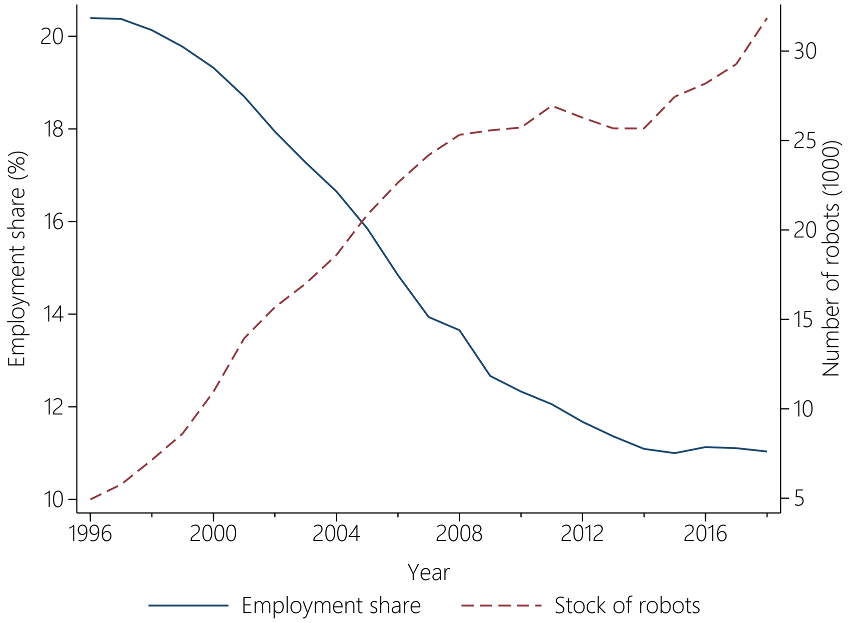
in-differences event study with Dutch micro-data. They find that incumbent workers in automating firms experience a 9% wage loss driven by decreases in days worked and have a higher probability of separating from their employees. Similarly, Koch et al. (2021) estimate a 5–7% reduction in labour cost share within four years of robot adoption in Spanish firms, together with output gains of 20%, and a net job creation at a rate of 10%. Finally, Dauth et al. (2021) follow a sample of German workers employed in manufacturing in 1994 for the subsequent 20 years. They detect a positive effect of industrial robots on earnings for workers who switched occupations within the same establishment, but significant losses for those who were displaced, either changing industries or leaving manufacturing altogether. Using a similar approach, Dottori (2021) finds comparable results for Italy, with an overall positive but small employment effect for incumbent manufacturing workers, conditional on remaining at the original firm.

To our knowledge, there is no work specifically focused on the losers, i.e., displaced workers, or on the effectiveness of the adjustment mechanisms they adopt. A study similar to ours is that of Huttunen et al. (2018), which looks at the impact of job loss on regional mobility in Norway. The authors consider displaced workers as the treatment group and all workers who were not displaced as the control group. They find that regional mobility is not always an effective coping strategy, as those who move to places where they have family or to rural areas face significant income losses. Czaller et al. (2021) investigate the role of urbanization in mitigating automation risk through occupational mobility in Sweden and find that moving to a larger region is a good adaptation strategy, but only for some groups, as the benefits vary depending on gender, migration status, and education. In our work we focus only on displaced workers, investigating whether exposure to robots pushes them towards lower quality jobs and assessing whether sector or spatial mobility are adequate coping strategies after job loss.

2.3 Data and Descriptive Statistics

Worker-level information is taken from the *Muestra continua de vidas laborales* (MCVL), an anonymised panel extracted from the Spanish Social Security records. The dataset comprises 4% of the reference population, roughly amounting to one million individuals, and provides reliable information on each person, including age, province of birth, gender, province of first job, and current place of residence. Furthermore, a detailed set of characteris-

Figure 2.1: Manufacturing employment share and stock of robots



Source: authors' own calculations.

tics is reported for every work and unemployment spell, such as start and termination date, *cause of contract termination*, province of work, economic sector, earnings, contract type, and number of workers employed in the same firm. Note that although the MCVL allows us to retrieve the labour history of each worker included in the sample, it is only representative of the population registered in the Social Security System in the years of reference, i.e., 2004 to 2019. However, assuming the composition of the labour market does not change drastically from one year to the following few years, we enlarge our observation window by three years, back-dating to 2001. Moving the starting point back to gain even a few years is important, as employment in manufacturing fell dramatically in Spain during the early 2000s (see Figure 2.1). Due to the unavailability of a few control variables for the most recent years, our final dataset covers displacements occurring between 2001 and 2017. In this period the Spanish labour market was characterised by high volatility of employment, high-coverage collective bargaining system, high firing costs and a generous benefit system (for a more exhaustive description of the Spanish labour market, see Ramos et al., 2015).

We follow the international literature and extract our measure of automation exposure from the International Federation of Robots dataset (IFR), which is based on surveys of robot suppliers and covers roughly 90% of the industrial robot market.[8] The dataset reports the stock of robots by country, industry, and year for the 1993-2018 period.[9] Robots stocks are recorded following the ISO 8373 norm, according to which a robot is "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications". This stringent definition has the disadvantage of leaving out several machines which serve the same purpose as robots but maybe are not reprogrammable or multipurpose, but it has the advantage of increasing comparability across countries and sectors. The IFR dataset adopts the NACE Rev.2 classification for economic sectors. However, the IFR codes do not match the NACE codes perfectly: several categories with few robots are aggregated, while those with many robots (such as automotive) are disaggregated into more sub-categories. Table 2.1 reports the aggregation strategies we employ in the study to merge IFR data with the sector codes included in the MCVL. The baseline aggregation scheme includes 19 categories. Note that a non-negligible share of robots is included in IFR "unspecified" classes. There are two reasons why a robot might be included in one of these categories. First, robot suppliers use "unspecified" classes to report robots for which they do not know the exact destination sector. Second, being an industry association, the IFR has to comply with antitrust regulations. Therefore, they are not allowed to provide a number if it does not contain data from at least four independent companies. If a data point is non-compliant, the IFR reclassifies it to "unspecified" and reports "0" in the original cell. Note that these robots are still included in the upper-level stock. For example, robots assigned to the category "279 - Electrical/electronics unspecified" are included in "26-27 - Electrical/electronics" and in "D - Manufacturing". In this sense, there is a trade-off between precision and the number of categories we can ex-

[8] An alternative data source for robot adoption could have been the "Survey on Business Strategies", ESEE (SEPI Foundation, 2022). Koch et al. (2021) compared data from ESEE and IFR for manufacturing firms concluding that they show a high degree of similarity. We decided to use the IFR because it has a more precise and stringent definition of how to define a robot and it is based on surveys of robot suppliers, while in the ESEE Spanish firms are asked whether they adopt robots or not.

[9] In fact, for some country-sector pairs the data start later. For our analysis we need robot data for the 1999-2016 period. For Spain, one sector ("35-39") has data starting from 2002, four sectors ("01-03," "05-09," "19-21," and "22") have data starting from 2004, and one sector ("27") starts in 2005. Given that this issue concerns five sectors out of the 19 we consider and that three of them are non-manufacturing (hence they involve few robots anyway), we prefer to set the number of robots to zero for these sector-year pairs and start our analysis from 2001, as the early 2000s are particularly interesting when studying displacement from manufacturing sectors. Table 2A.1 in the Appendix reports the year of start by sector for Spain and the countries we use (or considered using) as instruments.

Table 2.1: IFR categories and aggregation schemes

Code	Name	15 Gr.	17 Gr.	19 Gr.	20 Gr.
A-B	Agriculture, forestry, fishing	01–03	01–03	01–03	01–03
C	Mining and quarrying	05–09	05–09	05–09	05–09
D	Manufacturing				
10–12	Food and beverages	10–12	10–12	10–12	10–12
13–15	Textiles	13–15	13–15	13–15	13–15
16	Wood and furniture	16, 31	16, 31	16, 31	16, 31
17–18	Paper	17–18	17–18	17–18	17–18
19–22	Plastic and chemical prod.	19–22	19–22		
19	Pharmaceuticals, cosmetics	19–22	19–22	19–21	19
20–21	Other chemical prod. n.e.c.	19–22	19–22	19–21	20–21
22	Rubber and plastic prod.(non-autom.)	19–22	19–22	22	22
229	Chemical prod., unspecified				
23	Non-metallic mineral prod.	23	23	23	23
24–28	Metal	24, 25, 28			
24	Basic metals	24, 25, 28	24	24	24
25	Metal prod. (non-autom.)	24, 25, 28	25	25	25
28	Industrial machinery	24, 25, 28	28	28	28
289	Metal, unspecified				
26–27	Electrical/electronics	26–27	26–27		
275	Household/domestic appliances			27	27
271	Electrical machinery n.e.c. (non-autom.)			27	27
260	Electronic components/devices			26	26
261	Semiconductors, LCD, LED			26	26
262	Computers and peripheral equipment			26	26
263	Communication equipment			26	26
265	Medical, precision, optical instrum.			26	26
279	Electrical/electronics unspecified				
29	Automotive	29	29	29	29
291	Motor vehicles, engines and bodies				
293	Automotive parts				
2931	Metal (AutoParts)				
2932	Rubber and plastic (autom. parts)				
2933	Electrical/electronic (autom. parts)				
2934	Glass (autom. parts)				
2939	Other (autom. parts)				
2999	Unspecified autom. parts				
299	Automotive unspecified				
30	Other vehicles	30	30	30	30
91*	All other manufacturing				
E	Electricity, gas, water supply	35–39	35–39	35–39	35–39
F	Construction	41–43	41–43	41–43	41–43
P	Education/research/development	72, 85	72, 85	72, 85	72, 85
90*	All other non-manufacturing				
99*	Unspecified				

Notes: "*" indicates residual categories whose robots are excluded from all aggregation schemes.

ploit for identification. Finally, we exclude residual categories "90 - All other non-manufacturing branches", "91 - All other manufacturing branches", and "99 - Unspecified" from all aggregation schemes, as it is impossible to assign their robots to any specific sector.

Secondary data sources are: (1) *Instituto Nacional de Estadistica* (INE), from which we take the number of employees by sector in 1995, the share of urban population by province, and the share of employment in manufacturing by province; (2) EU-KLEMS (version 2017) from which we take investments in information and communication technologies (ICT); (3) UN-Comtrade, from which we take imports from China; (4) Eurostat, from which we retrieve the Harmonized Index of Consumer Prices (2015 = 100) and the average working days per month by country; and (5) the World Bank, from which we collect the Consumer Price index for the US (2010 = 100).

2.3.1 Measures of earnings and education

Our measure of labour earnings is derived from the base used to calculate Social Security contributions. This corresponds to monthly labour earnings, excluding other compensation payments (e.g., extra hours, death or dismissal compensations, travel and other expenses). For employees, this generally coincides with the actual average monthly remuneration, although this may not be the case for self-employed workers and workers registered with special regimes or agreements (Seguridad Social, 2021). Contribution bases are top and bottom-censored, with maximum and minimum caps varying over time and across occupation groups, also following the evolution of the minimum wage and inflation rate. We deflate earnings using the Eurostat Harmonized Index of Consumer Prices with base 2015. We compute daily wages as the ratio between the monthly contribution base and the number of "effective" days worked in a specific month. Effective days are computed as the product between the number of natural working days and the part-time coefficient.[10] For each transition analysed, we look at two measures of earnings: the mode of the earnings in the last 12 months before termination of the old job and the mode of the earnings in the first 12 months of the new job. If a job lasts $n < 12$ months, we take the mode in the n months. Rather than using contribution bases, we could extract earnings from tax records. We prefer contribution bases to tax records for three reasons. First, tax files are only available for the year of reference, hence we could not go back to 2001. Second, tax records are unavailable for many work spells, as there are several exceptions to employment incomes that must be included in the tax return. Third, tax records are unavailable for the Basque Country and Navarra, which used to have high shares of employment in manufacturing and are therefore of particular interest for this analysis.

Since records on the educational level of workers reported in the MCVL are unreliable, we divide workers into two skill groups based on the contribution category assigned to their previous job by the Social Security. Following De la Roca and Puga (2017), we consider five skill groups: (1) Very-high-skilled

[10]The MCVL does not report the number of hours worked, so we are unable to compute exact hourly wages. However, the panel includes a "part-time coefficient", which indicates the hours worked by the employee as a fraction, expressed in thousandths, of the usual full working day in the company. We assume a regular working day of 8 hours and adjust the monthly number of hours worked accordingly.

("Engineers, graduates and senior management"); (2) High-skilled ("Technical engineers, technicians and assistants" and "Administrative and workshop managers"); (3) Medium-high-skilled ("Non-graduate assistants," "Administrative officers," and "Subordinates"); (4) Medium-low-skilled ("Administrative assistants," "First and second officers," and "Third officers and specialists"); and (5) Low-skilled ("Unskilled (over 18)"). We then categorize workers whose previous occupation was in the first three groups as high-skilled (HS), while the last two groups are coded as middle- and low-skilled (MLS).

2.3.2 Sample restriction

We focus only on transitions to different employers following involuntary dismissals.[11]

This sample restriction involves two layers: (1) we focus on workers who change employer and exclude those who stay in the same firm; (2) we focus on workers who face an involuntary dismissal and exclude those who leave voluntarily and those who face the "natural" termination of their temporary employment contract.[12] While being aware that this sample restriction is hardly innocuous, we believe that it is the best approach to address our main research question, i.e., whether workers displaced from sectors with an increasing density of robots are re-employed in jobs of lower quality compared to workers dismissed from less exposed sectors. Regarding the first layer, as we do not want to analyse the overall effect of robots on all exposed workers but rather the impact on the "losers", we believe that restricting the analysis to those who leave reduces the risk of overlooking their losses, which might be obscured by the gains of the winners. As for the second layer, it is well known that workers facing involuntary dismissals differ from those who leave voluntarily. It is generally assumed that an involuntary dismissal can be a bad signal for the labour market and can result in worse conditions in the new job. Therefore, a common approach is to focus on plant closures or mass dismissals rather than on single involuntary dismissals. Unfortunately, we do not have enough cases of mass layoffs in our sample to adopt this approach. Therefore, we address concerns regarding the "quality" of workers who are voluntarily or involuntarily dismissed by comparing involuntary dismissals both in the "treated" group (i.e.

[11] The MCVL reports the reason for termination of the contract, and we retain only transitions from jobs with a dismissal coded as "*54 - Baja no voluntaria*" ("54 - Non-voluntary leave") by the Spanish Social Security.

[12] To make sure that our results are not driven by what could considered a hardly innocuous sample restriction, we perform a robustness check in which we repeat the regressions for transitions following a voluntary leave. See Section 2.7.

workers exposed to robots) and the "control" groups (i.e. workers in the less exposed sectors). In other words, we investigate whether there is a further penalty when the dismissal is due to exposure to automation.

Of course, it can be correctly argued that workers might voluntarily leave "early" in response to their firm announcing the plan to adopt robots. This process is likely to be selective, with more productive workers tending to be the ones who leave earlier. Hence, any estimated negative effects might overestimate the actual impact of robots on workers. For this reason, we never claim to estimate the overall effect of robots on workers but specifically restrict the interpretation of our results to the subgroup of workers who are involuntarily dismissed. Furthermore, we run several robustness checks in which we consider different causes for contract termination, including voluntary leave (see Section 2.7).

In our sample restriction we diverge from the papers that are closer to our study. We differ from Dauth et al. (2021) and Dottori (2021), as they look at changes in employer, but they do not restrict their analysis to involuntary dismissals. Consequently, they analyse global adjustments to the rise of industrial robots. Other papers consider a more limited sample of workers: while we consider workers in all sectors and firm sizes, Bessen et al. (2020) retain firms with automation cost data and with at least 50 employees; Koch et al. (2021) use only private sector workers aged 25-60, experiencing non-employment over more than 3 weeks; and Cortes (2016) restrict his analysis to male household heads, aged 16 to 64 and look at wages of those who are back to work.

Besides the main sample restriction, we perform a series of minor adjustments. First, we exclude all transitions to/from self-employment, because contribution bases for the self-employed may differ greatly from true labour-earnings. Second, we drop transition to/from spells whose daily earnings exceed the maximum base or are below the minimum base imposed by the Social Security.[13] Third, we drop very short spells (<30 days) and transitions (to/from spells) with missing or invalid information in any of the variables included in the regression. Finally, we only consider individuals aged 18 to 60, and we drop the top 1% of individuals by number of spells for computational reasons.

[13] We decide to drop these observations as any value exceeding the maximum or minimum base imposed by the Social security are most likely due to errors in the administrative data.

2.3.3 Descriptive statistics

Table 2.2 provides a descriptive overview of the estimation sample. About 41% of the transitions are to a job with lower pay and the majority are related to temporary contracts, especially for the MLS.[14,15] Almost half of all transitions involve a change of 1-digit sector, while the share of transitions to a different province is much lower: 15.3% for MLS workers and 21.4% for HS workers. The highly skilled are significantly more likely to transition to a job with lower qualifications. As for the correlation with the main dependent variable, the probability of transitioning to a job with lower pay is higher for those changing sectors, for contracts starting during the Great Recession, for temporary contracts, and for transitions from manufacturing. [16]

Figure 2.2 plots the flows across all 1-digit sectors (left panel) and within manufacturing (right panel). About 57% of the flows from "C - Manufacturing" are directed to other sectors. Among them, those receiving the largest flows are "N-Administrative and Support Service Activities" (12.74%), "G - Wholesale and retail trade" (12.84%), and "F - Construction" (12.31%). Quite worryingly, a large number (8.7%) of workers displaced from manufacturing end up in sector N's subsection "782 - Temporary employment agency activities".[17] The percentage of workers flowing into "N-Administrative and Support Service Activities" is highest in sectors with high robot density, i.e., "29 - Automotive" (22.19%) and "22-Rubber" (20.80%). Interestingly, a large fraction of the flows from "N - Administrative and Support Service Activities" are also towards "C - Manufacturing" (12.94%) and "G - Wholesale and retail trade" (12.51%), suggesting that, at least for some workers, employment through temporary employment agencies might be a transitional step.[18] The left panel of Figure 2.2 shows that workers who find a new job in manufacturing mostly remain in

[14] We compare the mode of earnings in the last 12 months before termination of the old job and the mode in the first 12 months of the new job.

[15] Since we focus on involuntary dismissals, temporary contracts tend to be overrepresented in our sample, as these contracts have lower termination costs. Still, Spain is the EU country with the highest share of temporary employment. At the beginning of our observation period, i.e., 2001, 32.2% of total dependent employment was temporary, against an EU27 average of 13.4% (OECD, 2021). We refer the interested readers to Dolado et al. (2002) for a thorough analysis on the extensive use of temporary employment contracts in Spain.

[16] Interested readers can find a balancing analysis in Appendix Table 2A.2.

[17] Workers employed through temporary employment agencies have been found to experience worse working conditions and receive lower compensation and less training than employees with a standard employment contract (Nienhüser and Matiaske, 2006).

[18] It is important to remark that the MCVL records industry at the firm level. Hence, part of the mobility between sectors could be explained by the specific occupation of the worker within the firm, which, unfortunately, we do not observe. For instance, it would not be too surprising if a worker employed within the retail department of an automotive firm

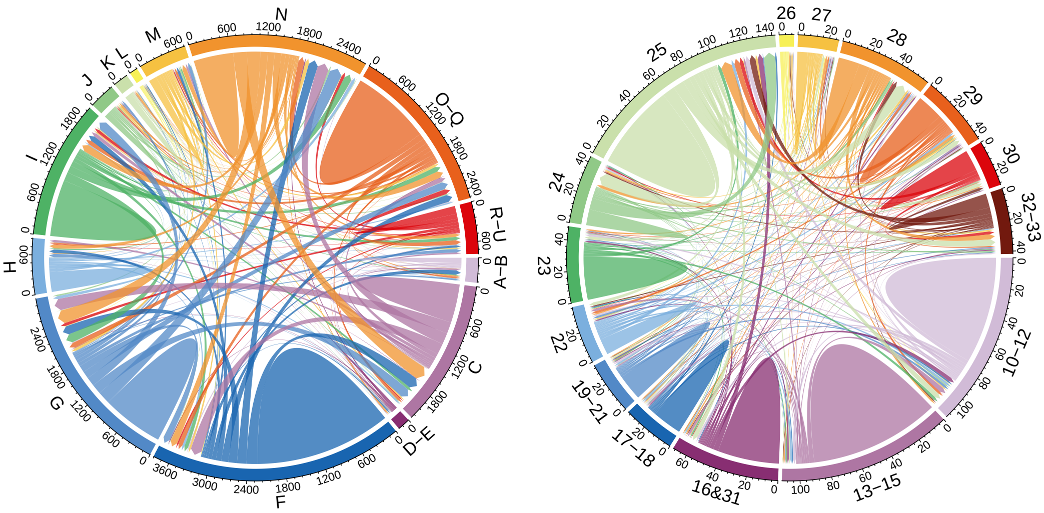
Table 2.2: Summary statistics, transition level

Qualitative	MLS		HS		Total	
	%	Corr.	%	Corr.	%	Corr.
Worse pay	41.19		40.24		40.96	
Worse security	8.25	-0.002	10.92	0.081	8.87	0.019
Lower skill	10.78	0.069	34.65	0.186	16.36	0.098
Employed in ETT firm	4.93	0.012	2.40	0.028	4.34	0.016
Female	36.24	-0.013	53.22	0.025	40.21	-0.005
Change sector	47.82	0.058	42.08	0.107	46.48	0.070
Change NUTS3	15.31	0.018	21.43	0.007	16.74	0.015
Temporary contract (prev.)	83.21	0.046	57.71	0.090	77.25	0.058
Manufacturing (prev.)	11.98	0.022	5.86	-0.007	10.55	0.017
Birth Place						
Spain	80.72	-0.011	91.44	-0.012	83.23	-0.012
Centre and South America	8.03	0.009	3.82	0.010	7.05	0.010
EU28	4.69	-0.000	3.06	0.006	4.31	0.001
Africa	4.58	0.006	0.71	0.002	3.67	0.006
Other	1.99	0.004	0.97	0.002	1.75	0.004
Year of start						
2001 - 2003	18.95	-0.008	16.81	-0.051	18.45	-0.017
2004 - 2006	25.09	-0.032	21.06	-0.054	24.15	-0.036
2007 - 2009	23.39	-0.004	22.30	-0.020	23.13	-0.008
2010 - 2012	18.18	0.032	21.74	0.061	19.01	0.039
2013 - 2015	9.22	0.021	11.89	0.060	9.84	0.031
2016 - 2018	5.17	0.002	6.19	0.019	5.41	0.006
Quantitative	MLS		HS		Total	
	Mean	Corr.	Mean	Corr.	Mean	Corr.
Pay ratio	111.308	-0.633	108.243	-0.612	110.592	-0.627
Δ robots	0.080	0.024	0.030	-0.008	0.068	0.019
Δ imports from China	0.076	0.004	0.038	-0.001	0.067	0.003
Δ ICT stock	0.386	-0.002	0.565	0.000	0.428	-0.002
Age	34.622	-0.011	35.954	-0.046	34.933	-0.019
Weeks unemployed	33.591	-0.028	28.062	0.056	32.299	-0.010
Unobs. ability	-0.043	0.038	0.055	0.029	-0.020	0.035
N	1,065,354		324,876		1,390,230	

Source: authors' own calculations. *Notes*: summary statistics on the estimation sample. Statistics on the 1-digit sector and NUTS2 area of the previous occupation are not included in this table but can be found in Figure 2.2 and 2.3, respectively. Columns "Corr." report the correlation between each variable and the dummy for "Worse pay".

Figure 2.2: Flows by sector (NACE Rev.2 codes)

(a) Across 1-digit sectors (b) Within manufacturing



Source: authors' own calculations. *Notes:* summary statistics on the estimation sample. Flows are reported in hundreds of transitions. 1-digit sectors: "A-B - Agriculture and mining", "C - Manufacturing", "D-E - Energy, water and waste", "F - Construction", "G - Wholesale and retail trade; repair of motor vehicles", "H - Transporting and storage", "I - Accommodation and food", "J - Information and communication", "K - Finance and insurance", "L - Real estate", "M - Professional, scientific and technical activities", "N - Administrative and support services", "O-Q - Public administration and defence, compulsory social security, education and social work", "R-U - Arts, entertainment and other services". 2-digit manufacturing sectors: "10-12 - Food and beverages", "13-15 - Textiles", "16&31 - Wood and Furniture", "17-18 - Paper", "19-21 - Refined petroleum, chemical and pharmaceutical products", "22 - Rubber", "23 - Non-metallic mineral products", "24 - Basic metals", "25 - Metal products", "26 - Computer, electronic and optical products", "27 - Electrical equipment", "28 - machinery and equipment n.e.c.", "29 - Motor vehicles, trailers and semi-trailers", "30 - Other transport equipment", "32-33 - Other manufacturing, repair and installation".

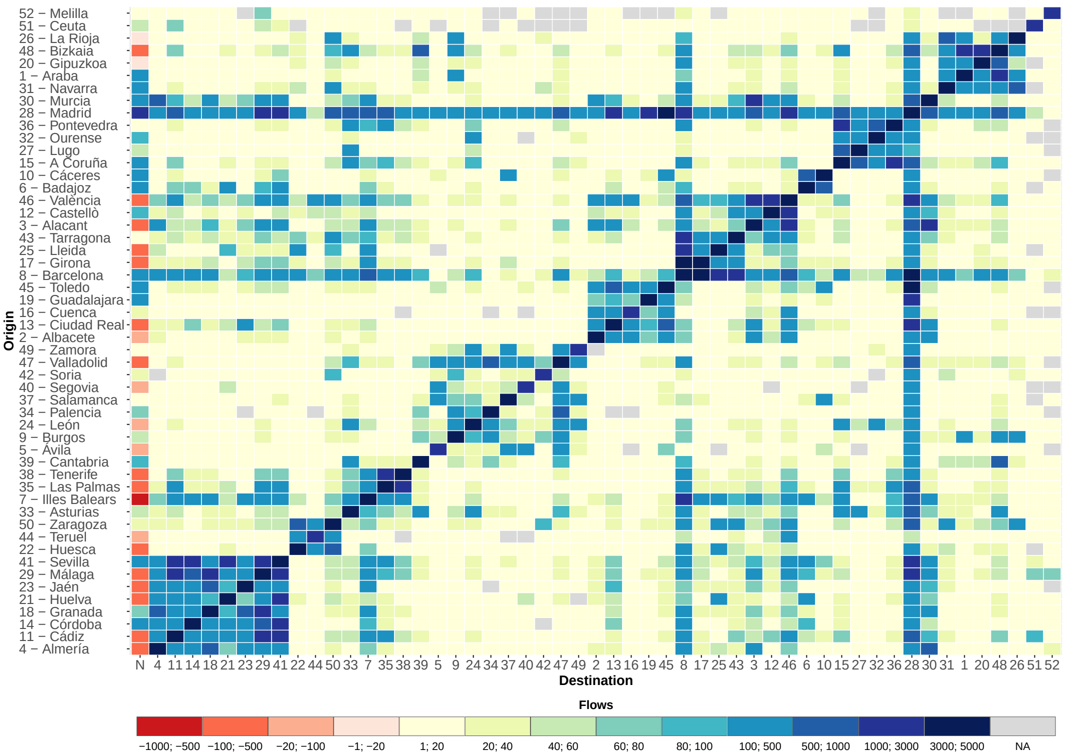
the same 2-digit sector. Geographic relocation appears to be far less common than sectoral relocation and it is less correlated with worse pay. From Figure 2.3 it is clear that most transitions occur within the same province or between provinces of the same *Comunidad Autonoma*. Notable exceptions are flows to/from Madrid and Barcelona.

2.4 Empirical Approach

The focus of the analysis is on individuals who are involuntarily dismissed at least once in the observation window. For every transition i of a worker w previously employed in sector s, being dismissed at time t and finding a new

found a new job in a retail company rather than in another automotive company after being dismissed.

Figure 2.3: Flows by province



Source: authors' own calculations. *Notes:* summary statistics on the estimation sample. For each row, column "N" reports the net inflows by province, while columns 1-52 report bilateral flows.

job at time τ, the equation of interest is:

$$\begin{aligned} Y_{wist\tau} \; = & \; c \; + \; \beta \cdot \Delta Exp_{s,t-1} \; + \; \pi \cdot \Delta Trade_{s,t-1} \; + \; \mu \cdot \Delta ICT_{s,t-1} \; + \\ & \boldsymbol{\Omega_0 \cdot X_{i,\tau}} \; + \; \eta_0 \cdot \theta_\tau \; + \; \lambda_0 \cdot NUTS2_{i,t} \; + \; \psi_0 \cdot Sector_{i,t} \; + \\ & \varphi_0 \cdot Contract_{i,t} \; + \; \kappa \cdot \Delta NUTS3_i \; + \; \nu \cdot \Delta Sector_i \; + \\ & \iota \cdot \Xi_w \; + \; \epsilon_{wist\tau} \end{aligned} \tag{1}$$

Dependent variables and skill groups

We consider five outcomes $Y_{wist\tau}$: (1) a binary indicator capturing whether the new job offers a lower daily pay than the previous job; (2) the ratio ($\times 100$) of the current pay over the previous pay; (3) a dummy for whether the current job requires lower qualification than the previous job;[19] (4) a dummy for whether the new job has a temporary contract (restricting the sample to transitions from jobs with permanent contracts); and (5) a dummy for whether the new job is with a temporary employment agency ("*Empresa de trabajo temporal*," ETT). As we expect the effect of robot exposure to vary greatly across skill groups, we perform all regressions separately for high-skilled versus middle- and low-skilled workers.

Exposure to robots

The change in exposure to industrial robots is measured as:

$$\Delta Exp_{s,t-1} = \frac{robots_{s,t-1} - robots_{s,t-2}}{employment_{s,1995}} \tag{2}$$

For every sector s, $robots_{s,t-1}$ ($robots_{s,t-2}$) is the total stock of robots in year $t-1$ ($t-2$), with t being the year in which the worker is displaced, while $employment_{s,1995}$ captures the sector size in 1995, measured in thousands of workers. Figure 2.4 reports the variation in robot adoption in Spain by sector and year: the great majority of installations are in manufacturing, especially in the automotive sector and there is a strong cyclical component, with lower values during the Great Recession.

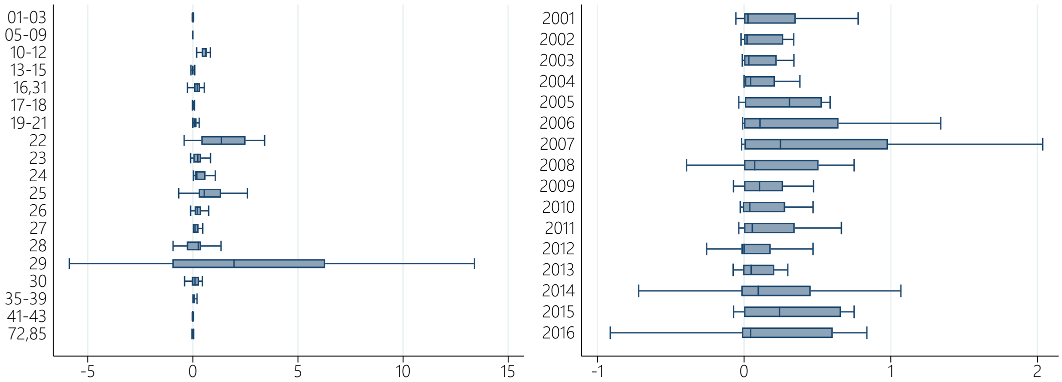
Clearly, robot adoption is not an exogenous random shock. Although NUTS3 region and broad sector fixed effects can purge certain trends, the coefficient

[19] This variable is *not* based on the two-group skill variable ("1: High-skilled" and "2: Middle- and low- skilled") but rather on the five-group variable ("1: Very high-skilled," "2: High-skilled," "3: Medium-high-skilled," "4: Medium-low-skilled," and "5: Low-skilled"). Hence, a person can transition from a high-skilled to another high-skilled job, but still have a skill-downgrading (e.g. from "1: Very-high-skilled" to "2: High-skilled" or "3: Medium-high-skilled").

Figure 2.4: Variation in robot adoption in Spain

(a) Variation by sector

(b) Variation by year



Source: authors' own calculations.

of interest, namely $\Delta Exp_{s,t-1}$, only captures the causal effect of robots when there are no parallel confounding unobservable shocks affecting both robot installations and labour market outcomes. To address this concern, we adopt an instrumental variable approach similar to the one used in Autor et al. (2013b), Acemoglu and Restrepo (2020), and Dauth et al. (2021). While these studies use a Bartik approach with robot installations across industries in other European countries to derive local labour market exposure, we adopt the measure of robot exposure affecting workers at a given sector and time. More precisely, we take the average robot adoption in Germany, France, Italy, and the UK. In this way, we try to capture robot adoption induced by exogenous improvements in technology and by the necessity to keep up with international competitors. We chose these countries as they have robot data for the whole period of interest, and they have similar socio-economic characteristics to Spain. As alternatives, among the countries that have available data for the whole period of interest, we also considered a group of Nordic countries (Norway, Finland, Sweden, and Denmark) and Japan. We did not consider the US as a possible instrument, because robot data for the US are unavailable for the early 2000s (see Appendix Table 2A.1). Figure 2A.1 in the Appendix plots the evolution of robot density across time for Spain and the instrument countries. Table 2A.3 reports several statistics on the suitability of the various instruments considered. Based on this table we chose not to use the Nordic countries or Japan as instruments. Finally, Table 2A.4 displays the OLS estimates and the 2SLS results showing that the correction of any bias is in fact enlarging the negative impact of robotisation, as the local measure of robotisation might be correlated with some reinstatement effect.

The role of the adjustment mechanisms is captured by replacing $\Delta Exp_{s,t-1}$ with its interaction with a binary indicator for sectoral or geographic relocation, i.e. $\Delta Exp_{s,t-1} \cdot \Delta NUTS3_i$ or $\Delta Exp_{s,t-1} \cdot \Delta Sector_i$, respectively.[20] Note that, as relocation is an endogenous response to the automation shock, we do not claim any causality for this part of the analysis. Nevertheless, we think it is still interesting to assess whether there are significant differences between the stayers and the leavers.

Controls
$\Delta Trade_{s,t-1}$ captures trade exposure by means of the change in net imports from China in sector s between year $t-1$ and $t-2$, while $\Delta ICT_{s,t-1}$ controls for investment in information and communication technologies (ICT), namely the change in real fixed capital stock per worker for ICT equipment in the same period. $\boldsymbol{X_{i,\tau}}$ is a matrix of basic worker-spell characteristics: gender, country of birth, age on the day of start of the new job, and length of the unemployment spell.[21] θ_τ is a set of fixed effects for the year in which the new job starts. $NUTS2_{i,t}$, $Sector_{i,t}$ and $Contract_{i,t}$ are sets of fixed effects referring to the previous job: NUTS2 region, 1-digit industry, and type of contract, i.e., permanent or temporary. Finally, $\Delta NUTS3_i$ and $\Delta Sector_i$ are binary indicators for whether the new job is in a different 1-digit sector or NUTS3 area than the previous job.

Unobserved ability
Despite the socio-economic controls included in the regression, individuals may still differ in their unobserved characteristics. To deal with this issue, we use a two-step procedure. First, for every job j held by worker w we estimate the following Mincerian wage regression:

$$\begin{aligned} ln(earning_{wj}) = {} & \alpha + \Xi \cdot \zeta_w + \\ & \pi \cdot Age_{wj} + \sigma \cdot Unempl_{wj} + \xi \cdot Tenure_{wj} + \\ & \varphi \cdot Skill_{wj} + \omega \cdot FullPart_{wj} + \nu \cdot Stab_{wj} + \\ & \rho \cdot YearStart_{wj} + \mu \cdot Sector_j + \lambda \cdot NUTS3_j + \\ & \psi \cdot NumWorkers_j + \epsilon_{wj} \end{aligned} \tag{3}$$

[20] We proxy local labour markets with Spanish provinces (NUTS3). This is not an uncommon choice, see Melguizo and Royuela (2020) and Diaz-Serrano and Nilsson (2020).

[21] We consider five categories for country of birth: Spain, Center and South America, EU28, Africa, and "other". In a few cases country of birth is missing while nationality is available. For these individuals we proxy the country of birth with nationality.

The dependent variable $ln(earning_{wj})$ is the natural logarithm of job earnings. For each job we use the mode of daily earnings in the last 12 months before termination. ζ_w is a worker-specific indicator capturing the worker's fixed effect. Age_{wj}, $Unempl_{wj}$, and $Tenure_{wj}$ are continuous worker-job controls: age at the beginning of the job, number of weeks unemployed between this spell and the previous spell, and total number of days in the job. $Skill_{wj}$, $FullPart_{wj}$, $Stab_{wj}$, and $YearStart_{wj}$ are categorical worker-job controls, i.e., skill group, a binary indicator for whether the job is full-time (*vs.* part time), a binary indicator for the type of contract (permanent *vs.* temporary), and a set of fixed effects for the year of the start of the job. Finally, $NUTS3_j$ and $Sector_j$ are sets of fixed effects for NUTS3 region and 2-digit industry, respectively, while $NumWorkers_j$ is a control for the number of workers employed in the firm. Note that to estimate this regression, we use each worker's whole working history (without restricting our sample to the 2001-2017 window), but we only keep spells that are at least 30 days long. The individual parameter (Ξ) associated to every worker fixed effect ζ_w should capture workers' unobserved ability. Therefore, the second step of the procedure is to include Ξ as an additional control in Equation 1. While previous literature has found a non-negligible role of firm sorting in the overall variance of log-earnings (Abowd et al., 1999; Card et al., 2018), the importance of this mechanism has been lessened in more recent studies (Abowd et al., 2019; Bonhomme et al., 2023). Overall, we believe that any remaining bias in our proxy of workers' unobserved ability will be captured by the set of controls in Equation 1.

2.4.1 Medium-term effects

The baseline analysis compares each job to the one coming immediately after. As such, it looks at the short-term effect of automation exposure on displaced workers. Arguably, any effect estimated by the baseline model, whether positive or negative, might be a temporary condition and the worker might converge back to the previous condition in the medium- to long-term. To investigate this hypothesis, we adopt the same approach as in Equation 1 but, rather than looking at the workers' next job, we consider their condition after n months, with $n \in \{3, 6, 12, 24, 36\}$.[22] For this analysis we also consider additional outcomes: (1) a dummy for working (either as an employee or self-employed); (2) a dummy for being unemployed (with benefits); (3) a dummy

[22] If the worker has more than one job in month n we consider the job providing the highest total earnings. In the case of ties, we take the job that lasted longer and then the job ending later.

for being out of the Social Security records (i.e., unemployed without benefits, out of the labour force, or working outside of Spain); (4) the number of contracts since dismissal; (5) the number of employers since dismissal; (6) the number of effective days worked in the n-th month; (7) a dummy for having lower total earnings (summing up work earnings and Social Security contributions); and (8) the ratio of total earnings in month n over the month before dismissal. In this way we hope to get a more complete picture of workers' conditions in the medium run in terms of earnings and employment stability.

2.5 Results

This section presents and discusses the empirical results for the short-term (Section 2.5.1) and for the medium-term (Section 2.5.2)

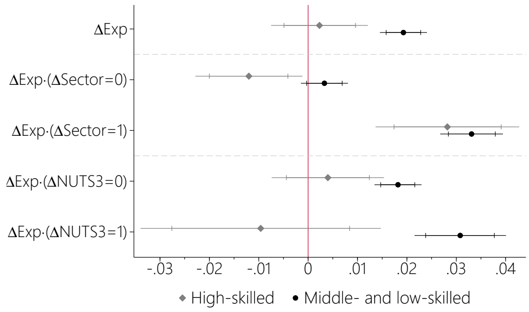
2.5.1 Short-term

We analyse the impact of job displacement using the specification of Equation 1 and we report the results of our regressions in Figure 2.5. The dependent variable in Panel 2.5a is a dummy for whether the new job offers a lower pay. Less-skilled workers displaced from sectors with higher exposure to robots face a higher probability of lower-paid re-employment, compared to workers displaced from less exposed sectors. Overall, one additional robot per 1,000 workers in the sector increases the probability of ending up in a lower-paid job by roughly 1.9 percentage points. The penalty is significantly higher for those whose new job is in a different sector, while migration does not seem to offer any protection. These results are consistent with previous findings: Lee and Wolpin (2006) report substantial sectoral mobility costs, both physical and monetary, at the individual level and Huttunen et al. (2018) report that regional mobility is not always an effective strategy to cope with job losses. In general, the highly-skilled appear to be less affected by robot exposure. However, there is considerable heterogeneity in their outcomes depending on the adjustment mechanisms they adopt. Exposure to robots lowers the probability of getting a lower-paid job for those who stay in the same sector, as they neither face mobility costs nor lose their accumulated work experience in the origin sector (Lee and Wolpin, 2006). On the contrary, workers who switch sectors suffer a significant penalty. Our baseline results do not show a significant difference in outcomes associated with geographic relocation.

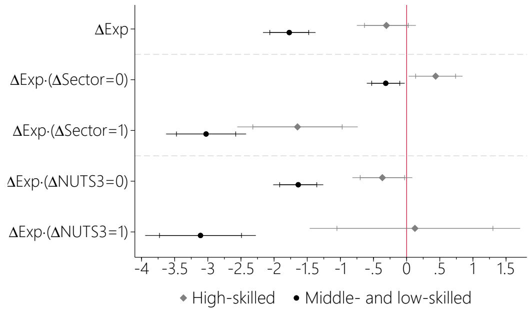
While a binary indicator has the advantage of clearly separating those scoring better or worse than before, a continuous measure of pay differentials allows

Figure 2.5: Effect of exposure to industrial robots on pay, employment security and qualification

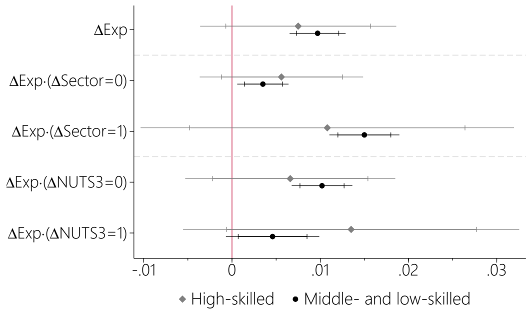
(a) Probability of lower pay



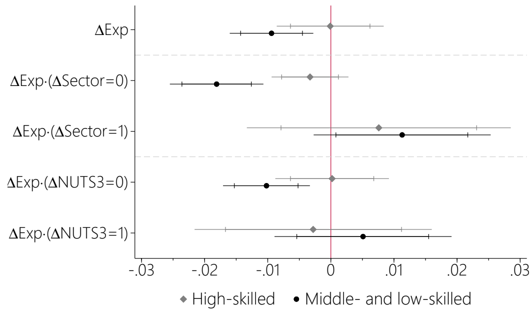
(b) Ratio of new pay over previous pay



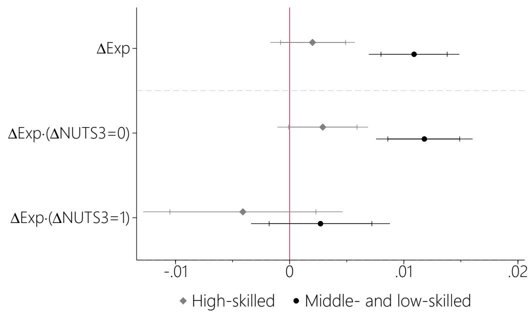
(c) Probability of lower qualification



(d) Probability of temporary contract



(e) Probability of being in ETT



Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal. Confidence intervals are reported both at the 95% (vertical bars) and 99% (horizontal lines) level. The sample size is 1,065,354 for middle- and low-skilled and 324,876 for high-skilled in Panel 2.5a, 2.5b and 2.5c. Panel 2.5d focuses on transitions from jobs with a permanent contract, hence the sample size is 172,629 for middle- and low-skilled and 114,843 for high-skilled. Panel 2.5e has a reduced sample too: 993,696 for MLS and 321,478 for HS. Olea and Pflueger (2013) first-stage F-Stat. is 409.6 (169.6) for middle- and low-skilled (high-skilled) in Panel 2.5a, 2.5b, and 2.5c; 274.3 (142.2) in Panel 2.5d; and 409.9 (169.6) in Panel 2.5e.

for a better understanding of the impact of robot exposure on individuals' re-employment prospects. Therefore, Panel 2.5b reports the estimates for the ratio of the previous pay over the new one ($\times 100$). The results mirror those of the binary indicator, with exposure having a worse effect for less skilled workers and reallocation to a different sector being the worst adjustment mechanism for both groups. However, while geographic reallocation makes no difference for highly skilled, it results in worse outcomes for middle- and low-skilled workers. This is in line with the results in Huttunen et al. (2018), who find that displaced movers see a larger decrease in earnings than displaced stayers, even though movers might be positively selected. We estimate that for middle- and low-skilled workers the effect of one additional robot on the wage ratio ranges between -0.3 points ($\Delta Exp \cdot (\Delta Sector = 0)$) and 3.1 points ($\Delta Exp \cdot (\Delta NUTS3 = 1)$).

In a first attempt to isolate the mechanisms through which automation leads to lower pay for displaced workers, Panel 2.5c looks at the effect of robot exposure on the probability of being re-employed in a job requiring a lower qualification. Despite the small coefficients, there seems to be some evidence that middle- and low-skilled exposed workers tend to downgrade in the new occupation, especially when moving to a different sector, which might explain the lower pay. No such effect is detected for high-skilled workers, which might signal more transferable accumulated work experience across sectors. Contrary to what we observed in Panel 2.5b for lower pay, spatial adjustment (migration) is not significantly associated with a higher probability of re-employment in a new job requiring lower qualifications, while stayers do suffer such a penalty.

Another dimension of job quality is employment security. Panel 2.5d explores whether exposed workers are more likely to be re-employed in jobs offering a less stable contract (i.e., a temporary contract), while Panel 2.5e investigates the probability of being re-employed in an ETT firm. As we are interested in observing whether workers are worse off than before, for Panel 2.5d we restrict the sample to individuals who had a permanent contract in the previous job, while for Panel 2.5e we only consider those who were not displaced from ETT firms. Starting from the downgrading from a permanent to a temporary contract, no effect is detected for high-skilled workers, while exposed middle- and low-skilled workers seem to be *less* likely to switch from a permanent to a temporary contract if compared to similar workers with a lower exposure. When interpreting these seemingly counter-intuitive results, it is important to highlight that the effect is driven by workers who stay in the same sector and, to a lesser extent, in the same region. This is in line with the argument that workers who stay employed in sectors and regions more exposed to robots enjoy some of the benefits stemming from automation. Furthermore, note that only a very small subgroup of medium- and low-skilled workers had a permanent contract in the first place (see Table 2.2). Arguably, these are workers with very specific characteristics, which can at least partially explain the different impact that robot exposure has on them. As for employment in ETT firms, exposure increases the probability of switching from a "regular" firm to an ETT firm by about 1.1 percentage points for middle- and low-skilled workers, while, on average, no effect is detected for the highly skilled. Contrary to our observations on the probability of a lower pay, geographic relocation seems to offer some sort of protection from unstable employment, as exposed workers who do not move have a higher probability of being reabsorbed by an ETT firm.

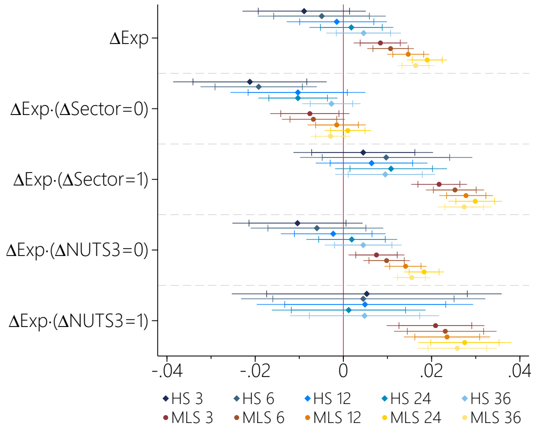
2.5.2 Medium-term

Figure 2.6 reports the regression results for the medium-term analysis. Concerning the five outcomes discussed in the previous section, the main result is that the negative effects we detected in the short-term for middle- and low-skilled workers are persistent over time (Panel 2.6a - Panel 2.6e). The only exception is the probability of being re-employed in an ETT firm, which becomes significantly smaller as months go by (Panel 2.6e).

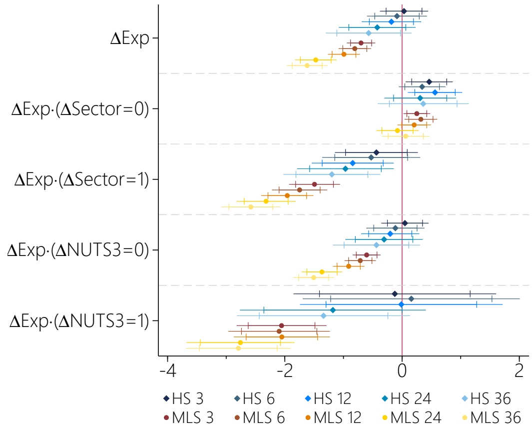
By shifting our focus from the next occupation to the situation after n months, we can also observe how robot exposure affects workers' lives in several other dimensions, such as the fragmentation of their employment history. Even more importantly, we have the chance to say something about those workers who do *not* find a new occupation and thus leave the labour market permanently. Panel 2.6f shows that, while there is no effect for high-skilled workers, middle- and low-skilled workers are less likely to be working (either as employees or as self-employed) after being displaced from a sector with an increasing density of robots. For each additional robot per 1,000 workers in the sector, the probability of being employed is about 0.97 percentage points lower after 3 months and 0.63 p.p. after 6 months. It then becomes insignificant between 12 and 24 months. These dynamics are mirrored in Panel 2.6g, which examines how robot exposure affects the probability of receiving unemployment benefits as the only source of income in month n. Once again, we observe no effect for high-skilled workers, while middle- and low-skilled workers have a higher probability of being unemployed within the first 3 months (1.4 percentage points) and 6 months (0.7 percentage points). Reassuringly, neither

Figure 2.6: Results - Medium term

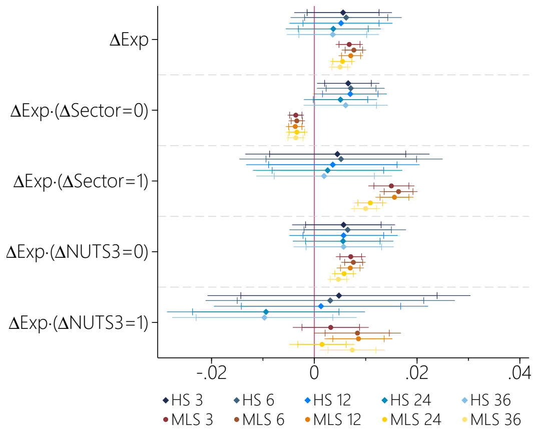
(a) Probability of lower pay



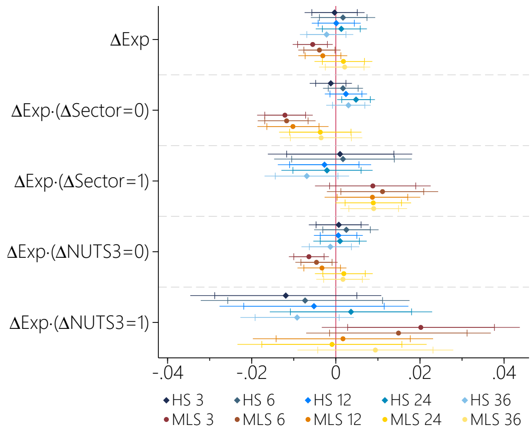
(b) Ratio of new pay over previous pay



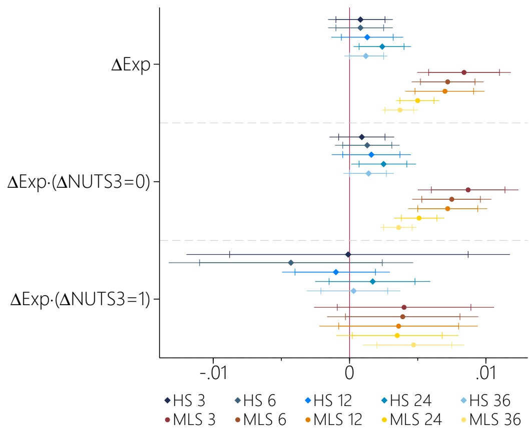
(c) Probability of lower qualification



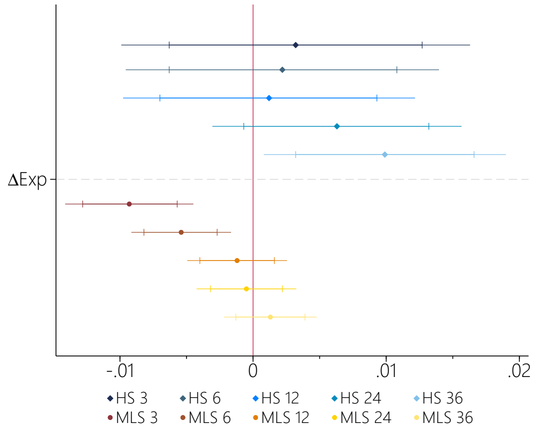
(d) Probability of temporary contract



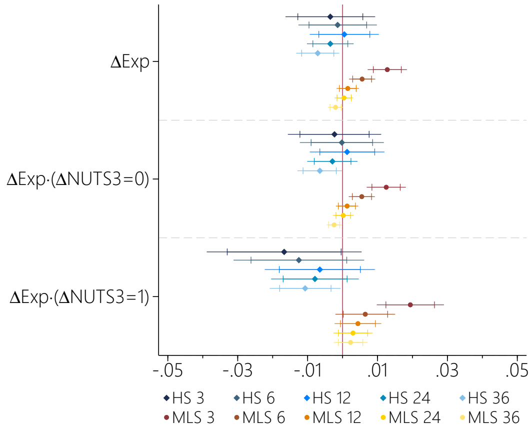
(e) Probability of being in ETT



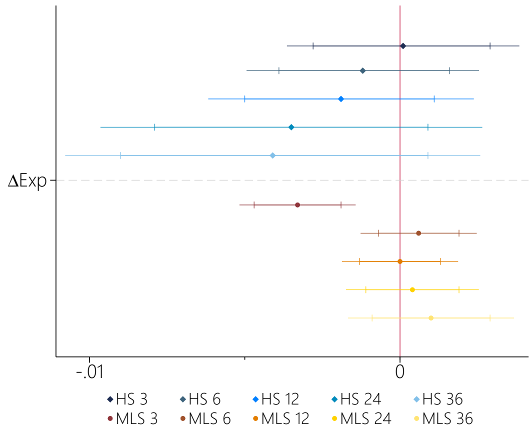
(f) Probability of being working



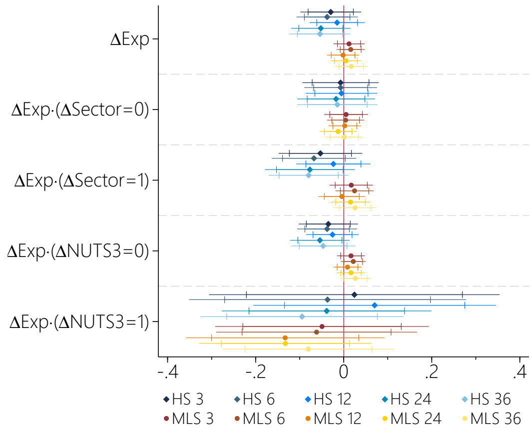
(g) Probability of being unemployed



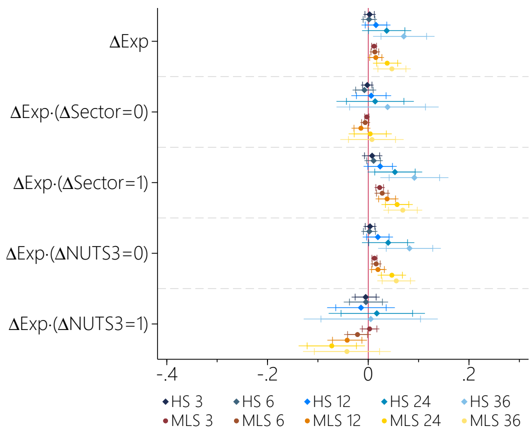
(h) Probability of being out of Seg.Soc.



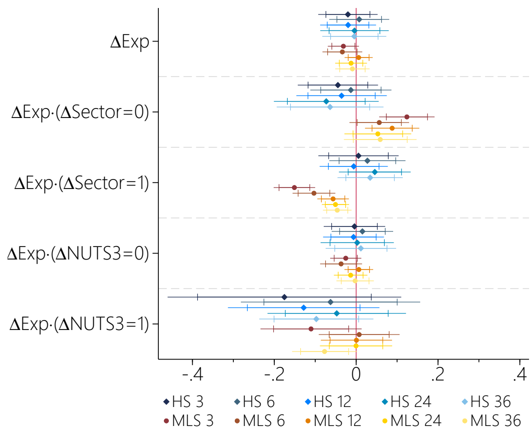
(i) Number of different employers



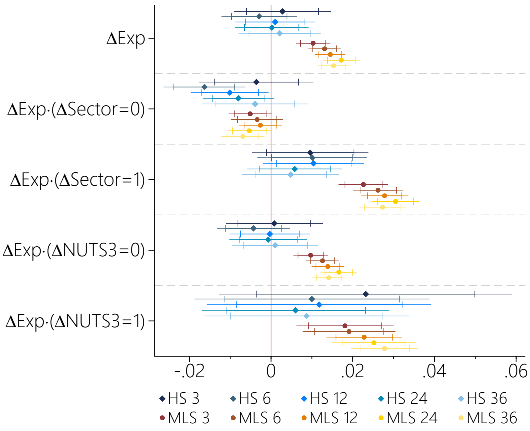
(j) Number of contracts



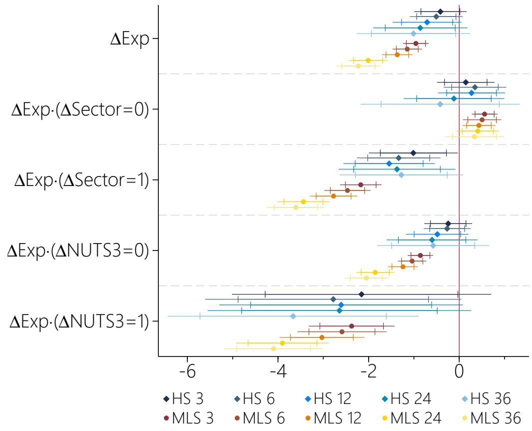
(k) Number of effective days worked in month



(l) Probability of lower monthly earnings



(m) Ratio of monthly earnings (×100)



Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal. Confidence intervals are reported both at the 95% (vertical bars) and 99% (horizontal lines) level.

for high-skilled nor for middle- and low-skilled workers there is an increase in the probability of being completely outside Spain's Social Security umbrella, i.e., neither working nor receiving any sort of benefit (Panel 2.6h). As for employment history fragmentation, exposure to robots seems to have no effect on the number of employers (Panel 2.6i) and a very small effect on the number of total contracts (Panel 2.6j) and number of effective days worked in month n (Panel 2.6k). Once again, there are heterogeneous outcomes for those who manage to remain in the same sector against those who change. Middle- and low-skilled workers who change sectors experience a more fragmented work-life, with multiple contracts and fewer days worked, while workers who remain in the same sector have a lower number of contracts (high-skilled) or higher number of effective days worked in a month (middle- and low-skilled). Finally, Panel 2.6l and Panel 2.6m replicate Panel 2.6a and Panel 2.6b substituting earnings from the main job with total earnings in month n.[23] Even accounting for earnings from multiple jobs and Social Security benefits, exposed middle- and low-skilled workers are still more likely to be worse off in the medium-term.

[23]We trim these earnings at the 5% and 95% levels to make sure our results are not driven by extreme values.

2.6 Heterogeneity

We look at heterogeneity by: gender, age, degree of urbanization, and share of manufacturing employment in 2001. The results are reported in Table 2.3 (lower pay and pay ratio), Table 2.4 (lower skill requirements and less employment security), and Table 2.5 (new employment in ETT).

The first result is that, in general, there are no large and significant differences across the groups considered for high-skilled workers. However, we detect significant differences for middle- and low-skilled workers across all four dimensions considered:

- Gender: Women are more negatively affected by exposure to robots than men, especially in terms of lower pay and probability of being re-employed in an ETT firm. Notably, less skilled women experience a negative effect on pay even when not changing sector ($\Delta Sector = 0$), while men do not. This suggests that, while men who stay employed in automating sectors enjoy some of the benefits of robot adoption, women are somehow excluded from these benefits.

- Age: Middle- and low-skilled workers who are younger than 40 are driving the increase in the probability of skills downgrading. They also suffer larger penalties in terms of pay ratio, especially when $\Delta NUTS3 = 0$.

- Urbanization: Workers from urban areas seem to be significantly less exposed to the risk of switching from a permanent to a temporary contract, especially when changing sector.

- Share of manufacturing employment in 2001: manufacturing intensive areas are associated with the negative effect on the pay of middle- and low-skilled workers who remain in the same sector. Territorial manufacturing specialization is also associated with a higher probability of being re-employed in new jobs with lower qualifications.

2.7 Robustness checks

We perform a wide array of robustness checks to make sure that our results are not the consequence of any specific choice of variables or sub-samples, and to identify any specific pattern resulting from alternative specifications or sample restrictions.

Table 2.3: Results - Heterogeneity - Lower pay and pay ratio

	HS			MLS		
	Group 1	Group 2	Diff.	Group 1	Group 2	Diff.
Lower Pay						
Gender						
ΔExp	0.008	-0.000	0.008	0.028***	0.016***	0.012***
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.014	-0.012***	-0.002	0.015***	0.000	0.014***
$\Delta Exp \cdot (\Delta Sector = 1)$	0.029***	0.026***	0.003	0.036***	0.032***	0.004
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.010	0.001	0.009	0.027***	0.015***	0.012***
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.009	-0.011	0.002	0.040***	0.027***	0.013*
N	172,917	151,964		386,061	679,300	
Age						
ΔExp	0.002	0.002	-0.000	0.011***	0.022***	-0.011**
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.007	-0.016***	0.009	-0.001	0.005**	-0.006
$\Delta Exp \cdot (\Delta Sector = 1)$	0.025***	0.029***	-0.005	0.031***	0.034***	-0.003
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.003	0.005	-0.002	0.010**	0.020***	-0.010**
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.008	-0.012	0.004	0.022***	0.033***	-0.011
N	102,072	222,809		311,147	754,214	
Urbanisation						
ΔExp	0.007	-0.004	0.011	0.019***	0.019***	-0.000
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.008	-0.017***	0.009	0.004*	0.002	0.002
$\Delta Exp \cdot (\Delta Sector = 1)$	0.031***	0.024***	0.007	0.031***	0.035***	-0.004
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.009	-0.002	0.011	0.018***	0.018***	-0.000
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.007	-0.011	0.004	0.034***	0.029***	0.005
N	137,695	187,186		338,822	726,539	
Empl. in Manufacturing						
ΔExp	0.006	-0.001	0.007	0.021***	0.017***	0.003
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.008*	-0.016**	0.008	0.007***	-0.001	0.008**
$\Delta Exp \cdot (\Delta Sector = 1)$	0.030***	0.026***	0.004	0.031***	0.035***	-0.004
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.006	0.002	0.004	0.020***	0.016***	0.004
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.004	-0.015	0.019	0.031***	0.027***	0.004
N	78,930	245,951		244,333	821,028	
Pay Ratio						
Gender						
ΔExp	-0.420	-0.235	-0.185	-2.579***	-1.492***	-1.087***
$\Delta Exp \cdot (\Delta Sector = 0)$	0.781	0.375***	0.407	-1.012***	-0.094	-0.919***
$\Delta Exp \cdot (\Delta Sector = 1)$	-1.625**	-1.597***	-0.028	-3.510***	-2.850***	-0.660*
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.460	-0.302*	-0.159	-2.463***	-1.356***	-1.107***
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.129	0.237	-0.365	-3.853***	-2.788***	-1.064
N	172,917	151,964		386,061	679,300	
Age						
ΔExp	-0.080	-0.515**	0.435	-1.026***	-1.973***	0.947***
$\Delta Exp \cdot (\Delta Sector = 0)$	0.483***	0.338	0.145	-0.014	-0.420***	0.406
$\Delta Exp \cdot (\Delta Sector = 1)$	-1.427***	-1.744***	0.317	-2.671***	-3.112***	0.442
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.138	-0.606***	0.467	-0.859***	-1.854***	0.995***
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.467	0.019	0.447	-3.478***	-3.056***	-0.422
N	102,072	222,809		311,147	754,214	
Urbanisation						
ΔExp	-0.447*	-0.148	-0.299	-1.749***	-1.759***	0.010
$\Delta Exp \cdot (\Delta Sector = 0)$	0.310	0.572**	-0.262	-0.481***	-0.153	-0.328
$\Delta Exp \cdot (\Delta Sector = 1)$	-1.647***	-1.660***	0.013	-2.783***	-3.219***	0.436
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.444*	-0.254	-0.190	-1.669***	-1.564***	-0.105
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.481	0.359	-0.840	-2.857***	-3.231***	0.374
N	137,695	187,186		338,822	726,539	
Empl. in Manufacturing						
ΔExp	-0.538**	-0.104	-0.434	-1.831***	-1.597***	-0.234
$\Delta Exp \cdot (\Delta Sector = 0)$	0.272	0.583**	-0.311	-0.543***	-0.071	-0.472**
$\Delta Exp \cdot (\Delta Sector = 1)$	-2.016***	-1.329***	-0.687	-2.823***	-3.100***	0.276
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.587**	-0.154	-0.433	-1.756***	-1.416***	-0.341
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.119	0.141	-0.022	-2.687***	-3.111***	0.424
N	78,930	245,951		244,333	821,028	

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions. Gender: (1) Female, (2) Male. Age: (1) $\geq$ 40, (2) $<$ 40. Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no.

Table 2.4: Results - Heterogeneity - Lower skill and less security

	HS			MLS		
	Group 1	Group 2	Diff.	Group 1	Group 2	Diff.
Lower skill						
Gender						
ΔExp	0.014**	0.005	0.009	0.013***	0.009***	0.004
$\Delta Exp \cdot (\Delta Sector = 0)$	0.009	0.004	0.005	0.010***	0.003**	0.007**
$\Delta Exp \cdot (\Delta Sector = 1)$	0.020*	0.006	0.013	0.014***	0.015***	-0.001
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.016**	0.003	0.012	0.013***	0.009***	0.004
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.002	0.014*	-0.012	0.004	0.005**	-0.001
N	172,917	151,964		386,061	679,300	
Age						
ΔExp	0.002	0.012**	-0.010	0.003*	0.011***	-0.009***
$\Delta Exp \cdot (\Delta Sector = 0)$	0.002	0.008*	-0.006	0.001	0.005***	-0.004**
$\Delta Exp \cdot (\Delta Sector = 1)$	0.002	0.017**	-0.015	0.006**	0.017***	-0.011***
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.000	0.013**	-0.013*	0.003*	0.012***	-0.010***
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.022	0.006	0.015	0.002	0.005**	-0.003
N	102,072	222,809		311,147	754,214	
Urbanisation						
ΔExp	0.006	0.008*	-0.001	0.010***	0.008***	0.002
$\Delta Exp \cdot (\Delta Sector = 0)$	0.002	0.009	-0.007	0.001	0.005***	-0.005**
$\Delta Exp \cdot (\Delta Sector = 1)$	0.014	0.006	0.009	0.018***	0.011***	0.008**
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.007	0.006	0.001	0.011***	0.009***	0.002
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.004	0.016*	-0.011	0.005	0.004*	0.001
N	137,695	187,186		338,822	726,539	
Empl. in Manufacturing						
ΔExp	0.003	0.011*	-0.008	0.011***	0.007***	0.004*
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.001	0.010**	-0.012	0.003	0.003**	-0.001
$\Delta Exp \cdot (\Delta Sector = 1)$	0.010	0.011	-0.001	0.018***	0.011***	0.007**
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.002	0.010	-0.007	0.011***	0.008***	0.004
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.011	0.015*	-0.004	0.009***	0.001	0.008**
N	78,930	245,951		244,333	821,028	
Worse sec						
Gender						
ΔExp	-0.001	-0.001	0.000	-0.009*	-0.009***	0.000
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.000	-0.005**	0.005	-0.023***	-0.017***	-0.006
$\Delta Exp \cdot (\Delta Sector = 1)$	-0.001	0.011	-0.012	0.008	0.012**	-0.004
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.002	-0.001	0.003	-0.011**	-0.010***	-0.002
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.026*	0.001	-0.027	0.020**	-0.000	0.021*
N	49,643	65,202		77,690	94,932	
Age						
ΔExp	-0.003	0.004	-0.007	-0.011***	-0.008**	-0.003
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.005*	-0.004	-0.002	-0.019***	-0.017***	-0.002
$\Delta Exp \cdot (\Delta Sector = 1)$	0.001	0.018*	-0.018	0.015**	0.009*	0.006
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.002	0.002	-0.004	-0.011***	-0.010***	-0.001
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.021**	0.018	-0.038**	-0.014	0.015***	-0.029**
N	51,185	63,660		70,703	101,919	
Urbanisation						
ΔExp	0.004	-0.005	0.009	-0.013***	-0.005	-0.008
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.002	-0.006	0.004	-0.018***	-0.018***	-0.000
$\Delta Exp \cdot (\Delta Sector = 1)$	0.014	-0.004	0.018	-0.001	0.026***	-0.027***
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.004	-0.005	0.010	-0.013***	-0.006	-0.007
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.004	-0.003	-0.000	-0.003	0.011	-0.014
N	60,226	54,619		67,711	104,911	
Empl. in Manufacturing						
ΔExp	-0.004	0.002	-0.006	-0.012***	-0.007*	-0.005
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.005	-0.002	-0.003	-0.019***	-0.017***	-0.002
$\Delta Exp \cdot (\Delta Sector = 1)$	-0.001	0.012	-0.013	0.001	0.023***	-0.022**
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.004	0.003	-0.007	-0.013***	-0.008**	-0.005
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.004	-0.002	-0.002	0.001	0.008	-0.007
N	30,923	83,922		47,281	125,341	

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions. Gender: (1) Female, (2) Male. Age: (1) ≥ 40, (2) < 40. Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no.

Table 2.5: Results - Heterogeneity - In ETT firm

	HS			MLS		
	Group 1	Group 2	Diff.	Group 1	Group 2	Diff.
Gender						
ΔExp	0.004	0.001	0.003	0.015***	0.009***	0.006*
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.007**	0.001	0.006	0.016***	0.011***	0.005
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.017***	0.001	-0.018**	0.013***	0.000	0.014**
N	78,930	245,951		244,333	821,028	
Age						
ΔExp	0.001	0.003	-0.002	0.008***	0.011***	-0.004
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.000	0.005**	-0.004*	0.007***	0.013***	-0.005*
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.002	-0.008*	0.011*	0.011*	0.001	0.011
N	78,930	245,951		244,333	821,028	
Urbanisation						
ΔExp	0.004*	-0.001	0.005*	0.009***	0.011***	-0.001
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.005*	-0.000	0.005*	0.010***	0.012***	-0.002
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.003	-0.003	0.001	0.003	0.002	0.002
N	78,930	245,951		244,333	821,028	
Empl. in Manufacturing						
ΔExp	0.002	0.001	0.001	0.009***	0.009***	-0.000
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.003	0.002	0.001	0.011***	0.010***	0.001
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.005	-0.003	-0.003	-0.005**	0.008**	-0.013***
N	78,930	245,951		244,333	821,028	

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions. Gender: (1) Female, (2) Male. Age: (1) ≥ 40, (2) < 40. Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no.

Sample restriction

Tables 2A.5 to 2A.14 report the estimates for the several sub-samples we tested:

- Workers: (1) keep only transitions from manufacturing; (2) for each individual, keep only the transition from their longest spell; (3) keep only transitions from spells at least 6 months long; (4) look only at transitions with at least 4 or 24 months of unemployment between jobs; (5) exclude transitions from the automotive sector; (6) keep only transitions from and to jobs in the general regime; (7) consider only prime-age workers (25-55 years old); (8) consider only spells of at least 180 or 365 days long.

  While transitions from manufacturing, which represent a small fraction of the overall sample of workers, are very close to the overall results, the exclusion of the automotive sector shows a different pattern. As shown in the descriptive statistics section, the largest variation in robot adoption is observed for "29 - Motor vehicles, trailers, and semi-trailers." In order to identify the role of automation in the motor vehicle sector in the overall results, we exclude this sector from the full sample. The strongest difference with respect to the overall results is found for MLS workers: those who manage to stay in any sector outside of the automobile sector experience lower probability of decreasing pay associated with the introduction of robots or move to jobs with worse qualifications. As for employment security, being out of the automobile sector, usually represented by large firms, implies a further penalty when a worker is displaced by robots. Another remarkable difference compared to the baseline results is the effect of long-term unemployment. While our results are not driven by this subgroup, we find that the return to work of MLS workers after long unemployment spells is not followed by a lower probability of temporary contracts, as happens with the overall population.

- Time: (9) consider only displacements occurring between 2006 and 2017 (i.e., the time window with complete robot data for all sectors); (10) consider only displacements occurring between 2001 and 2007 (pre-crisis); (11) consider only displacements occurring between 2008 and 2017 (post-crisis); (12) consider a list of time cuts associated with labour market reforms in 2010 and 2012. While the obtained results for the sub-periods are much less precise than the overall estimates, we find some heterogeneity for different parts of the business cycle: those who managed to find a job in the same sector during the Great Recession were not affected by wage losses. Interestingly, the sub-samples linked with the labour market reform do not display worse prospects in terms of lower pay.

- Sectors: (13) keep only transitions to the same NUTS3 area and the same 1-digit sector; (14) keep only transitions to a different NUTS3 area and a different 1-digit sector.

IFR categories aggregation schemes
Since there is a trade-off between the number of IFR categories we employ and measurement error, we test the robustness of our results across different sector aggregation schemes for the robot density. While in the baseline specification we adopt a scheme with 19 categories, we also test schemes with 15, 17, and 20 classes (Table 2.1 reports the composition of each scheme). We find only marginal differences across our aggregation schemes. The results are in Tables 2A.5 - 2A.14.

Migration
In the baseline specification we employ a migration dummy that is equal to one if the new job is in a different NUTS3 area than the previous job. In Tables 2A.5 to 2A.14 we test a more stringent measure of geographic relocation, i.e., a dummy equal to one only if workers move to a non-neighbouring NUTS3 area. The results are very similar to the overall picture and the parameter associated with a change of province only shows marginally different results.

Longer distance moves are associated with a lower probability of temporary contracts or working for ETT firms.

Fixed effects
In the baseline models we include three sets of fixed effects for the previous job (NUTS2 region, 1-digit industry, and type of contract, i.e., permanent or temporary), and we control for the year of start of the new job. In Tables 2A.5 to 2A.14 we assess the robustness of results to: (1) adding the same set of fixed effects for the previous job and for the new job; (2) adding the interaction between NUTS2 region of the previous job and year of dismissal; (3) adding the interaction between NUTS2 region of the new job and year of start of the new job. These new specifications display the same sign of the baseline models for all variables.

Sector FE and ΔSec
In the baseline specification we control for the 1-digit sector of the previous job, and we include a dummy equal to one if the new job is in a different 1-digit sector than the previous job. In total, we have 20 1-digit sectors. We test two more refined sector aggregations, i.e., one with 62 categories and one with 66 categories. Tables 2A.5 - 2A.14 report the estimates for each set of fixed effects, while Table 2A.15 reports the sectors included in each approach. More refined branch changes imply that workers remaining in the same activity are able to exploit sector-specific skills from a narrower perspective. As for the pay, we observe that those who find a job in the same narrowly defined sector as the previous job have indeed a lower probability of facing a lower pay. They also have a lower probability of finding a new job with lower qualifications or less secure contracts. When workers find a new job in an activity similar to their previous job, they face smaller reallocation frictions and can benefit from the higher productivity due to automation.

Reason for termination of the contract
Throughout the study we focus on transitions following an involuntary dismissal (code “54 - Non-voluntary leave”, see Appendix Table 2A.16 for a summary of all causes of termination). In Tables 2A.5 to 2A.14 we check whether the same conclusions apply to transitions following: (1) “93 - End of temporary contract”; (2) “77 - Collective dismissal”; (3) “51 - Voluntary leave”; (4) “77 - Collective dismissal”, “91 - Dismissal for objective reasons of the company”, and “55 – Dismissal due to merger or absorption of company”; (5) Causes 51, 54, 55, 77, and 91.

Checking whether the results hold for transitions following a voluntary leave is particularly important because workers who have some knowledge of what is happening in their firm might decide to voluntarily leave early. Furthermore, this process is probably selective, with more productive workers being more likely to be the ones who leave earlier. What emerges from this robustness check is that, although the estimated effects have indeed a smaller magnitude, exposed workers who ended their contract voluntarily experience the same struggles as those who faced an involuntary dismissal. The main results also hold when pooling together spells terminating due to causes 51, 54, 55, 77, and 91.

As for collective dismissals, the sample is small and, consequently, the estimates are very volatile. We estimated the models and reported the regression results for a matter of transparency, but we warn the reader that the results of this test shall be taken with a grain of salt. For this reason, we also tried the regressions summing all "external causes" (codes 77, 55, and 91), but the sample remains small.

We find little to no effect of automation exposure on individuals whose previous work spell ended due to the termination of a temporary contract. This is not surprising since this is likely to be a very heterogeneous group.

Sensitivity of the worse pay binary indicator
In Appendix Tables 2A.5 and 2A.6 we test three more stringent binary indicators to determine whether the new job offers a lower daily pay than the previous job. These indicators switch from zero to one only if the ratio of the new pay over the previous job is below 0.95, 0.90, or 0.80. The results are in line with those of the baseline specification.

Skill groups
Throughout the study we divide workers into "High-skilled" and "Middle- and low-skilled" groups. In Table 2A.17 we report the regression results by five rather than two skill groups. Appendix Table 2A.18 summarizes the aggregation schemes for these skill groups. Differences in the estimated parameters are mainly driven by workers moving from the "Middle-high" to the "Middle-low" category.

Timing of the automation shock
In our baseline regressions we explore the effect of the variation in the stock of robots between t-1 and t-2, with t being the year in which the worker is dismissed. As a robustness check we explore the effect of automation shocks

measured with different, but still "legitimate", time frames: "t-1 vs. t-3", "t-1 vs. t-4", "t-1 vs. t-5", "t-2 vs. t-3", "t-3 vs. t-4", and "t-4 vs. t-5". Furthermore, we also tried lagging the instrument more than the exposure in Spain. The results are comparable to those of the baseline estimations and are reported in Tables 2A.19 and 2A.20.

Validity of the instrument

In Appendix Table 2A.3 we report two statistics on the validity of all our potential instruments. First, we report the R^2 relative to the regression of robot adoption in Spain over several instruments plus a battery of industry and year fixed effects. These regressions are performed at the country-year-industry level. Second, we show the Olea and Pflueger (2013) effective F-statistic, performed on the full sample using the dummy for a lower pay as dependent variable and without separating "high-skilled" and "middle- and low-skilled". Both statistics show a higher validity of our baseline instrument compared to the alternatives.

Tables 2A.21 and 2A.22 present the results when alternative sets of instruments are adopted in our main regressions. Using less relevant instruments (such as Japan or the average of Nordic countries) results in less accurate estimates, but the overall patterns are confirmed across all scenarios.

Inverse propensity weights (IPW)

We repeat our main set of regressions using inverse propensity weights (IPW) to balance our sample and provide more evidence that we are comparing workers who were on similar trends prior to being laid off. Since we do not have a binary treatment but rather a continuous one, we rely on generalised propensity scores, as theorized in Hirano and Imbens (2004). Being T our continuous treatment (i.e., robot exposure), t the given values of such treatment, X our covariates of interest, and x their realizations, we could compute IPW as:

$$\frac{1}{f(T|X)^{(t|x)}} \tag{4}$$

However, given that such weights can result in infinite variance, we follow Austin (2019) and compute our "stabilized" weights as

$$\frac{f(T)^{(t)}}{f(T|X)^{(t|x)}} \tag{5}$$

with the numerator being equal to the marginal density of treatment

$$f(T)^{(t)} = \frac{1}{\sqrt{2\pi\widehat{\sigma}_t^2}} e^{-\frac{(t-\mu_t)^2}{2\pi\widehat{\sigma}_t^2}} \tag{6}$$

Our treatment is assigned at the sector-year level. Hence, to compute our propensity score we use all covariates used in the main equation (Eq. 1) except for the sector-level covariates (sector fixed effects, $\Delta Trade_{s,t-1}$ and $\Delta ICT_{s,t-1}$. We also exclude the two binary indicators for $\Delta Sector$ and $\Delta NUTS3$ as the relocation decision takes place after the "treatment assignment".

The estimation results of the regressions using inverse propensity weights (IPW) are reported in Tables 2A.23 and 2A.24. The overlap plots are reported in Figure 2A.2. While the magnitudes of the estimated effects vary, the main patterns found in the non-weighted regressions are confirmed.

2.8 Conclusion

While considerable attention has been devoted to the impact of automation on employment levels, little has been said about the *quality* of the new match for workers displaced by the introduction of robots. This study provides empirical evidence that middle- and low-skilled workers in Spain who are displaced from sectors with an increasing density of industrial robots have a higher probability of being re-employed in jobs of lower quality. More precisely, they are more likely to receive lower pay and face less stable employment. The pay differential might be explained by the fact that they are more likely to be re-employed in jobs requiring lower qualifications. This is in line with Raposo et al. (2021), who find that job title downgrading is the largest component of the wage losses of Portuguese displaced workers.

Relocation to different sectors or local labour markets offers little to no advantage. If anything, those who change sectors have an even higher probability of securing a worse job. Our findings show that workers remaining in the same activity are able to exploit their sector-specific skills. This is in line with Lachowska et al. (2020), who find that the match effect is the main factor explaining the wage losses of long-term workers after mass layoffs.

Some categories of middle- and low-skilled workers who stay employed in sectors and regions more exposed to robots enjoy some of the benefits of automation. In particular, those who already had a permanent contract are less likely to switch to a temporary contract. Robot exposure does not only affect workers in the short term: the majority of these effects persists for up to 36 months. Furthermore, 6 months after displacement exposed middle- and low-skilled workers are still more likely to be unemployed. Moreover, they are slightly more likely to experience a fragmented work-life, with multiple contracts and fewer days worked. In general, high-skilled workers are less negatively affected by exposure, although they also incur a penalty when changing sectors.

The results of the empirical analysis suggest that workers endowed with high human capital face better job opportunities as they benefit from more transferable skills that are relevant across sectors. In fact, automation implies better opportunities for some workers, as robots create new opportunities for some industries and firms. As Lachowska et al. (2020) indicate, if displaced workers are the ones with lower productivity, and are hired somewhere else at lower salaries, such private losses represent a transfer of rents rather than a social loss. Still, finding a good job after a dismissal linked to automation can be a long and difficult process, particularly when the worker is forced to switch sectors and she faces a loss of occupation-specific skills. Active labour market policies, such as re-training and/or job search assistance programs, might be necessary to alleviate the depreciation of sector-specific human capital.

2.9 Appendix 2A: Additional Tables and Figures

Table 2A.1: Year of start of robot data by country and sector

Sector	ES	IT	FR	DE	UK	SE	DK	FI	NO	US	JP
01–03	2004	2005	2005	1998	1995	2004	2002	2000	2000	2007	1995
05–09	2004	2000	2006	2008	1998	2010	1999	2008	2015	2007	1996
10–12	1995	1995	1995	1995	1995	1995	1996	1995	1995	2004	1995
13–15	1995	1995	1995	1995	1995	1995	1996	1995	2002	2007	1995
16,31	1995	1995	1995	1995	1995	1995	1997	1995	1995	2006	1995
17–18	1995	1995	1995	1995	1997	1995	2004	1995	1995	2007	1995
19–21	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2010
22	2004	2004	2004	2004	2004	2004	2004	2004	2005	2004	2010
23	1995	1995	1995	1995	1995	1995	2005	1995	1995	2006	1995
24	1995	1995	1995	1995	1995	1995	1996	1995	1995	2008	1995
25	1995	1995	1995	1995	1995	1995	1996	1995	1995	2004	1995
26	1996	1995	2005	1995	1996	1995	1998	1995	1995	2007	1995
27	2005	2005	2004	2004	2004	2004	2004	2004	2004	2007	2010
28	1995	1995	1995	1995	1995	1995	1996	1995	1995	2007	1995
29	1995	1995	1995	1995	1995	1995	1996	1995	1995	2004	1995
30	1995	1995	1995	1996	1995	1995	2005	1995	1995	2006	1995
35–39	2002	2000	2005	1998	1997	1997	2013	2015	2000	2011	1996
41–43	1995	2000	2005	1997	1996	1996	2004	1997	2014	2006	1996
72,85	1995	1996	2005	1996	1996	1995	1998	1996	1996	2005	1996

Source: IFR. *Notes*: in our baseline specification we consider displacements occurring between 2001 and 2017. For a displacement taking place in year t we compute $\Delta Exp_{s,t-1}$ as the variation in the stock of robots in sector s between year $t-1$ and year $t-2$. Hence, we need robot data from 1999 to 2016. For all country-sector pairs the last year available in our dataset is 2018.

Table 2A.2: Balancing analysis - Individual level (June 2001)

	Unconditional		Conditional	
	Coefficient	SE	Coefficient	SE
All workers				
Monthly earnings	16.9936***	0.1613	7.4957***	0.6113
Female	-0.0119***	0.0002	-0.0017***	0.0006
Foreign	-0.0016***	0.0001	0.0002	0.0001
Age	0.0177***	0.0040	-0.0228	0.0188
Middle- and low-skilled	0.0102***	0.0002	0.0036***	0.0004
Permanent contract	0.0160***	0.0002	0.0018**	0.0007
Temporary contract	-0.0029***	0.0002	-0.0000	0.0006
Self employed	-0.0069***	0.0001	-0.0000	0.0001
1-9 Employees	-0.0031***	0.0001	-0.0025***	0.0004
10-49 Employees	0.0007***	0.0001	-0.0046***	0.0006
50-249 Employees	0.0034***	0.0001	-0.0006	0.0006
More than 250 Employees	0.0088***	0.0001	0.0126***	0.0022
N	546,657		546,657	
Manufacturing workers				
Monthly earnings	13.4947***	0.2088	4.8336***	0.4898
Female	-0.0037***	0.0002	-0.0010	0.0007
Foreign	-0.0003***	0.0001	-0.0000	0.0001
Age	0.0192***	0.0054	-0.0437***	0.0165
Middle- and low-skilled	0.0032***	0.0002	0.0024***	0.0004
Permanent contract	0.0064***	0.0002	0.0006	0.0006
Temporary contract	-0.0023***	0.0002	-0.0002	0.0005
Self employed	-0.0037***	0.0001	-0.0000	0.0001
1-9 Employees	-0.0030***	0.0001	-0.0018***	0.0003
10-49 Employees	-0.0038***	0.0002	-0.0031***	0.0005
50-249 Employees	0.0010***	0.0002	-0.0011*	0.0006
More than 250 Employees	0.0148***	0.0002	0.0110***	0.0021
N	96,465		96,465	

Source: authors' own calculations. *Notes*: coefficients from 2SLS regressions of the respective transition characteristics on the change in robot exposure per 1,000 workers between 2001 and 2017 (instrumented with robot installations across industries in other European countries). The sample includes *all* workers with an on-going working spell on June 1, 2001. For workers with more than one spell in this month we selected the one with the highest earnings. All work-related characteristics refer to this spell only. The "Unconditional" column reports coefficient and standard error when the listed variables are regressed on predicted robot exposure and a constant, while column "Conditional" adds a series of standard control variables. The Control variables are wage, sex, foreign nationality, age, skill level (two categories), contract type (permanent, temporary, and self-employed), size of firm (four categories and missing), 1-digit sector dummies, NUTS2 area dummies and tenure. In each regression, all controls that are constructed from the dependent variable are not included in the estimation. Standard errors are clustered by 1-digit sector and NUTS3 area.

Table 2A.3: Statistics on instruments - R^2 and F-statistic

	R^2	F-statistic
Year and sector FE	0.273	
Japan	0.280	5.1
Average: all 8 European countries	0.629	356.9
Average: Italy, France, UK, Germany	0.632	374.6
Average: Italy, France, UK	0.662	276.0
Average: Sweden, Denmark, Finland, Norway	0.285	117.3
Average: Sweden, Denmark, Finland, Norway, Japan	0.280	7.6
N	361	1,390,230

Source: authors' own calculations. *Notes:* the R^2 column refers to the regression of robot adoption in Spain over the instrument plus a battery of industry and year fixed effects. These regressions are performed at the country-year-industry level. The other column reports the Olea and Pflueger (2013) effective F-statistic, performed on the full sample using the dummy for a lower pay as dependent variable and without separating "high-skilled" and "middle- and low-skilled". Regarding the issue of weak instruments, the rule of thumb is to consider the instrument valid when the Olea and Pflueger (2013) effective F-statistic is greater than 10.

Table 2A.4: Results 2SLS and OLS

	HS - 2SLS	HS - OLS	MLS - 2SLS	MLS - OLS
Lower Pay				
ΔExp	0.0023	-0.0008	0.0193***	0.0147***
	[0.0037]	[0.0029]	[0.0018]	[0.0014]
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.0120***	-0.0090**	0.0033*	0.0011
	[0.0041]	[0.0036]	[0.0018]	[0.0016]
$\Delta Exp \cdot (\Delta Sector = 1)$	0.0282***	0.0169***	0.0331***	0.0272***
	[0.0055]	[0.0040]	[0.0024]	[0.0018]
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.0040	-0.0014	0.0182***	0.0139***
	[0.0043]	[0.0032]	[0.0018]	[0.0014]
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.0096	0.0040	0.0308***	0.0232***
	[0.0092]	[0.0069]	[0.0035]	[0.0029]
N	324,876	324,876	1,065,354	1,065,354
Pay ratio (×100)				
ΔExp	-0.3056*	-0.1635	-1.7707***	-1.4315***
	[0.1684]	[0.1363]	[0.1498]	[0.1129]
$\Delta Exp \cdot (\Delta Sector = 0)$	0.4374***	0.2819**	-0.3150***	-0.1806*
	[0.1538]	[0.1184]	[0.1080]	[0.0954]
$\Delta Exp \cdot (\Delta Sector = 1)$	-1.6466***	-1.1264***	-3.0258***	-2.5798***
	[0.3438]	[0.2755]	[0.2282]	[0.1704]
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.3660**	-0.1938	-1.6355***	-1.3380***
	[0.1709]	[0.1360]	[0.1428]	[0.1114]
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.1252	0.0493	-3.1101***	-2.3871***
	[0.6004]	[0.4244]	[0.3157]	[0.2470]
N	324,876	324,876	1,065,354	1,065,354
Lower skill				
ΔExp	0.0075*	0.0031	0.0097***	0.0071***
	[0.0042]	[0.0027]	[0.0012]	[0.0012]
$\Delta Exp \cdot (\Delta Sector = 0)$	0.0056	0.0035	0.0035***	0.0025**
	[0.0035]	[0.0027]	[0.0011]	[0.0010]
$\Delta Exp \cdot (\Delta Sector = 1)$	0.0108	0.0022	0.0150***	0.0114***
	[0.0080]	[0.0048]	[0.0015]	[0.0015]
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.0066	0.0018	0.0102***	0.0076***
	[0.0045]	[0.0027]	[0.0013]	[0.0012]
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.0135*	0.0118**	0.0046**	0.0024
	[0.0072]	[0.0056]	[0.0020]	[0.0018]
N	324,876	324,876	1,065,354	1,065,354
Lower security				
ΔExp	-0.0001	-0.0027	-0.0094***	-0.0085***
	[0.0032]	[0.0021]	[0.0025]	[0.0019]
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.0033	-0.0041**	-0.0181***	-0.0141***
	[0.0023]	[0.0020]	[0.0028]	[0.0022]
$\Delta Exp \cdot (\Delta Sector = 1)$	0.0076	0.0012	0.0113**	0.0069
	[0.0079]	[0.0048]	[0.0053]	[0.0046]
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.0002	-0.0026	-0.0102***	-0.0094***
	[0.0034]	[0.0022]	[0.0026]	[0.0020]
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.0028	-0.0044	0.0051	0.0079*
	[0.0071]	[0.0061]	[0.0053]	[0.0046]
N	114,843	114,843	172,629	172,629
ETT firm				
ΔExp	0.0020	0.0008	0.0109***	0.0074***
	[0.0014]	[0.0010]	[0.0015]	[0.0011]
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.0029*	0.0014	0.0118***	0.0082***
	[0.0015]	[0.0011]	[0.0016]	[0.0011]
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.0041	-0.0036	0.0027	-0.0008
	[0.0033]	[0.0023]	[0.0023]	[0.0018]
N	321,478	321,478	993,696	993,696

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV and OLS regression results. In the 2SLS regressions Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are reported between square brackets and are clustered by province, 2-digit sector and year of dismissal.

Table 2A.5: Robustness - Lower pay (HS)

		ΔSec		$\Delta NUTS$		
	ΔExp	No	Yes	No	Yes	N
Baseline	0.0023	-0.0120***	0.0282***	0.0040	-0.0096	324,876
Subsamples						
Manufacturing	0.0026	-0.0054	0.0165***	0.0037	-0.0049	19,024
One transition	0.0052	-0.0043	0.0264***	0.0057	0.0013	159,201
Previous 6 months	0.0036	-0.0064	0.0240***	0.0047	-0.0044	203,984
4 months unemployed	0.0075*	-0.0112	0.0179***	0.0127**	-0.0101	170,323
24 months unemployed	0.0091*	-0.0104	0.0174***	0.0137**	-0.0083	91,152
Previous not automotive	0.0248***	-0.0192	0.0498***	0.0373***	-0.0414**	324,099
Only general regime	0.0024	-0.0119***	0.0280***	0.0040	-0.0095	319,575
Age 25-55	0.0020	-0.0125***	0.0274***	0.0041	-0.0120	280,958
Spell length >= 180 days	-0.0014	-0.0083**	0.0135**	0.0001	-0.0124	204,669
Spell length >= 365 days	0.0024	-0.0039	0.0164***	0.0043	-0.0126*	134,862
Displaced in 2006-2017	-0.0107	-0.0364***	0.0150	-0.0036	-0.0435**	213,386
Displaced in 2001-2007	0.0035	-0.0074*	0.0250***	0.0042	-0.0020	161,115
Displaced in 2008-2017	-0.0207	-0.0710**	0.0147	-0.0064	-0.0667**	163,761
Displaced in 2004-2010	0.0042	-0.0197***	0.0310***	0.0097	-0.0352**	170,287
Displaced in 2011-2017	0.0069	-0.0400	0.0402	0.0031	0.0161	88,132
Displaced in 2008-2012	-0.0272*	-0.0778***	0.0107	-0.0110	-0.0852***	123,242
Displaced in 2013-2017	0.0019	-0.0346	0.0168	-0.0106	0.0225	40,519
Displaced in 2006-2009	0.0053	-0.0095	0.0215*	0.0085	-0.0125	101,333
Displaced in 2010-2013	-0.0339	-0.1384**	0.0486	-0.0103	-0.1119*	81,357
Displaced in 2014-2017	-0.0002	-0.0190	0.0071	-0.0007	0.0005	30,696
Same Sec and NUTS3	-0.0050					144,636
Different Sec and NUTS3	-0.0019					26,091
IFR aggregation schemes						
15 Groups	-0.0010	-0.0151***	0.0298***	-0.0004	-0.0052	324,876
17 Groups	0.0004	-0.0156***	0.0288***	0.0021	-0.0115	324,876
20 Groups	0.0026	-0.0115***	0.0281***	0.0044	-0.0098	324,876
Migration						
Non-neighbouring NUTS3	0.0023	-0.0121***	0.0284***	0.0031	-0.0083	324,876
Fixed effects						
Add Current spell FE	0.0031	-0.0068*	0.0206***	0.0048	-0.0090	324,876
NUTS2(Prev.)*Year Exit	0.0026	-0.0115***	0.0278***	0.0042	-0.0090	324,876
NUTS2*Year Entry	0.0024	-0.0123***	0.0285***	0.0039	-0.0081	324,876
Sector FE and ΔSec						
FE20 and ΔSec62	0.0012	-0.0160***	0.0147***	0.0030	-0.0119	324,876
FE20 and ΔSec66	0.0012	-0.0170***	0.0153***	0.0030	-0.0117	324,876
FE62 and ΔSec20	0.0083	-0.0089	0.0312***	0.0101	-0.0034	324,876
FE62 and ΔSec62	0.0072	-0.0110	0.0184***	0.0093	-0.0059	324,876
FE62 and ΔSec66	0.0068	-0.0126*	0.0181***	0.0088	-0.0061	324,876
FE66 and ΔSec20	0.0028	-0.0129**	0.0248***	0.0046	-0.0093	324,876
FE66 and ΔSec62	0.0021	-0.0148**	0.0128**	0.0041	-0.0114	324,876
FE66 and ΔSec66	0.0017	-0.0163**	0.0127**	0.0036	-0.0116	324,876
Reason termination						
93 - End of temp. contr.	-0.1845	-0.1636	-0.2252	-0.1900	-0.1714	47,579
77 - Collective dismissal	0.0926	0.0876	0.2453	0.1932	2.9327	1,636
51 - Voluntary leave	-0.0020	-0.0080*	0.0021	-0.0041	0.0060	133,453
77+55+91	-0.1126	-0.1318	-0.0120	-0.1106	-0.1280	14,850
51+54+55+77+91	-0.0007	-0.0117***	0.0131***	0.0001	-0.0046	473,179
Dummy worse pay						
Limit 95%	0.0024	-0.0131***	0.0304***	0.0047	-0.0144**	324,876
Limit 90%	0.0046	-0.0084***	0.0281***	0.0058	-0.0036	324,876
Limit 80%	0.0057**	-0.0043***	0.0239***	0.0064**	0.0011	324,876

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector, and year of dismissal.

Table 2A.6: Robustness - Lower pay (MLS)

		ΔSec		$\Delta NUTS$		
	ΔExp	No	Yes	No	Yes	N
Baseline	0.0193***	0.0033*	0.0331***	0.0182***	0.0308***	1,065,354
Subsamples						
Manufacturing	0.0183***	0.0071***	0.0279***	0.0170***	0.0303***	127,593
One transition	0.0174***	0.0020	0.0345***	0.0161***	0.0324***	393,349
Previous 6 months	0.0204***	0.0043*	0.0377***	0.0190***	0.0348***	447,100
4 months unemployed	0.0256***	0.0172***	0.0293***	0.0251***	0.0297***	688,927
24 months unemployed	0.0274***	0.0185***	0.0306***	0.0267***	0.0330***	355,564
Previous not automotive	0.0253***	-0.0015	0.0407***	0.0252***	0.0259***	1,058,908
Only general regime	0.0192***	0.0032*	0.0332***	0.0181***	0.0309***	1,022,066
Age 25-55	0.0171***	0.0008	0.0322***	0.0161***	0.0266***	831,093
Spell length >= 180 days	0.0194***	0.0074***	0.0362***	0.0181***	0.0317***	439,871
Spell length >= 365 days	0.0162***	0.0058*	0.0346***	0.0142***	0.0392***	212,105
Displaced in 2006-2017	0.0305***	0.0015	0.0492***	0.0301***	0.0339***	641,964
Displaced in 2001-2007	0.0181***	0.0041**	0.0306***	0.0170***	0.0301***	612,875
Displaced in 2008-2017	0.0262***	-0.0107	0.0469***	0.0257***	0.0285***	452,479
Displaced in 2004-2010	0.0274***	0.0062*	0.0414***	0.0262***	0.0366***	606,372
Displaced in 2011-2017	0.0314***	-0.0327**	0.0748***	0.0266**	0.0575***	210,460
Displaced in 2008-2012	0.0273***	-0.0025	0.0439***	0.0269***	0.0296***	363,462
Displaced in 2013-2017	0.0024	-0.0939*	0.0660**	0.0022	0.0028	89,017
Displaced in 2006-2009	0.0363***	0.0101*	0.0533***	0.0364***	0.0355***	361,866
Displaced in 2010-2013	0.0211	-0.0157	0.0439**	0.0159	0.0534**	212,607
Displaced in 2014-2017	-0.0179	-0.1170	0.0449	-0.0198	-0.0115	67,491
Same Sec and NUTS3	0.0066***					470,662
Different Sec and NUTS3	0.0383***					77,833
IFR aggregation schemes						
15 Groups	0.0206***	0.0021	0.0371***	0.0191***	0.0352***	1,065,354
17 Groups	0.0191***	0.0024	0.0336***	0.0178***	0.0324***	1,065,354
20 Groups	0.0192***	0.0033*	0.0330***	0.0181***	0.0306***	1,065,354
Migration						
Non-neighbouring NUTS3	0.0193***	0.0032*	0.0332***	0.0192***	0.0229***	1,065,354
Fixed effects						
Add Current spell FE	0.0187***	0.0087***	0.0274***	0.0176***	0.0302***	1,065,354
NUTS2(Prev.)*Year Exit	0.0193***	0.0035*	0.0328***	0.0182***	0.0300***	1,065,354
NUTS2*Year Entry	0.0199***	0.0039**	0.0337***	0.0188***	0.0311***	1,065,354
Sector FE and ΔSec						
FE20 and ΔSec62	0.0187***	-0.0061***	0.0274***	0.0175***	0.0305***	1,065,354
FE20 and ΔSec66	0.0189***	-0.0059**	0.0273***	0.0177***	0.0307***	1,065,354
FE62 and ΔSec20	0.0017	-0.0144***	0.0146***	0.0004	0.0133***	1,065,354
FE62 and ΔSec62	0.0015	-0.0229***	0.0100***	0.0001	0.0134***	1,065,354
FE62 and ΔSec66	0.0017	-0.0236***	0.0095***	0.0003	0.0137***	1,065,354
FE66 and ΔSec20	0.0019	-0.0141***	0.0149***	0.0005	0.0137***	1,065,354
FE66 and ΔSec62	0.0017	-0.0227***	0.0101***	0.0003	0.0138***	1,065,354
FE66 and ΔSec66	0.0016	-0.0236***	0.0096***	0.0002	0.0138***	1,065,354
Reason termination						
93 - End of temp. contr.	-0.0653	-0.1094**	-0.0348	-0.0585	-0.1036	193,851
77 - Collective dismissal	-0.0226	-0.0583	-0.0054	-0.0297	0.0050	2,146
51 - Voluntary leave	0.0105***	0.0039	0.0148***	0.0101***	0.0133**	384,743
77+55+91	-0.0148	-0.0220	-0.0033	-0.0212	0.0316	24,059
51+54+55+77+91	0.0181***	0.0034**	0.0303***	0.0172***	0.0267***	1,474,156
Dummy worse pay						
Limit 95%	0.0202***	0.0049**	0.0333***	0.0191***	0.0307***	1,065,354
Limit 90%	0.0201***	0.0049**	0.0332***	0.0190***	0.0311***	1,065,354
Limit 80%	0.0176***	0.0037**	0.0296***	0.0166***	0.0281***	1,065,354

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector, and year of dismissal.

Table 2A.7: Robustness - Ratio of new pay over previous one (×100) (HS)

		ΔSec		$\Delta NUTS$		
	ΔExp	No	Yes	No	Yes	N
Baseline	-0.3056*	0.4374***	-1.6466***	-0.3660**	0.1252	324,876
Subsamples						
Manufacturing	-0.2584*	0.2069	-1.0585***	-0.3183**	0.1666	19,024
One transition	-0.4191**	0.1896	-1.7657***	-0.3914**	-0.6494	159,201
Previous 6 months	-0.3246*	0.2600*	-1.5175***	-0.3626**	-0.0351	203,984
4 months unemployed	-0.8176**	1.1656**	-1.9106***	-1.1466***	0.3069	170,323
24 months unemployed	-1.1586**	0.5309	-1.8735***	-1.3964***	-0.2586	91,152
Previous not automotive	-1.2591***	0.9721	-2.5325***	-1.4769***	-0.1143	324,099
Only general regime	-0.3006*	0.4250***	-1.6061***	-0.3628**	0.1424	319,575
Age 25-55	-0.2865*	0.4426***	-1.5624***	-0.3964**	0.4424	280,958
Spell length >= 180 days	-0.0756	0.2962*	-0.8800**	-0.0899	0.0276	204,669
Spell length >= 365 days	-0.1415	0.2297	-0.9775**	-0.1301	-0.2328	134,862
Displaced in 2006-2017	-0.2136	1.7622**	-2.1827***	-0.3051	0.2120	213,386
Displaced in 2001-2007	-0.4070**	0.2234	-1.6603***	-0.4657***	0.0538	161,115
Displaced in 2008-2017	0.4775	3.7298***	-1.8089	0.4207	0.6602	163,761
Displaced in 2004-2010	-0.8137***	0.3706	-2.1400***	-1.1079***	1.3014	170,287
Displaced in 2011-2017	-0.2342	4.1821**	-3.3766*	1.0474	-3.3774	88,132
Displaced in 2008-2012	0.9027	3.5611***	-1.0862	0.5781	2.0666	123,242
Displaced in 2013-2017	-0.2394	8.4259	-3.7610	2.7705	-5.1689*	40,519
Displaced in 2006-2009	-0.6016	1.1359	-2.5044***	-0.7452	0.1949	101,333
Displaced in 2010-2013	-0.0479	3.0536	-2.4945	-0.0155	-0.1548	81,357
Displaced in 2014-2017	0.9005	8.7431	-2.1697	3.1857	-2.3587	30,696
Same Sec and NUTS3	0.0282					144,636
Different Sec and NUTS3	-0.3431					26,091
IFR aggregation schemes						
15 Groups	-0.4572**	0.3952**	-2.3247***	-0.4835**	-0.2857	324,876
17 Groups	-0.3926**	0.4179**	-1.8407***	-0.4740**	0.1641	324,876
20 Groups	-0.2983*	0.4240***	-1.5999***	-0.3634**	0.1647	324,876
Migration						
Non-neighbouring NUTS3	-0.3037*	0.4409***	-1.6475***	-0.3595**	0.4462	324,876
Fixed effects						
Add Current spell FE	-0.3364**	0.1209	-1.1482***	-0.4000**	0.1154	324,876
NUTS2(Prev.)*Year Exit	-0.4272**	0.2740*	-1.6847***	-0.4709***	-0.1166	324,876
NUTS2*Year Entry	-0.3234*	0.4347***	-1.6771***	-0.3799**	0.0774	324,876
Sector FE and ΔSec						
FE20 and ΔSec62	-0.2759*	0.4088**	-0.8145***	-0.3421**	0.1966	324,876
FE20 and ΔSec66	-0.2778*	0.4744***	-0.8574***	-0.3438**	0.1932	324,876
FE62 and ΔSec20	-0.3336	0.5661**	-1.5352***	-0.3932	0.0503	324,876
FE62 and ΔSec62	-0.3049	0.3873	-0.7281**	-0.3736	0.1380	324,876
FE62 and ΔSec66	-0.2910	0.4748*	-0.7373**	-0.3586	0.1445	324,876
FE66 and ΔSec20	-0.1941	0.6562***	-1.3879***	-0.2528	0.1978	324,876
FE66 and ΔSec62	-0.1758	0.4744*	-0.5902*	-0.2424	0.2689	324,876
FE66 and ΔSec66	-0.1622	0.5613**	-0.6063*	-0.2278	0.2759	324,876
Reason termination						
93 - End of temp. contr.	5.6637	6.4671	4.0896	5.8965	5.1170	47,579
77 - Collective dismissal	-4.8411	-4.2669	-22.3920	-4.0650	17.0686	1,636
51 - Voluntary leave	-0.5523**	0.1661	-1.0472***	-0.5192**	-0.6791	133,453
77+55+91	7.9611	9.8656	-1.9860	8.2508	5.6687	14,850
51+54+55+77+91	-0.3026**	0.3977***	-1.1787***	-0.3509**	-0.0380	473,179

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector, and year of dismissal.

Table 2A.8: Robustness - Ratio of new pay over previous one (×100) (MLS)

		ΔSec		$\Delta NUTS$		
	ΔExp	No	Yes	No	Yes	N
Baseline	-1.7707***	-0.3150***	-3.0258***	-1.6355***	-3.1101***	1,065,354
Subsamples						
Manufacturing	-1.6286***	-0.5757***	-2.5347***	-1.4918***	-2.9648***	127,593
One transition	-1.5975***	-0.1798	-3.1604***	-1.4516***	-3.2114***	393,349
Previous 6 months	-1.7745***	-0.2673**	-3.3947***	-1.6139***	-3.4064***	447,100
4 months unemployed	-2.4710***	-1.0387***	-3.0994***	-2.3582***	-3.2916***	688,927
24 months unemployed	-2.7240***	-0.9343***	-3.3715***	-2.5886***	-3.7266***	355,564
Previous not automotive	-1.5426***	1.2908***	-3.1702***	-1.2319***	-3.4438***	1,058,908
Only general regime	-1.7609***	-0.3267***	-3.0084***	-1.6289***	-3.0898***	1,022,066
Age 25-55	-1.6081***	-0.1670	-2.9373***	-1.4664***	-2.9640***	831,093
Spell length >= 180 days	-1.7993***	-0.6034***	-3.4688***	-1.6375***	-3.3181***	439,871
Spell length >= 365 days	-1.4689***	-0.4410**	-3.2957***	-1.2748***	-3.6951***	212,105
Displaced in 2006-2017	-2.7284***	0.5822*	-4.8546***	-2.5422***	-4.0349***	641,964
Displaced in 2001-2007	-1.7059***	-0.4838***	-2.7939***	-1.5902***	-2.9252***	612,875
Displaced in 2008-2017	-2.1267***	2.3864***	-4.6674***	-1.8878**	-3.4036***	452,479
Displaced in 2004-2010	-2.3231***	-0.4764**	-3.5401***	-2.1287***	-3.7680***	606,372
Displaced in 2011-2017	-3.5229***	3.9366***	-8.5683***	-2.9225***	-6.7564***	210,460
Displaced in 2008-2012	-2.2449***	1.6104***	-4.3960***	-2.0288**	-3.4205***	363,462
Displaced in 2013-2017	-0.7985	9.7195**	-7.7529***	-0.1974	-3.2978	89,017
Displaced in 2006-2009	-3.2819***	-0.2374	-5.2529***	-3.1716***	-4.0993***	361,866
Displaced in 2010-2013	-1.4445	3.1942***	-4.3116**	-0.7432	-5.8305**	212,607
Displaced in 2014-2017	0.0723	9.6582	-6.0055*	0.8394	-2.6242	67,491
Same Sec and NUTS3	-0.6346***					470,662
Different Sec and NUTS3	-3.7136***					77,833
IFR aggregation schemes						
15 Groups	-2.0211***	-0.2483**	-3.6135***	-1.8747***	-3.5036***	1,065,354
17 Groups	-1.7952***	-0.2901**	-3.1017***	-1.6593***	-3.1556***	1,065,354
20 Groups	-1.7608***	-0.3153***	-3.0069***	-1.6261***	-3.0945***	1,065,354
Migration						
Non-neighbouring NUTS3	-1.7687***	-0.3148***	-3.0223***	-1.7256***	-2.9009***	1,065,354
Fixed effects						
Add Current spell FE	-1.7076***	-0.7037***	-2.5758***	-1.5690***	-3.0784***	1,065,354
NUTS2(Prev.)*Year Exit	-1.7679***	-0.3306***	-3.0055***	-1.6400***	-3.0352***	1,065,354
NUTS2*Year Entry	-1.8236***	-0.3673***	-3.0751***	-1.6894***	-3.1488***	1,065,354
Sector FE and ΔSec						
FE20 and ΔSec62	-1.7718***	0.3063**	-2.5048***	-1.6366***	-3.1112***	1,065,354
FE20 and ΔSec66	-1.7718***	0.2532*	-2.4560***	-1.6365***	-3.1113***	1,065,354
FE62 and ΔSec20	0.1077	1.5655***	-1.0629***	0.2645	-1.2236***	1,065,354
FE62 and ΔSec62	0.1082	2.1357***	-0.5954***	0.2649	-1.2231***	1,065,354
FE62 and ΔSec66	0.1097	2.1610***	-0.5286***	0.2664	-1.2211***	1,065,354
FE66 and ΔSec20	0.0067	1.4649***	-1.1776***	0.1641	-1.3611***	1,065,354
FE66 and ΔSec62	0.0071	2.0352***	-0.6978***	0.1646	-1.3606***	1,065,354
FE66 and ΔSec66	0.0075	2.0630***	-0.6377***	0.1649	-1.3602***	1,065,354
Reason termination						
93 - End of temp. contr.	3.0889	9.1258**	-1.0871	3.0029	3.5695	193,851
77 - Collective dismissal	1.5891	3.4714	0.6874	2.2621	-0.9995	2,146
51 - Voluntary leave	-1.4028***	-0.0552	-2.2740***	-1.3258***	-1.8596***	384,743
77+55+91	1.9018	3.1051	-0.0326	2.2022	-0.2735	24,059
51+54+55+77+91	-1.7843***	-0.3518***	-2.9631***	-1.6667***	-2.8321***	1,474,156

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector, and year of dismissal.

Table 2A.9: Robustness - Lower qualification (HS)

	ΔExp	ΔSec No	ΔSec Yes	$\Delta NUTS$ No	$\Delta NUTS$ Yes	N
Baseline	0.0075*	0.0056	0.0108	0.0066	0.0135*	324,876
Subsamples						
Manufacturing	0.0025	-0.0036	0.0130**	0.0028	0.0001	19,024
One transition	0.0008	0.0007	0.0011	0.0007	0.0012	159,201
Previous 6 months	0.0048	0.0051	0.0043	0.0042	0.0097	203,984
4 months unemployed	0.0026	0.0292***	-0.0121*	0.0029	0.0015	170,323
24 months unemployed	0.0028	0.0258**	-0.0069	0.0045	-0.0036	91,152
Previous not automotive	0.0456***	0.0693***	0.0320**	0.0496***	0.0244	324,099
Only general regime	0.0072*	0.0051	0.0109	0.0062	0.0139*	319,575
Age 25-55	0.0081*	0.0056	0.0125	0.0076*	0.0117	280,958
Spell length >= 180 days	0.0032	0.0033	0.0031	0.0022	0.0109	204,669
Spell length >= 365 days	0.0020	0.0011	0.0039	0.0022	0.0001	134,862
Displaced in 2006-2017	0.0023	0.0410**	-0.0363***	-0.0015	0.0198	213,386
Displaced in 2001-2007	0.0053	-0.0006	0.0170**	0.0058	0.0009	161,115
Displaced in 2008-2017	0.0118	0.0838***	-0.0388**	0.0015	0.0451**	163,761
Displaced in 2004-2010	0.0132*	0.0090	0.0179	0.0139	0.0079	170,287
Displaced in 2011-2017	0.0110	0.1112***	-0.0603**	-0.0070	0.0553*	88,132
Displaced in 2008-2012	0.0044	0.0659***	-0.0416**	-0.0039	0.0343*	123,242
Displaced in 2013-2017	0.0427	0.2102	-0.0254	0.0214	0.0776*	40,519
Displaced in 2006-2009	0.0061	0.0243	-0.0139	0.0057	0.0083	101,333
Displaced in 2010-2013	-0.0102	0.1117***	-0.1063***	-0.0228	0.0316	81,357
Displaced in 2014-2017	0.0514	0.2369	-0.0212	0.0295	0.0827*	30,696
Same Sec and NUTS3	-0.0022					144,636
Different Sec and NUTS3	0.0095					26,091
IFR aggregation schemes						
15 Groups	-0.0001	0.0045	-0.0102*	-0.0031	0.0191**	324,876
17 Groups	0.0048	0.0041	0.0061	0.0040	0.0107	324,876
20 Groups	0.0076*	0.0055	0.0115	0.0068	0.0136*	324,876
Migration						
Non-neighbouring NUTS3	0.0074*	0.0058*	0.0105	0.0066	0.0189*	324,876
Fixed effects						
Add Current spell FE	0.0071*	0.0020	0.0162**	0.0062	0.0136*	324,876
NUTS2(Prev.)*Year Exit	0.0070	0.0047	0.0112	0.0062	0.0126*	324,876
NUTS2*Year Entry	0.0070	0.0046	0.0112	0.0060	0.0139*	324,876
Sector FE and ΔSec						
FE20 and ΔSec62	0.0043	0.0022	0.0060	0.0038	0.0079	324,876
FE20 and ΔSec66	0.0045	0.0012	0.0070	0.0040	0.0082	324,876
FE62 and ΔSec20	0.0160***	0.0136***	0.0193**	0.0154**	0.0205**	324,876
FE62 and ΔSec62	0.0133**	0.0106**	0.0149**	0.0130**	0.0147*	324,876
FE62 and ΔSec66	0.0123**	0.0083*	0.0146**	0.0120**	0.0142*	324,876
FE66 and ΔSec20	0.0108*	0.0094*	0.0128	0.0102*	0.0147*	324,876
FE66 and ΔSec62	0.0087	0.0071	0.0098	0.0085	0.0100	324,876
FE66 and ΔSec66	0.0078	0.0048	0.0096	0.0075	0.0095	324,876
Reason termination						
93 - End of temp. contr.	0.1578	0.1931	0.0886	0.1636	0.1442	47,579
77 - Collective dismissal	-0.1116	-0.0993	-0.4870	0.3186	12.0307	1,636
51 - Voluntary leave	-0.0088**	0.0026	-0.0166***	-0.0092*	-0.0072	133,453
77+55+91	-0.1478	-0.1003	-0.3961	-0.1435	-0.1822	14,850
51+54+55+77+91	0.0006	0.0046	-0.0044	0.0001	0.0035	473,179

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector, and year of dismissal.

Table 2A.10: Robustness - Lower qualification (MLS)

		ΔSec		$\Delta NUTS$		
	ΔExp	No	Yes	No	Yes	N
Baseline	0.0097***	0.0035***	0.0150***	0.0102***	0.0046**	1,065,354
Subsamples						
Manufacturing	0.0090***	0.0036***	0.0137***	0.0090***	0.0097***	127,593
One transition	0.0086***	0.0009	0.0171***	0.0091***	0.0028	393,349
Previous 6 months	0.0093***	0.0021*	0.0171***	0.0096***	0.0067***	447,100
4 months unemployed	0.0129***	0.0126***	0.0130***	0.0141***	0.0042*	688,927
24 months unemployed	0.0140***	0.0144***	0.0139***	0.0147***	0.0088**	355,564
Previous not automotive	0.0026	0.0011	0.0035	0.0053**	-0.0134***	1,058,908
Only general regime	0.0097***	0.0029***	0.0156***	0.0101***	0.0053***	1,022,066
Age 25-55	0.0084***	0.0022**	0.0142***	0.0091***	0.0024	831,093
Spell length >= 180 days	0.0064***	0.0042***	0.0096***	0.0064***	0.0067**	439,871
Spell length >= 365 days	0.0043***	0.0019	0.0086***	0.0042***	0.0062**	212,105
Displaced in 2006-2017	0.0128***	0.0085***	0.0156***	0.0151***	-0.0035	641,964
Displaced in 2001-2007	0.0097***	0.0031***	0.0156***	0.0100***	0.0071***	612,875
Displaced in 2008-2017	0.0114**	0.0079	0.0135*	0.0148**	-0.0067	452,479
Displaced in 2004-2010	0.0135***	0.0065***	0.0181***	0.0146***	0.0053*	606,372
Displaced in 2011-2017	0.0132	0.0024	0.0205*	0.0172*	-0.0080	210,460
Displaced in 2008-2012	0.0130**	0.0114**	0.0139*	0.0167**	-0.0071	363,462
Displaced in 2013-2017	-0.0187	-0.0389*	-0.0054	-0.0190	-0.0176	89,017
Displaced in 2006-2009	0.0156***	0.0099***	0.0193***	0.0176***	0.0005	361,866
Displaced in 2010-2013	0.0112	0.0093	0.0124	0.0155	-0.0154	212,607
Displaced in 2014-2017	-0.0225	-0.0392	-0.0120	-0.0216	-0.0258	67,491
Same Sec and NUTS3	0.0037***					470,662
Different Sec and NUTS3	0.0135***					77,833
IFR aggregation schemes						
15 Groups	0.0094***	0.0031***	0.0151***	0.0100***	0.0031	1,065,354
17 Groups	0.0097***	0.0033***	0.0153***	0.0102***	0.0050**	1,065,354
20 Groups	0.0097***	0.0036***	0.0149***	0.0102***	0.0046**	1,065,354
Migration						
Non-neighbouring NUTS3	0.0097***	0.0035***	0.0150***	0.0100***	0.0006	1,065,354
Fixed effects						
Add Current spell FE	0.0089***	0.0051***	0.0121***	0.0093***	0.0047**	1,065,354
NUTS2(Prev.)*Year Exit	0.0095***	0.0034***	0.0148***	0.0101***	0.0042**	1,065,354
NUTS2*Year Entry	0.0097***	0.0035***	0.0151***	0.0102***	0.0049**	1,065,354
Sector FE and ΔSec						
FE20 and ΔSec62	0.0090***	-0.0041***	0.0137***	0.0095***	0.0044**	1,065,354
FE20 and ΔSec66	0.0093***	-0.0039***	0.0137***	0.0098***	0.0046**	1,065,354
FE62 and ΔSec20	0.0016	-0.0046***	0.0065***	0.0021	-0.0028	1,065,354
FE62 and ΔSec62	0.0013	-0.0111***	0.0056***	0.0018	-0.0027	1,065,354
FE62 and ΔSec66	0.0015	-0.0114***	0.0055***	0.0020	-0.0024	1,065,354
FE66 and ΔSec20	0.0009	-0.0052***	0.0058***	0.0014	-0.0035	1,065,354
FE66 and ΔSec62	0.0006	-0.0117***	0.0049***	0.0011	-0.0035	1,065,354
FE66 and ΔSec66	0.0006	-0.0121***	0.0046***	0.0011	-0.0034	1,065,354
Reason termination						
93 - End of temp. contr.	-0.0433	-0.0414	-0.0445	-0.0318	-0.1070**	193,851
77 - Collective dismissal	-0.0268	-0.0396	-0.0206	-0.0105	-0.0893	2,146
51 - Voluntary leave	0.0039***	0.0063***	0.0023	0.0044***	0.0010	384,743
77+55+91	-0.0233	-0.0303	-0.0120	-0.0169	-0.0693**	24,059
51+54+55+77+91	0.0087***	0.0038***	0.0127***	0.0093***	0.0034**	1,474,156

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector, and year of dismissal.

Table 2A.11: Robustness - Temporary contract (HS)

	ΔExp	ΔSec No	ΔSec Yes	$\Delta NUTS$ No	$\Delta NUTS$ Yes	N
Baseline	-0.0001	-0.0033	0.0076	0.0002	-0.0028	114,843
Subsamples						
Manufacturing	-0.0015	-0.0053**	0.0069	-0.0008	-0.0083	11,777
One transition	-0.0017	-0.0048*	0.0059	-0.0008	-0.0110	82,586
Previous 6 months	-0.0012	-0.0032	0.0039	-0.0002	-0.0117	99,829
4 months unemployed	-0.0100*	-0.0027	-0.0140**	-0.0085	-0.0158	45,453
24 months unemployed	-0.0120*	-0.0130	-0.0116	-0.0105	-0.0184	28,525
Previous not automotive	0.0314***	0.0309***	0.0317**	0.0325***	0.0241	114,275
Only general regime	-0.0003	-0.0037	0.0076	-0.0002	-0.0020	113,276
Age 25-55	0.0008	-0.0029	0.0096	0.0012	-0.0021	104,826
Spell length >= 180 days	-0.0017	-0.0028	0.0013	-0.0013	-0.0057	96,719
Spell length >= 365 days	-0.0010	-0.0028	0.0037	-0.0005	-0.0063	79,342
Displaced in 2006-2017	0.0106	0.0135	0.0072	0.0093	0.0187	79,811
Displaced in 2001-2007	-0.0008	-0.0032	0.0056	0.0000	-0.0093	50,649
Displaced in 2008-2017	0.0023	0.0084	-0.0027	-0.0024	0.0210	64,194
Displaced in 2004-2010	0.0026	-0.0038	0.0118	0.0049	-0.0226	56,767
Displaced in 2011-2017	0.0112	0.0264	-0.0038	-0.0161	0.0925*	37,214
Displaced in 2008-2012	-0.0019	-0.0040	-0.0001	-0.0020	-0.0013	45,179
Displaced in 2013-2017	0.0096	0.0473	-0.0158	-0.0365	0.0955	19,015
Displaced in 2006-2009	0.0203*	0.0143	0.0283*	0.0213*	0.0133	34,102
Displaced in 2010-2013	0.0062	0.0178	-0.0048	0.0092	-0.0054	31,076
Displaced in 2014-2017	-0.0071	0.0605	-0.0552	-0.0500	0.0614	14,633
Same Sec and NUTS3	-0.0041*					58,943
Different Sec and NUTS3	-0.0084					6,973
IFR aggregation schemes						
15 Groups	-0.0058**	-0.0054**	-0.0068	-0.0060**	-0.0037	114,843
17 Groups	-0.0029	-0.0053**	0.0027	-0.0024	-0.0074	114,843
20 Groups	0.0002	-0.0033	0.0084	0.0005	-0.0027	114,843
Migration						
Non-neighbouring NUTS3	-0.0001	-0.0035	0.0078	0.0008	-0.0147*	114,843
Fixed effects						
Add Current spell FE	0.0014	-0.0025	0.0107	0.0018	-0.0021	114,843
NUTS2(Prev.)*Year Exit	-0.0002	-0.0034	0.0072	0.0001	-0.0037	114,843
NUTS2*Year Entry	0.0004	-0.0028	0.0078	0.0007	-0.0027	114,843
Sector FE and ΔSec						
FE20 and ΔSec62	-0.0021	-0.0066***	0.0027	-0.0018	-0.0056	114,843
FE20 and ΔSec66	-0.0020	-0.0062**	0.0025	-0.0016	-0.0054	114,843
FE62 and ΔSec20	0.0048	-0.0002	0.0134	0.0050	0.0026	114,843
FE62 and ΔSec62	0.0025	-0.0032	0.0073	0.0030	-0.0013	114,843
FE62 and ΔSec66	0.0017	-0.0038	0.0061	0.0021	-0.0017	114,843
FE66 and ΔSec20	-0.0010	-0.0049	0.0060	-0.0007	-0.0042	114,843
FE66 and ΔSec62	-0.0026	-0.0072*	0.0014	-0.0021	-0.0068	114,843
FE66 and ΔSec66	-0.0033	-0.0077*	0.0004	-0.0029	-0.0072	114,843
Reason termination						
77 - Collective dismissal	0.0350	0.0051	0.9521	-0.1326	-4.6960	1,636
51 - Voluntary leave	-0.0037	-0.0047	-0.0030	-0.0042	-0.0017	133,453
77+55+91	-0.0148	-0.0372	0.1023	-0.0336	0.1339	14,850
51+54+55+77+91	-0.0011	-0.0073***	0.0067	-0.0016	0.0015	473,179

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector, and year of dismissal.

Table 2A.12: Robustness - Temporary contract (MLS)

		ΔSec		$\Delta NUTS$		
	ΔExp	No	Yes	No	Yes	N
Baseline	-0.0094***	-0.0181***	0.0113**	-0.0102***	0.0051	172,629
Subsamples						
Manufacturing	-0.0076***	-0.0154***	0.0096*	-0.0083***	0.0041	30,725
One transition	-0.0092***	-0.0189***	0.0136***	-0.0098***	0.0017	131,948
Previous 6 months	-0.0090***	-0.0171***	0.0107**	-0.0097***	0.0026	140,663
4 months unemployed	-0.0010	0.0028	-0.0027	-0.0012	0.0004	92,665
24 months unemployed	0.0014	0.0002	0.0018	0.0015	0.0006	57,425
Previous not automotive	0.0134*	-0.0172*	0.0358***	0.0158*	-0.0091	170,920
Only general regime	-0.0089***	-0.0176***	0.0120**	-0.0100***	0.0091*	166,318
Age 25-55	-0.0089***	-0.0174***	0.0108**	-0.0098***	0.0057	147,897
Spell length >= 180 days	-0.0076***	-0.0121***	0.0049	-0.0085***	0.0085	132,795
Spell length >= 365 days	-0.0070***	-0.0103***	0.0025	-0.0071***	-0.0060	99,653
Displaced in 2006-2017	-0.0127**	-0.0302***	0.0079	-0.0137**	-0.0030	121,480
Displaced in 2001-2007	-0.0064***	-0.0138***	0.0129**	-0.0073***	0.0096*	75,635
Displaced in 2008-2017	-0.0140	-0.0329**	0.0009	-0.0142	-0.0121	96,994
Displaced in 2004-2010	-0.0042	-0.0227***	0.0208***	-0.0046	0.0011	92,914
Displaced in 2011-2017	-0.0702***	-0.1541***	0.0049	-0.0768***	-0.0157	51,885
Displaced in 2008-2012	-0.0155*	-0.0278*	-0.0053	-0.0158	-0.0129	69,724
Displaced in 2013-2017	0.0004	-0.1389	0.0407	0.0007	-0.0012	27,270
Displaced in 2006-2009	-0.0005	-0.0110	0.0126*	-0.0017	0.0121	56,110
Displaced in 2010-2013	-0.0556***	-0.1073***	-0.0005	-0.0595***	-0.0146	44,484
Displaced in 2014-2017	0.0107	-0.1716	0.0176	0.0128	0.0049	20,886
Same Sec and NUTS3	-0.0145***					89,120
Different Sec and NUTS3	0.0053					9,356
IFR aggregation schemes						
15 Groups	-0.0129***	-0.0194***	0.0046	-0.0141***	0.0089	172,629
17 Groups	-0.0103***	-0.0194***	0.0119**	-0.0114***	0.0089	172,629
20 Groups	-0.0092***	-0.0179***	0.0114**	-0.0100***	0.0051	172,629
Migration						
Non-neighbouring NUTS3	-0.0095***	-0.0183***	0.0116**	-0.0097***	-0.0007	172,629
Fixed effects						
Add Current spell FE	-0.0080***	-0.0149***	0.0080	-0.0086***	0.0030	172,629
NUTS2(Prev.)*Year Exit	-0.0094***	-0.0183***	0.0111**	-0.0103***	0.0056	172,629
NUTS2*Year Entry	-0.0092***	-0.0181***	0.0110**	-0.0101***	0.0055	172,629
Sector FE and ΔSec						
FE20 and ΔSec62	-0.0108***	-0.0242***	0.0047	-0.0116***	0.0028	172,629
FE20 and ΔSec66	-0.0102***	-0.0239***	0.0052	-0.0110***	0.0043	172,629
FE62 and ΔSec20	0.0041	-0.0073**	0.0254***	0.0029	0.0206***	172,629
FE62 and ΔSec62	0.0037	-0.0118***	0.0190***	0.0026	0.0189***	172,629
FE62 and ΔSec66	0.0041	-0.0120***	0.0190***	0.0029	0.0208***	172,629
FE66 and ΔSec20	0.0002	-0.0103***	0.0206***	-0.0009	0.0156***	172,629
FE66 and ΔSec62	-0.0002	-0.0147***	0.0147***	-0.0012	0.0142**	172,629
FE66 and ΔSec66	-0.0002	-0.0151***	0.0143***	-0.0013	0.0156***	172,629
Reason termination						
77 - Collective dismissal	0.0765	0.0999	0.0653	0.0701	0.1012	2,146
51 - Voluntary leave	-0.0082***	-0.0095***	-0.0073***	-0.0082***	-0.0082**	384,743
77+55+91	-0.0336	-0.0649	0.0167	-0.0490	0.0780	24,059
51+54+55+77+91	-0.0062***	-0.0076***	-0.0050***	-0.0064***	-0.0036*	1,474,156

Source: authors' own calculations. *Notes*: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector, and year of dismissal.

Table 2A.13: Robustness - ETT firm (HS)

	ΔExp	$\Delta NUTS$ No	$\Delta NUTS$ Yes	N
Baseline	0.0020	0.0029*	-0.0041	321,478
One transition	0.0005	0.0010	-0.0039	159,223
Previous 6 months	0.0011	0.0019	-0.0052**	203,288
4 months unemployed	0.0021	0.0049	-0.0076	168,888
24 months unemployed	0.0059	0.0087*	-0.0044	90,473
Previous not automotive	0.0103***	0.0144***	-0.0108	320,701
Only general regime	0.0020	0.0029*	-0.0041	316,187
Age 25-55	0.0025*	0.0031**	-0.0019	278,233
Spell length >= 180 days	0.0005	0.0004	0.0008	203,854
Spell length >= 365 days	0.0002	0.0002	0.0003	134,606
Displaced in 2006-2017	0.0032	0.0063	-0.0111**	211,496
Displaced in 2001-2007	0.0016	0.0022	-0.0029	158,888
Displaced in 2008-2017	0.0027	0.0071	-0.0116	162,590
Subsamples				
Manufacturing	0.0025*	0.0030*	-0.0016	19,024
Displaced in 2004-2010	0.0043	0.0057*	-0.0059	168,245
Displaced in 2011-2017	0.0054	0.0145	-0.0171	87,665
Displaced in 2008-2012	0.0063	0.0110	-0.0103	122,179
Displaced in 2013-2017	-0.0298	-0.0319	-0.0263	40,411
Displaced in 2006-2009	0.0060	0.0083*	-0.0067	100,083
Displaced in 2010-2013	0.0020	0.0099	-0.0241*	80,778
Displaced in 2014-2017	-0.0375	-0.0423	-0.0307	30,635
Same Sec and NUTS3	0.0000			144,094
Different Sec and NUTS3	-0.0031			25,782
IFR aggregation schemes				
15 Groups	0.0007	0.0015	-0.0045	321,478
17 Groups	0.0013	0.0023	-0.0055	321,478
20 Groups	0.0019	0.0028*	-0.0040	321,478
Migration				
Non-neighbouring NUTS3	0.0020	0.0028*	-0.0087**	321,478
Fixed effects				
Add Current spell FE	0.0011	0.0020**	-0.0050*	321,478
NUTS2(Prev.)*Year Exit	0.0021	0.0029*	-0.0039	321,478
NUTS2*Year Entry	0.0022	0.0031*	-0.0042	321,478
Sector FE				
FE62	0.0004	0.0013	-0.0055	321,478
FE66	-0.0009	0.0000	-0.0072*	321,478
Reason termination				
93 - End of temp. contr.	0.0646	0.0950	-0.0068	47,579
77 - Collective dismissal	0.0399	0.0295	-0.2531	1,636
51 - Voluntary leave	-0.0010	-0.0008	-0.0017	133,453
77+55+91	0.0208	0.0267	-0.0258	14,850
51+54+55+77+91	0.0007	0.0014	-0.0036*	473,179

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector, and year of dismissal.

Table 2A.14: Robustness - ETT firm (MLS)

		$\Delta NUTS$		
	ΔExp	No	Yes	N
Baseline	0.0109***	0.0118***	0.0027	993,696
One transition	0.0103***	0.0107***	0.0058*	383,208
Previous 6 months	0.0104***	0.0108***	0.0062*	439,324
4 months unemployed	0.0137***	0.0151***	0.0036	649,902
24 months unemployed	0.0142***	0.0155***	0.0046	338,829
Previous not automotive	0.0106***	0.0128***	-0.0028	987,250
Only general regime	0.0109***	0.0118***	0.0027	952,045
Age 25-55	0.0113***	0.0118***	0.0056**	780,251
Spell length >= 180 days	0.0030***	0.0031***	0.0022	429,916
Spell length >= 365 days	0.0002	0.0004	-0.0017	210,259
Displaced in 2006-2017	0.0176***	0.0197***	0.0029	603,438
Displaced in 2001-2007	0.0109***	0.0115***	0.0041	563,040
Displaced in 2008-2017	0.0178***	0.0214***	-0.0011	430,656
Subsamples				
Manufacturing	0.0091***	0.0094***	0.0057**	127,593
Displaced in 2004-2010	0.0165***	0.0181***	0.0048	561,746
Displaced in 2011-2017	0.0462***	0.0510***	0.0203	202,668
Displaced in 2008-2012	0.0177***	0.0206***	0.0020	343,591
Displaced in 2013-2017	0.0222	0.0345	-0.0289	87,065
Displaced in 2006-2009	0.0181***	0.0199***	0.0046	334,590
Displaced in 2010-2013	0.0292**	0.0309**	0.0182	202,661
Displaced in 2014-2017	0.0091	0.0209	-0.0326	66,187
Same Sec and NUTS3	-0.0001			455,639
Different Sec and NUTS3	0.0114***			72,360
IFR aggregation schemes				
15 Groups	0.0120***	0.0131***	0.0010	993,696
17 Groups	0.0115***	0.0125***	0.0023	993,696
20 Groups	0.0108***	0.0116***	0.0026	993,696
Migration				
Non-neighbouring NUTS3	0.0109***	0.0115***	-0.0050**	993,696
Fixed effects				
Add Current spell FE	0.0067***	0.0074***	-0.0004	993,696
NUTS2(Prev.)*Year Exit	0.0109***	0.0118***	0.0027	993,696
NUTS2*Year Entry	0.0109***	0.0118***	0.0029	993,696
Sector FE				
FE62	-0.0009	0.0000	-0.0089***	993,696
FE66	-0.0010	-0.0001	-0.0090***	993,696
Reason termination				
93 - End of temp. contr.	0.0771	0.0921*	-0.0069	193,851
77 - Collective dismissal	0.0331	0.0372	0.0174	2,146
51 - Voluntary leave	0.0047***	0.0050***	0.0030	384,743
77+55+91	0.0105	0.0072	0.0346	24,059
51+54+55+77+91	0.0101***	0.0109***	0.0031	1,474,156

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector, and year of dismissal.

Table 2A.15: Sector fixed effects and change of sector - NACE Rev.2 codes

20 sectors	**62 sectors**	**66 sectors**
A - Agriculture, forestry, fishing	A	A
B - Mining and quarrying	B	B
C - Manufacturing	10–12	10–12
	13–15	13–15
	16, 31	16, 31
	17–18	17–18
	19–22	19–21
		22
	23	23
	24, 25, 28	24
		25
		28
	26–27	26
		27
	29	29
	30	30
	32	32
	33	33
D and E - Energy, Water, Sewerage, and Waste	D and E	D and E
F - Construction	F	F
G - Wholesale and retail	45	45
	46	46
	47	47
H - Transporting and storage	49	49
	50	50
	51	51
	52	52
	53	53
I - Accommodation and food service	55	55
	56	56
J - Information and communication	58	58
	59	59
	60	60
	61	61
	62	62
	63	63
K - Finance and insurance	64	64
	65	65
	66	66
L - Real estate	68	68
M - Professional, scientific, and technical act.	69	69
	70	70
	71	71
	73	73
	74	74
	75	75

N - Administrative and support services	77	77
	78	78
	79	79
	80	80
	81	81
	82	82
O - Public administration and defence	84	84
P - Education and research	72, 85	72, 85
Q - Health and social work	86	86
	87	87
	88	88
R - Arts, entertainment, and recreation	90	90
	91	91
	92	92
	93	93
S - Other services	94	94
	95	95
	96	96
T - Activities of households as employer	97	97
U - Extraterrit. organis. and bodies	99	99

Source: authors' aggregation of NACE Rev. 2 codes.

Table 2A.16: Causes for termination of the previous contract

Code	Cause
51	Voluntary leave
54	Non-voluntary leave
55	Dismissal due to merger or absorption of company
56	Dismissal due to death
58	Dismissal due to retirement
60	Retirement
61	Dismissal due to military service
63	Forced or voluntary leave of absence
64	Leave due to legal strike or lockout
65	Leave for exhaustion of temp. incapacity
67	Leave due to seasonal unemployment
68	Leave of absence due to childcare
69	Temporary suspension due to ERE
73	Leave of absence to care for family members
74	Leave of absence due to contract suspension
77	Collective dismissal
81	Ex officio leave due to scheme revision
84	Transfer to another social security scheme
91	Dismissal for objective reasons of the company
92	Dismissal for objective reasons of the worker
93	End of temporary contract
94	Inactivity pass of discontinuous fixed-term contract
96	Modification of contract
99	Other causes

Source: MCVL.

Table 2A.17: Robustness - Disaggregated skill groups

		ΔSec		$\Delta NUTS$		
	ΔExp	No	Yes	No	Yes	N
Lower Pay						
Aggregated:						
High-skilled	0.0023	-0.0120***	0.0282***	0.0040	-0.0096	324,876
Middle and low-skilled	0.0193***	0.0033*	0.0331***	0.0182***	0.0308***	1,065,354
Subgroups:						
Very high	0.0034	-0.0092	0.0276***	0.0053	-0.0048	53,542
High	0.0069	-0.0040	0.0344***	0.0097	-0.0157	85,979
Middle-high	0.0008	-0.0166***	0.0267***	0.0015	-0.0050	185,355
Middle low	0.0200***	0.0029	0.0350***	0.0186***	0.0335***	739,942
Low	0.0128***	0.0030	0.0200***	0.0128***	0.0129	325,412
Pay ratio ($\times$100)						
Aggregated:						
High-skilled	-0.3056*	0.4374***	-1.6466***	-0.3660**	0.1252	324,876
Middle and low-skilled	-1.7707***	-0.3150***	-3.0258***	-1.6355***	-3.1101***	1,065,354
Subgroups:						
Very high	-0.4130	-0.0304	-1.1461**	-0.4934*	-0.0698	53,542
High	-0.3734	0.0607	-1.4660**	-0.3983	-0.1701	85,979
Middle-high	-0.2045	0.7777***	-1.6627***	-0.2897	0.5382	185,355
Middle low	-1.8471***	-0.4041***	-3.1233***	-1.7071***	-3.2430***	739,942
Low	-0.8876***	0.7490***	-2.0878***	-0.7790***	-1.9258***	325,412
Lower skill						
Aggregated:						
High-skilled	0.0075*	0.0056	0.0108	0.0066	0.0135*	324,876
Middle and low-skilled	0.0097***	0.0035***	0.0150***	0.0102***	0.0046**	1,065,354
Subgroups:						
Very high	0.0086	0.0062	0.0134	0.0046	0.0258	53,542
High	0.0008	-0.0064	0.0190	-0.0003	0.0100	85,979
Middle-high	0.0088**	0.0098**	0.0073	0.0098**	-0.0002	185,355
Middle low	0.0081***	0.0024*	0.0132***	0.0087***	0.0022	739,942
Lower security						
Aggregated:						
High-skilled	-0.0001	-0.0033	0.0076	0.0002	-0.0028	114,843
Middle and low-skilled	-0.0094***	-0.0181***	0.0113**	-0.0102***	0.0051	172,629
Subgroups:						
Very high	0.0054	0.0000	0.0160*	0.0104*	-0.0172**	18,072
High	-0.0071*	-0.0128***	0.0107	-0.0075*	-0.0033	28,939
Middle-high	0.0023	0.0013	0.0046	0.0012	0.0210	67,832
Middle low	-0.0091***	-0.0174***	0.0122**	-0.0102***	0.0091	135,439
Low	0.0016	-0.0077	0.0073	0.0039	-0.0229	37,190
ETT firm						
Aggregated:						
High-skilled	0.0020			0.0029*	-0.0041	321,478
Middle and low-skilled	0.0109***			0.0118***	0.0027	993,696
Subgroups:						
Very high	0.0012			0.0019	-0.0019	53,358
High	0.0006			0.0011	-0.0030	85,581
Middle-high	0.0033			0.0043*	-0.0051	182,539
Middle low	0.0112***			0.0122***	0.0017	704,404
Low	0.0108***			0.0110***	0.0095	289,292

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.

Table 2A.18: Skill groups

<table>
<tr><th>MCVL groups</th><th>5 groups</th><th>2 groups</th></tr>
<tr><td>1. Engineers, graduates and senior management</td><td>1. Very-high-skilled</td><td rowspan="6">1. High-skilled</td></tr>
<tr><td>2. Technical engineers, technicians and assistants</td><td rowspan="2">2. High-skilled</td></tr>
<tr><td>3. Administrative and workshop managers</td></tr>
<tr><td>4. Non-graduate assistants</td><td rowspan="3">3. Middle-high-skilled</td></tr>
<tr><td>5. Administrative officers</td></tr>
<tr><td>6. Subordinates</td></tr>
<tr><td>7. Administrative assistants</td><td rowspan="3">4. Middle-low-skilled</td><td rowspan="4">2. Middle- and low-skilled</td></tr>
<tr><td>8. First and second officers</td></tr>
<tr><td>9. Third officers and specialists</td></tr>
<tr><td>10. Unskilled (over 18)</td><td>5. Low-skilled</td></tr>
<tr><td>11. Workers under 18 years of age</td><td>Drop</td><td>Drop</td></tr>
</table>

Source: author's aggregation of MCVL categories. *Notes:* the 5 groups scheme follows the one adopted in De la Roca and Puga (2017).

Table 2A.19: Robustness - Timing of robot exposure (HS)

			ΔSec		$\Delta NUTS$		
Time Exp.	Time instr.	ΔExp	No	Yes	No	Yes	N
Worse pay							
t-1 vs. t-2	t-1 vs. t-2	0.0023	-0.0120***	0.0282***	0.0040	-0.0096	324,876
t-1 vs. t-3	t-1 vs. t-3	0.0009	-0.0054***	0.0133***	0.0014	-0.0019	324,876
t-1 vs. t-4	t-1 vs. t-4	0.0002	-0.0043***	0.0086***	0.0003	-0.0011	324,876
t-1 vs. t-5	t-1 vs. t-5	0.0003	-0.0031***	0.0065***	0.0004	-0.0009	324,876
t-2 vs. t-3	t-2 vs. t-3	0.0005	-0.0093**	0.0181***	0.0004	0.0017	324,876
t-3 vs. t-4	t-3 vs. t-4	-0.0008	-0.0136***	0.0196***	-0.0008	-0.0003	324,876
t-4 vs. t-5	t-4 vs. t-5	-0.0007	-0.0123***	0.0160***	0.0003	-0.0070	324,876
t-1 vs. t-2	t-2 vs. t-3	0.0003	-0.0098**	0.0236***	0.0001	0.0018	324,876
t-2 vs. t-3	t-3 vs. t-4	-0.0001	-0.0144***	0.0261***	-0.0002	0.0005	324,876
t-3 vs. t-4	t-4 vs. t-5	-0.0021	-0.0144***	0.0178***	-0.0009	-0.0100	324,876
Pay ratio (×100)							
t-1 vs. t-2	t-1 vs. t-2	-0.3056*	0.4374***	-1.6466***	-0.3660**	0.1252	324,876
t-1 vs. t-3	t-1 vs. t-3	-0.1477*	0.1750**	-0.7767***	-0.1535*	-0.1084	324,876
t-1 vs. t-4	t-1 vs. t-4	-0.1190**	0.1153**	-0.5631***	-0.1195**	-0.1154	324,876
t-1 vs. t-5	t-1 vs. t-5	-0.0977**	0.0814**	-0.4268***	-0.0976**	-0.0977	324,876
t-2 vs. t-3	t-2 vs. t-3	-0.2188	0.2581	-1.0708***	-0.1751	-0.4957	324,876
t-3 vs. t-4	t-3 vs. t-4	-0.3410**	0.3501**	-1.4373***	-0.3262*	-0.4330	324,876
t-4 vs. t-5	t-4 vs. t-5	-0.2720	0.3365*	-1.1446***	-0.2749	-0.2531	324,876
t-1 vs. t-2	t-2 vs. t-3	-0.2351	0.2705	-1.4030***	-0.1842	-0.5852	324,876
t-2 vs. t-3	t-3 vs. t-4	-0.4124**	0.3693*	-1.8512***	-0.3930*	-0.5354	324,876
t-3 vs. t-4	t-4 vs. t-5	-0.3130	0.3547*	-1.3934***	-0.3136	-0.3091	324,876
Lower security							
t-1 vs. t-2	t-1 vs. t-2	-0.0001	-0.0033	0.0076	0.0002	-0.0028	114,843
t-1 vs. t-3	t-1 vs. t-3	-0.0004	-0.0014	0.0025	-0.0005	0.0007	114,843
t-1 vs. t-4	t-1 vs. t-4	0.0000	-0.0007	0.0018	-0.0002	0.0019	114,843
t-1 vs. t-5	t-1 vs. t-5	-0.0000	-0.0005	0.0011	-0.0003	0.0021	114,843
t-2 vs. t-3	t-2 vs. t-3	-0.0012	-0.0021	0.0010	-0.0020	0.0051	114,843
t-3 vs. t-4	t-3 vs. t-4	0.0002	-0.0012	0.0032	-0.0012	0.0109	114,843
t-4 vs. t-5	t-4 vs. t-5	-0.0003	-0.0012	0.0013	-0.0021	0.0135	114,843
t-1 vs. t-2	t-2 vs. t-3	-0.0013	-0.0021	0.0011	-0.0022	0.0063	114,843
t-2 vs. t-3	t-3 vs. t-4	0.0001	-0.0014	0.0037	-0.0016	0.0122	114,843
t-3 vs. t-4	t-4 vs. t-5	0.0001	-0.0008	0.0020	-0.0018	0.0155	114,843
Lower skill							
t-1 vs. t-2	t-1 vs. t-2	0.0075*	0.0056	0.0108	0.0066	0.0135*	324,876
t-1 vs. t-3	t-1 vs. t-3	0.0035*	0.0038*	0.0031	0.0025	0.0107***	324,876
t-1 vs. t-4	t-1 vs. t-4	0.0022*	0.0027**	0.0014	0.0015	0.0075***	324,876
t-1 vs. t-5	t-1 vs. t-5	0.0015*	0.0017*	0.0011	0.0009	0.0058***	324,876
t-2 vs. t-3	t-2 vs. t-3	0.0057	0.0089**	0.0000	0.0025	0.0263***	324,876
t-3 vs. t-4	t-3 vs. t-4	0.0038	0.0068*	-0.0010	0.0014	0.0185***	324,876
t-4 vs. t-5	t-4 vs. t-5	0.0033	0.0031	0.0035	0.0009	0.0187**	324,876
t-1 vs. t-2	t-2 vs. t-3	0.0068	0.0096**	0.0005	0.0031	0.0321***	324,876
t-2 vs. t-3	t-3 vs. t-4	0.0042	0.0073	-0.0017	0.0014	0.0218**	324,876
t-3 vs. t-4	t-4 vs. t-5	0.0043	0.0039	0.0050	0.0016	0.0228**	324,876
ETT firm							
t-1 vs. t-2	t-1 vs. t-2	0.0020			0.0029*	-0.0041	321,478
t-1 vs. t-3	t-1 vs. t-3	0.0012*			0.0015**	-0.0011	321,478
t-1 vs. t-4	t-1 vs. t-4	0.0008*			0.0010**	-0.0006	321,478
t-1 vs. t-5	t-1 vs. t-5	0.0006*			0.0007*	-0.0002	321,478
t-2 vs. t-3	t-2 vs. t-3	0.0024*			0.0028*	-0.0002	321,478
t-3 vs. t-4	t-3 vs. t-4	0.0021			0.0025	-0.0006	321,478
t-4 vs. t-5	t-4 vs. t-5	0.0013			0.0013	0.0015	321,478
t-1 vs. t-2	t-2 vs. t-3	0.0027			0.0031*	-0.0002	321,478
t-2 vs. t-3	t-3 vs. t-4	0.0025			0.0030	-0.0007	321,478
t-3 vs. t-4	t-4 vs. t-5	0.0016			0.0015	0.0018	321,478

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions. Column "Time Exp." indicates the two years considered for the variation in the stock of robots in Spain (with t being the year in which the worker was dismissed). Column "Time Instr." indicates the two years considered for the variation in the stock of robots for the instrument. The baseline specification has "t-1 vs. t-2" both in "Time Exp." and in "Time Instr.".

Table 2A.20: Robustness - Timing of robot exposure (MLS)

			ΔSec		$\Delta NUTS$		
Time Exp.	Time instr.	ΔExp	No	Yes	No	Yes	N
Worse pay							
t-1 vs. t-2	t-1 vs. t-2	0.0193***	0.0033*	0.0331***	0.0182***	0.0308***	1,065,354
t-1 vs. t-3	t-1 vs. t-3	0.0102***	0.0017*	0.0174***	0.0097***	0.0153***	1,065,354
t-1 vs. t-4	t-1 vs. t-4	0.0071***	0.0012*	0.0118***	0.0067***	0.0104***	1,065,354
t-1 vs. t-5	t-1 vs. t-5	0.0056***	0.0011**	0.0091***	0.0054***	0.0082***	1,065,354
t-2 vs. t-3	t-2 vs. t-3	0.0194***	0.0030	0.0326***	0.0186***	0.0265***	1,065,354
t-3 vs. t-4	t-3 vs. t-4	0.0192***	0.0031	0.0309***	0.0184***	0.0261***	1,065,354
t-4 vs. t-5	t-4 vs. t-5	0.0208***	0.0049**	0.0315***	0.0199***	0.0284***	1,065,354
t-1 vs. t-2	t-2 vs. t-3	0.0217***	0.0038*	0.0374***	0.0208***	0.0314***	1,065,354
t-2 vs. t-3	t-3 vs. t-4	0.0215***	0.0035*	0.0355***	0.0204***	0.0321***	1,065,354
t-3 vs. t-4	t-4 vs. t-5	0.0223***	0.0053**	0.0341***	0.0211***	0.0326***	1,065,354
Pay ratio (×100)							
t-1 vs. t-2	t-1 vs. t-2	-1.7707***	-0.3150***	-3.0258***	-1.6355***	-3.1101***	1,065,354
t-1 vs. t-3	t-1 vs. t-3	-0.9579***	-0.1621***	-1.6290***	-0.8930***	-1.5978***	1,065,354
t-1 vs. t-4	t-1 vs. t-4	-0.6792***	-0.1281***	-1.1239***	-0.6350***	-1.1056***	1,065,354
t-1 vs. t-5	t-1 vs. t-5	-0.5418***	-0.1077***	-0.8795***	-0.5075***	-0.8641***	1,065,354
t-2 vs. t-3	t-2 vs. t-3	-1.8515***	-0.2706**	-3.1310***	-1.7436***	-2.8797***	1,065,354
t-3 vs. t-4	t-3 vs. t-4	-1.9080***	-0.3824***	-3.0248***	-1.7978***	-2.8615***	1,065,354
t-4 vs. t-5	t-4 vs. t-5	-2.0026***	-0.3765***	-3.0917***	-1.8909***	-2.9237***	1,065,354
t-1 vs. t-2	t-2 vs. t-3	-2.0673***	-0.3327***	-3.5757***	-1.9388***	-3.3899***	1,065,354
t-2 vs. t-3	t-3 vs. t-4	-2.1410***	-0.4320***	-3.4720***	-1.9996***	-3.5180***	1,065,354
t-3 vs. t-4	t-4 vs. t-5	-2.1459***	-0.4129***	-3.3574***	-2.0113***	-3.3643***	1,065,354
Lower security							
t-1 vs. t-2	t-1 vs. t-2	-0.0094***	-0.0181***	0.0113**	-0.0102***	0.0051	172,629
t-1 vs. t-3	t-1 vs. t-3	-0.0055***	-0.0094***	0.0037	-0.0060***	0.0035	172,629
t-1 vs. t-4	t-1 vs. t-4	-0.0037***	-0.0062***	0.0020	-0.0041***	0.0039**	172,629
t-1 vs. t-5	t-1 vs. t-5	-0.0027***	-0.0047***	0.0015	-0.0031***	0.0033**	172,629
t-2 vs. t-3	t-2 vs. t-3	-0.0115***	-0.0183***	0.0029	-0.0127***	0.0084	172,629
t-3 vs. t-4	t-3 vs. t-4	-0.0096***	-0.0161***	0.0025	-0.0115***	0.0180***	172,629
t-4 vs. t-5	t-4 vs. t-5	-0.0087***	-0.0170***	0.0045	-0.0103***	0.0127**	172,629
t-1 vs. t-2	t-2 vs. t-3	-0.0123***	-0.0184***	0.0032	-0.0135***	0.0092	172,629
t-2 vs. t-3	t-3 vs. t-4	-0.0108***	-0.0173***	0.0027	-0.0127***	0.0223***	172,629
t-3 vs. t-4	t-4 vs. t-5	-0.0095***	-0.0175***	0.0052	-0.0112***	0.0145**	172,629
Lower skill							
t-1 vs. t-2	t-1 vs. t-2	0.0097***	0.0035***	0.0150***	0.0102***	0.0046**	1,065,354
t-1 vs. t-3	t-1 vs. t-3	0.0052***	0.0021***	0.0078***	0.0054***	0.0028***	1,065,354
t-1 vs. t-4	t-1 vs. t-4	0.0037***	0.0015***	0.0054***	0.0038***	0.0021***	1,065,354
t-1 vs. t-5	t-1 vs. t-5	0.0029***	0.0012***	0.0043***	0.0031***	0.0018***	1,065,354
t-2 vs. t-3	t-2 vs. t-3	0.0097***	0.0041***	0.0142***	0.0101***	0.0057***	1,065,354
t-3 vs. t-4	t-3 vs. t-4	0.0100***	0.0041***	0.0143***	0.0105***	0.0054***	1,065,354
t-4 vs. t-5	t-4 vs. t-5	0.0109***	0.0041***	0.0154***	0.0113***	0.0073***	1,065,354
t-1 vs. t-2	t-2 vs. t-3	0.0108***	0.0045***	0.0162***	0.0111***	0.0068***	1,065,354
t-2 vs. t-3	t-3 vs. t-4	0.0113***	0.0046***	0.0165***	0.0117***	0.0068***	1,065,354
t-3 vs. t-4	t-4 vs. t-5	0.0117***	0.0045***	0.0168***	0.0121***	0.0085***	1,065,354
ETT firm							
t-1 vs. t-2	t-1 vs. t-2	0.0109***			0.0118***	0.0027	993,696
t-1 vs. t-3	t-1 vs. t-3	0.0058***			0.0062***	0.0021*	993,696
t-1 vs. t-4	t-1 vs. t-4	0.0042***			0.0044***	0.0016**	993,696
t-1 vs. t-5	t-1 vs. t-5	0.0033***			0.0035***	0.0014**	993,696
t-2 vs. t-3	t-2 vs. t-3	0.0112***			0.0118***	0.0051**	993,696
t-3 vs. t-4	t-3 vs. t-4	0.0119***			0.0128***	0.0048**	993,696
t-4 vs. t-5	t-4 vs. t-5	0.0127***			0.0135***	0.0060***	993,696
t-1 vs. t-2	t-2 vs. t-3	0.0123***			0.0129***	0.0061**	993,696
t-2 vs. t-3	t-3 vs. t-4	0.0135***			0.0142***	0.0061**	993,696
t-3 vs. t-4	t-4 vs. t-5	0.0137***			0.0145***	0.0071***	993,696

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions. Column "Time Exp." indicates the two years considered for the variation in the stock of robots in Spain (with t being the year in which the worker was dismissed). Column "Time Instr." indicates the two years considered for the variation in the stock of robots for the instrument. The baseline specification has "t-1 vs. t-2" both in "Time Exp." and in "Time Instr.".

Table 2A.21: Robustness - Alternative instruments (HS)

		ΔSec		$\Delta NUTS$			
	ΔExp	No	Yes	No	Yes	F-stat.	N
Lower pay							
Baseline	0.0023	-0.0120***	0.0282***	0.0040	-0.0096	169.6	324,876
Avg. 4 Nordic	0.0098	-0.0094	0.0310***	0.0112	0.0010	122.5	324,876
Avg. 8 European	0.0022	-0.0125***	0.0281***	0.0039	-0.0102	150.6	324,876
Japan	0.1060	0.0350	0.1788*	0.0916	0.1864	2.9	324,876
Avg. Nordic and Japan	0.0912	0.0318	0.1525**	0.0802	0.1532	4.3	324,876
Pay ration (×100)							
Baseline	-0.3056*	0.4374***	-1.6466***	-0.3660**	0.1252	169.6	324,876
Avg. 4 Nordic	-0.3588	0.9045**	-1.7526***	-0.4733	0.3387	122.5	324,876
Avg. 8 European	-0.2916*	0.4475***	-1.6024***	-0.3412**	0.0609	150.6	324,876
Japan	-4.2695	-3.8464	-4.7037	-3.9666	-5.9674	2.9	324,876
Avg. Nordic and Japan	-3.7877	-3.1643	-4.4308	-3.4371	-5.7658	4.3	324,876
Lower skill							
Baseline	0.0075*	0.0056	0.0108	0.0066	0.0135*	169.6	324,876
Avg. 4 Nordic	0.0195**	0.0285***	0.0096	0.0176**	0.0310**	122.5	324,876
Avg. 8 European	0.0077*	0.0058*	0.0109	0.0068	0.0141*	150.6	324,876
Japan	0.0435	-0.0204	0.1090	0.0180	0.1866	2.9	324,876
Avg. Nordic and Japan	0.0411	-0.0072	0.0910	0.0223	0.1471*	4.3	324,876
Lower security							
Baseline	-0.0001	-0.0033	0.0076	0.0002	-0.0028	142.2	114,843
Avg. 4 Nordic	0.0188**	0.0117*	0.0287**	0.0166**	0.0364*	76.3	114,843
Avg. 8 European	0.0003	-0.0030	0.0080	0.0005	-0.0015	128.5	114,843
Japan	0.0959	0.0554	0.1561	0.0903	0.1412	1.8	114,843
Avg. Nordic and Japan	0.0821	0.0498	0.1290	0.0787	0.1089	2.8	114,843
ETT firm							
Baseline	0.0020			0.0029*	-0.0041	169.6	321,478
Avg. 4 Nordic	0.0070**			0.0090***	-0.0053	122.5	321,478
Avg. 8 European	0.0021			0.0030*	-0.0043	150.6	321,478
Japan	-0.0045			0.0015	-0.0381	2.9	321,478
Avg. Nordic and Japan	-0.0023			0.0029	-0.0314	4.3	321,478

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.

Table 2A.22: Robustness - Alternative instruments (MLS)

	ΔExp	ΔSec No	ΔSec Yes	$\Delta NUTS$ No	$\Delta NUTS$ Yes	F-stat.	N
Lower pay							
Baseline	0.0193***	0.0033*	0.0331***	0.0182***	0.0308***	409.6	1,065,354
Avg. 4 Nordic	0.0116***	-0.0088***	0.0275***	0.0114***	0.0138**	111.9	1,065,354
Avg. 8 European	0.0191***	0.0029	0.0331***	0.0180***	0.0302***	396.6	1,065,354
Japan	0.0707**	0.0796	0.0678***	0.0752**	0.0439	5.2	1,065,354
Avg. Nordic and Japan	0.0620***	0.0578	0.0637***	0.0657***	0.0400	7.7	1,065,354
Pay ration (×100)							
Baseline	-1.7707***	-0.3150***	-3.0258***	-1.6355***	-3.1101***	409.6	1,065,354
Avg. 4 Nordic	-0.8092***	1.3063***	-2.4456***	-0.7156***	-1.5108***	111.9	1,065,354
Avg. 8 European	-1.7516***	-0.2649**	-3.0289***	-1.6155***	-3.0871***	396.6	1,065,354
Japan	-6.6990***	-3.0709	-7.8623***	-6.6951**	-6.7215**	5.2	1,065,354
Avg. Nordic and Japan	-5.8452***	-2.3457	-7.1679***	-5.7870***	-6.1991**	7.7	1,065,354
Lower skill							
Baseline	0.0097***	0.0035***	0.0150***	0.0102***	0.0046**	409.6	1,065,354
Avg. 4 Nordic	-0.0024	-0.0035*	-0.0015	-0.0004	-0.0174***	111.9	1,065,354
Avg. 8 European	0.0094***	0.0034***	0.0146***	0.0100***	0.0040**	396.6	1,065,354
Japan	0.0331**	-0.0009	0.0440***	0.0373**	0.0088	5.2	1,065,354
Avg. Nordic and Japan	0.0288***	0.0019	0.0389***	0.0324***	0.0068	7.7	1,065,354
Lower security							
Baseline	-0.0094***	-0.0181***	0.0113**	-0.0102***	0.0051	274.3	172,629
Avg. 4 Nordic	-0.0019	-0.0220***	0.0296***	-0.0026	0.0070	73.5	172,629
Avg. 8 European	-0.0091***	-0.0181***	0.0118**	-0.0099***	0.0048	264.3	172,629
Japan	0.0032	-0.0166	0.0155	0.0010	0.0261	2.7	172,629
Avg. Nordic and Japan	0.0032	-0.0169	0.0181	0.0016	0.0208	4.1	172,629
ETT firm							
Baseline	0.0109***			0.0118***	0.0027	409.9	993,696
Avg. 4 Nordic	0.0025			0.0047**	-0.0141***	112.0	993,696
Avg. 8 European	0.0107***			0.0116***	0.0021	396.8	993,696
Japan	0.0470***			0.0466**	0.0497**	5.3	993,696
Avg. Nordic and Japan	0.0407***			0.0406***	0.0411**	7.8	993,696

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 2.4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.

Table 2A.23: Robustness - IPW (HS)

		ΔSec		$\Delta NUTS$		
	ΔExp	No	Yes	No	Yes	N
Lower pay						
Baseline	0.0023	-0.0120***	0.0282***	0.0040	-0.0096	324,876
Trimmed 1%	0.0331	-0.1405**	0.1206***	0.0729**	-0.1238*	317,905
Trimmed 5%	0.0671	-0.2009*	0.2107***	0.1295*	-0.1406	291,953
Pay ratio ($\times$100)						
Baseline	-0.3056*	0.4374***	-1.6466***	-0.3660**	0.1252	324,876
Trimmed 1%	-3.9149*	3.4195	-7.6156***	-4.3096*	-2.3621	317,905
Trimmed 5%	-9.4296*	-1.7851	-13.5257**	-8.0134	-14.1472	291,953
Lower skill						
Baseline	0.0075*	0.0056	0.0108	0.0066	0.0135*	324,876
Trimmed 1%	0.0507**	0.1222***	0.0146	0.0421*	0.0845**	317,905
Trimmed 5%	0.0565	-0.1119	0.1468**	0.0598	0.0457	291,953
Lower security						
Baseline	-0.0001	-0.0033	0.0076	0.0002	-0.0028	114,843
Trimmed 1%	0.0047	0.0007	0.0089	0.0025	0.0196	112,386
Trimmed 5%	0.0048	0.0140	-0.0041	-0.0043	0.0476	103,212
ETT firm						
Baseline	0.0020			0.0029*	-0.0041	321,478
Trimmed 1%	0.0080			0.0179*	-0.0317	314,575
Trimmed 5%	-0.0109			0.0170	-0.1132**	288,895

Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Regressions weighted by inverse propensity weights (IPW) computed as described in Section 2.7. Weights trimmed at the top and bottom 1% or top and bottom 5%.

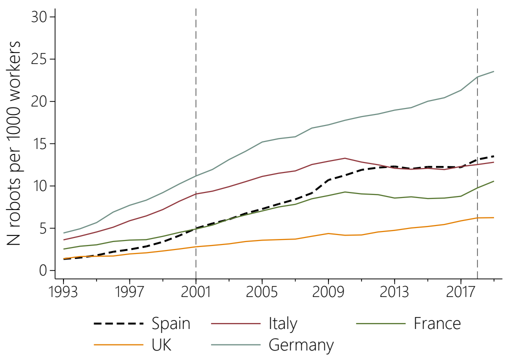
Table 2A.24: Robustness - IPW (MLS)

	ΔExp	ΔSec No	ΔSec Yes	$\Delta NUTS$ No	$\Delta NUTS$ Yes	N
Lower pay						
Baseline	0.0193***	0.0033*	0.0331***	0.0182***	0.0308***	1,065,354
Trimmed 1%	0.0441***	0.0038	0.0635***	0.0443***	0.0429***	1,042,470
Trimmed 5%	0.0663***	0.0125	0.0931***	0.0690***	0.0503**	957,370
Pay ratio (×100)						
Baseline	-1.7707***	-0.3150***	-3.0258***	-1.6355***	-3.1101***	1,065,354
Trimmed 1%	-3.4049***	0.9960**	-5.5149***	-3.2548***	-4.4178***	1,042,470
Trimmed 5%	-5.3978***	1.3555	-8.7670***	-5.3972***	-5.4017**	957,370
Lower skill						
Baseline	0.0097***	0.0035***	0.0150***	0.0102***	0.0046**	1,065,354
Trimmed 1%	0.0124***	0.0080*	0.0145***	0.0167***	-0.0169**	1,042,470
Trimmed 5%	0.0042	0.0132*	-0.0003	0.0109*	-0.0351***	957,370
Lower security						
Baseline	-0.0094***	-0.0181***	0.0113**	-0.0102***	0.0051	172,629
Trimmed 1%	-0.0114**	-0.0288***	0.0079	-0.0123**	-0.0008	168,986
Trimmed 5%	-0.0188**	-0.0410***	0.0027	-0.0174**	-0.0331	155,192
ETT firm						
Baseline	0.0109***			0.0118***	0.0027	993,696
Trimmed 1%	0.0201***			0.0224***	0.0031	972,246
Trimmed 5%	0.0280***			0.0308***	0.0094	892,878

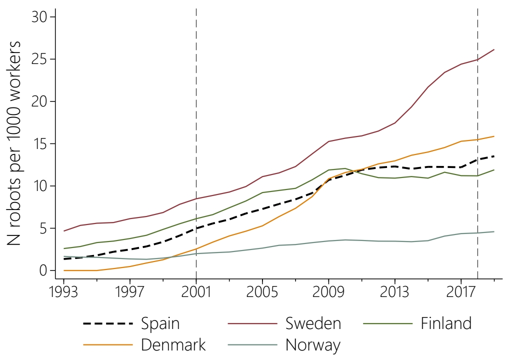
Source: authors' own calculations. *Notes*: two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in four other European countries. Regressions weighted by inverse propensity weights (IPW) computed as described in Section 2.7. Weights trimmed at the top and bottom 1%, or top and bottom 5%.

Figure 2A.1: Robot density in manufacturing - Spain and possible instruments

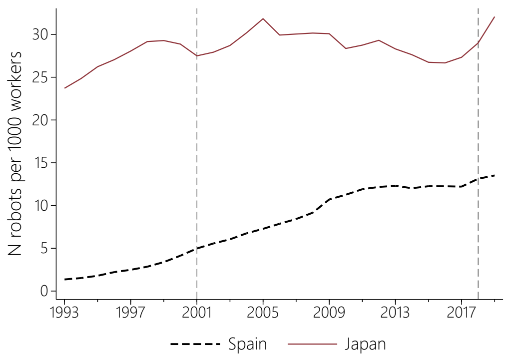
(a) Southern and Western Countries



(b) Nordic Countries

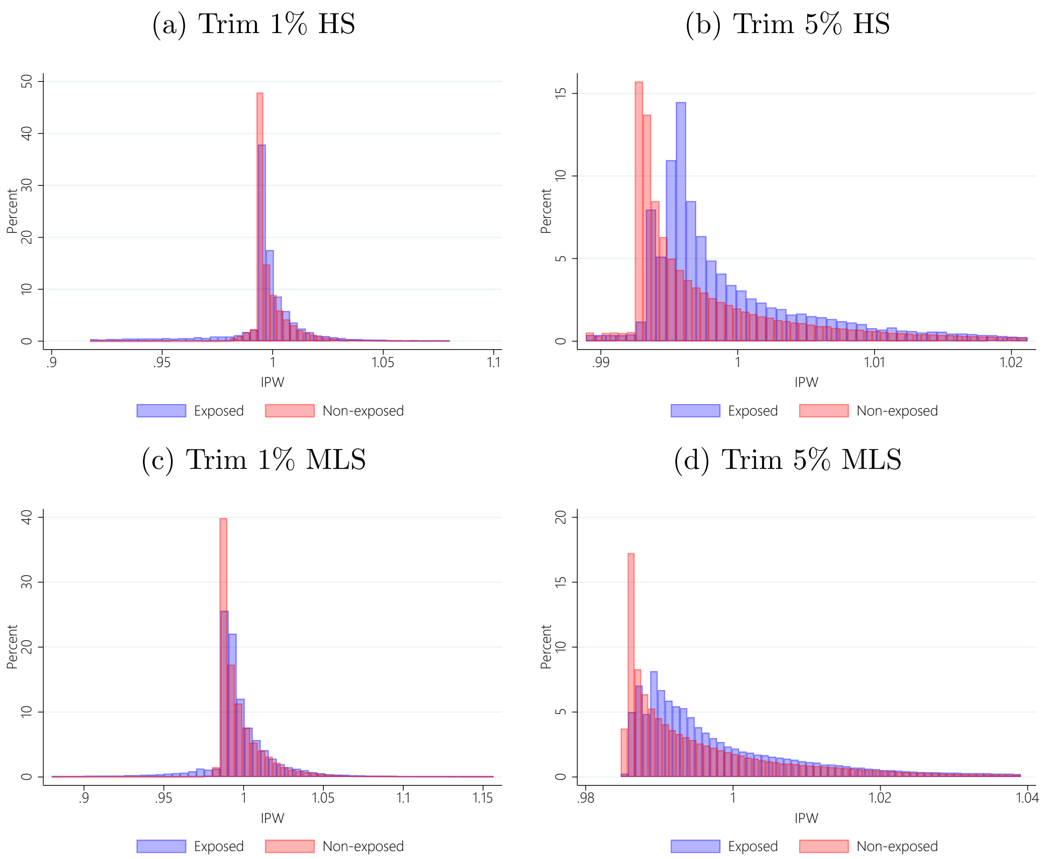


(c) Japan



Source: Authors' own calculations.

Figure 2A.2: Robustness - Overlap IPW



Source: authors' own calculations. *Notes:* we defined as "Exposed" workers who were previously employed in sectors with $\Delta Exp = 0$ and as "Non-Exposed" all other workers. Trim 1% (5%) indicate inverse propensity weights trimmed at the top and bottom 1% (5%).

3 The Growth of Involuntary Part-Time Employment in Italian Provinces: a Study of Technological Change, Skill Groups, and Gender[1]

3.1 Introduction

Starting in the early 2000s, Italy experienced a strong precarisation of labour, as employers started relying increasingly on temporary and/or part-time workers instead of hiring full-time employees with open-ended contracts. These types of work arrangements result in a more flexible workforce for the employer, but can also involve higher job insecurity, lower wages, and limited access to benefits and training for workers (Connolly and Gregory, 2010; Nicolaisen et al., 2019; O'Reilly and Bothfeld, 2002). Making use of the Italian section of the European Labour Force Survey (LFS), we investigate the rise of Involuntary Part Time (IPT) in Italy between 2004 and 2019. In this time frame the share of employees with a part-time contract surged from 13.8% to 21.2%. In principle, an increase in part-time is not bad *per se*, as it might reflect workers' preference for more flexible work arrangement. Indeed, for a long time part-time employment has primarily been linked to women attempting to balance their familial and professional obligations (Blossfeld and Hakim, 1997). However, in this same time period the non-voluntary component in part-time employment passed from 39.1% to 63.6% and the share of employees in involuntary part-time more than doubled, from 5.4% to 13.5%.

The increase in IPT is part of a wider process of dualisation of the labour market, i.e., the growing trend of polarization between "insiders" and "outsiders", where the outsider-insider distinction is not just between employed and unemployed but also between employees with different levels of protection, security, and opportunities (Rueda, 2005). The existence of a part-time/full-time hourly wage differential has been widely documented (Aaronson and French, 2004; Fernández-Kranz and Rodríguez-Planas, 2011). The part-time penalty is not limited to a wage gap but also includes disadvantages in access to training and opportunities to learn and grow at work (Kauhanen and Nätti, 2015). In fact, several studies showed that a significant share of part-time jobs offer little opportunity for career development and transition into full time employment, often turning into a dead-end or trap to workers' labour market progression

[1] Paper co-authored with Vicente Royuela and Sergio Scicchitano.

(Connolly and Gregory, 2010; O'Reilly and Bothfeld, 2002). Finally, in many European countries part-time employment can reduce access to social security benefits, since access is often restricted to those who worked for a minimum number of hours, and/or have earnings above a certain threshold (Matsaganis et al., 2015).

As described more in detail in Section 3.3, the growth of IPT in Italy was not uniform across socio-demographic groups and macro-regions. Indeed, a distinctive trait of the dualisation process is that it tends to target already marginalised categories of the labour force, such as women, young workers, and non-native workers (Nicolaisen et al., 2019). We document which groups experienced the largest growth in IPT and provide some preliminary evidence on how much of the asymmetric growth between men and women is due to women's increasing selection into certain occupations and economic sectors. Furthermore, we attempt to estimate the role of local labour market characteristics, and in particular their specialisation in occupations more affected by routine-biased technological change. Our interpretation of the link between IPT and routine-biased technological change aligns with Van Doorn and Van Vliet's (2022) hypothesis, which suggests that, as technology advances and replaces middle-skill routine jobs, medium-educated workers are compelled to seek low-skill jobs, thereby expanding the labour supply and corroding the bargaining power for this segment of the job market. As a result, individuals who depend on such jobs are forced to accept part-time positions, even if they would prefer to work more hours. This mechanism is also in line with Acemoglu and Restrepo's (2022) explanation of how the impact of automation on can extend beyond the directly affected occupations and sectors, through an increased competition for non-automated jobs.

We contribute to the literature on IPT in two ways. Firstly, we approach the topic from an economic geography perspective. Most of the research on IPT has primarily centred around demographic and business-cycle factors, thereby neglecting the spatial aspect, and especially the large disparities that exist at the regional level within countries. We attempt to fill this gap by investigating the role of local labour market (NUTS3) characteristics in explaining IPT growth in Italy. In particular, we test Van Doorn and Van Vliet's (2022) hypothesis on the connection between routine-biased technological change (RBTC) and IPT focusing on the sub-national level and using more refined occupation-specific indicators. Regarding the first point, moving from a cross-country to a NUTS3 set-up is a substantial improvement as involuntary part-time varies significantly within countries, depending on regional factors such as local industry mix and demographics. Additionally, in a country like Italy, where internal migration is low (Bonifazi et al., 2021; Bonifazi et al., 2017), focusing on the local level is crucial to identify any effect resulting from increased competition for non-automated jobs. Regarding the use of more refined indicators, we combine the INAPP-ISTAT Survey on Italian Occupations (ICP) with the Italian section of the EU labour force survey to build province-level indicators of routine-task specialisation based on the occupational mix in each province.[2] Another key advantage of using the ICP survey is that it allows to capture the distinctive features of Italian jobs. By contrast, many previous studies have relied on the assumption of comparability with US data, matching O*NET task-content information to European labour market data. Our second contribution to the literature on involuntary part-time is our attempt to disentangle the extent to which the uneven growth in IPT among genders can be attributed to the RBTC theory, as opposed to a rise in women's selection into occupations and sectors that rely more heavily on part-time work.

By means of a partial adjustment model, our study provides evidence that RBTC is linked to a higher incidence of IPT at the local labour market level. These findings highlight that the impact of automation extends beyond its effect on (un-)employment rates and can also affect other aspects of job quality. While RBTC does not appear to be the main driver of the higher growth in IPT for women compared to men, our analysis indicates that women are more significantly affected than men by the rise in employment share in "household substitution" services, which include bars, restaurants, and all activities related to private households employing domestic personnel such as caretakers, cleaning personnel, cooks, and babysitters. These results suggest that factors beyond RBTC, such as sector segregation, an increase in demand for household-substitution services, and gender norms, may also contribute to the higher IPT levels observed among women.

The rest of the paper is organised as follows. Section 3.2 presents a short review of the literature on the determinants of (involuntary) part-time. Section 3.3 describes the data, while Section 3.4 presents some stylized facts on IPT in Italy. Section 3.5 describes our empirical approach and discusses the results of our analysis. Section 3.6 concludes.

[2]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.

3.2 Literature review

The literature focusing on involuntary part-time is relatively recent but growing at a fast pace. A large group of studies investigated which worker characteristics are associated with a higher probability of being employed in IPT (Busilacchi et al., 2022; Cam, 2012; Denia and Guilló, 2019; Green and Livanos, 2017; Green and Livanos, 2015; Livanos et al., 2018; Livanos and Tzika, 2022). These studies highlighted one of the distinctive characteristics of the dualization process theorised by Rueda (2005), i.e., its tendency to target already marginalised groups. All these studies documented substantially higher shares of IPT among the most vulnerable categories of workers, in particular women, young workers, non-nationals, and those with low education. A few studies also marginally considered the geographic aspect, documenting higher levels of IPT in the 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), Western Greece, Attica, Central Macedonia, and the Ionian Islands in Greece (Livanos and Tzika, 2022). Green and Livanos (2017) took a cross-country approach, showing higher levels of IPT in Southern and Eastern EU countries (Spain, Portugal, and Poland), and lower levels in countries with Anglo-Saxon and Nordic welfare state models.

A second strand of the literature analysed the patterns of flows between employment states and their variations along business cycles. These studies are particularly relevant for what concerns the discussion of part-time work being a stepping stone into full-time employment or rather a "career trap". Canon et al. (2014) analysed changes in the transition probabilities to and from involuntary part-time following the Great Recession in the US and found that the flows were mainly associated with changes in the composition of employment (full- versus part-time, and voluntary versus involuntary PT) rather than with changes in the distribution of individuals between employment and non-employment. Similar conclusions were reached by Borowczyk-Martins and Lalé (2020), who showed that turnover between IPT and unemployment is low and the cyclical fluctuations in IPT represent a distinct labour-adjustment mechanism, separate from the job creation and destruction that drive the cyclical changes in unemployment rates. Quite remarkably, they provide evidence that, in the US, the cyclical dynamics of IPT seems to be not only a within-employment phenomenon, but even a within-employer one. Insarauto (2021) analysed female vulnerability to IPT in the aftermath of the Great recession in Spain and concluded that, during the crisis, women were more affected by the IPT increase and this was due to gender norms in the distribution of family burdens. Similar conclusions were reached by Busilacchi et al. (2022) for Italy. This study focused on the dualisation process, by looking at the variation in the involuntary component of PT (involuntary PT over voluntary PT) rather than at IPT levels (IPT over total employment). Other studies focused on explaining structural variations in IPT shares over time. Among them, Valletta et al. (2020) analysed the variation in IPT shares using a US state-level panel data for the years 2003–2016 and found that, while the cyclical component fully dissipated between 2010 and 2016, the persistent increase in the IPT rate following the Great Recession's recovery phase was mainly due to structural changes in the industry composition of employment. The economic crisis did not affect all workers equally but contributed to increasing pre-existing gaps.

Only a few papers started investigating the role of global mega-trends, such as automation, offshorability, and trade. Malo and Cueto (2019) studied to what extent automation and offshorability risks overlap with non-standard employment. They investigated the case of Spain, and found that, while offshorability risk has a small overlap with non-standard employment, automation risks affect those with non-standard work arrangements slightly more. However, having a higher level of education can help mitigate this risk regardless of contract type or working time. Van Doorn and Van Vliet (2022) analysed the relationship between lower middle-skill employment, which they consider to be a consequence of RBTC, and involuntary part-time employment across 16 European countries between 1999 and 2010. They found an association between lower middle-skill employment and an increase in involuntary part-time employment, particularly for certain groups, such as women and low-skilled workers, who are overrepresented in part-time work. However, the authors demonstrate that active labour market policies, such as training and job creation programs, can help mitigate these negative effects by providing medium-educated workers with the necessary skills to transition into high-skill jobs or increasing employment opportunities.

3.3 Data and measures

We employ 103 provinces (which are roughly equivalent to NUTS3 regions) as proxies of local labour markets. This approach is commonly used, partly due to the scarcity of data available at more granular levels, see for example Bratti and Conti (2018), Cerciello et al. (2019), and Dotti et al. (2013). The following paragraphs describe the sources and the characteristics of the data we gathered on Italian local labour markets.

3.3.1 IPT and socio-demographic characteristics

We take worker-level information on involuntary non-standard employment and socio-demographic characteristics from ISTAT's "*Rilevazione sulle Forze di Lavoro*" (RFL), which is the Italian section of the EU Labour Force Survey (ISTAT, 2023). The population of interest of the RFL consists of all household members residing in Italy. The sample includes around 600.000 individuals per year, distributed across about 1.400 Italian municipalities. The survey is conducted every three months and samples from different quarters are partially overlapped according to a rotation scheme whereby a household is included in the sample for two successive surveys and, after a break of two quarters, is reinserted in the sample for two more surveys. We cover the period between 2004-Q1 to 2019-Q4. ISTAT's labour force survey started back in 1959, but it went through several changes over the years. In particular, ISTAT warns that in 2004 the survey was profoundly restructured, introducing substantial technical, methodological, and analytical changes. For these reasons, these files are not comparable with the micro-data files for the following years. We define a worker as employed in involuntary part time if she is employed with a part-time contract and, when asked why she has such a contract, she replied that she "Has not found a full-time job" (the other options are "Does not want a full-time job", "Other reasons", and "Does not know"). We impose two restrictions to our sample: (1) we keep only individuals aged 16-64; (2) we keep only employees. Regarding the second restriction, the RFL divides employed individuals in three groups: (1) employees, (2) self-employed, and (3) independent contractors ("*collaboratori*"). We exclude self-employed because they do not have IPT by definition. We drop independent contractors because they are not asked the question on whether their part-time contract is voluntary or not. Employees represented 71.5% of total workers in 2004 and 76.3% in 2019.[3] Besides the share of IPT, we rely on the RFL to compute a series of control variables used in our analysis. In particular, we compute: (1) the share of population aged ≥ 65; (2) the share of foreign population; (3) the share of population with a high-school degree; (4) the share of 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.[4] Lastly, we obtain estimates of province-level value added per worker

[3] Appendix Table 3A.1 reports the share of workers in each category and their evolution over time.

[4] 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.

and annual percentage growth in value added by utilizing ISTAT's online data warehouse.[5]

3.3.2 Employment share in routine tasks

We take information on the task-composition and general characteristics of occupations from the INAPP-ISTAT Survey on Italian Occupations (ICP). The ICP has been realized twice (2007 and 2013, we use the latter) and each wave covers about 16,000 workers, ensuring representativeness with respect to sector, occupation, firm size, and macro-regions. About 20 workers are interviewed for each Italian occupation, providing representative information at the five-digit CP-2011 classification (around 800 occupations). 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 Labour. 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 is the only European survey replicating the rich and detailed US O*NET structure. Similar to the US O*NET, in the ICP occupation-level variables are built relying on both survey-based worker-level information as well as on post-survey validation by experts' focus groups. The characteristics of each occupation are captured through a well-structured questionnaire articulated in seven sections (knowledge, skills, attitudes, generalized work activities, values, work styles, and working conditions). The survey reports more than 400 variables on skills, attitudes, and tasks.

We follow Barbieri et al. (2022), Carbonero and Scicchitano (2021), and Cirillo et al. (2021) for the definition of various occupation-level indexes based on the ICP. The main index we consider is the "classic" routine-task index (RTI), which is substantially close to the one of Acemoglu and Autor (2011), and is defined as

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

[5]Value added data are adjusted for inflation using ISTAT's deflator with base 2015.

The index is computed for 126 three-digit CP-2011 occupations o.[6] The Routine component takes into account the degree of repetitiveness and standardization of tasks, as well as the importance of being exact and accurate. It combines the Routine Cognitive (RC) indicator, which measures factors such as the precision and consistency of tasks and the importance of accuracy, with the Routine Manual (RM) indicator, which assesses the level of repetitiveness and pre-determination of manual operations. The Non-Routine component is divided into three terms: Non-Routine Cognitive Analytical (NRCA), Non-Routine Cognitive Interpersonal (NRCI), and Non-Routine Manual (NRM). NRCA measures the relevance of tasks that require creative thinking, analysis, and interpretation of data and information. NRCI refers to the importance of social relationships, interaction, managing, and coaching colleagues. NRM measures the level of manual dexterity required to perform non-routine operations. We also consider an "augmented" version of the RTI, which is more in line with Autor et al. (2003), by including a "Non-routine manual: interpersonal adaptability" (NRMIA) component. Furthermore, we look at two specific routine task indexes, i.e. RTCI (Routine task index - cognitive) and RTMI (Routine task index - manual). Table 3.1 reports a brief description and the source of all indexes we considered, while Appendix Table 3A.2 reports the top and bottom five two-digit occupations for each index.

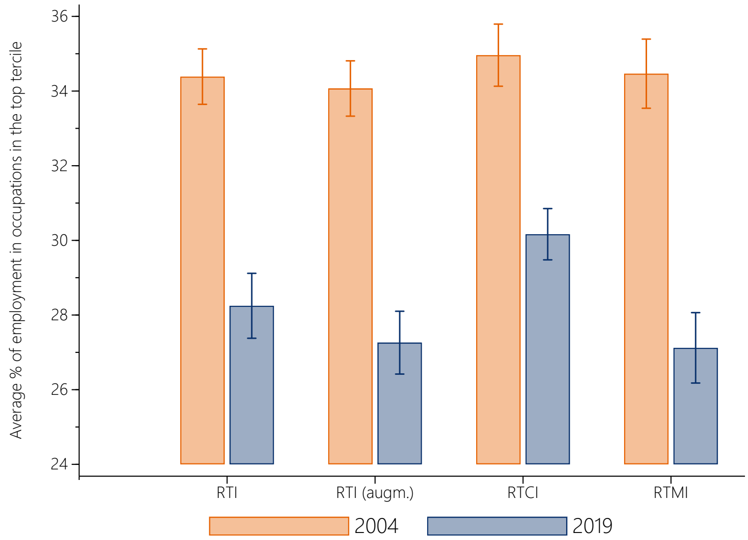
Following the approach of Autor and Dorn (2013) for the definition of a routine employment share, we calculate the percentage of local employment in the top tercile of the employment weighted distribution of each index at the three-digit occupation level. For each index, the specialisation of each province 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 $Index^{66}$. Figure 3.1 shows that, on average, the proportion of employment in routine-intensive occupations decreased significantly across Italian provinces from 2004 to 2019. Interestingly, the decline was more pronounced for manual routine-intensive jobs than for

[6] Note that there are 129 three-digit CP-2011 occupations. The ICP does not collect information of three of them, i.e. "911. Armed Forces Officers", "931. Sergeants, superintendents and marshals of the armed forces", and "931. Armed forces troops".

Figure 3.1: Indexes variation over time (average across provinces)



Source: authors' own calculations. *Notes:* sample restricted to: (1) individuals aged 16-64; (2) employees (exclude self-employed and independent contractors).

cognitive routine-intensive ones. To provide a general idea of the type of activities captured by each index, Appendix Table 3A.3 reports the top and bottom five sectors per employment share in each index (the shares are computed with same approach described in Equation 2 but using sector rather than province). For comparability with Van Doorn and Van Vliet (2022), we also computed the province-level share of employment in middle-wage occupations.[7] Finally, in order to have a rough idea 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 also take into account the province-level share of employment in manufacturing.

Note that there were important changes in the classification of both occupations and economic activities across the RFL waves. The occupation classification changed from CP-2001 to CP-2011 (the Italian equivalent of the ISCO-08 ILO's classification) starting from the 2011 wave. We converted four-digit CP-2001 codes for years 2004-2010 to three-digit CP-2011 occupations using the correspondence table provided by ISTAT. In case of four-digit CP-2001 codes assigned to more than one three-digit CP-2011 occupation, we assigned the code to the occupation with the largest share of workers. The economic sector classification switched from ATECO-2002 (Italian version of the NACE Rev.1)

[7]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 3A.4 reports the list of occupations, average net hourly wage in 2011, and the tercile they belong to.

Table 3.1: 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 and Autor (2011) and Carbonero and Scicchitano (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 and Autor (2011) and Carbonero and Scicchitano (2021)
RTCI	Routine task index - cognitive. Computed as: $RC - NRCA - NRCI$	Acemoglu and Autor (2011) and Carbonero and Scicchitano (2021)
RTMI	Routine task index - manual. Computed as: $RM - NRM - NRMIA$	Acemoglu and Autor (2011) and Carbonero and Scicchitano (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 3A.4 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).

to ATECO-2007 (Italian version of the NACE Rev.2) starting from the 2007 wave. We converted three- and four-digit ATECO-2002 to two- and one-digit ATECO-2007 codes using the correspondence table provided by ISTAT.[8]

3.4 The growth of IPT in Italy: Stylized facts

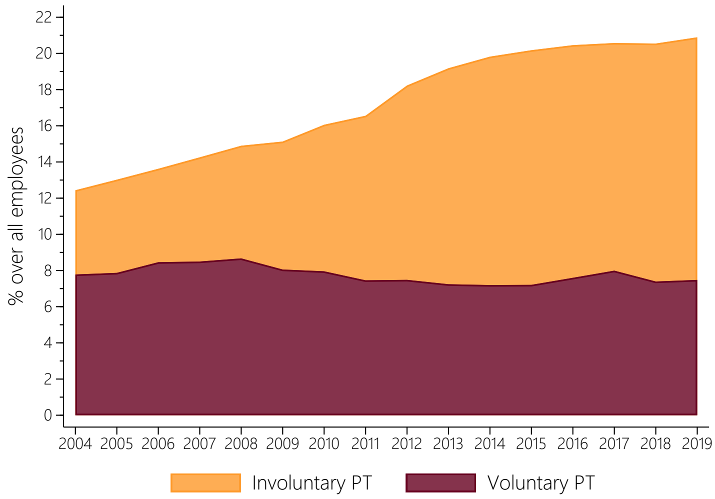
Figure 3.2 plots the evolution over time of part-time employment, divided into its voluntary and involuntary components. Between 2004 and 2019, the proportion of workers on involuntary part-time contracts increased almost threefold. This growth was most rapid following the 2008 Great Recession, but there has not been a subsequent decrease in IPT employment. Notably, the rise in involuntary part-time employment was primarily due to an increase in the involuntary aspect of part-time employment, rather than an increase in the proportion of part-time employees relative to the total workforce. Figure 3.3 shows the evolution of IPT over time across several socio-demographic groups. This figure confirms that the process of dualisation has a tendency to focus on groups that were already marginalized: 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. One notable exception in this general dualisation trend is represented by the 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 was not due to a decrease in the percentage of involuntary part-time employment in the South, but rather an increase of the same in the North.

Figure 3.4 plots the variation in the share of IPT within one-digit sectors (panel a) and between one-digit sectors (panel b) between 2004 and 2019. The incidence of IPT increased in all sectors in the observed period, with the largest increase taking place in sector "I. Hotel and catering". In 2019, Sector "I. Hotel and catering" was also among the highest contributors to the overall share of IPT, accounting for approximately 14.8%, only sector "G. Retail" had even higher levels (15.7%).

Figure 3.5 plots the estimates of a simple linear probability model regressing a binary indicator for IPT on (1) basic socio-demographic characteristics, (2) 12

[8] In case of ATECO-2002 codes assigned to more than one ATECO-2007 sector, we assigned the code to the sector more in continuity with the one-digit ATECO-2002. For example, the four-digit ATECO-2002 code "3002" corresponds to two one-digit ATECO-2007 groups, i.e., "C - Manufacturing" and "J - Information and communication services". We assign it to "C - Manufacturing" because it belonged to the one-digit ATECO-2002 group "D - Manufacturing".

Figure 3.2: 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).

broad economic activity groups, (3) 2-digit occupations.[9] 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):

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

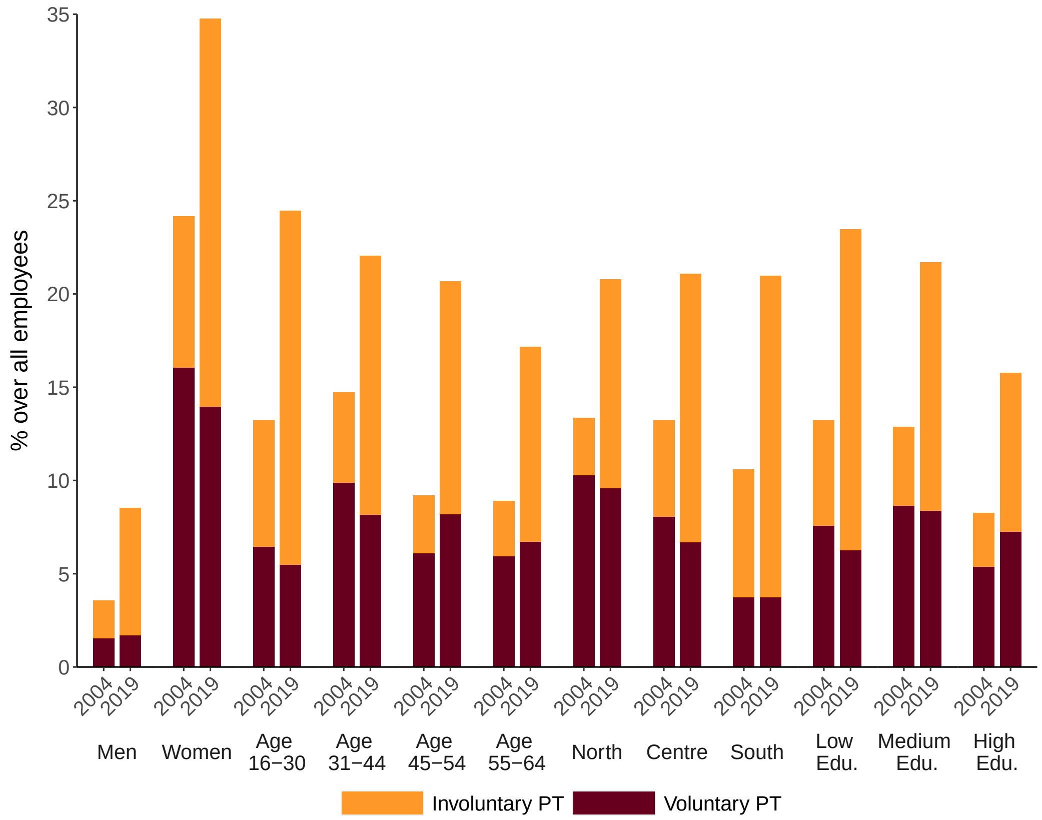
$$IPT_i = \alpha + SocioDem_i + Sector_i + \epsilon_i \tag{4}$$

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

The dependent variable IPT_i is a binary indicator equal to one for involuntary part-time and zero for all other workers. The scope of this exercise is twofold. First, exploring which groups became more or less exposed over time, e.g., are young workers more exposed at the end of the period compared to the beginning? Second, observing whether and to what extent the share of "extra-risk" associated to some groups which can be attributed to their selection into certain sectors or occupations varied over time. In general, the higher risks

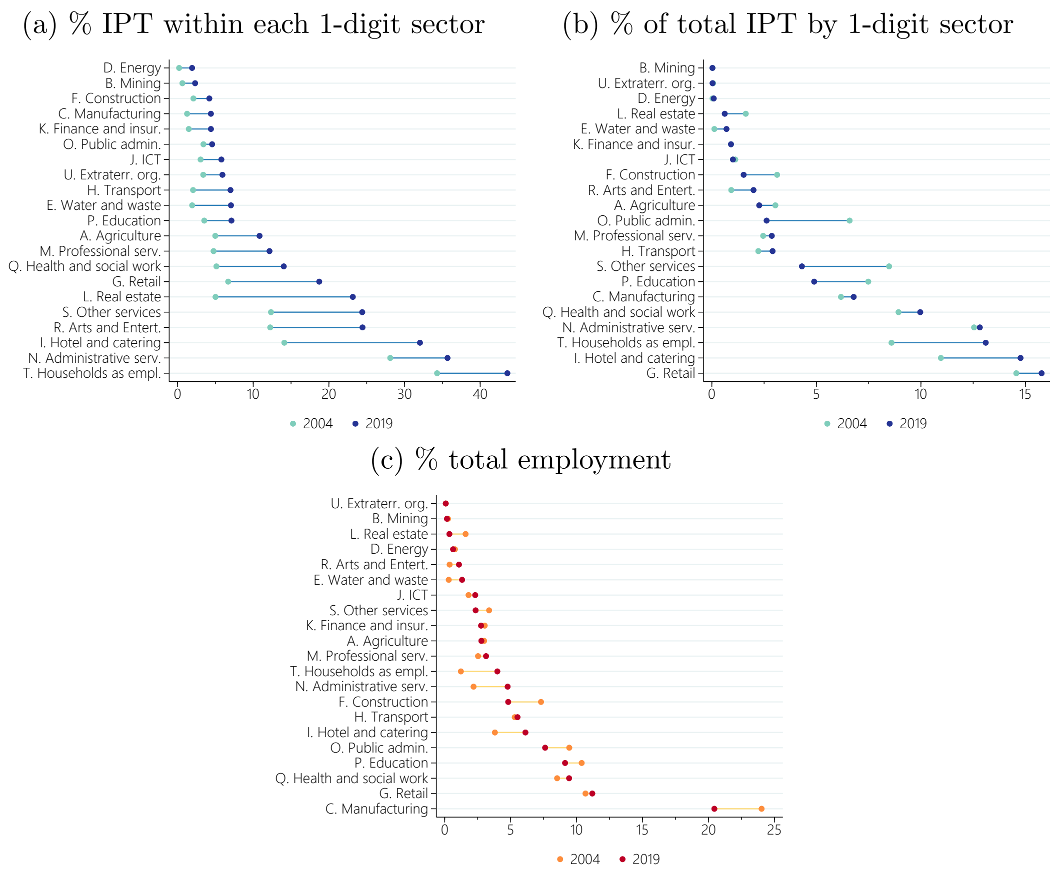
[9]The socio-demographic characteristic included are: (1) gender; (2) binary indicator for Italian citizenship; (3) age-group ("16-30", "31-44", "45-54", and "55-64"); (4) urban or rural municipality (use the OECD definition of functional urban areas FUA: "No FUA", "FUA", "FUA core"); (5) education ("No 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.

Figure 3.3: Variation in share of IPT over time by socio-demographic group



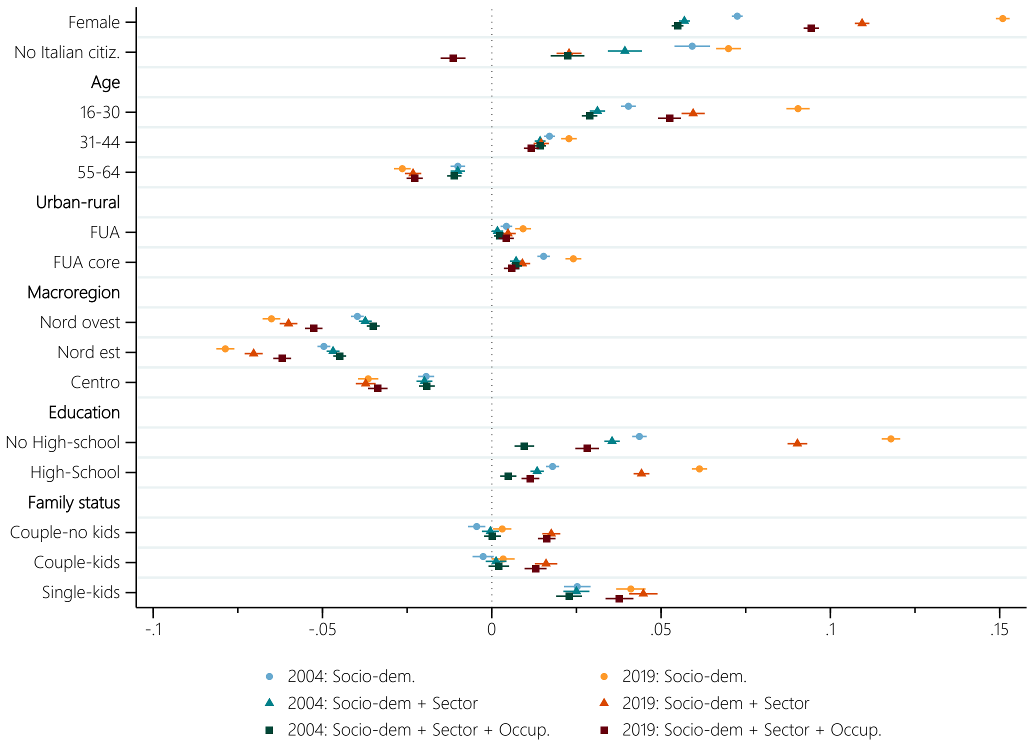
Source: authors' own calculations. *Notes:* sample restricted to: (1) individuals aged 16-64; (2) employees (exclude self-employed and independent contractors). "Low Edu." refers to individuals without a high-school degree; "Medium Edu." indicates individuals with a high-school degree; "High Edu." indicates individuals with a tertiary education.

Figure 3.4: 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 3A.5

Figure 3.5: Determinants of Involuntary part-time



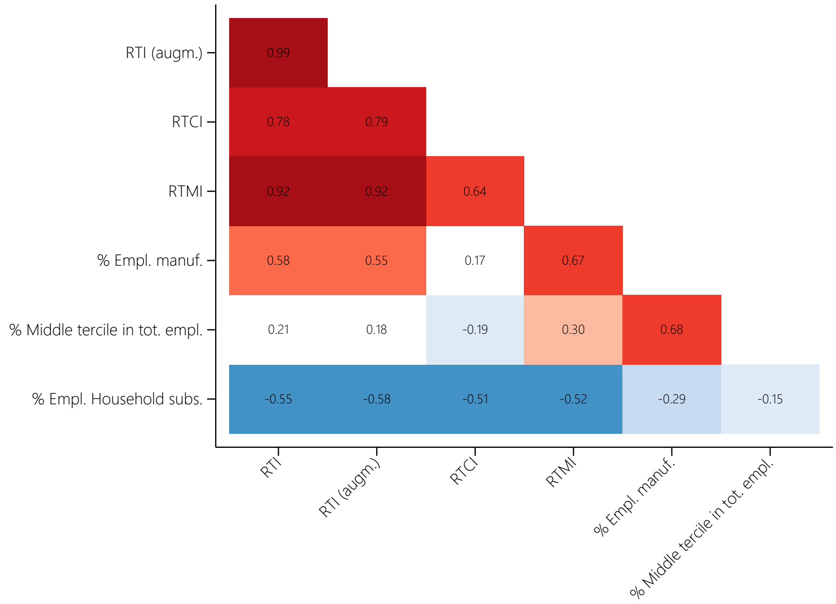
Source: authors' own calculations. *Notes:* sample restricted to: (1) individuals aged 16-64; (2) employees (exclude self-employed and independent contractors). To mitigate concerns about small sample sizes, given the large number of sector and occupation fixed effects, the models for 2019 use pooled 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 3A.6. Robust standard errors.

associated to some groups (e.g. women and young workers) decreases after adding sector and occupation (meaning that higher shares of IPT for these groups is explained at least in part by sorting into certain sectors and occupations). However, the estimates remain positive and significant, indicating that there is still some sort of "discrimination". As for the variation over time, we can isolate two trends. First, more exposed groups became even more exposed. Second, segregation into more exposed occupations and sectors increases over time. This can be seen by comparing the "distance" between the model just with socio-demographics and the one with sector and occupation for 2004 *vs.* 2019.[10]

Figure 3.6 plots the correlation between the various $Index_{pt}$ described in Section 3.3.2 in 2004. This Figure conveys three main messages. First, as it could

[10] Appendix Figure 3A.1 plots this measure with the relative confidence intervals.

Figure 3.6: Correlation of province-level indexes $Index_{pt}$



Source: Authors' own calculations.

be expected, RTMI correlates strongly with the manufacturing employment share. Second, the areas with high manufacturing employment are not the same areas with high employment in household substitution services. This aspect will be relevant when analysing the differences in the IPT growth among men and women, as manufacturing decline and growth in household substitution services affect men and women differently. Finally, household substitution services are negatively correlated with the routine indexes, signalling that the areas in which such services are more prevalent are the ones with less employment exposed to routinisation.

3.5 Analysis

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

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

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 3.3.2 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 3A.2 reports the correlation among these controls. Finally, τ_t are a set of year dummies, $NUTS1_p$ is a set of five macro-region (NUTS1) fixed effects, and $\epsilon_{p,t}$ is an error term.[11] 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 3.2 reports the estimated β_1, which captures the "short-term" or "transitory" effect of each of our indexes on IPT, while Table 3.3 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 remains consistent regardless of the measure used, whether it be the RTI index, the share of employment in middle-wage occupations, or the employment share in manufacturing. Notably, the estimates for RTI indexes and employment share in manufacturing are quite similar, suggesting that the decline of routine occupations can be mainly attributed to the decline of manufacturing, rather than advancements in artificial intelligence (AI) technologies. This aligns with the fact that Italy has been slow in adopting new technologies. While the utilization of industrial robots is widespread in Italian manufacturing, owing to their long-standing presence, it is probable that the adoption of state-of-the-art AI technologies during the time window we observe was modest.[12] 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, our results differ from Van Doorn and Van Vliet's (2022) ones, as they predict an increase in IPT predominantly in low-paid jobs,

[11] 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.

[12] 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, 2018a).

Table 3.2: Partial adjustment model

		Education		Pay tercile	
	All	No HS	HS	Low	Middle
RTI	-0.036***	-0.062***	-0.057***	-0.021	-0.046***
	(0.012)	(0.021)	(0.015)	(0.022)	(0.013)
	0.27	0.23	0.30	0.27	0.23
RTI (augm.)	-0.034***	-0.061***	-0.054***	-0.014	-0.045***
	(0.012)	(0.021)	(0.015)	(0.023)	(0.013)
	0.27	0.23	0.30	0.27	0.23
RTCI	-0.043***	-0.076***	-0.055***	-0.033	-0.045***
	(0.012)	(0.021)	(0.015)	(0.023)	(0.013)
	0.27	0.23	0.30	0.27	0.23
RTMI	-0.027**	-0.041**	-0.049***	-0.017	-0.040***
	(0.012)	(0.021)	(0.014)	(0.021)	(0.013)
	0.27	0.22	0.30	0.27	0.22
% Middle tercile in tot. empl.	-0.027**	-0.042**	-0.036**	-0.017	-0.031**
	(0.012)	(0.020)	(0.016)	(0.022)	(0.013)
	0.27	0.22	0.30	0.27	0.22
% Empl. manuf.	-0.026***	-0.058***	-0.032***	-0.049***	-0.014**
	(0.007)	(0.012)	(0.009)	(0.013)	(0.007)
	0.27	0.23	0.30	0.27	0.22

Source: authors' own calculations. *Notes:* each estimate comes from a separate regression including the full battery of controls described in Section 3.5 (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 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=1,545 (103 provinces and 15 years).

a pattern that only emerges in our results when we use the employment share in manufacturing as a measure of RBTC.

Table 3.4 reports the results by gender. The existence of a relationship between RBTC and IPT is confirmed for both men and women. To shed some light on the higher levels of IPT among women, we considered an additional group of indicators capturing the share of employment in "Household substitution" services. "Household substitution" (or "Household production") services include all services provided by households for their own consumption, such as cooking meals, cleaning, childcare, or elderly care. Specifically, we consider a composite indicator, "% Empl. Household subs." which captures the employment in the following three NACE Rev.1 sectors: "553. Restaurants", "554. Bars", and "950. Activities of private households employing domestic personnel". Additionally, we also include the employment share of each of these three sectors separately, to check which one has a stronger effect. Compared to men, the incidence of involuntary part time among women is significantly

Table 3.3: Partial adjustment model - Long run multiplier

		Education		Pay tercile	
	All	No HS	HS	Low	Middle
RTI	-0.111***	-0.180***	-0.118***	-0.064	-0.114***
	(0.035)	(0.060)	(0.030)	(0.067)	(0.032)
RTI (augm.)	-0.107***	-0.177***	-0.112***	-0.044	-0.112***
	(0.036)	(0.061)	(0.031)	(0.069)	(0.033)
RTCI	-0.131***	-0.215***	-0.114***	-0.100	-0.111***
	(0.036)	(0.059)	(0.031)	(0.071)	(0.033)
RTMI	-0.085**	-0.121**	-0.102***	-0.051	-0.100***
	(0.035)	(0.060)	(0.029)	(0.064)	(0.031)
% Middle tercile in tot. empl.	-0.084**	-0.123**	-0.076**	-0.053	-0.081**
	(0.037)	(0.058)	(0.033)	(0.068)	(0.032)
% Empl. manuf.	-0.077***	-0.157***	-0.067***	-0.141***	-0.036**
	(0.019)	(0.031)	(0.018)	(0.036)	(0.018)

Source: authors' own calculations. *Notes:* each estimate comes from a separate regression including the full battery of controls described in Section 3.5 (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 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=1,545 (103 provinces and 15 years).

higher in provinces with a higher share of employment in household substitution services. This may be due to a combination of factors. One possible explanation is that, following the increase in employment shares among high-skilled women, the demand for these services has increased, leading to more job opportunities in this sector. Additionally, there may be gender norms that lead to women being more likely to work in these types of jobs.

3.5.1 Endogeneity

Our framework might suffer from endogeneity issues. For example, our routine-task indexes might be correlated with some cyclical unobservable factor simultaneously affecting changes in IPT. To tackle this issue, we adapt the strategy proposed by Autor and Dorn (2013) to our setup. For every indicator we compute an instrument *á-la-Bartik* by interacting local sectoral employment shares in 1991 (14 years before the start of period of our empirical analysis), with national index of routine employment share for every sector.[13] We further avoid endogeneity by trimming the information corresponding to the actual province of interest from the national evolution of the index. The instrument is defined

[13]We use the year 1991 as the 1991 Census of Industry and Services is the oldest Census using a comparable sector classification.

Table 3.4: Partial adjustment model - By gender

	All		No high-school		High-school	
	Men	Women	Men	Women	Men	Women
RTI	-0.036***	-0.043**	-0.042***	-0.071***	-0.074***	-0.045*
	(0.010)	(0.020)	(0.011)	(0.024)	(0.016)	(0.027)
	0.21	0.28	0.20	0.28	0.29	0.30
RTI (augm.)	-0.037***	-0.039*	-0.044***	-0.065***	-0.078***	-0.033
	(0.010)	(0.020)	(0.012)	(0.024)	(0.016)	(0.028)
	0.21	0.28	0.20	0.28	0.29	0.30
RTCI	-0.038***	-0.036*	-0.044***	-0.062***	-0.062***	-0.039
	(0.010)	(0.021)	(0.012)	(0.024)	(0.016)	(0.028)
	0.21	0.28	0.20	0.28	0.29	0.30
RTMI	-0.028***	-0.037*	-0.034***	-0.057**	-0.064***	-0.042
	(0.010)	(0.019)	(0.011)	(0.023)	(0.016)	(0.026)
	0.21	0.28	0.20	0.28	0.28	0.30
% Middle tercile in tot. empl.	-0.029***	-0.012	-0.030***	-0.032	-0.039**	-0.001
	(0.010)	(0.020)	(0.011)	(0.023)	(0.016)	(0.027)
	0.21	0.28	0.20	0.28	0.28	0.30
% Empl. manuf.	-0.021***	-0.045***	-0.025***	-0.066***	-0.036***	-0.019
	(0.006)	(0.012)	(0.006)	(0.014)	(0.009)	(0.016)
	0.21	0.29	0.20	0.29	0.29	0.30
% Empl. Household subs.	0.069***	0.177***	0.070***	0.243***	0.116***	0.153***
	(0.023)	(0.045)	(0.026)	(0.052)	(0.035)	(0.055)
	0.21	0.29	0.20	0.29	0.28	0.31
% Empl. Restaurants	0.097**	0.220***	0.102**	0.216**	0.213***	0.248**
	(0.039)	(0.080)	(0.044)	(0.095)	(0.062)	(0.101)
	0.21	0.29	0.20	0.28	0.28	0.30
% Empl. Bars	0.056	0.400***	0.043	0.433***	0.148	0.116
	(0.066)	(0.126)	(0.073)	(0.147)	(0.101)	(0.161)
	0.20	0.29	0.20	0.28	0.28	0.30
% Empl. Domestic personnel	0.071**	0.105	0.075*	0.244***	0.076	0.143*
	(0.035)	(0.064)	(0.039)	(0.076)	(0.056)	(0.081)
	0.21	0.28	0.20	0.29	0.28	0.30

Source: authors' own calculations. *Notes:* each estimate comes from a separate regression including the full battery of controls described in Section 3.5 (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).

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 an IV fixed-effects panel data model, with heteroskedasticity- and autocorrelation-robust (HAC) standard errors. We assume standard errors to follow an AR(1) autocorrelation structure. The model includes all controls present in Equation 6, excluding the time-invariant NUTS1 indicators.

Table 3.5 reports the results of the IV fixed-effects panel data model. Overall, the results confirm the main trends observed in Table 3.2. Notably, the estimates for IPT among workers without a high school degree remain negative but turn not statistically significant.

3.6 Conclusion

In this paper we analysed the impact of local specialization in routine tasks on the growth of involuntary part-time across Italian provinces between 2004 and 2019. In particular, we tested the hypothesis that, as technology replaces middle-skill routine jobs, medium-educated workers are pushed towards low-skill jobs, leading to a reduction in their bargaining power and to an expansion of the labour supply for this segment. This puts more pressure on individuals who rely on these jobs to accept part-time positions even if they would prefer to work more hours. Additionally, we investigate another mechanism that contributes to the increase in IPT, particularly among women. As high-skilled women increase their employment shares, job opportunities arise in sectors that substitute for household activities, such as restaurants, bars, and domestic services. These new jobs are generally lower-skilled and require higher flexibility, causing an aggregate shift in employment toward part-time positions in these sectors.

To investigate these hypotheses, we combined the INAPP-ISTAT ICP with the Italian section of the European Labour Force Survey to build province-level indicators of routine-task specialisation based on the occupational mix in each province. This allowed us to capture the distinctive features of Italian jobs, as opposed to studies matching O*NET task-content information to European

Table 3.5: IV fixed-effects panel data model

		Education		Pay tercile	
	All	No HS	HS	Low	Middle
RTI	-0.271*	-0.048	-0.589***	-0.050	-0.432**
	(0.138)	(0.236)	(0.200)	(0.250)	(0.169)
F-stat.	20.02	20.21	19.02	20.32	19.38
R^2	0.17	0.24	0.03	0.28	0.10
RTI (augm.)	-0.296**	-0.091	-0.611***	-0.107	-0.444**
	(0.143)	(0.236)	(0.206)	(0.250)	(0.176)
F-stat.	21.54	21.69	20.44	21.71	20.73
R^2	0.15	0.24	0.01	0.28	0.09
RTCI	-0.299*	-0.035	-0.692***	-0.029	-0.491**
	(0.177)	(0.295)	(0.250)	(0.300)	(0.219)
F-stat.	16.68	17.12	15.99	17.26	16.10
R^2	0.15	0.24	-0.07	0.28	0.06
RTMI	-0.321**	-0.229	-0.609***	-0.257	-0.392**
	(0.132)	(0.220)	(0.201)	(0.233)	(0.157)
F-stat.	27.11	27.04	24.93	26.38	26.05
R^2	0.08	0.20	-0.04	0.24	0.09

Source: authors' own calculations. *Notes:* each estimate comes from a separate regression including the full battery of controls described in Section 3.5 (Equation 6), excluding the time-invariant NUTS1 FE. IV fixed-effects panel data model. Standard errors are heteroskedasticity- and autocorrelation-robust (HAC) - AR(1). 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).

labour market data. Our findings support the hypothesis that provinces witnessing a decline in employment in routine-intensive occupations also experience an increase in involuntary part-time work. This trend remains consistent regardless of the measure used, whether it be the RTI index, the share of employment in middle-wage occupations, or the employment share in manufacturing. When analysing the results by gender, we observed that women are significantly more affected by another aspect, namely the increase in employment share in "Household substitution" services, including bars, restaurants, and all activities of private households employing domestic personnel (e.g. caretakers, cleaning personnel, cooks, and babysitters). This suggests that, in addition to RBTC, various other factors such as sector segregation, a surge in household-substitution services demand, and gender norms, may also be playing a role in explaining higher IPT levels among women.

Finally, we argue that it is crucial to adopt a spatial perspective when examining the labour market. It is implausible to assume that the workers displaced from routinised sectors will end up solely in household substitution services. Nevertheless, there is a redistribution of workers across sectors at the local labour market level, likely driven by factors such as the bargaining power of workers or social stereotypes of certain activities, some of which are deemed "more acceptable" for women. The result is a further deepening of the dualisation in the labour market, with a particular intensity for those groups that were previously marginalized.

3.7 Appendix 3A: Additional Tables and Figures

Table 3A.1: 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 3A.2: Indexes by two-digit occupation

	RTI	RTI (augm.)	RTCI	RTMI
11. Members of executive legislative bodies	<u>0.0</u>	<u>0.0</u>	<u>0.0</u>	<u>15.0</u>
12. Entrepreneurs, directors and managers of large companies	<u>15.8</u>	<u>22.4</u>	<u>14.4</u>	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	<u>23.5</u>	35.8	<u>26.4</u>	48.9
23. Specialists in the life sciences	43.0	33.5	38.7	23.5
24. Health care specialists	39.8	<u>25.6</u>	42.3	<u>0.0</u>
25. Specialists in humanities, social sciences, arts and management	<u>31.0</u>	34.2	<u>29.0</u>	41.2
26. Education and research specialists	<u>17.1</u>	<u>11.6</u>	<u>23.9</u>	<u>0.5</u>
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	<u>14.7</u>
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	<u>31.7</u>	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	<u>10.1</u>
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 3A.3: 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 3A.4: 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 3A.5: 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	

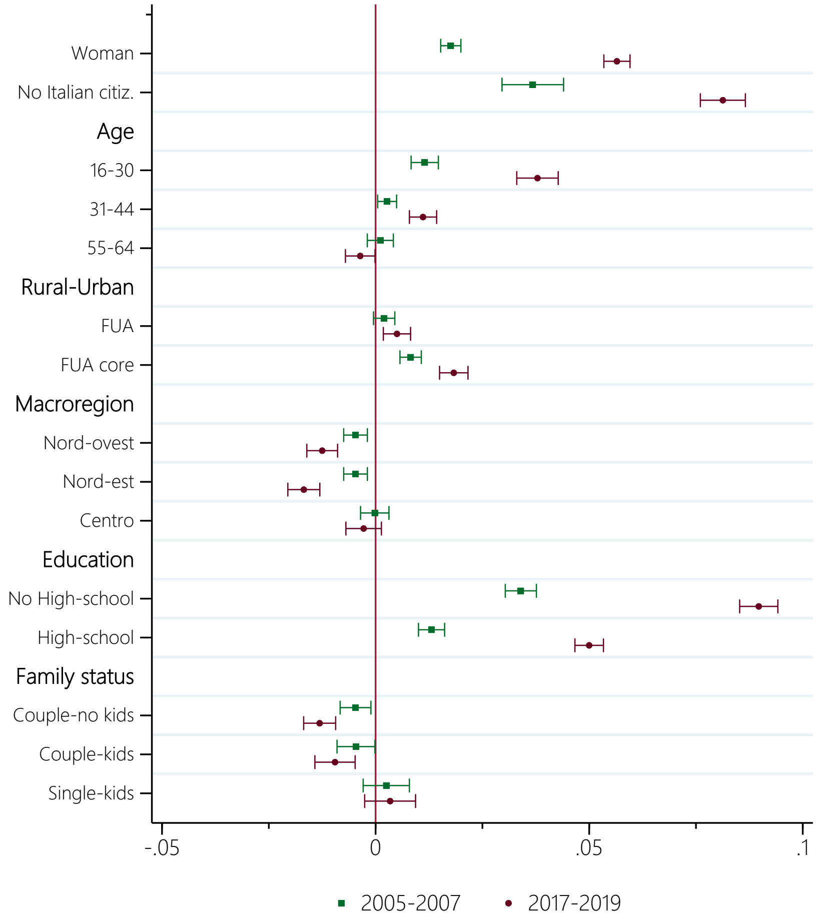
Source: author's own calculations. *Notes:* "%Empl. 04" is each sector's employment share in 2004; "Δ Empl." is the growth in each sector's employment share between 2004 and 2019 (in percentage points); "%IPT 04 (Within)" is the IPT share within each sector in 2004; "Δ IPT (Within)" is the variation 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 3A.6: 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***
Sector						
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. two-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

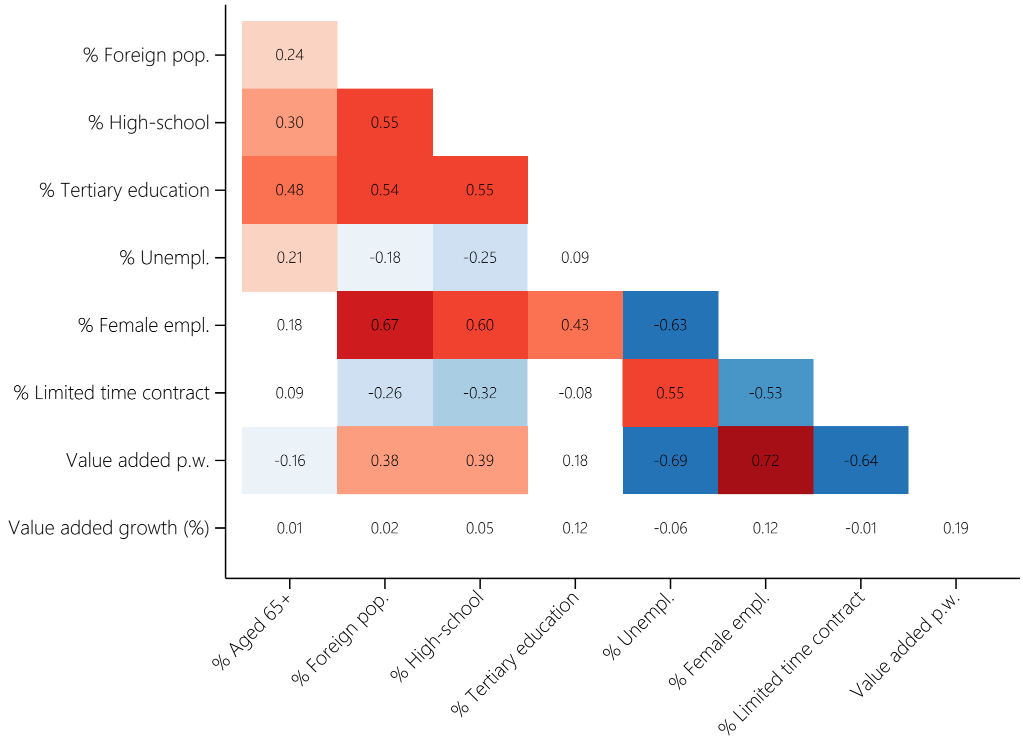
Source: author's own calculations. *Notes:* sample restricted to: (1) individuals aged 16-64; (2) employees (exclude self-employed and independent contractors). To avoid small sample issues, models for 2019 pool observations from 2017, 2018, and 2019, while models for 2004 pool observations from year 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: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$.

Figure 3A.1: IPT - Selection into exposed sectors and occupations



Source: author's own calculations. *Notes:* for each of the two time periods considered in Table 3A.6, 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 3A.2: Correlation of control variables



Source: author's own calculations.

4 Logistic Hubs and Support for Radical-right Populism: Evidence from Italy[1]

4.1 Introduction

Europe is experiencing an unprecedented surge in support for populist parties. In 2019 elections for the European Parliament, populist authoritarian and Eurosceptic parties obtained about a quarter of all seats (European Parliament, 2019; Mudde, 2019). Most notably, populist parties achieved more than 10% of votes in 22 out of 26 countries and more than 30% of votes in 9 of them, with Italy registering the highest share, 66.6% (Zulianello and Larsen, 2021). This ascent is not at all limited to European Parliament elections. In fact, the number of countries with a 20% or higher share of votes for populist parties in national elections more than doubled between 2008 and 2018, rising from 9 to 19, with three countries (Hungary, Greece, and Italy) breaking the 50% threshold (Timbro, 2019).

Growing support for populist and radical-right parties has been attributed to factors generating economic hardship, such as trade-competition (Autor et al., 2020; Milner, 2021; Rodrik, 2021) and technological progress (Anelli et al., 2021a; Caselli et al., 2020b; Milner, 2021), but also to cultural drivers, including status-threat perceptions (Gidron and Hall, 2017; Kurer, 2020) and xenophobic attitudes (Abbondanza and Bailo, 2018; Diehl et al., 2021; Hochschild, 2018; Pellegrini et al., 2022). Socio-economic insecurity boosts consensus to populist factions by dismantling trust in traditional parties and institution (Akkerman et al., 2017; Boeri et al., 2021; Guiso et al., 2017; Ziller and Schübel, 2015). Populist parties were particularly able at gaining support by capitalizing on social anxiety and channelling people's frustration against traditional parties, which were accused of not doing enough to protect the "ordinary working people" from the many threats of the modern world (Frank, 2007; Gaffney, 2020; Gidron and Hall, 2017; Hertz, 2021; Hochschild, 2018; Norris and Inglehart, 2019).

We contribute to the literature on political discontent by investigating the relationship between socio-economic changes and political discontent. In particular, we exploit the logistics revolution as a source of strong economic and cultural shock. Over the past two decades, the Italian logistics sector has expe-

[1]Paper co-authored with Nicola Pontarollo.

rienced significant growth due to the effects of globalization and the escalating trend of outsourcing transport and logistics activities in manufacturing (Mariotti, 2015). The construction of large logistic hubs has a strong economic and social impact on local communities, especially when it comes to small towns and villages. In this sense, the rapid and sizeable expansion of logistics provides a good setting to investigate the relationship between socio-economic grievances and support for the populist radical right, as the construction of new hubs works as a sort of exogenous shock. Using an instrumental variable (IV) and a difference-in-differences (DiD) approach, we provide evidence of a causal relationship between the establishment of new logistics hubs and the rise in support for an Italian populist radical-right party, *Lega*. Our findings remain robust across a variety of different specifications. As discussed in detail in Section 4.2.3, we believe there are at least three channels through which large logistic hubs might foster support for populist radical-right parties, and *Lega* in particular. First, with the rise in the number of workers employed in logistics, which is characterised by a wide use of low-paid and precarious work arrangements, there might be an increase in the feeling of economic insecurity. Second, the sector employs a large number of foreign workers. A large inflow of foreign workers into rural areas, that are usually not a migration destination, might lead to a surge in anti-immigration sentiment. Third, logistic revolution resulted in the externalisation of logistic tasks to specialised firms, often large multinational corporations. This might generate dissatisfaction among those who want to protect Italian small and medium enterprises from the threat of (foreign) multinational companies. *Lega*, as a conservative, regionalist, and anti-immigration right-wing party, might have capitalized on the discontent stemming from the combination of these factors and gathered support among those who just want to keep things "as they were before". Given the limitations of our data, we were only able to conduct preliminary testing on the first two mechanisms, finding no evidence in favour of the first channel and some indications in support of the second one. Nonetheless, further investigation is required to gain a comprehensive understanding of the overall effect of logistics hubs on local communities.

The rest of this paper is organized as follows. Section 4.2 and Section 4.3 present a short review of literature on the evolution of the logistics sector and on political discontent, respectively. Section 4.4 describes the data, Section 4.5 presents the instrumental variable approach, while Section 4.6 contains the Difference-in-Differences analysis. Section 4.7 concludes.

4.2 Growth and transformation of logistics

In the last decades the logistics sector experienced a period of extraordinary growth and structural reorganisation. Starting from the 1990s, logistics evolved from being just an auxiliary function to emerging as an independent factor of production and a key source of competitive advantage for firms (Vahrenkamp, 2010). The "logistic revolution" (Bonacich and Wilson, 2008) was the result of several interrelated global trends, including: (1) the reduction in trade barriers and fall in transportation costs; (2) the emergence of a mass consumption society; (3) the evolution of internet-based systems.[2]

The reduction in trade barriers and the fall in transportation costs fostered an unprecedented globalisation of the economy, resulting in enormous volumes of goods needing to be transported. Due to the international fragmentation of production (Arndt and Kierzkowski, 2001), the increase in flows was not at all limited to finished products, but also included intermediate and unfinished goods. This is because the manufacturing paradigm shifted from having the whole production process being executed in one place, to fabricating distinct parts in various areas of the world – mostly those with cheap labour, scarcely enforced workers' rights, and feeble environmental regulations - and then assembling them somewhere else (Helg and Tajoli, 2005).

The logistics revolution was not circumscribed to a steep increment in goods' flows. The emergence of a mass consumption society, with the associated growing request for customised products and extremely fast deliveries, dramatically heightened the complexity of logistics processes. The ability to transport goods quickly and efficiently became a central part of firms' competitive advantage. As a consequence, manufacturing firms started outsourcing transport and other logistic functions to specialised operators (Elia et al., 2011; Lieb and Bentz, 2005), which can guarantee the management of such complexity thanks to a heavy reliance on sophisticated internet-based information systems and technological innovations in freight moving and handling (McCann, 2008).

All these phenomena radically altered the geography of logistics and freight distribution (Hesse and Rodrigue, 2004; Holl and Mariotti, 2018b). As the standard moved from large but infrequent shipments to frequent and rapid deliveries, being close to main transport arteries (harbours, airports, highways) became of crucial importance (Bowen, 2008). One of the consequences of

[2] An exhaustive description and discussion of all the factors behind the logistics revolution is behind the scope of this work. We redirect interested readers to dedicated studies (Bonacich and Wilson, 2008; Vahrenkamp, 2010; Vahrenkamp, 2012).

this re-organisation is the so-called logistics sprawl, which refers to the "trend towards spatial deconcentration of logistics terminals in metropolitan areas" (Dablanc and Rakotonarivo, 2010, p. 6087) and more in general to the tendency of logistics facilities (e.g. warehouses, cross-dock facilities, intermodal terminals) to move away from congested urban areas and be closer to highways (Bowen, 2008; Woudsma et al., 2008).

4.2.1 Logistics in Italy

The logistics revolution was quite vigorous in Italy too. Between the 1991 and the 2001 industry censuses, workers in the ATECO 1991 sector "631 - Freight handling and warehousing" more than doubled (119%), growing from 60,221 to 131,980 workers.[3] The largest growth was registered in the North-West (158%) and the Centre (112%). Despite a marked slow-down due to the 2008 Great recession, the sector kept growing at fast rates. Based on ISTAT data, in 2017 the ATECO 2007 sector "52 - Warehousing and support activities for transportation" counted 367,860 workers (2.2% of total workforce), while the sector "4941 - Freight transport by road" had 331,828 workers (1.94% of total workforce). The expansion in the last years was so substantial that logistics is indicated in the 2022 National Environmental Protection System's report on soil consumption as one of the main causes of the increase in the amount of soil consumed in Italy (Munafò, 2022). In the period analysed in the report (2006-2021), the soil consumption due to logistic (warehouses, parking lots, link roads) amounted to 2,290 hectares (22,900,000 m^2), mostly concentrated in the North-West, the North-East, and the Centre. Most of the hubs are built from scratch, rather than by reconverting pre-existing industrial buildings. This is due to two reasons. First, as discussed above, geographic position is crucial when it comes to logistics and even a few kilometres of distance to main roads make a difference. Most of the existing available industrial buildings are not located close enough to highways, as manufacturing plants tend to be less concentrated around transportation infrastructure than (modern) logistic hubs (Holl and Mariotti, 2018a). Second, it is often cheaper to build a new warehouse than to adapt or restructure an existing (old) one (De Vidi, 2022; Invernizzi, 2022).

[3] The ATECO (ATtività ECOnomiche) classification of economic activities is a type of classification adopted by the Italian National Statistical Institute (ISTAT) for national statistical surveys. It is the Italian translation of the Nomenclature of Economic Activities (NACE) created by Eurostat, adapted to the Italian context by the Italian Statistical Institute (ISTAT).

The indiscriminate proliferation of new logistic buildings and infrastructures is seldom hindered by public institutions. The competence on building permits belongs to municipalities. However, there is a dramatic disparity of means between multinational logistics corporations, which can rely on countless professionals and abundant monetary resources, and small municipalities, which do not have the competences to analyse the dozens of folders with all the technical project documentation that arrive in their offices (Invernizzi and Lovato, 2022). Furthermore, the companies promise to create many new jobs and to pay for new schools, cycle paths, parks, and protected natural areas (Pozzi, 2018; Prato, 2021; Rasero, 2020; Stroppa, 2021). Such investments can be much larger than many small rural municipalities' yearly budgets. For instance, the municipality of Trivolzio, in the province of Pavia, Lombardy, which has 2,300 inhabitants and in 2021 counted on about 1.6 million Euro of yearly tax revenues, was promised investments for 2.5 million Euro in compensation measures, 6 million Euro for road redevelopment works (including a link road to connect the hub with the closest highway), and the creation of 900 new jobs in exchange for the permission to build a new 18-meters tall 60 thousand squared meters large logistic hub (Prato, 2021).[4] Similarly, the municipality of Ferno (6,752 inhabitants in the province of Varese, Lombardy), was promised the creation of 700 jobs, two bike lanes, and a series of investments in the local road infrastructure in exchange for the permission to build a 70 thousand squared meters large logistic hub (Morandi, 2022).

4.2.2 Territorial implications of Italian logistics

Large logistic centres can affect the well-being of people living nearby through increased air pollution, traffic congestion, noise, and whopping soil consumption (Aljohani and Thompson, 2016). In the Italian case, compensation funds were often dedicated to the municipality in which the hub was created, but negative externalities also affect the surrounding areas. This sparked social discontent in the neighbouring municipalities (Trespidi, 2022).

The promise of the creation of hundreds of open-ended high-qualified jobs was also often unmet: most of the new jobs are low-skilled and fixed-term or delegated to cooperatives. About 93.7% of the 208,595 workers employed in transports and warehousing in Lombardy in 2017 did not have a university

[4]We retrieved Trivolzio's yearly tax and contribution revenues for 2021 from the municipality's balance sheet document for 2021. All official documents from the municipality can be downloaded from http://www.tecuting.it/c018163/zf/index.php/trasparenza/index/index/categoria/119 (last accessed on 25/11/2022).

degree, and 45.4% not even a high-school degree (PoliS-Lombardia, 2019). In the period 2016-2018, 57% of new contracts in the sector were fixed-term and 14% were agency work contracts (PoliS-Lombardia, 2019). Over the same period, 75% of all new contracts in logistics were fixed-term in Veneto (Veneto Lavoro, 2022). Large logistics companies can work in Italy with very few direct employees. This is because they rely on a chain of contracts and subcontracts made up of cooperatives, mini-contractors, and micro-companies that apply contracts with much lower labour costs than the national collective agreement (Invernizzi and Lovato, 2021). Table 4.1 reports the number of workers and the share employed through cooperatives by sector in 2017 based on ISTAT Business Register ASIA. Among the sectors covered by the register, sector "H. Transportation and storage" has by far the highest percentage of workers employed through cooperatives: 18% against an average of 4%. The sector-level average masks large disparities. While the share of workers employed through cooperatives is modest in sectors "50. Water transport" (1.2%), "51. Air transport" (0%), and "53. Postal and courier activities" (0.8%), it raises to 10.2% in sector "49. Land transport" and reaches 42.2% in sector "52. Warehousing and support activities for transportation", with a peak of 80.7% in the sub-sector "5224. Cargo handling". Widespread employment through cooperatives covers the real share of unstable work relationships in at least two ways. First, although workers are often hired through open-ended contracts, at the end of an agreement between the client and the cooperative the rehiring of workers is not assured (Sacchetto et al., 2016). Second, cooperatives often close suddenly, in order to not pay part of the promised wages and social security contributions (Massarelli, 2014; Sacchetto et al., 2016). When a cooperative closes, it is very difficult to find a responsible entity that can be sued. Labour-related issues in the sector are not limited to unstable contracts but also involve irregularities with regard to payrolls, forced overtime, long and irregular working hours (Benvegnù, 2015). Following the 2018 annual report of the national labour inspectorate, 70.5% of inspected firms in sector "H. Transportation and storage" had irregularities in the analysed year (Ispettorato Nazionale del Lavoro, 2018).

4.2.3 Potential channels connecting logistic hubs to support for *Lega*

We identify three potential channels which might connect the opening of a new logistic hub to an increase in votes for *Lega*:

Table 4.1: Number of workers and share of workers employed through cooperatives by sector

NACE	Sector name	N. workers	% Coop.
	All 1-digit sectors (except agriculture)		
B	Mining and quarrying	30,226	2.2
C	Manufacturing	3,684,581	1.9
D	Electricity, gas and steam	88,222	0.9
E	Water, sewage, and waste	196,969	3.5
F	Construction	1,309,650	2.2
G	Wholesale and retail trade	3,414,645	2.6
H	**Transportation and storage**	1,142,144	**18.3**
I	Accommodation and food	1,497,423	2.6
J	Information and communication	569,093	1.9
K	Financial and insurance	567,106	9.1
L	Real estate	299,881	0.4
M	Professional, scientific, and technical	1,280,024	1.4
N	Administrative and support services	1,302,186	13.6
P	Education	110,196	4.9
Q	Health and social work	904,214	0.5
R	Arts, entertainment, and recreation	186,315	6.0
S	Other services	476,606	2.8
	Total	17,059,480	**4.3**
	Sub-sectors in "H. Transportation and storage"		
49	Land transport	548,227	10.2
50	Water transport	51,194	1.2
51	Air transport	19,959	0.0
52	Warehousing and support activities for transp.	367,860	41.3
521	Warehousing and storage	24,212	42.2
522	Support activities for transp.	343,648	41.2
5221	Service activities to land transp.	75,775	9.4
5222	Service activities incidental to water transp.	14,407	11.2
5223	Service activities incidental to air transp.	25,910	0.0
5224	Cargo handling	105,844	80.7
5229	Other transportation support activities	121,712	38.9
53	Postal and courier activities	154,904	0.8

Source: authors' own calculations. *Notes*: the register does not include workers in NACE Rev.2 sections: A, O, T, and U. The Register is updated yearly through a process of integration of administrative and statistical sources. Employment is measured in terms of yearly average of job positions, calculated on the base of the weekly presence of workers. Employment is formed by internal workers (employees or self-employed) and so-called external workers, i.e., all those workers who are not classified as employees or self-employed workers within the enterprise but participate to its productive process on the base of a contract. The group of external workers includes also temporary workers from temporary employment agencies. Data refer to the year 2017.

i. (Perceived) economic insecurity. With the rise in the number of workers employed in logistics, which is characterised by low-paid unstable jobs, there might be an increase in the feeling of socio-economic insecurity. Kurer and Palier (2019) argue that the recent wave of (far-right) populism is a consequence of profound labour market transformations as, differently from mainstream parties, populists were able to recognize the anxiety caused in the middle-class by workplace automation and digitalisation. Several studies provided empirical evidence of the connection between (perceived) economic insecurity and support for populist parties. Anelli et al. (2021a) demonstrated a link between the increase in insecurity triggered by automation and the support for radical right parties in 13 western European countries, including Italy, between 1999 and 2015. Similarly, Im et al. (2019) showed that workers who are both threatened by automation and are still "just about managing" economically are those more inclined to vote for the radical right in 11 European countries between 2012 and 2016. Frey et al. (2018) documented that the support for Donald Trump in 2016 US presidential elections was significantly higher in local labour markets more exposed to the adoption of robots. Moving from automation to trade, Autor et al. (2020) provided evidence of a relationship between adverse economic conditions due to greater exposure to Chinese import competition and support for nativist or extreme politicians in US congressional and presidential elections between 2000 and 2016.

ii. Anti-immigration sentiment. Besides the role of actual economic hardship and the grievances of the "losers of globalisation", several studies highlighted the importance of social identity, cultural backlash, and individual perceptions in explaining the success of populist parties (Ferrari, 2021; Guriev, 2018; Margalit, 2019; Mutz, 2018; Norris and Inglehart, 2019; Spruyt et al., 2016). Populist parties have been particularly able at exploiting people's social and economic anxiety, channelling their frustration against traditional parties, accused of promoting policies that favour people unlike them in terms of nationality, skin colour, sexual orientation, gender, or religion (Frank, 2007; Gaffney, 2020; Gidron and Hall, 2017; Hertz, 2021; Hochschild, 2018; Norris and Inglehart, 2019). Italian logistic hubs employ a large number of foreign workers (Massarelli, 2014; Sacchetto et al., 2016). In Veneto, for example, 36% of new hires in the logistic sector between 2016 and 2018 were foreigners (Veneto Lavoro, 2022), while foreign population in the region is around 11% (ISTAT, 2022a). A substantial inflow of migrants into mostly rural areas (due to the logistic sprawl) might increase the support for *Lega*, which has been always characterised by a strong anti-immigration attitude. Several studies showed a (causal) relationship between immigration and votes for the far-right, which is due not only to economic factors but also to social and cultural ones (Dustmann et al., 2019; Edo et al., 2019; Halla et al., 2017). In the context of Italian logistics, hostility towards migrants might be also driven by a cultural backlash and people's willingness to "defend" their culture and way of life more than by concerns about labour-market competition, as foreign workers in logistics are mostly employed in very low skilled occupations (Hainmueller and Hiscox, 2007).

iii. Hostility towards foreign multinationals. The logistic revolution resulted in the externalisation of logistic tasks to specialised firms, often large multinationals (Carbone and Stone, 2005; Elia et al., 2011; Lieb and Bentz, 2005; Maggi and Mariotti, 2011). *Lega* might gather support among those who want to protect Italian small and medium enterprises against large foreign logistic multinationals. In *Lega*'s program for the 2018 electoral campaign, it is explicitly reported that "The Euro is the main cause of our economic decline, a currency tailor-made for Germany and multinationals and contrary to the needs of Italy and small business" (Lega, 2018: p.9).[5] Thus, *Lega*'s sovranism does not only result in harsh critique of the EU but also in strong hostility towards the activity of large foreign firms in Italy. This is not surprising since the party emerged (and is still stronger) in areas of the North characterised by the predominance of small, family-owned businesses (Huysseune, 2006). One example of this attitude was the reaction to the EU "Bolkestein Directive", adopted at the end of 2006 and implemented in 2009, which aimed at reallocating beach concessions in Italy through tender procedures. *Lega* has strongly opposed the directive alleging to protect the interests of small and medium Italian enterprises, which felt threatened by free competition and the potential integration of foreign interests and large multinationals into the local markets (Il Sole 24 Ore, 2022). The Party's hostility towards multinationals clearly emerged also from their communication in the social media (Zattin, 2020).

4.3 Political discontent in Italy

Italy's fascination for populist leaders is not a new phenomenon: Silvio Berlusconi started dominating the political scene with his party "*Forza Italia*" back in 1994. The current populist wave has three new protagonists: "*Lega*" (the League), "*Movimento 5 Stelle*" (Five Star Movement, M5S), and "*Fratelli d'Italia*" (Brothers of Italy, FdI).[6]

[5] According to Beirich and Woods (2000), Sorens (2004), and Woods (2009), *Lega* promoted "new" issues on the defence of the local community, the local economy, and local identities in opposition to globalization, having a deep impact on Italian society. As shown by Passarelli and Tuorto (2012), this narrative helped *Lega* gaining consensus in a traditionally left-wing region like Emilia-Romagna already in 2008 elections.

[6] Our definition of populist and radical-right populist parties relies on the 2019 Chapel Hill Expert Survey (Jolly et al., 2022). As shown in Table 4.2, these three parties obtain the

Starting in the late 90s, *Lega* gradually evolved from being a regionalist protest party, strongly advocating for the independence of the Northern regions, to becoming a national movement more similar to other European extreme-right parties, especially in its authoritarian and anti-immigrant rhetoric (Ignazi, 2005). The main political approach of the party did not change, as it is still based on a "us *vs.* them" type of rhetoric. What has changed is the content of the "us *vs.* them" slogan. While before the fight was between "us (Northern Italians) *vs.* them (Southern Italians)", now "us" comprehends all Italians, while "them" refers to a series of external enemies, including migrants, EU bureaucrats, and foreign multinationals (Albertazzi et al., 2018; Brunazzo and Gilbert, 2017; Chari et al., 2004). In this process, the party aggressively focused its communication strategy on portraying itself as the defender of "the people" against these external threats which want to destroy the Italian identity (Newth, 2019; Zattin, 2020).

The M5S gained a striking 30.2% of votes in 2018 elections. It was born as the anti-party, being deliberately focused on the "protest", and having no clear positions on economic policies and immigration issues (Corbetta and Gualmini, 2013; Passarelli and Tuorto, 2018). Differently from *Lega*, it did not find external enemies, but it rather focused on fighting the corrupted and privileged Italian political caste (Bordignon and Ceccarini, 2013). In this study we do not focus on the M5S as it did not exist in 2006 (it was founded in 2009) and it gained most of its support in the South (Chaykina et al., 2022), while the logistics revolution mostly took place in the North. We also exclude FdI from our analysis as, it did not exist in 2006 (it was founded in 2012) and it only obtained 4.1% of votes in 2018 elections.

As a consequence of the raising support for populist parties in Italy, a growing literature empirically investigated the factors behind this growth in the last decades. Caselli et al. (2020b) analysed the effect of three global factors, i.e., flows of migrants, foreign competition in international trade, and diffusion of robots, on the support for *Lega* and M5S at the local labour market level in the 2001, 2008, and 2013 general elections. They found that all three factors were associated with an increase in votes for *Lega* in the period 2001-2008, but only robotisation remained significant in the following period. The results for automation were confirmed by Anelli et al. (2021a), who investigated the impact of industrial robot adoption on individual voting behaviour

highest scores in the "Anti-elite" item, which is commonly used as a measure of populism in the literature on political discontent. *Lega* and FdI are also assigned the highest values in the ideological stance item, where higher scores indicate more extreme-right ideologies.

in 13 western European countries, including Italy, between 1999 and 2015, and found that individuals more exposed to automation were more likely to display higher support for the radical right (represented by *Lega* for Italy). Di Matteo and Mariotti (2021) focused on the 2014 and 2019 European elections and showed that unemployment, long-term cultural change, and immigration were the main drivers of the right-wing populism intensity growth at the municipal level. Similarly, Albertazzi and Zulianello (2021) showed that, while *Lega* has thrived in areas characterised by "cultural backlash", Euroscepticism, and societal malaise, the success of the M5S is associated to poor economic and institutional performances. Finally, Albanese et al. (2022) provided causal evidence of the importance of fiscal redistribution in reducing the feeling of economic insecurity exploited by populist parties. By comparing municipalities on the two opposite sides of the geographical border that determines eligibility to the EU structural funds, they showed that larger EU financing caused a substantial drop in votes for populist parties in the 2013 general election.

4.4 Data

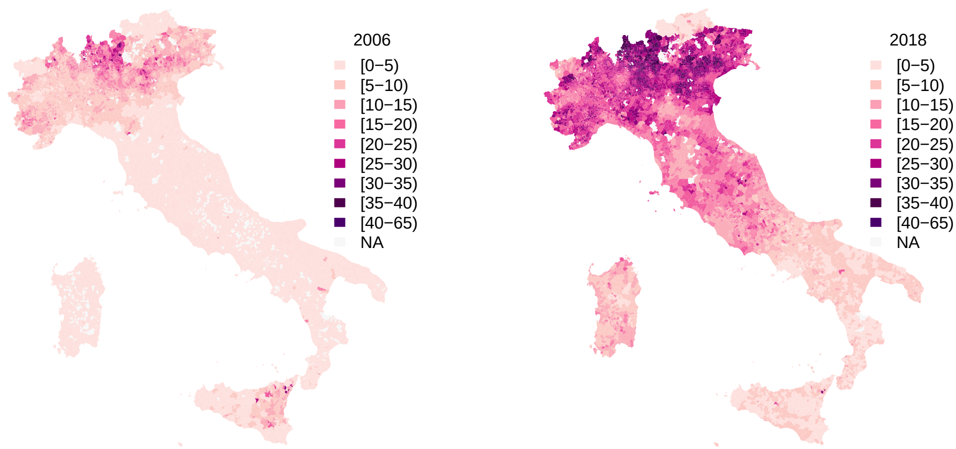
We collected municipal level information from several administrative and statistical sources. Italian municipalities correspond to LAU2 level in Eurostat nomenclature of territorial units (Eurostat, 2022). The next two subsections describe our dependent variable and main explanatory variable, respectively. Table 4.3 reports the data sources of all our control variables.

4.4.1 Support for populist radical-right parties

To build our measures of political discontent we rely on official voting results from the Italian Ministry of the interior. For each election, the data report a series of key information at the municipal level: the number of registered voters, the number of actual voters, the number of white or invalid votes, and the number of votes obtained by each candidate. Data are available for all electoral levels (City Council, Province, Region, Chamber of Deputies, Senate, and European Parliament) but we focus on elections for the Italian Chamber of Deputies. This is because we consider the Chamber of Deputies to be more representative of the situation given that all citizens above 18 can vote.

Our measure of populist radical-right parties relies on the 2019 Chapel Hill Expert Survey (Jolly et al., 2022). As shown in Table 4.2, *Lega* consistently figures among the parties with the highest scores in terms of extreme-right, traditional-authoritarian, anti-EU, against immigration, pro "law & order",

Figure 4.1: *Lega*'s vote share at municipal level in 2006 and 2018 elections



Source: authors' own calculations. *Notes*: electoral results for the Chamber of Deputies.

nationalist, and populist attitudes in all four elections between 2006 and 2018. There also other parties with a clear radical-right attitude, such as *Fratelli d'Italia*, but we chose to focus on *Lega* because it is the only party present in the whole period we observe.

We then measure the variation in support for populist radical-right parties as the difference in the share of votes *Lega* received in the 2018 compared to 2006 elections for the Chamber of Deputies. As shown in Figure 4.1, *Lega*'s support grew substantially between 2006 and 2018 both in intensity and in geographic extension. The extension from the North to the Centre of the country, and even some areas of the South, demonstrates that the party managed to change its identity from localist to national movement. We chose not to analyse the 2022 elections because these elections were heavily influenced by the Covid-19 pandemic and the energy crisis caused by Russia's war in Ukraine.

4.4.2 Logistics

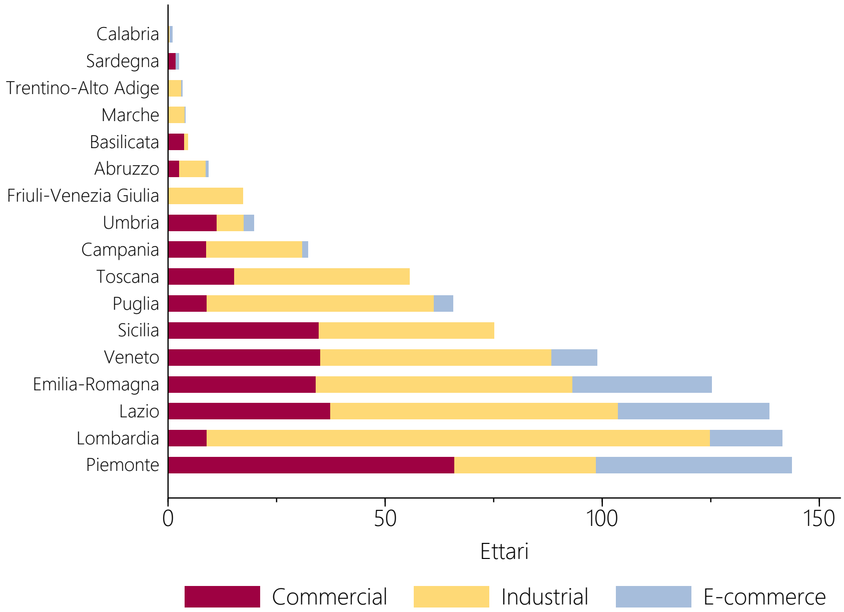
Geographically disaggregated data on logistic activity are scant. We rely on land use data to identify the size of new logistic centres. The work of photo-interpretation, classification, data validation, and processing of Italian aerial and satellite images for the period between 2006 and 2017 was executed by the Italian Institute for Environmental Protection and Research (ISPRA), which kindly provided the data to us. For each municipality, the dataset provides the new surface area occupied by the logistics hubs in the examined period. The hectares count includes warehouses, yards, and offices belonging to the logistic

Table 4.2: Vote share and ideological stance of Italian political parties

Year	Party	Vot.	Vot. CN	LR	Gal.	EU	Imm.	LO	Nat.	AE
2006	Rifondazione Comunista	5.7	5.8	1.3	0.8	3.0	2.0	1.0		
	L'Ulivo (Dl)	30.3	31.7	4.0	5.1	7.0	3.2	4.0		
	Unione di Centro	6.6	6.2	5.9	7.6	6.3	5.8	7.1		
	Forza Italia	23.0	21.9	7.1	7.0	4.1	6.7	6.9		
	Alleanza Nazionale	12.0	12.0	8.0	8.9	4.8	7.0	9.1		
	Lega	4.4	6.0	8.7	8.8	1.5	8.2	9.7		
2008	Partito Democratico	31.9	33.6	3.2	3.1	6.6	3.0	4.1		
	Di Pietro Italia dei Valori	4.2	4.0	4.0	3.5	6.1	3.8	6.1		
	Unione di Centro	5.4	4.6	5.3	7.4	6.3	4.9	5.9		
	Il Popolo della Libertà	35.9	32.4	7.6	8.4	4.7	8.3	7.6		
	Lega	8.0	11.9	8.6	8.4	2.7	9.9	8.9		
2013	Sinistra Ecologia Libertà	3.1	2.8	1.3	0.3	3.1	1.3	1.2	2.0	
	Partito Democratico	24.5	26.6	3.6	2.4	6.6	3.3	3.6	3.4	
	Movimento 5 Stelle	24.6	24.0	4.7	2.6	1.4	4.3	4.2	3.8	
	Scelta Civica	8.0	8.9	5.4	5.4	6.9	5.0	6.0	3.8	
	Il Popolo della Libertà	20.7	18.6	6.1	8.0	5.7	7.5	8.0	6.6	
	Lega	3.9	5.7	8.9	9.1	1.1	9.5	9.0	9.6	
2018	Partito Democratico	17.3	19.8	3.2	2.3	6.8	3.1	2.8	2.0	2.1
	Movimento 5 Stelle	30.2	24.0	4.8	3.7	3.5	6.6	4.6	4.3	9.5
	Forza Italia	13.2	11.3	6.9	6.8	4.9	7.0	6.8	6.4	4.1
	Lega	16.4	21.5	8.8	9.2	1.7	9.9	9.3	9.1	6.9
	Fratelli d'Italia	4.1	4.4	9.1	9.4	1.9	9.8	9.6	9.8	6.6

Source: vote shares are computed by the authors on official voting results from the Italian Ministry of the interior. Ideological stance measures are from the 2019 Chapel Hill Expert Survey (Jolly et al., 2022). *Notes*: the column "Vot." reports the share of votes obtained at the national level for the Chamber of deputies elections, while "Vot. CN" is the vote share in the Centre and North. "LR" is the position of the party in terms of its overall ideological stance, it goes from "0 - Extreme left" to "10 - Extreme right"; "Gal." is the party position in terms of their views on social and cultural values (Galtan scale), it ranges from "0 - Libertarian/Postmaterialist" to "10 - Traditional/Authoritarian"; "EU" is the overall orientation of the party towards European integration, it goes from "1 - Strongly opposed" to "7 - Strongly in favour"; "Imm." is the position on immigration policy, it varies between "0 - Strongly favours a liberal policy on immigration" to "10 - Strongly favours a restrictive policy on immigration"; "LO" is the position on civil liberties *vs.* law and order, it goes from "0 - Strongly promotes civil liberties" to "10 - Strongly supports tough measures to fight crime"; "Nat." is the position on cosmopolitanism *vs.* nationalism, it goes from "0 - Strongly promotes cosmopolitan conceptions of society" to "10 - Strongly promotes nationalist conceptions of society"; "AE" is the position on the "anti-elite" item which ranges from "0 - Elected office holders should make the most important decisions" to "10 = 'The people', not politicians, should make the most important decisions". The table only reports parties which obtained at least 3% of votes in the election (this is also the electoral threshold to access the parliament).

Figure 4.2: Hectares of new logistic surface between 2006 and 2017



Source: authors' own calculations.

hub. ISPRA's monitoring is carried out using satellite images available during the reference period, which is set in May, with a time variability of plus/minus two months. Therefore, for each municipality i, our indicator measures the hectares occupied by new logistic hubs between May/2006 and May/2017:

$$\Delta 06 - 17 HectaresLog = SurfaceLog_{2017} - SurfaceLog_{2006} \tag{1}$$

As discussed in Section 4.2.2, individuals are not affected only by what happens in their municipality but also by what takes place in the surrounding areas. In our baseline estimations, we calculate $\Delta 06 - 17 HectaresLog$ by considering the total area of all newly constructed logistics facilities in the municipality and neighbouring municipalities. However, particularly in the case of small municipalities, individuals may also be affected by developments beyond neighbouring municipalities. As there is no defined distance at which individuals "lose interest", we considered radii of varying sizes. As discussed in Section 4.5.2, our results are robust to different selections of the radius around each municipality.[7] Note that ISPRA's observation time is set approximately in May, hence we observe the construction of new hubs up until May 2017, while the 2018 elections took place in March 2018.

[7] Appendix Table 4A.1 reports summary statistics on all the radii we considered.

The largest share of new logistics surface built in the period 2006-2017 is dedicated to industrial flows (55.4%), followed by commercial sites (28.6%), and e-commerce (15.9%). As shown in Figure 4.2, a great part of new structures was built in the North (56%), followed by the Centre (23%), and the South (20%). Appendix Table 4A.2 reports more statistics on new logistics surface by NUTS2 region and time period.

4.5 Instrumental variable approach

Our units of analysis are municipalities of the North and the Centre of Italy.[8] We focus on the North and the Centre for three reasons. First, the logistic boom happened mostly in the North and the Centre (see Figure 4.2). Second, this area encompasses the majority of Italian population (64.7%) and GDP (76.2%).[9] Third, discontent in the South was mostly expressed with votes for M5S (Chaykina et al., 2022). Furthermore, since we expect large urban centres to be differently affected by logistics and to follow different dynamics than the other areas, we exclude urban cores as defined by the OECD (OECD, 2022).[10]

For each of the remaining municipalities i, we estimate the following equation:

$$\begin{aligned} \Delta 06-18Lega_i = \alpha + \beta \cdot \Delta 06-17HectaresLog_i \\ + \rho \cdot SocioDem_i + \theta \cdot Trends_i + \epsilon_i \end{aligned} \tag{2}$$

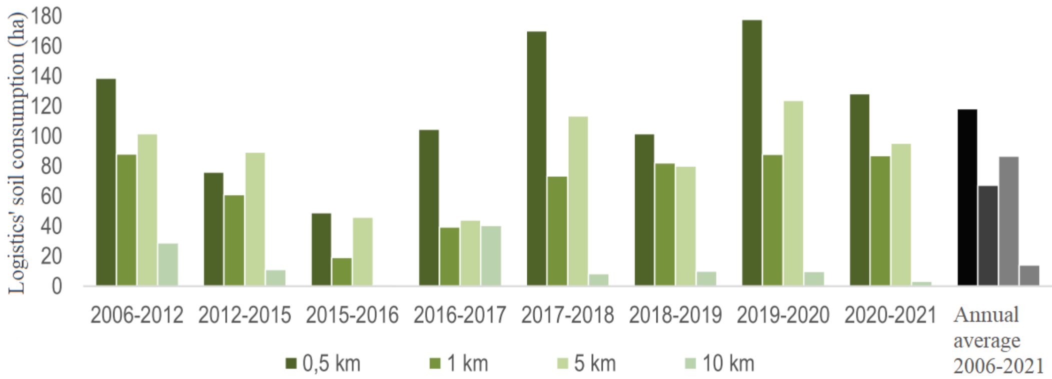
The dependent variable $Delta06-18Lega_i$ is the change in the share of votes for *Lega* between 2018 and 2006. $\Delta 06-17HectaresLog_i$ is our measure of logistic activity. We expect its coefficient, β, to be positive and significant, meaning that an increase in logistics activity in the municipality's area leads to an increase in votes for *Lega*. $SocioDem_i$ is a vector containing NUTS2 dummies and a series of municipality's demographic, social, and economic characteristics, all measured at the beginning of the observation period, which might affect citizens' propensity to support the League. $Trends_i$ includes two

[8] We classify North and Centre as Eurostat's NUTS1 "North-West" (ITC), "North-East" (ITH), and "Centre" (IRI). This corresponds to the following regions (NUTS2): Piemonte (ITC1), Valle d'Aosta (ITC2), Liguria (ITC3), Lombardia (ITC4), Trentino-Alto Adige (ITH10 / ITH20), Veneto (ITH3), Friuli-Venezia Giulia (ITH4), Emilia-Romagna (ITH5), Toscana (ITI1), Umbria (ITI2), Marche (ITI3), and Lazio (ITI4).

[9] Shares based on ISTAT's official statistics for 2006. The values for 2017 are similar: 65.7% of population and 77.7% of GDP.

[10] Note that we keep core urban areas when computing measures at the radius level but we drop them from the sample when running the regressions. To make sure that this sample restriction is not the main driver of our results, we run two robustness checks, one in which we keep urban cores and one in which we drop all municipalities included in functional urban areas. The results of these tests are reported in Section 4.5.2.

Figure 4.3: Distance of logistics hubs from main roads in Italy



Source: Munafò (2022).

controls for other long-term trends which might affect people's attitudes, i.e., the decline in manufacturing employment and the variation in imports from China. Table 4.3 reports the description and data source of each variable, Appendix Table 4A.3 contains the main descriptive statistics on the variables used in Equation 2, and Appendix Figure 4A.1 plots the correlation level across control variables. Finally, α is the coefficient of the intercept and ϵ_i is an error term.

4.5.1 Instrumental variable

The geographic location of new logistic hubs is not random. The decision concerning a hub's location is likely to be driven by actual development or growth potential of the area, so that our estimation might suffer from both reverse causality and omitted variables bias. Since logistics firms show a special attraction to highways (Bowen, 2008; Holl and Mariotti, 2018a; Sakai et al., 2020; Verhetsel et al., 2015) and the great majority of Italian freight flows are moved by road (Confetra, 2022), a possible instrument could be the distance to highways. Indeed, as shown in Figure 4.3, the majority of new logistics centres built in Italy between 2006 and 2021 is concentrated in the distance between 0 and 500 metres from major roads, with only a negligible share being built beyond 10 kilometres.

However, highways' location is also not exogenous. Hence, following Combes et al. (2010), we rely on a historical instrument, precisely on the Roman road network. For each municipality i, our instrument measures the density of Roman roads (in meters over hectares) within the municipality's radius.[11] We

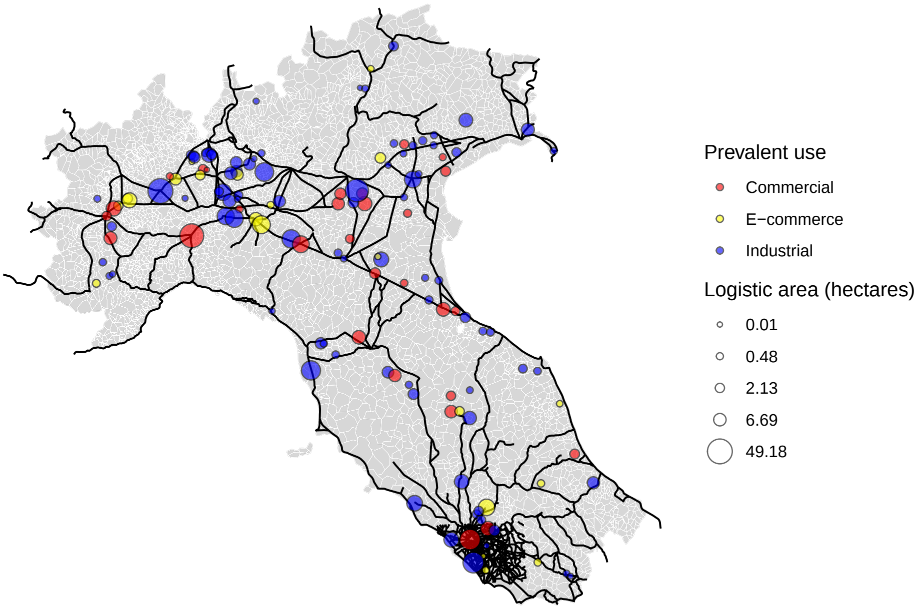
[11]We extracted the municipal-level meters of Roman roads from the shapefiles provided by McCormick et al. (2008).

Table 4.3: Control variables

Name	Description	Year - level - data source
Socio-demographic characteristics		
% HS	% Population with high-school degree	2001 or 2011 - LAU2 - ISTAT (Census)
% Unempl.	% Unemployed workers	2001 or 2011 - LAU2 - ISTAT (Census)
% Pop. 55-100	% Population aged 55-100	2004 or 2012 - LAU2 - ISTAT
% Foreign	% Foreign inhabitants in population registers.	2004 or 2012 - LAU2 - ISTAT
Pop. (th.)	Population (thousands)	2004 or 2012 - LAU2 - ISTAT
New-borns	Number of new-born babies per 100 inhabitants	2004 or 2012 - LAU2 ISTAT
No FUA	Binary indicator equal to one if municipality is not part of a functional urban area	LAU2 - OECD
% Fem. city council	% Female city counsellors (proxy for social capital)	2002 or 2012 - LAU2 - Ministry of the Interior
Income p.c. (10th.)	Imposable yearly income per taxpayer (10 thousand Euro) - computed from tax returns (IRPEF)	2004 or 2012 - LAU2 - Ministry of Economy and Finance
% Manuf. (rad.)	% Workers employed manufacturing	2004 or 2012 - Radius - ISTAT
IQI prov.	Institutional quality index. The index assumes values in the range $[0, 1]$ with higher values indicating higher institutional quality	2004 or 2012 - NUTS3 - Nifo and Vecchione (2014)
VA p.w. (th. EUR) prov.	Value added per worker (thousands of Euro)	2004 or 2012 - NUTS3 - ISTAT
NUTS2	NUTS2 dummies	NUTS2 - Eurostat
Macro-trends		
Δ04-17 Workers manuf. (rad)	Change in number of workers in manufacturing (per 100 workers)	2004-2017 - Radius - ISTAT
Δ96-17 IPW China (rad.)	Change in imports from China (thousands of constant 2015 US dollars per worker). Detailed description of the measure in Appendix 4B	1996-2017 - Radius - Comtrade and ISTAT's Census of Industry and Services 1991

Notes: controls from the early 2000s (2001-2004) are used for estimations comparing the elections 2006-2018, while controls from the early 2010s (2011-2012) are used when comparing electoral results of the 20136-2018 elections. There are two exceptions: we chose to use "Δ04-17 Workers manuf. (rad)" and "Δ96-17 IPW China (rad.)" in both groups of estimations to control for areas most affected by macro-trends. The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory of the EU and the UK. NUTS0 refers to country, NUTS1 to macro-regions within countries, NUTS2 generally to regions, and NUTS3 to provinces. Local Administrative Units (LAUs) are the building blocks of the NUTS and includes the municipalities and communes of the European Union. In the Italian context, after the NUTS3 level there is the LAU level 2, or LAU2, corresponding to municipalities.

Figure 4.4: Roman roads and logistic hubs in North and Centre Italy



Source: plot created by the authors.

believe the Roman road density to respect the exclusion restriction as it is reasonable to assume it to be correlated with past trade and urbanization dynamics, which are directly correlated with actual levels of urbanization and economic characteristics, but uncorrelated to the change in *Lega*'s support between 2006 and 2018. The validity of Roman road density is corroborated by Dalgaard et al. (2022), who stressed the key role that they had in today economic activity and urban expansion of Europe, despite being constructed for military reasons, thereby excluding a direct economic reason for their location (Licio, 2021). Several other studies used Roman roads (or other ancient roads) as an instrument for current economic activity and development, which they affect through their relationship with highways and other forms of modern transport infrastructure (Bottasso et al., 2022; Garcia-López, 2019; Holl and Mariotti, 2018a; Möller and Zierer, 2018; Percoco, 2016). As reflected in Figure 4.4, logistic hubs tend to be located along the Roman network, which is a good predictor of current Italian infrastructures (Maggi, 2009).

4.5.2 Results - 2SLS

Table 4.4 reports the regression results for the ordinary least-squares (OLS) estimator with robust standard errors and the two-stage least-squares (2SLS) estimator with robust standard errors. The relatively high values for the first stage F-statistic imply that the instrument used is informative for our endogenous variables.[12] The 2SLS results tend to be larger than the ones based on the OLS estimator, suggesting that unobservable characteristics can reduce in absolute terms the estimated effect of logistics activity. $\Delta 0617 HectaresLog$ shows a positive and significant relation with the increase in support for *Lega* at the municipal level. In terms of magnitude, one additional hectare of logistic surface increases *Lega*'s vote share in the municipality by 0.16 percentage points.

The signs of our control variables' estimates are mostly in line with expectations based on papers from the related literature. Starting from basic socio-economic controls, larger population size, a higher share of inhabitants with tertiary education, a higher income, and higher value added per worker are associated with lower *Lega*'s support. Less dynamic municipalities, i.e., those with a higher unemployment rate and more elderly people, are characterized by a higher growth of political discontent. *Lega*'s support is positively correlated with the share of foreign inhabitants at the beginning of the period. Our proxy of social capital, i.e., the share of female city councillors, is negatively correlated with *Lega*'s vote share. The two controls for long-term trends are not significant, but this might be due to their correlation with other controls.

Table 4.5 reports the results of the battery of robustness checks we performed. The tests can be divided in four groups:

i. Alternative radii. In our main specification we define a radius around each municipality which only includes neighbouring municipalities. To make sure our results do not depend on the radius we picked, we re-estimated our models using: (a) ISTAT's 2001 local labour markets; (b) fixed cut-off points for all municipalities (between 10 and 30 kilometres); (c) municipality-specific radii based on commuting-levels: to account for different levels of mobility across municipalities, we use ISTAT's 2001 census commuting matrix (ISTAT, 2022b) to estimate the minimum distance at which each municipality reaches (c1) 80%, 85%, 90%, and 95% of its workers, or (c2) 80%, 85%, 90%, and 95% of its workers and students (these radii are generally larger than the ones based on workers only). Appendix Table 4A.1 reports several statistics on the number of municipalities included in each type of radius, while Appendix Figure 4A.2 reports some statistics on commuting distances.

[12] A commonly followed rule-of-thumb is that the F-statistic should be greater than 10 (Stock et al., 2002).

Table 4.4: Regression results 2SLS – Base model

	OLS (1)	OLS (2)	2SLS (1)	2SLS (2)
Δ06-17 HectaresLog	0.066***	0.065***	0.155***	0.159***
	(0.010)	(0.010)	(0.044)	(0.044)
% High-School dipl. 01	-0.081***	-0.079***	-0.085***	-0.083***
	(0.020)	(0.020)	(0.020)	(0.020)
% Unempl. 01	0.126***	0.126***	0.130***	0.130***
	(0.042)	(0.042)	(0.042)	(0.042)
% Pop. 55-100 04	0.073***	0.073***	0.079***	0.079***
	(0.018)	(0.018)	(0.018)	(0.018)
Pop. (th.) 04	-0.046***	-0.046***	-0.053***	-0.054***
	(0.007)	(0.007)	(0.008)	(0.008)
% Foreign pop. 04	0.082***	0.080***	0.075***	0.073**
	(0.028)	(0.028)	(0.028)	(0.028)
Newborns (x100 inhab.) 04	-0.329	-0.321	-0.309	-0.301
	(0.312)	(0.312)	(0.312)	(0.312)
% Manuf. (rad.) 04	0.001	0.005	0.006	0.010
	(0.006)	(0.007)	(0.007)	(0.007)
% Soil used 06	0.004	0.005	0.004	0.004
	(0.008)	(0.008)	(0.008)	(0.008)
Income p.c. (10th. EUR) 04	-1.435***	-1.434***	-1.393***	-1.390***
	(0.384)	(0.384)	(0.385)	(0.385)
No FUA	0.178	0.182	0.273	0.280
	(0.164)	(0.164)	(0.171)	(0.171)
% Fem. city council 02	-0.025***	-0.025***	-0.027***	-0.027***
	(0.006)	(0.006)	(0.006)	(0.006)
VA p.w. (th. EUR) prov. 04	-0.022***	-0.021***	-0.021***	-0.020***
	(0.004)	(0.004)	(0.004)	(0.004)
IQI prov 04	0.450	0.275	0.385	0.225
	(1.298)	(1.288)	(1.299)	(1.289)
Δ04-17 Manuf work. (x100 inhab.) (rad.)		0.002		0.002
		(0.013)		(0.013)
Δ96-17 IPW China (th. USD) (rad.)		-0.064		-0.057
		(0.043)		(0.043)
Constant	19.664***	19.668***	19.085***	19.059***
	(1.541)	(1.540)	(1.569)	(1.572)
NUTS2 FE	✓	✓	✓	✓
Adjusted R^2	0.18	0.18	0.18	0.17
N	5,169	5,169	5,169	5,169
First stage F-stat.			64.98	65.65
Endogeneity test (p-value)			0.032	0.023

Source: authors' own calculations. *Notes*: 2SLS columns report two-stage least squares regressions where logistics activity in the radius around each municipality is instrumented with the density of Roman roads. Robust standard errors in parentheses. Olea and Pflueger (2013) first-stage F-Statistic and Wooldridge (1995) robust score test of endogenous regressors are reported at the bottom of the table for 2SLS regressions. All regressions include NUTS2 dummies. A description of each control variable is reported in Table 4.3. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$.

Table 4.5: Regression results 2SLS – Robustness checks

	β_{OLS}	SE_{OLS}	R^2_{OLS}	β_{2SLS}	SE_{2SLS}	F-stat.	N
Baseline	0.065***	0.010	0.19	0.159***	0.044	65.6	5,169
i. Alternative radii							
Shocks at LLM level	0.015***	0.004	0.19	0.042***	0.011	186.6	5,169
10 km	0.043***	0.009	0.19	0.345**	0.137	17.4	5,169
15 km	0.034***	0.006	0.19	0.186***	0.062	32.4	5,169
20 km	0.031***	0.005	0.19	0.093***	0.026	88.1	5,169
25 km	0.030***	0.004	0.20	0.060***	0.015	175.1	5,169
30 km	0.028***	0.003	0.20	0.043***	0.010	318.0	5,169
80% workers	0.018***	0.004	0.19	0.057***	0.018	151.7	5,169
85% workers	0.021***	0.003	0.19	0.053***	0.014	165.9	5,169
90% workers	0.019***	0.003	0.19	0.053***	0.011	147.7	5,169
95% workers	0.018***	0.002	0.20	0.053***	0.009	102.2	5,169
80% workers and students	0.019***	0.004	0.19	0.068***	0.021	114.1	5,169
85% workers and students	0.018***	0.004	0.19	0.056***	0.016	159.1	5,169
90% workers and students	0.017***	0.003	0.19	0.049***	0.012	157.3	5,169
95% workers and students	0.018***	0.002	0.20	0.043***	0.009	94.1	5,169
ii. Sample restriction							
Exclude Lazio	0.070***	0.012	0.19	0.429***	0.111	35.7	4,796
Exclude FUA	0.067***	0.015	0.17	0.274**	0.120	26.9	3,893
Keep FUA cores	0.063***	0.010	0.19	0.149***	0.043	65.5	5,223
Add South	0.035***	0.009	0.64	0.142***	0.043	72.6	7,570
iii. Additional controls							
Earthquake 2012	0.065***	0.010	0.19	0.160***	0.044	65.8	5,169
Δ06–18 Turnout	0.070***	0.010	0.20	0.181***	0.046	65.5	5,169
Turnout 06	0.065***	0.010	0.19	0.157***	0.044	65.2	5,169
Δ06–18 Turnout and Turnout 06	0.070***	0.010	0.21	0.177***	0.045	65.3	5,169
%*Lega* 06	0.065***	0.009	0.20	0.126***	0.042	65.6	5,169
%*Lega* 01	0.063***	0.010	0.19	0.141***	0.043	64.5	5,169
%*Lega* 01 and Turnout 01	0.061***	0.010	0.20	0.134***	0.043	63.1	5,169
Δ04–17 Foreign pop. (x 100 inhab.)	0.059***	0.010	0.19	0.148***	0.045	62.9	5,169
iv. Other checks							
Δ06–18 Potential votes *Lega*	0.046***	0.008	0.14	0.138***	0.038	65.6	5,169
Conley SE (Bartlett 20 km)				0.159**	0.072		5,169
Δ13–18 *Lega* - (Δ12-17 Log)	0.070***	0.013	0.26	0.269***	0.071	52.4	5,169
Δ13–18 *Lega* - (Δ15-17 Log)	0.066***	0.018	0.26	0.904***	0.276	21.4	5,169

Source: authors' own calculations. *Notes*: all regressions include the battery of controls described in Table 4.3 measured in the early 2000s (2001-2004), except for regressions with Δ13-18 *Lega* as dependent variable, whose controls are recorded in the early 2010s (2011-2012). 2SLS columns refer to two-stage least squares regressions where logistics activity in the radius around each municipality is instrumented with the density of Roman roads. Olea and Pflueger (2013) first-stage F-Statistic for the 2SLS regressions is reported in column "F-stat.". Robust standard errors. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$.

ii. Sample restriction. To exclude the possibility that our results are driven by a specific group of "special" municipalities, we tried varying our sample restriction: (a) excluding municipalities in Lazio region (as shown in Figure 4.4, the region has a very high density of Roman roads as Rome is located there. Another reason to test the exclusion of this region is that it is not included in the DiD analysis as *Lega* did not run there in the 2008 elections); (b) excluding municipalities belonging to OECD functional urban areas; (c) including OECD urban cores; (d) including municipalities from Southern regions.

iii. Additional controls. We test whether results are sensitive to the inclusion of the following additional controls: (a) a binary indicator for municipalities hit by the 2012 earthquake (Cerqua et al., 2021); (b) the variation in electoral turnout between 2006 and 2018 ("Δ06-18 Turnout"); (c) the turnout level in 2006 ("Turnout 06"); (d) both "Δ06-18 Turnout" and "Turnout 06"; (e) *Lega*'s vote share in 2006 ("% LN 06"); (f) as *Lega*'s vote share in 2006 is used to compute our dependent variable, we tried controlling for *Lega*'s vote share in the previous elections, i.e. 2001 elections ("%LN 01"); (g) to better control for the municipality's electoral behaviour in the past, we tried adding both *Lega*'s vote share in 2001 and the electoral turnout in 2001 ("% LN 01" and "Turnout 01"); (h) the variation in the number of foreign inhabitants between 2006 and 2018.

iv. Other checks. Finally, we performed the following tests: (a) our dependent variable (Δ06-18 *Lega*) measures the change in *Lega*'s vote share as votes for *Lega* over total votes, in this section we tried an alternative dependent variable ("Δ06-18 Potential votes *Lega*") measured as votes for *Lega* over total eligible voters; (b) since our units of analysis may not be Independent and Identically Distributed (i.i.d.) due to spatial dependence, we check whether results are robust to estimating Spatial HAC standard errors following Conley (1999); (c) as in the DiD analysis we compare the elections in 2018 with those in 2013, we tried repeating the estimation in Equation 2 using "$\Delta 13-18$ *Lega*" as our dependent variable and "$\Delta 12-17 HectaresLog$" or "$\Delta 15-17 HectaresLog$" as our measure of logistics activity shock.

While the magnitude of our estimates varies depending on the specification, the positive and significant relationship between logistics activities and the increase in support for *Lega* between 2006 and 2018 is confirmed in all estimations.

An alternative approach to capture logistics activity could have been using employment data at the municipal level from ISTAT "Statistical Register of Local Units" dataset (ASIA UL). For each municipality, the register provides the number of local units and the number of workers by three-digits NACE Rev.2 codes for the period 2004-2018. As discussed more in detail in Appendix 4C, we analysed these data and we found them to be too unreliable to be used in our main analysis. However, for a matter of transparency, we still tested our instrumental variable approach using a variable based on these data. The results are reported in Appendix Table 4C.1.

4.6 Difference-in-Differences

Besides the instrumental variable approach, we adopt an alternative estimation method: a Difference-in-Differences (DiD) analysis. The setup of our DiD analysis is complicated by the fact that we do not have the information on hectares of logistics surface on a yearly basis. In fact, we only have data for the following spells: (1) 2006-2012; (2) 2012-2015; (3) 2015-2016; (4) 2016-2017; (5) 2017-2018; (6) 2018-2019. Note that ISPRA's monitoring is carried out using satellite images available during the reference period, which is set in May, with a time variability of plus/minus two months. For example, the spell 2012-2015, indicates the new surface covered between May 2012 and May 2015.

Keeping these limitations in mind, we built our DiD comparing results of the elections in 2018 versus the ones in 2013. This approach allows us to: (1) have three elections before the "shock" to check the pre-trends assumption; (2) have information on the construction of new logistics sites before our main shock to correctly select our control group. The DiD is estimated as follows:

$$y_{m,t} = \alpha + \beta \cdot (Treated_m \times T_{2018}) + \epsilon_{m,t} \tag{3}$$

where $y_{m,t}$ is the electoral outcome in municipality m in election year t, $Treated_m$ is a binary indicator for treated municipalities, T_{2018} is an indicator for the 2018 election, and $t \in \{2013, 2018\}$. We select the treated units based on the new surface built in the two years between May/2015 and May/2017. We do not include municipalities treated between May/2017 and May/2018 as the 2018 elections took place in March. In our main specification we do not consider the municipalities treated in the period May/2012-May/2015 as it starts before the 2013 elections. However, we still consider this period in one of our robustness checks.

For this sort of analysis we need to turn our continuous variable, i.e. the new hectares of logistics surface built in a given period, into a binary indica-

Table 4.6: Hectares cut-off and size of treated and control groups

	Treated		Control	
	Cut-off (Ha)	N	Cut-off (Ha)	N
Treated 80th - Control 10th	8.2	103	0.2	3,955
Treated 80th - Control 50th	8.2	103	2.8	4,338
Treated 85th - Control 10th	9.4	77	0.2	3,955
Treated 85th - Control 50th	9.4	77	2.8	4,338
Treated 90th - Control 10th	10.3	51	0.2	3,955
Treated 90th - Control 50th	10.3	51	2.8	4,338

Source: authors' own calculations. *Notes*: statistics on Centre and North only. Thresholds for the treated groups refer to the two years between May/2015 and May/2017, while for control groups we consider the whole period between May/2006 and May/2018.

tor for "treated" versus "control" municipalities. Given that we do not have any theory-based indication on the number of hectares necessary for a municipality to be considered as treated, we tested several cut-off points (some more "stringent" and others more "loose") based on the observed distribution of our variables.[13] To be more specific, we categorized as "Control group" those municipalities that, in the whole period between May-2006 and May-2018, registered a logistics soil consumption in the municipality itself and in the neighbouring ones below the 10th or the 50th percentile. We do not set the limit for the control group to zero to ensure we are not only selecting very remote municipalities in our control group. "Treated" municipalities are those with a newly consumed surface above the 80th, 85th, or 90th percentile in the two years between May/2015 and May/2017. Table 4.6 reports the number of hectares for each cut-off and the size of the relative treated and control groups. We chose the 80th percentile for treatment and the 50th for control ("t80-c50") as our main specification, because we think it provides a good trade-off between selecting municipalities that experienced a large shock and providing a sample large enough for our estimations. As described in the following paragraphs, we use a series of matching and weighting techniques to select the most suitable control for each treated municipality. All 103 treated units are concentrated in five regions only: Piemonte (31), Veneto (23), Lombardia (23), Emilia-Romagna (17), and Friuli-Venezia Giulia (9). Note that Lazio had to be excluded from this analysis because *Lega* did not run in this region for the 2008 elections.

[13] For both the control and the treatment group the percentiles refer to the distribution among municipalities with some new logistics surface in the surrounding areas in the observed period. If we used all municipalities, looking at percentiles would not help as they would be all equal to zero.

The identification assumption in our DiD approach is that electoral outcomes would have evolved similarly in municipalities with higher and lower logistics activity in 2015-2017 in the absence of the treatment. As shown in Table 4.7, treated and control units differ in the distribution of several characteristics. Hence, using an approach that helps us comparing municipalities as similar as possible is fundamental for the solidity of our analysis. We use the Sant'Anna and Zhao (2020) improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (DRIMP). By using both matching and weighting, DRIMP can achieve better balance between the treatment and control groups on confounding covariates than either method alone. Moreover, by using a doubly robust approach, DRIMP can produce consistent estimates of the treatment effect even if the propensity score model is misspecified or if there is unobserved confounding, as long as either the matching or the weighting model is correctly specified. This method is particularly suitable in our setting as, being the location of logistics hubs not exogenous, the parallel trends assumption might hold potentially only after conditioning on observed pre-treatment characteristics. Therefore, we control for all variables in Table 4.3 measured before the treatment, i.e. in 2011-2012. Standard errors are clustered at the municipality level.

The existence of a common trend is the key identifying assumption for DiD estimates to be unbiased. In our analysis, the assumption implies that, in the absence logistics centres, the affected areas would have had the same trends in their support for *Lega* as in not exposed municipalities. Since we observe three elections before the shock, i.e. the elections in 2006, 2008, and 2013, we are able to test this assumption. Specifically, we estimated Equation 3 for 2008 *vs.* 2006 and 2013 *vs.* 2008.

4.6.1 Results - DiD

Figure 4.5 reports the estimates of the Difference-in-Differences models and their 95% confidence intervals. Both in the more "stringent" and in the more "loose" specifications, the point estimates of treated municipalities showed a larger increase in support for *Lega*, with the estimated effect ranging between 1.95 and 2.88 percentage points. The pre-trends assumption appears to be satisfied as all effects for the 2006-2008 and 2008-2013 elections, i.e., those before the "shock", are not statistically significant.

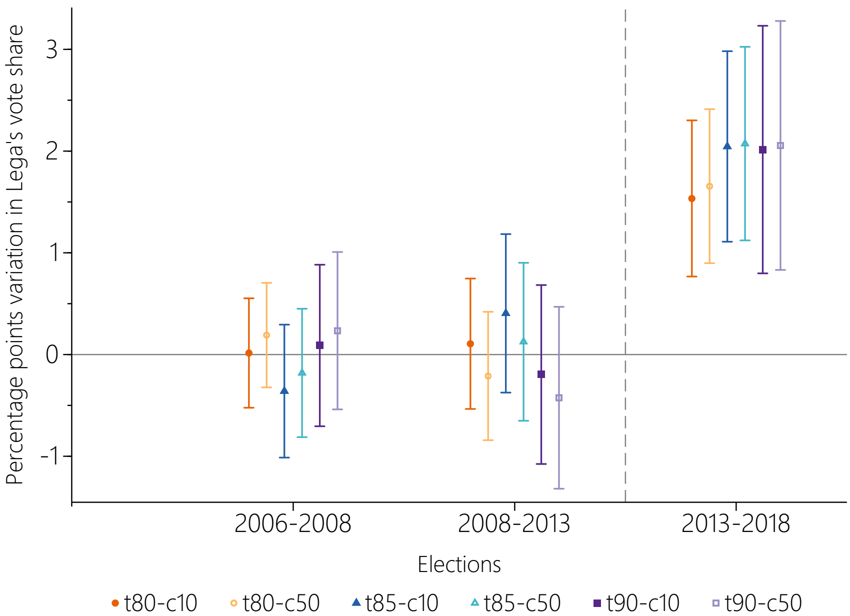
Table 4.8 compares the results for *Lega*, with the ones for the Democratic party (PD) and the Five Stars Movement (M5S). The latter two did not exist in all

Table 4.7: Comparison between treated and control group in DiD (unmatched)

	T(avg.)	C(avg.)	Diff.	p-val.	T(SD)	C(SD)	T(N)	C(N)
% High-School dipl. 11	35.40	32.84	2.56	0.000	6.22	6.69	103	4,338
% Unempl. 11	6.73	6.37	0.35	0.041	1.72	2.28	103	4,338
% Pop. 55-100 12	33.13	36.15	-3.02	0.000	5.73	6.75	103	4,338
Pop. (th.) 12	9.00	4.49	4.51	0.000	11.76	7.07	103	4,338
% Foreign pop. 12	10.04	7.92	2.12	0.000	4.22	4.33	103	4,338
Newborns (x100 inhab.) 12	0.82	0.75	0.07	0.005	0.26	0.33	103	4,338
% Manuf. (rad.) 12	23.36	30.08	-6.72	0.000	10.11	13.39	103	4,338
% Soil used 12	15.45	10.20	5.25	0.000	9.62	9.70	103	4,338
Income p.c. (10th. EUR) 12	1.99	1.89	0.10	0.000	0.24	0.29	103	4,338
No FUA	0.56	0.80	-0.23	0.000	0.50	0.40	103	4,338
% Fem. city council 12	22.62	24.09	-1.47	0.216	11.93	11.97	103	4,338
VA p.w. (th. EUR) prov. 12	62.81	63.00	-0.18	0.920	18.18	16.58	103	4,338
IQI prov 12	0.81	0.80	0.01	0.197	0.08	0.10	103	4,338
Δ04-17 Manuf work. (x100 inhab.) (rad.)	-6.29	-6.68	0.39	0.304	3.68	6.84	103	4,338
Δ96-17 IPW China (th. USD) (rad.)	1.66	2.00	-0.34	0.000	0.85	2.05	103	4,338
Emilia-Romagna	0.17	0.05	0.12	0.002	0.37	0.22	103	4,338
Friuli-Venezia Giulia	0.09	0.04	0.04	0.123	0.28	0.21	103	4,338
Liguria	0.00	0.05			0.00	0.22	103	4,338
Lombardia	0.22	0.31	-0.09	0.035	0.42	0.46	103	4,338
Marche	0.00	0.05			0.00	0.21	103	4,338
Piemonte	0.30	0.25	0.05	0.297	0.46	0.43	103	4,338
Toscana	0.00	0.05			0.00	0.21	103	4,338
Trentino-Alto Adige	0.00	0.06			0.00	0.23	103	4,338
Umbria	0.00	0.02			0.00	0.13	103	4,338
Valle d'Aosta	0.00	0.02			0.00	0.13	103	4,338
Veneto	0.22	0.10	0.12	0.004	0.42	0.30	103	4,338

Source: authors' own calculations. *Notes*: statistics on Centre and North only, using 80th percentile for treatment and 50th percentile for control. We chose these two groups as they offer the largest samples. We then apply matching techniques to select the most suitable control(s) for each of our treated municipalities. The column "Diff." reports the difference in the two groups' means ("T(avg.)" minus "C(avg.)") and column "p-value" the relative p-value. Column "T(SD)" ("C(SD)") reports the standard deviation for the treated (control) group, while column "T(N)" ("C(N)") reports the number of municipalities included in the treated (control) group. Table 4.6 reports the hectares cut-off and size of each group.

Figure 4.5: Results of the Difference-in-Differences analysis (DRIMP)



Source: authors' own calculations. *Notes*: Sant'Anna and Zhao (2020) improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (DRIMP). We use all controls reported in Table 4.3 measured in 2011-2012. Standard errors are clustered at the municipal level. We categorized as "Control group" those municipalities that, in the whole period between May/2006 and May/2018, registered a logistics soil consumption in the municipality itself and in the neighbouring ones below the 10th percentile or the 50th percentile. Treated municipalities are those with a newly consumed surface above the 80th, 85th, or 90th percentile in the two years between May/2015 and May/2017. For both the control and the treatment group, the percentiles refer to the distribution among municipalities with some new logistics surface in the surrounding areas in the observed period. Table 4.6 reports the cut-offs and size of each group. Note that Lazio had to be excluded from this analysis because *Lega* did not run in this region for the 2008 elections. Bars represent the 95% level confidence intervals.

four elections. Hence, we can only compare 2008, 2013, and 2018 for PD, and 2013 and 2018 for M5S. While we find no effect at all for the M5S, we estimate a negative impact for the PD, signalling that the party lost appeal among the working class (Diamond and Guidi, 2019).

The first robustness check we perform consists in repeating the main estimations with a classic two-way fixed effects specification (TWFE):

$$y_{m,t} = \alpha + \sum_{t=2006}^{2018} \beta \cdot (Treated_m \times T_t) + \zeta_t + \xi_m + \epsilon_{m,t} \tag{4}$$

where $y_{m,t}$ are the electoral outcomes in municipality m in election year t. We interact our treatment dummy ($Treated_m$) with indicators for the election years 2006, 2008, and 2018 (T_t). The 2013 election serves as the base year. By including municipality (ξ_m) and year(ζ_t) fixed effects, we control for time-invariant municipality characteristic and time-varying shocks affecting all municipalities. We used our baseline specification for control and treated groups: the 80th percentile for treatment and the 50th percentile for control ("t80-c50"). In order to compare municipalities as similar as possible, we adopt two strategies: (1) using nearest neighbour propensity score matching (PSM - NN); (2) using kernel propensity score matching (PSM - Kernel).[14] We match each treated unit to its control(s) using all variables in Table 4.3 measured in 2011-2012. Standard errors are clustered at the municipality level. Appendix Table 4A.4 shows that both approaches are successful in significantly reducing the differences between the control and the treated group. Table 4.9 reports the results of the TWFE. The unweighted model shows some pre-trends, confirming that using matching and weighting techniques is necessary to obtain reliable results. The results of both weighted estimators are in line with the ones of Table 4.8.

Figure 4.6 compares the estimates of our DRIMP with other three estimators: (1) DRIPW is the Sant'Anna and Zhao (2020) doubly robust DiD estimator based on stabilized inverse probability weighting and ordinary least squares; (2) OLS is the outcome regression DiD estimator based on ordinary least squares; (3) STDIPW is the inverse probability weighting DiD estimator with stabilized weights. As for the DRIMP, we use all controls reported in Table 4.3 measured

[14]While with "PSM - NN" each treated unit is matched with the closest control, in "PSM - Kernel" every treated unit is matched with the weighted average of the control municipalities, with the weights being inversely proportional to the distance between the treated and control group's propensity scores. In both cases we excluded observations outside the common support.

Table 4.8: DRIMP - *Lega*, PD, and M5S

Spec.	Party	2006-2008	2008-2013	2013-2018	T(N)	C(N)
t80-c10	*Lega*	0.015 (0.275)	0.106 (0.327)	1.534*** (0.392)	103	3,955
t80-c10	PD		–0.029 (0.234)	–0.855** (0.350)	103	3,955
t80-c10	M5S			0.302 (0.342)	103	3,955
t80-c50	*Lega*	0.191 (0.262)	–0.211 (0.322)	1.655*** (0.386)	103	4,338
t80-c50	PD		0.171 (0.227)	–0.694** (0.353)	103	4,338
t80-c50	M5S			0.115 (0.340)	103	4,338
t85-c10	*Lega*	–0.360 (0.333)	0.405 (0.397)	2.045*** (0.478)	77	3,955
t85-c10	PD		0.120 (0.296)	–1.800*** (0.401)	77	3,955
t85-c10	M5S			0.288 (0.430)	77	3,955
t85-c50	*Lega*	–0.181 (0.322)	0.126 (0.396)	2.073*** (0.486)	77	4,338
t85-c50	PD		0.326 (0.294)	–1.639*** (0.403)	77	4,338
t85-c50	M5S			0.190 (0.431)	77	4,338
t90-c10	*Lega*	0.089 (0.405)	–0.196 (0.449)	2.015*** (0.621)	51	3,955
t90-c10	PD		0.182 (0.293)	–1.022*** (0.383)	51	3,955
t90-c10	M5S			–0.127 (0.552)	51	3,955
t90-c50	*Lega*	0.234 (0.395)	–0.425 (0.456)	2.055*** (0.624)	51	4,338
t90-c50	PD		0.366 (0.302)	–0.911** (0.386)	51	4,338
t90-c50	M5S			–0.221 (0.554)	51	4,338

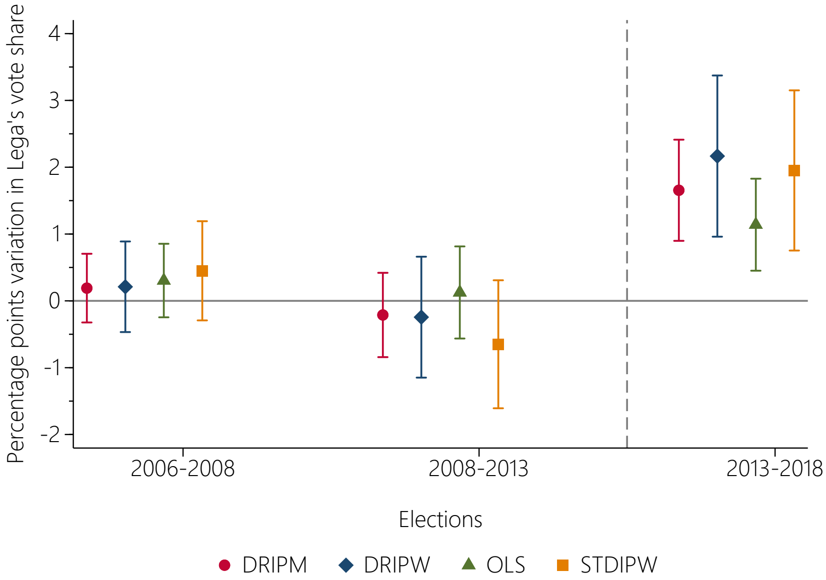
Source: authors' own calculations. *Notes*: Sant'Anna and Zhao (2020) improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (DRIMP). We use all controls reported in Table 4.3 measured in 2012. Standard errors clustered at the municipal level are reported between parentheses. We categorized as "Control group" those municipalities that, in the whole period between May/2006 and May/2018, registered a logistics soil consumption in the municipality itself and in the neighbouring ones below the 10th percentile or the 50th percentile. Treated municipalities are those with a newly consumed surface above the 80th, 85th, or 90th percentile in the two years between May/2015 and May/2017. For both the control and the treatment group, the percentiles refer to the distribution among municipalities with some new logistics surface in the surrounding areas in the observed period. Table 4.6 reports the hectares cut-off and size of each group. Note that Lazio had to be excluded from this analysis because *Lega* did not run in this region for the 2008 elections. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$.

Table 4.9: TWFE - *Lega*, PD, and M5S

	Unweighted	**PSM - Kernel**	**PSM - NN**
***Lega* 2006-2018**			
Treated x 2006	0.069	0.027	0.293
	(0.193)	(0.224)	(0.418)
Treated x 2008	1.265**	0.367	-0.336
	(0.572)	(0.596)	(0.804)
Treated x 2018	1.684***	1.712***	2.017***
	(0.377)	(0.408)	(0.650)
Municipality FE	✓	✓	✓
Year FE	✓	✓	✓
Adj. R^2	0.89	0.90	0.90
Mun contr.	4,338	3,299	90
Mun tr.	103	103	103
N	17,764	13,608	772
PD 2008-2018			
Treated x 2008	0.054	0.009	0.250
	(0.305)	(0.329)	(0.433)
Treated x 2018	-1.019***	-0.638*	-1.568***
	(0.340)	(0.377)	(0.548)
Municipality FE	✓	✓	✓
Year FE	✓	✓	✓
Adj. R^2	0.86	0.87	0.89
Mun contr.	4,338	3,299	90
Mun tr.	103	103	103
N	13,323	10,206	579
M5S 2013-2018			
Treated x 2018	-0.174	0.129	-0.176
	(0.340)	(0.385)	(0.591)
Municipality FE	✓	✓	✓
Year FE	✓	✓	✓
Adj. R^2	0.78	0.75	0.72
Mun contr.	4,338	3,299	90
Mun tr.	103	103	103
N	8,882	6,804	386

Source: authors' own calculations. *Notes*: TWFE with year and municipality fixed effects. Standard errors clustered at the municipality level are reported between parentheses. "PSM - Kernel" is kernel propensity score matching, while "PSM - NN" is nearest neighbour propensity score matching. Matching is done using all controls reported in Table 4.3 measured in 2011-2012. In both matching approaches we exclude observations outside the common support. We categorized as "Control group" those municipalities that, in the whole period between May/2006 and May/2018, registered a logistics soil consumption in the municipality itself and in the neighbouring ones below the 50th percentile. Treated municipalities are those with a newly consumed surface above the 80th percentile in the two years between May/2015 and May/2017. For both the control and the treatment group, the percentiles refer to the distribution among municipalities with some new logistics surface in the surrounding areas in the observed period. Table 4.6 reports the hectares cut-off and size of each group. Note that Lazio had to be excluded from this analysis because *Lega* did not run in this region for the 2008 elections. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$.

Figure 4.6: Robustness checks - Different Difference-in-Differences estimators



Source: authors' own calculations. *Notes*: DRIMP is the Sant'Anna and Zhao (2020) improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares; DRIPW is the Sant'Anna and Zhao (2020) doubly robust DiD estimator based on stabilized inverse probability weighting and ordinary least squares; OLS is the outcome regression DiD estimator based on ordinary least squares; STDIPW is the inverse probability weighting DiD estimator with stabilized weights. We use all controls reported in Table 4.3 measured in 2011-2012. Standard errors are clustered at the municipal level. We categorized as "Control group" those municipalities that, in the whole period between May/2006 and May/2018, registered a logistics soil consumption in the municipality itself and in the neighbouring ones below the 10th percentile or the 50th percentile. Treated municipalities are those with a newly consumed surface above the 80th, 85th, or 90th percentile in the two years between May/2015 and May/2017. For both the control and the treatment group, the percentiles refer to the distribution among municipalities with some new logistics surface in the surrounding areas in the observed period. Table 4.6 reports the cut-offs and size of each group. Note that Lazio had to be excluded from this analysis because *Lega* did not run in this region for the 2008 elections. Bars represent the 95% level confidence intervals. Appendix Table 4A.5 reports the exact estimates and their standard errors.

in 2011-2012 and standard errors are clustered at the municipal level. The results of all three methods are comparable with the ones based on the DRIMP.

The last two tests we perform concern the definition of control and treatment groups: (1) treated municipalities are those with a newly consumed surface above the 80th, 85th, or 90th percentile in the two years between May/2015 and May/2017 and a consumed surface below the same cut-off in the period May/2006-May/2012; (2) treated municipalities are those with a newly consumed surface above the 80th, 85th, or 90th percentile in the years between May/2012 and May/2017. The results are in line with those of our baseline specification and are reported in Table 4.10.

Table 4.10: DRIMP - Robustness checks

Test	Spec.	2006-2008	2008-2013	2013-2018	T(N)	C(N)
Baseline	t80-c10	0.015	0.106	1.534***	103	3,955
		(0.275)	(0.327)	(0.392)		
Baseline	t80-c50	0.191	–0.211	1.655***	103	4,338
		(0.262)	(0.322)	(0.386)		
Baseline	t85-c10	–0.360	0.405	2.045***	77	3,955
		(0.333)	(0.397)	(0.478)		
Baseline	t85-c50	–0.181	0.126	2.073***	77	4,338
		(0.322)	(0.396)	(0.486)		
Baseline	t90-c10	0.089	–0.196	2.015***	51	3,955
		(0.405)	(0.449)	(0.621)		
Baseline	t90-c50	0.234	–0.425	2.055***	51	4,338
		(0.395)	(0.456)	(0.624)		
Δ 15–17 (limit 06-12)	t80-c10	–0.034	0.329	1.576***	80	3,955
		(0.275)	(0.296)	(0.445)		
Δ 15–17 (limit 06-12)	t80-c50	0.170	–0.021	1.745***	80	4,338
		(0.255)	(0.288)	(0.427)		
Δ 15–17 (limit 06-12)	t85-c10	0.051	0.071	1.743***	63	3,955
		(0.346)	(0.391)	(0.524)		
Δ 15–17 (limit 06-12)	t85-c50	0.252	–0.234	1.791***	63	4,338
		(0.331)	(0.391)	(0.526)		
Δ 15–17 (limit 06-12)	t90-c10	0.089	–0.196	2.015***	51	3,955
		(0.405)	(0.449)	(0.621)		
Δ 15–17 (limit 06-12)	t90-c50	0.234	–0.425	2.055***	51	4,338
		(0.395)	(0.456)	(0.624)		
Δ 12–17	t80-c10	0.225	–0.143	1.409***	145	3,955
		(0.236)	(0.293)	(0.336)		
Δ 12–17	t80-c50	0.374*	–0.461	1.545***	145	4,338
		(0.226)	(0.285)	(0.320)		
Δ 12–17	t85-c10	–0.097	0.125	1.558***	99	3,955
		(0.269)	(0.338)	(0.434)		
Δ 12–17	t85-c50	0.014	–0.125	1.699***	99	4,338
		(0.260)	(0.335)	(0.422)		
Δ 12–17	t90-c10	–0.033	–0.080	1.863***	72	3,955
		(0.356)	(0.424)	(0.502)		
Δ 12–17	t90-c50	0.050	–0.248	1.916***	72	4,338
		(0.348)	(0.425)	(0.494)		

Source: authors' own calculations. *Notes*: Sant'Anna and Zhao (2020) improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (DRIMP). We use all controls reported in Table 4.3 measured in 2012. Standard errors clustered at the municipal level are reported between parentheses. We categorized as "Control group" those municipalities that, in the whole period between May/2006 and May/2018, registered a logistics soil consumption in the municipality itself and in the neighbouring ones below the 10th percentile or the 50th percentile. In this table we report the estimation results of three distinct strategies for selecting the treatment group: (1) treated municipalities are those with a newly consumed surface above the 80th, 85th, or 90th percentile in the two years between May/2015 and May/2017 (Baseline); (2) treated municipalities are those with a newly consumed surface above the 80th, 85th, or 90th percentile in the two years between May/2015 and May/2017 and consumed surface below the same cut-off in the period May/2006-May/2012; (3) treated municipalities are those with a newly consumed surface above the 80th, 85th, or 90th percentile in the years between May/2012 and May/2017. For both the control and the treatment group, the percentiles refer to the distribution among municipalities with some new logistics surface in the surrounding areas in the observed period. Table 4.6 reports the hectares cut-off and size of each group. Note that Lazio had to be excluded from this analysis because *Lega* did not run in this region for the 2008 elections. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$.

4.6.2 Potential channels

In an attempt to investigate the mechanisms connecting the opening of a logistic hub with the increase in the local support for *Lega*, we conduct an event study. We adopt a DiD approach similar to the one described above but with two differences. First, we observe all years between 2012 and 2019, and not just the election years. We stop at 2019 to avoid any overlap with the Covid-19 pandemic, which started in early 2020. Second, we consider a series of outcomes that can help us understanding what happens to treated municipalities after the shock. We look at six outcomes: (1) "% Employed", (2) "Income p.c.", (3) "Labour Income p.w.", (4) "Pop.", (5) "Pop. Ita.", and (6) "Pop. For.". The first three measures are computed on tax returns data (IRPEF) from the Ministry of Economy and Finance. "% Employed" is calculated by dividing the number of individuals paying labour income tax at the municipal level by the number of inhabitants of the municipality.[15] We had to build this proxy of the employment share using income tax data because we only have unemployment share at the municipal level for 2001 and 2011, as these variables come from ISTAT's Census. In 2011, the only year for which we have both measures, "% Employed" has a correlation of 0.76 with Census' employment rate, and -0.48 with Census' unemployment rate. "Income p.c." is the imposable yearly income per taxpayer (measured in Euro). "Labour Income p.w." is a proxy of local wages, computed by diving the total yearly labour income at the municipal level (measured in Euro) by the number of individuals paying labour income tax.[16] Finally, "Pop.", "Pop. Ita.", and "Pop. For." are ISTAT's measures of the municipality's total resident population, resident population with Italian citizenship, and resident population without the Italian citizenship, respectively. Appendix Table 4A.6 reports basic descriptive statistics on each of the outcomes analysed in this section.

Compared to the previous section, there are some slight differences in the way we select our treated group, while the control group is selected in the exact same way as in the "basic" DiD. We consider as treated in 2016 those municipalities with a newly consumed surface above the 80th percentile in the two years between May/2015 and May/2017, and a new surface below the same threshold in the years May/2012 - May/2015. We add this second condition because, differently for what we did in the "basic" DiD approach, here we

[15]Note that workers whose yearly labour income is below a certain threshold (around 8.000 Euro per year) are exempt from filing tax returns.

[16]Both "Income p.c." and "Labour Income p.w." are corrected for inflation using ISTAT's deflator with base 2015.

observe the development of the effect year after year. Hence, considering as treated in 2016 municipalities which were already treated in the 2012-2015 period would bias the results. This was less of an issue in the "basic" DiD as there we only compared outcomes in 2013 and in 2018.

The results of the event study are reported in Table 4.11. Significant post-treatment positive effect is observed for "% Employed" and "Pop.", signalling that logistics centres attracted new inhabitants to the municipality but also increased the employment share. Both the estimates for "Pop. Ita." and "Pop. For." are positive, although only the former is statistically significant. While the estimates of both "Income p.c." and "Labour income p.w." have a negative sign, they are of modest size and not significantly different from zero. Overall, there is reasonable evidence that the hubs are not responsible for a large increase of economic hardship, at least in the short term. In fact, the employment share increases and there are no sizeable negative effects neither on total income nor on labour income. On the other hand, there is a significant increase in population, which seems not to be exclusively driven by Italian citizens, providing some support in favour of the second channel. Note that our data on local population come from the official registers. Foreign citizens might take longer than native ones to sign-up into city registers due to several factors, including language barriers, low familiarity with the system, or lack of legal permits.

It should be noted that the evidence presented in this study is preliminary and further research is necessary to fully comprehend the overall impact of logistic hubs on local communities. Specifically, more research is needed to understand the effects on the medium and long term. Unfortunately, in this study we could only analyse a limited time window because we observed yearly constructions only starting from 2015 and we had to stop our analysis at 2019 to avoid any overlap with the Covid-19 pandemic. Future studies should also delve into the effects on housing prices and on how affected municipalities utilize compensation funds and extra tax revenues. Do they choose to lower local taxes or do they allocate resources towards infrastructures and services? If the latter, which types of public goods benefit the most?

4.7 Conclusion

Increasing discontent and the associated growing support for populist parties have been linked to several factors, such as globalisation, technological change, and migration waves. We contribute to the literature on political discontent

Table 4.11: DRIMP - Channels

	% Employed	Income p.c.	Labour Income p.w.	Pop.	Pop. Ita.	Pop. For.
Avg. Pre	0.060	-3.955	9.772	-1.945	4.453	-6.398
	(0.048)	(17.215)	(18.910)	(8.656)	(5.729)	(7.612)
Avg. Post	0.291**	-18.874	-87.030	29.807**	21.800*	8.007
	(0.127)	(31.777)	(64.351)	(14.462)	(13.201)	(7.174)
-3 (2012-2013)	0.083	9.909	18.371	-6.640	8.836	-15.476
	(0.100)	(33.349)	(40.985)	(10.567)	(7.770)	(9.870)
-2 (2013-2014)	0.000	-10.598	12.757	-7.198	0.473	-7.670
	(0.096)	(23.989)	(48.336)	(11.538)	(7.677)	(8.625)
-1 (2014-2015)	0.095	-11.174	-1.811	8.003	4.051	3.952
	(0.102)	(32.894)	(34.667)	(8.929)	(6.506)	(6.861)
0 (2015-2016)	0.106	46.804	-6.080	1.715	2.701	-0.986
	(0.137)	(47.538)	(43.526)	(8.552)	(6.768)	(5.590)
+1 (2015-2017)	0.307**	11.803	-43.094	19.744	13.947	5.797
	(0.148)	(35.383)	(50.363)	(12.893)	(11.477)	(5.934)
+2 (2015-2018)	0.338**	-65.142	-106.091	40.006**	26.813	13.193
	(0.158)	(43.555)	(100.593)	(19.052)	(17.297)	(8.732)
+3 (2015-2019)	0.413**	-68.963	-192.856	57.762**	43.739**	14.023
	(0.185)	(66.299)	(131.961)	(23.519)	(21.009)	(12.294)
N treated	85	85	85	85	85	85
N control	4,338	4,338	4,338	4,338	4,338	4,338

Source: authors' own calculations. *Notes*: Sant'Anna and Zhao (2020) improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (DRIMP). We use all controls reported in Table 4.3 measured in 2011-2012. Standard errors clustered at the municipal level are reported between parentheses. We categorized as "Control group" those municipalities that, in the whole period between May/2006 and May/2018, registered a logistics soil consumption in the municipality itself and in the neighbouring ones below the 50th percentile. Treated municipalities are those with a newly consumed surface above the 80th percentile in the two years between May/2015 and May/2017, and a new surface below the same threshold in the years May/2012 - May/2015. We assign the treatment to calendar year 2016. For both the control and the treatment group, the percentiles refer to the distribution among municipalities with some new logistics surface in the surrounding areas in the observed period. Note that Lazio had to be excluded from this analysis because *Lega* did not run in this region for the 2008 elections. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$.

by examining the link between socio-economic changes and political discontent, exploiting the logistics revolution as a source of significant economic and cultural shock. The results of our empirical analysis indicate that there is a positive causal relationship between the increase in logistics activity and the support for the populist radical-right party *Lega* in Italian municipalities. This relationship might be driven by different mechanisms: increase in the feeling of economic insecurity, a surge in the anti-immigration sentiment, hostility towards foreign multinationals. While we found no evidence in support of the first mechanism, preliminary results suggest that anti-immigration sentiment may be a potential driver. However, given the constraints of our data, additional research is necessary to fully comprehend the specific mechanisms through which logistics hubs increase dissatisfaction within local communities. Our work calls for a more thorough evaluation of the costs and benefits from hosting a logistic hub as, for many municipalities, the expected benefits might be outweighed by negative effects. Local administrators are attracted by the promise of an increase of the overall employment, large investments, positive effects for the other firms in the area, and increase in land prices. However, once the hub is built the reality they have to face might be different, paving the way for social discontent, which, among other ways, is expressed through an increase in support for populist radical-right parties.

4.8 Appendix 4A: Additional Tables and Figures

Table 4A.1: Number of municipalities by type of radius

	Mean	**Min**	**10th**	**25th**	**50th**	**75th**	**95th**	**Max**	**N**
80% Work Comm.	35.5	0	3	10	21	44	123	771	5,159
85% Work Comm.	49.9	0	5	14	28	61	174	771	5,159
90% Work Comm.	75.1	0	8	21	44	95	249	810	5,159
95% Work Comm.	133.1	1	15	41	82	181	418	889	5,159
80% All Comm.	33.3	0	3	9	20	42	110	790	5,159
85% All Comm.	47.9	0	5	13	28	59	165	928	5,159
90% All Comm.	72.7	0	8	21	44	92	238	1,762	5,159
95% All Comm.	139.1	1	15	41	83	183	456	1,287	5,159
5 Km	3.4	0	0	1	3	5	10	21	5,159
10 Km	15.3	0	2	7	13	21	40	61	5,159
15 Km	33.7	0	7	16	28	45	86	122	5,159
20 Km	58.3	1	13	28	48	80	149	193	5,159
25 Km	88.6	3	20	43	72	122	223	276	5,159
30 Km	124.3	4	30	60	100	173	310	352	5,159
35 Km	165.0	5	41	81	133	229	402	443	5,159
40 Km	210.5	7	54	104	170	293	497	553	5,159
45 Km	260.3	10	69	128	214	367	597	661	5,159
50 Km	314.2	13	85	153	263	447	700	779	5,159
Neighbours	5.9	1	3	5	6	7	9	21	5,159
SLL 2001	14.4	1	2	4	9	19	44	121	358

Source: authors' own calculations. *Notes*: statistics on Centre and North only.

Table 4A.2: Logistics hubs' soil consumption at municipality level

	Sum	**Mean**	**SD**	**25th**	**50th**	**75th**	**Max**	**N**
By time period								
2006-2012	247.6	9.2	6.1	5.3	6.5	12.8	21.7	27
2012-2015	186.7	2.9	3.8	0.4	1.1	3.8	19.7	65
2015-2016	102.3	2.1	4.2	0.2	0.7	2.1	22.0	48
2016-2017	211.3	4.2	7.3	0.4	2.2	5.3	40.1	50
2017-2018	319.8	4.8	9.1	0.6	1.3	4.8	52.4	67
Total	1,067.8	4.2	6.8	0.4	1.7	5.2	52.4	257
Aggregated time periods								
2012-2016	289.1	2.6	4.0	0.3	0.9	3.2	22.0	113
2012-2017	500.4	3.1	5.2	0.3	1.0	3.8	40.1	163
2015-2017	313.7	3.2	6.0	0.3	1.0	3.8	40.1	98
By NUTS2 (2015-2017)								
Emilia-Romagna	51.2	3.2	4.7	0.5	1.8	3.0	18.8	16
Friuli-Venezia Giulia	17.3	4.3	4.8	0.2	4.0	8.4	9.1	4
Lazio	27.6	2.1	3.2	0.3	0.7	2.4	11.4	13
Liguria	0.2	.16		0.2	0.2	0.2	0.2	1
Lombardia	64.7	3.1	5.0	0.2	1.3	4.6	22.0	21
Marche	1.6	.82	0.0	0.8	0.8	0.8	0.8	2
Piemonte	68.8	5.3	10.7	0.5	2.3	4.4	40.1	13
Toscana	11.8	1.7	2.4	0.3	0.5	3.5	6.4	7
Trentino-Alto Adige	2.7	1.4	1.8	0.1	1.4	2.6	2.6	2
Umbria	2.1	2.1		2.1	2.1	2.1	2.1	1
Veneto	65.8	3.7	7.5	0.4	0.8	3.8	32.1	18

Source: authors' own calculations. *Notes*: statistics on Centre and North only.

Table 4A.3: Descriptive statistics of variables used in 2SLS

	Mean	**SD**	**Min**	**25th**	**50th**	**75th**	**Max**
Δ Lega 06-18	17.34	5.20	-4.93	14.31	17.11	20.33	58.32
Δ06-17 HectaresLog	1.32	5.65	0.00	0.00	0.00	0.00	62.63
Roman roads (m/ha) (rad.)	0.64	0.95	0.00	0.00	0.39	0.94	8.80
% High-School dipl. 01	25.20	6.43	3.85	21.10	24.76	28.92	70.69
% Unempl. 01	5.33	3.39	0.00	3.39	4.49	6.13	31.45
% Pop. 55-100 04	34.09	7.06	12.60	29.17	33.30	37.90	74.70
Pop. (th.) 04	4.93	7.73	0.04	0.95	2.32	5.62	93.35
% Foreign pop. 04	4.83	2.86	0.00	2.82	4.31	6.25	24.61
Newborns (x100 inhab.) 04	0.84	0.33	0.00	0.66	0.84	1.02	4.40
% Manuf. (rad.) 04	33.86	14.55	0.00	22.35	34.06	44.84	81.43
% Soil used 06	10.16	9.50	0.24	3.82	7.21	13.05	69.71
Income p.c. (10th. EUR) 04	1.72	0.32	0.79	1.52	1.69	1.89	5.40
No FUA	0.75	0.43	0.00	1.00	1.00	1.00	1.00
% Fem. city council 02	19.21	10.81	0.00	12.50	16.67	25.00	66.67
VA p.w. (th. EUR) prov. 04	58.64	13.87	45.82	53.35	56.17	58.58	122.76
IQI prov. 04	0.66	0.11	0.35	0.62	0.67	0.75	1.00
Δ04-17 Manuf work. (x100 inhab.) (rad.)	-6.57	6.55	-41.09	-9.80	-5.98	-2.67	61.23
Δ96-17 IPW China (th. USD) (rad.)	1.92	1.94	-0.49	1.00	1.65	2.38	45.41
Emilia-Romagna	0.06	0.24	0.00	0.00	0.00	0.00	1.00
Friuli-Venezia Giulia	0.04	0.20	0.00	0.00	0.00	0.00	1.00
Lazio	0.07	0.26	0.00	0.00	0.00	0.00	1.00
Liguria	0.04	0.21	0.00	0.00	0.00	0.00	1.00
Lombardia	0.28	0.45	0.00	0.00	0.00	1.00	1.00
Marche	0.04	0.20	0.00	0.00	0.00	0.00	1.00
Piemonte	0.22	0.42	0.00	0.00	0.00	0.00	1.00
Toscana	0.05	0.21	0.00	0.00	0.00	0.00	1.00
Trentino-Alto Adige	0.05	0.22	0.00	0.00	0.00	0.00	1.00
Umbria	0.02	0.13	0.00	0.00	0.00	0.00	1.00
Valle d'Aosta	0.01	0.12	0.00	0.00	0.00	0.00	1.00
Veneto	0.11	0.31	0.00	0.00	0.00	0.00	1.00

Source: authors' own calculations. *Notes*: statistics on estimation sample.

Table 4A.4: Compare balance - Treated group *vs.* control group

	Unmatched		PSM - Kernel		PSM - NN	
	Diff.	p-val.	Diff.	p-val.	Diff.	p-val.
% High-School dipl. 11	2.56	0.000	0.55	0.383	-0.31	0.746
% Unempl. 11	0.35	0.041	0.02	0.918	0.00	0.988
% Pop. 55-100 12	-3.02	0.000	-0.70	0.226	0.40	0.634
Pop. (th.) 12	4.51	0.000	0.82	0.483	-0.87	0.601
% Foreign pop. 12	2.12	0.000	0.46	0.277	-0.03	0.958
Newborns (x100 inhab.) 12	0.07	0.005	0.02	0.454	-0.01	0.730
% Manuf. (rad.) 12	-6.72	0.000	-1.77	0.083	1.56	0.336
% Soil used 12	5.25	0.000	0.34	0.729	-1.44	0.403
Income p.c. (10th. EUR) 12	0.10	0.000	0.01	0.772	0.00	0.940
No FUA	-0.23	0.000	-0.03	0.552	-0.02	0.787
% Fem. city council 12	-1.47	0.216	-0.28	0.812	3.06	0.071
VA p.w. (th. EUR) prov. 12	-0.18	0.920	-1.45	0.426	-3.31	0.285
IQI prov. 12	0.01	0.197	0.01	0.394	-0.00	0.865
Δ04-17 Manuf work. (x100 inhab.) (rad.)	0.39	0.304	0.14	0.712	-0.76	0.256
Δ96-17 IPW China (th. USD) (rad.)	-0.34	0.000	-0.12	0.185	0.07	0.566
Emilia-Romagna	0.12	0.002	0.02	0.600	0.05	0.332
Friuli-Venezia Giulia	0.04	0.123	-0.00	0.958	0.00	1.000
Liguria						
Lombardia	-0.09	0.035	-0.06	0.148	-0.08	0.223
Marche						
Piemonte	0.05	0.297	-0.01	0.810	0.03	0.656
Toscana						
Trentino-Alto Adige						
Umbria						
Valle d'Aosta						
Veneto	0.12	0.004	0.05	0.198	0.00	1.000
Treated	103		103		103	
Controls	4,338		3,299		90	

Source: authors' own calculations. *Notes*: "PSM - Kernel" is kernel propensity score matching, while "PSM - NN" is nearest neighbour propensity score matching. Matching is done using all controls reported in Table 4.3 measured in 2011-2012. In both matching approaches we exclude observations outside the common support. We categorized as "Control group" those municipalities that, in the whole period between May/2006 and May/2018, registered a logistics soil consumption in the municipality itself and in the neighbouring ones below the 50th percentile. Treated municipalities are those with a newly consumed surface above the 80th percentile in the two years between May/2015 and May/2017. For both the control and the treatment group, the percentiles refer to the distribution among municipalities with some new logistics surface in the surrounding areas in the observed period. Table 4.6 reports the hectares cut-off and size of each group. Note that Lazio had to be excluded from this analysis because *Lega* did not run in this region for the 2008 elections. 80th percentile for treatment and 50th percentile for control. We chose these two groups as they offer the largest samples. The column "Diff." reports the difference in the two groups' means (treated minus control) and column "p-value" the relative p-value.

Table 4A.5: Robustness checks DiD

	DRIMP	DRIPW	OLS	STDIPW
2006-2008	0.191	0.211	0.304	0.450
	(0.262)	(0.346)	(0.281)	(0.379)
2008-2013	-0.211	-0.244	0.126	-0.650
	(0.322)	(0.462)	(0.352)	(0.489)
2013-2018	1.655***	2.167***	1.140***	1.952***
	(0.386)	(0.615)	(0.351)	(0.612)
N. treated	103	103	103	103
N. controls	4,338	4,338	4,338	4,338

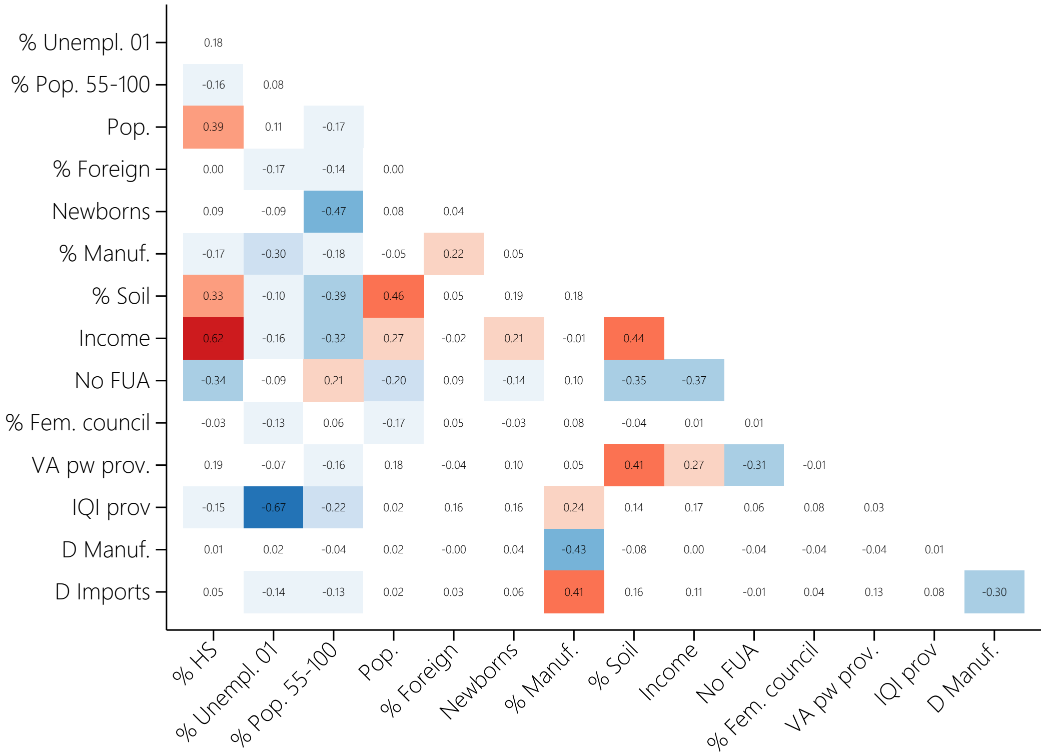
Source: authors' own calculations. *Notes*: DRIMP is the Sant'Anna and Zhao (2020) improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares; DRIPW is the Sant'Anna and Zhao (2020) doubly robust DiD estimator based on stabilized inverse probability weighting and ordinary least squares; OLS is the outcome regression DiD estimator based on ordinary least squares; STDIPW is the inverse probability weighting DiD estimator with stabilized weights. We use all controls reported in Table 4.3 measured in 2011-2012. Standard errors clustered at the municipal level are reported between parentheses. We categorized as "Control group" those municipalities that, in the whole period between May/2006 and May/2018, registered a logistics soil consumption in the municipality itself and in the neighbouring ones below the 10th percentile or the 50th percentile. Treated municipalities are those with a newly consumed surface above the 80th, 85th, or 90th percentile in the two years between May/2015 and May/2017. For both the control and the treatment group, the percentiles refer to the distribution among municipalities with some new logistics surface in the surrounding areas in the observed period. Table 4.6 reports the cutoffs and size of each group. Note that Lazio had to be excluded from this analysis because Lega did not run in this region for the 2008 elections. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$.

Table 4A.6: Descriptive statistics - Potential channels

	Mean	**SD**	**Min**	**25th**	**50th**	**75th**	**Max**
% Employed	35.6	6.3	5.0	32.2	35.9	38.9	90
Income p.c.	13,694.5	2,100.4	3,084.5	12,452.3	13,582.0	14,851.9	30,658
Labour Income p.w.	20,636.6	3,080.8	7,488.7	18,762.1	20,447.6	22,151.3	53,540
Pop.	4,591.9	7,246.7	34.0	891.0	2,178.0	5,194.0	96,930
Pop. Ita	4,173.5	6,544.1	33.0	819.0	2,010.0	4,767.0	87,808
Pop. For.	418.4	763.4	0.0	54.0	157.0	448.0	11,698

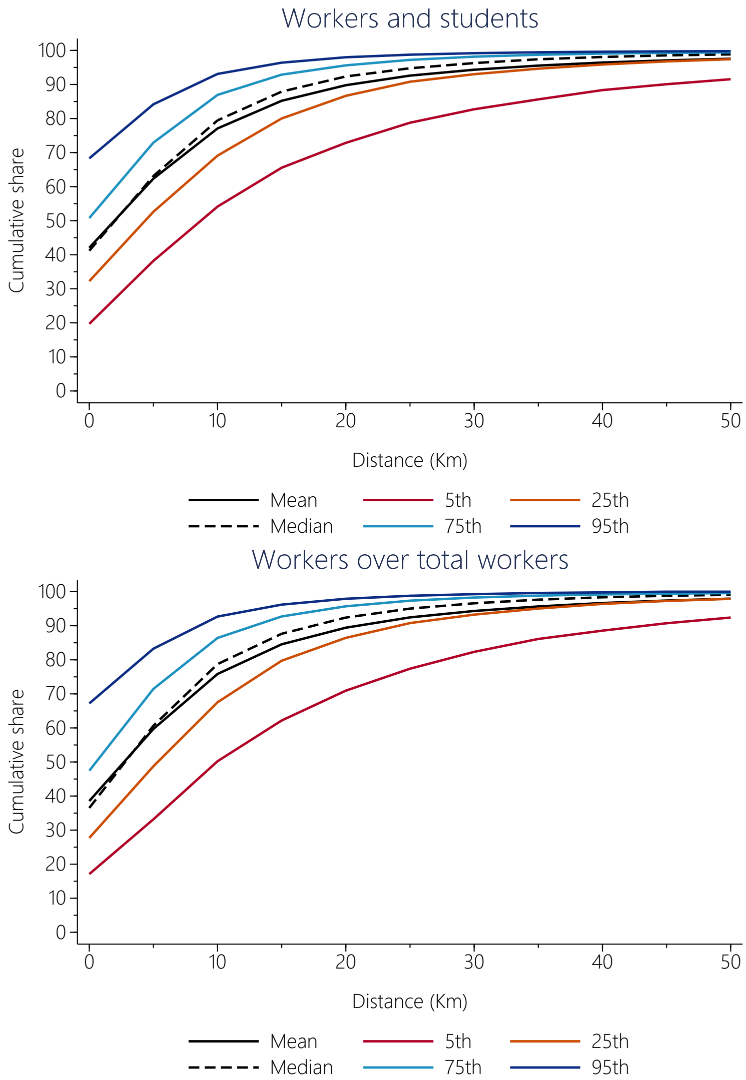
Source: authors' own calculations. *Notes*: statistics on Centre and North only.

Figure 4A.1: Control variables' correlation



Source: authors' own calculations. *Notes*: all variables are described in Table 4.3. Variables measured in 2001-2004.

Figure 4A.2: Municipalities' commuting habits



Source: authors' own calculations. *Notes*: commuting patterns for 2001. Statistics on Centre and North only. ISTAT's commuting matrix includes workers and students.

4.9 Appendix 4B: Imports from China

Following Autor et al. (2013b) and Caselli et al. (2020a), we compute the variation in Chinese imports for each municipality m between 1996 and 2017 as

$$\Delta IMP^{chn}_{m,96-17} = \sum_s \frac{L_{ms,91}}{L_{s,91}} \Delta IMP^{chn}_{s,96-17}$$

where $\Delta IMP^{chn}_{s,96-17} = IMP^{chn}_{s,17} - IMP^{chn}_{s,96}$, $IMP^{chn}_{s,t}$ indicates the value (expressed in thousands of constant 2015 US dollars) of imports from China of goods belonging to the three-digit NACE Rev.1 sector s at time t (with $t \in \{1996, 2017\}$), $L_{s,91}$ is the national-level employment in the three-digit NACE Rev.1 sector s in 1991, and $L_{ms,91}$ is the employment of municipality m in sector s in 1991. We measure the employment structure in 1991 to ensure that local specialization is not due to contemporaneous trade exposure.

We then compute the variation in imports per worker (IPW) at the radius levels as

$$\Delta IPW^{chn}_{r,96-17} = \frac{1}{L_{r,91}} \sum_m \Delta IMP^{chn}_{m,96-17}$$

where $L_{r,91} = \sum_m L_{m,91}$ is the sum of the total employment across all municipalities m belonging to the radius r. Note that, for notational simplicity, we refer to $\Delta IPW^{chn}_{r,96-17}$ as Δ96-17 IPW China (rad.) in all Tables.

Employment information by municipality and NACE Rev.1 sector is extracted from ISTAT's 1991 Census of Industry and Services. Data on the imports from China, disaggregated at the six-digit product level of the WCO Harmonized System (HS), have been drawn from the United Nations International Trade Statistics Database (Comtrade). We matched six-digit HS product codes to three-digit NACE Rev.1 codes using Eurostat RAMON correspondence tables.

4.10 Appendix 4C: Alternative measure of Logistics activity

An alternative approach to capture logistics activity could be using employment data at the municipal level from ISTAT's "Statistical Register of Local Units" dataset (ASIA UL). For each municipality, the register provides the number of local units and the number of workers by 3-digits NACE Rev.2 codes for the period 2004-2018.

We analysed these data and, unfortunately, we found them to be problematic for several reasons:

- Only local units that carried out a productive activity for at least six months in the reference year are included in the dataset.
- Given the widespread habit of relying on subcontracts and cooperatives that last an average of just two years before disappearing (Ganz, 2019), official statistics on the number of workers employed in logistics are likely to be geographically imprecise and sub-estimate the real size of the workforce.
- Due to confidentiality reasons, ISTAT provides the number of workers at the municipal level only up to the 3-digit sector level. As shown in Table 4.1, Sector 52 includes "Warehousing" but also a series of other activities related to transport. Being forced to rely on 3-digit sector data only, we faced the trade-off between representativeness (i.e., covering as many logistics workers as possible) and precision (i.e., capturing actual shocks in logistics and not in other related activities). Focusing only on workers employed in the sector "521 Warehousing and storage" would provide high precision but low representativeness. Including sector "522 Support activities for transportation" would cover many more workers but also introduce a sizeable amount of imprecision in our estimations, because this sector also includes many activities that are present in many municipalities but are not directly classifiable as logistics but. We chose to focus on workers from sector "521 Warehousing and storage" as our "baseline", but also reported the results using workers from whole NACE Sector 52 in Table 4C.1.

When analysing the raw data, we noticed large fluctuations in the data, which affected a considerable number of municipalities. For instance, we could see a municipality having one employee in Sector 521 in 2009, then 172.01 employees in 2010, and then 2.5 employees in 2011. We discussed this issue with ISTAT's staff, who confirmed that these inconsistencies are due to cooperatives changing their administrative headquarters. Given the unreliability of these data, we decided not to use them in our main analysis. However, for a matter of transparency, we still tested our instrumental variable approach using a variable based on these data. For each municipality i, we built an indicator measuring the variation in the number of workers employed in sector 521 per 1000 total workers between 2017 and 2004:

$$\Delta 0417 WorkersLog = 1000 \times \frac{WorkersLog_{2017} - WorkersLog_{2004}}{WorkersTot_{2004}} \tag{5}$$

where $WorkersLog$ is the number of workers in sector 521 and $WorkersTot$ the total number of workers. As municipalities belong to labour markets, we count the number of workers in all municipalities within a certain radius around the centroid of each municipality i. The choice of the radius is discussed in section 4.4.

As shown in Table 4C.1, the results of the analysis using this variable confirm the ones obtained using our main measure of logistic activity, as one additional worker in the sector "521 Warehousing and storage" per 1,000 total workers increases *Lega*'s vote share in the municipality by 0.8 percentage points.

Table 4C.1: Regression results – Δ0417 Workers sector 521

	β_{OLS}	SE_{OLS}	R^2_{OLS}	β_{2SLS}	SE_{2SLS}	F-stat.	N
Baseline	0.020**	0.009	0.18	0.889*	0.469	4.8	5,169
i. Alternative radii							
Shocks at LLM level	0.140***	0.015	0.20	0.825***	0.240	43.7	5,169
10 km	0.048***	0.011	0.19	1.609	1.353	1.6	5,169
15 km	0.079***	0.016	0.19	1.260*	0.716	3.8	5,169
20 km	0.141***	0.017	0.20	1.181**	0.493	7.7	5,169
25 km	0.201***	0.021	0.20	1.059***	0.332	17.3	5,169
30 km	0.290***	0.025	0.20	0.958***	0.250	36.2	5,169
80% workers	0.081***	0.012	0.19	0.519***	0.180	23.4	5,169
85% workers	0.097***	0.015	0.19	0.683***	0.224	18.7	5,169
90% workers	0.166***	0.022	0.20	0.732***	0.171	37.9	5,169
95% workers	0.310***	0.030	0.21	1.312***	0.241	47.2	5,169
80% workers and students	0.074***	0.012	0.19	0.580***	0.202	21.3	5,169
85% workers and students	0.096***	0.014	0.19	0.734***	0.244	17.3	5,169
90% workers and students	0.134***	0.021	0.20	0.783***	0.228	19.7	5,169
95% workers and students	0.287***	0.025	0.21	0.909***	0.189	54.0	5,169
ii. Sample restriction							
Exclude Lazio	0.009	0.009	0.19	0.784**	0.361	6.3	4,796
Exclude FUA	0.021*	0.012	0.17	1.154	1.193	1.1	3,893
Keep FUA cores	0.021**	0.009	0.18	0.816*	0.417	5.3	5,223
Add South	0.021***	0.008	0.64	0.774*	0.398	5.5	7,570
iii. Additional controls							
Earthquake 2012	0.020**	0.009	0.19	0.897*	0.472	4.8	5,169
Δ06–18 Turnout	0.023**	0.009	0.20	1.030*	0.535	4.6	5,169
Turnout 06	0.019**	0.009	0.19	0.892*	0.479	4.6	5,169
Δ06–18 Turnout and Turnout 06	0.021**	0.009	0.20	1.022*	0.538	4.5	5,169
%*Lega* 06	0.021**	0.009	0.20	0.690*	0.374	5.3	5,169
%*Lega* 01	0.020**	0.009	0.19	0.789*	0.422	5.0	5,169
%*Lega* 01 and Turnout 01	0.018**	0.009	0.19	0.779*	0.438	4.6	5,169
Δ04–17 Foreign pop. (x 100 inhab.)	0.018**	0.009	0.19	0.851*	0.482	4.2	5,169
iv. Other checks							
NACE 52	0.006*	0.004	0.18	0.208***	0.071	20.7	5,169
Δ06–18 Potential votes *Lega*	0.013*	0.007	0.14	0.771*	0.402	4.8	5,169
Conley SE (Bartlett 20 km)				0.889	0.833		5,169
Δ13–18 *Lega* - Δ 13-17 Log	0.006	0.016	0.26	1.263**	0.567	7.2	5,169

Source: authors' own calculations. *Notes*: 2SLS columns refer to two-stage least squares IV regressions where logistics activity in the radius around each municipality is instrumented with the density of Roman roads. Olea and Pflueger (2013) first-stage F-Statistic for the 2SLS regressions is reported in column "F-stat.". Robust standard errors. Significance levels: * $\rho < 0.10$, ** $\rho < 0.05$, *** $\rho < 0.01$.

5 Concluding remarks

The question of whether automation will cause mass unemployment has been a pressing concern in recent years. While estimates on the number of automatable occupations vary, the prospect of a substantial share of jobs disappearing in the near future presents a significant challenge to the stability of our societies. In addition to the potential for job destruction, automation can significantly widen the inequality gap between workers belonging to different skill groups. This is because the bulk of employment and wage losses are suffered by low- and middle-skilled workers, while the roles typically covered by the high-skilled are complemented by new technologies, resulting in a rise in demand for their skills and higher wages (Autor and Dorn, 2013; Blanas et al., 2019). This dissertation offered three independent yet complementary studies presenting empirical evidence of how technological advancements can harm workers. Throughout the whole dissertation, particular emphasis was placed on identifying the groups that are most vulnerable to disruptive innovations, as recognizing and addressing the needs of these ”losers” is crucial for developing effective policies. The dissertation also highlighted how ignoring workers' grievances may have serious implications for society at large, as it can fuel the growth of populist radical-right movements.

Chapter 2 challenged the concept of "reallocation" as a solution to displacement caused by automation. Concerns over widespread technological unemployment are often dismissed with the argument that human labour is not destroyed by automation but rather reallocated to other tasks, occupations, or sectors. When focusing on pure employment levels, the idea that workers are not permanently excluded but "just" reallocated might be reassuring. However, while considerable attention has been devoted to the impact of automation on employment levels, little has been said about the *quality* of new job matches for displaced workers. Using an administrative longitudinal panel covering a large sample of Spanish workers from 2001 to 2017, the study investigated the short- and medium-term re-employment prospects of workers displaced from sectors with an increasing density of industrial robots. Furthermore, the study examined the role of reallocation to other sectors or local labour markets as adjustment mechanisms. As the adoption of robots is not an exogenous random shock, the analysis was based on an instrumental variable approach (IV) similar to the one used in Autor et al. (2013b), Acemoglu and Restrepo (2020), and Dauth et al. (2021): industry level robot adoption in Spain was instrumented with robot installations across industries in other European countries. The analysis revealed that exposed middle- and low-skilled workers are more likely than non-exposed workers to remain unemployed six months after displacement. Among those who find a new occupation, an additional robot per 1,000 workers increases the probability of being re-employed in a lower-paying job by about 1.9 percentage points for middle- and low-skilled workers, with significantly higher penalties for those who relocate to a different sector. Moreover, these workers tend to face a qualification downgrading in the new job and are more likely to be re-employed through temporary employment agencies. High-skilled workers are less negatively affected by exposure, although they can also incur a penalty when changing sectors.

Chapter 3 investigated the relationship between routine-biased technological change (RBTC) and the increase in Involuntary Part-Time (IPT). Specifically, the study examined the effect of local specialization in routine tasks on the increase of involuntary part-time work across 103 provinces in Italy between the years 2004 and 2019. The analysis drew on the combination of the INAPP-ISTAT Survey on Italian Occupations with the Italian section of the EU labour force survey to build province-level indicators of routine-task specialisation based on the occupational mix in each province. The econometric approach was based on a partial adjustment model, which is well-suited for investigating the dynamics of labour market variables that exhibit gradual or sluggish adjustment over time. Furthermore, endogeneity concerns were addressed by an IV fixed-effects panel data model with an instrument *á-la-Bartik*. The study provided evidence that routine-biased technological change is correlated with a higher incidence of IPT in Italian local labour markets, indicating that automation's impact goes beyond affecting unemployment rates and can impact job quality in other ways. Although the study confirmed the association between RBTC and IPT for both genders, the results suggested that the stronger growth of IPT among women cannot be solely attributed to RBTC. Instead, the analysis described in Chapter 3 indicated that low-skilled women are disproportionately affected by the expansion of employment in "household substitution" services compared to men. This implies that, in addition to RBTC, various other factors such as sector segregation, a surge in household-substitution services demand, and gender norms, may also be playing a role in explaining higher IPT levels among women.

Chapter 4 took a step ahead and examined the potential outcomes that may arise when individuals who consider themselves disadvantaged by technological advancements and globalisation perceive that their concerns are not adequately being addressed by relevant institutions. Specifically, the study exploited the proliferation of large logistic hubs into mostly rural towns and villages to investigate the relationship between socio-economic grievances and support for the populist radical right. The Italian logistics industry is characterized by a heavy reliance on low-paying and precarious contracts, it employs a large number of foreign workers, and is dominated by multinational corporations. In this, the construction of large logistic hubs can create a favourable environment for populist radical right-wing parties that portray themselves as protectors of traditional values and national identity, and as defenders of the working class against the threats of the modern world (Frank, 2007; Gaffney, 2020; Gidron and Hall, 2017; Hertz, 2021; Hochschild, 2018; Norris and Inglehart, 2019). Through an IV and a DiD approach, Chapter 4 provided causal evidence that there is indeed a positive relationship between the socio-economic shock caused by the construction of large logistic hubs and the surge in support for the *Lega* in Italian municipalities between 2006 and 2018. This relationship might be driven by different mechanisms: an increase in the feeling of economic insecurity, a surge in the anti-immigration sentiment, the hostility towards foreign multinationals. These potential channels were investigated through an event study. While the event study did not provide any strong evidence in support of the first mechanism, it suggested that anti-immigration sentiment may be a potential driver. The findings presented in Chapter 4 call for a more thorough evaluation of the costs and benefits from hosting a logistic hub as for many municipalities the expected benefits might be outweighed by negative effects. Local administrators are lured by the prospect of increased employment, investments, and positive spillover effects. However, once the hub is built, the reality they have to face might be different, paving the way for social discontent, which, among other ways, is expressed through an increase in support for populist radical-right parties. Chapter 4 also emphasized the potential negative impact on social cohesion when institutions fail to address the concerns of those who feel disadvantaged by disruptive innovations.

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