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Essays on Non-Standard forms of Employment in Italy

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Abstract

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Since the 1990s, there has been an increase in the number of workers employed in precarious or atypical jobs in Italy and many other industrialised countries. The term "non-standard jobs" encompasses contractual arrangements for work that is not full-time, indefinite, part of a subordinate bilateral employment relationship, or performed at the employer's premises. This dissertation examines the impact of the rise in non-standard jobs on the Italian labour market and on the working conditions of those involved.

Chapter 1 introduces the subject of study and the process that has led to the rise in non-standard forms of employment. The meaning of "standard employment" is explained and why the standard employment relationship (SER) became the most popular contractual arrangement in the 20th century. The economic and social processes that led to a crisis of SER and the consequent rise in non-standard employment are discussed. The chapter concludes by illustrating recent labour market trends, including the rise in gig-economy jobs: crowdwork and work on demand via apps, highlighting their similarities with more established forms of non-standard work.

Chapter 2 analyses the wage differential between temporary and permanent workers in Italy. Using microdata from the 2012 wave of the Italian Survey on Income and Living Conditions, we apply an Oaxaca-Blinder decomposition and a Quantile Counterfactual Decomposition to investigate the composition of this wage gap. The results suggest that the pay gap is positive and tends to be wider in the left tail of the income distribution. In the whole sample, the differences in the distribution of personal characteristics in the two groups help explain the wage gap, however when we focus on younger and non-European workers, we notice that the wage gap is fully explained by differences in the coefficients associated with worker characteristics.

Chapter 3 deals with voucher work, typically for very short-lived activities, a few hours of work, and a pay-as-you-go scheme. Voucher work shares many features with crowdwork and work on demand via apps. Based on administrative data on vouchers used in Tuscany between 2010 and 2017, we estimate the impact of a restrictive policy change regarding the spread of this instrument. To do so we first apply a sharp regression discontinuity design and then calculate a difference-in-differences estimator to compare the behaviour of private employers to that of employers in the public sector. The results of the two approaches are consistent and show a significant negative impact of the reform on the use of this instrument.

Chapter 4 treats the effects of home-based telework on workers' mental wellbeing. Using microdata from the 2013 wave of the Italian EU-Labour Force Survey and related ad-hoc module, we apply a multinomial logit and semi-parametric estimation of multivalued treatment effects to achieve three main objectives: i) to investigate the characteristics of regular and occasional home-workers; ii) to understand whether home-based teleworkers are more likely to suffer deterioration in mental well-being due to time pressure or work overload than office-based workers; iii) to calculate the difference in usual hours of work and usual overtime between the different groups. The results suggest that occasional home-based workers are more likely to suffer from time pressure and work overload, while regular home-based workers are associated with longer working hours than the other groups.

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Chapter 1

The rise of non-standard forms of employment

1.1 Standard and non-standard employment

Since the early 1990s, all over Europe, societal and economic transformations have given rise to forms of employment different from the standard labour relationship. These transformations encompass the need for increased labour market flexibility, felt by employers and workers, the broader use of advanced information and communication technologies (ICT), and the enhanced importance of specific business activities and occupations.

This phenomenon has raised concerns about its implications for workers, including the effect of non-standard employment on job tenure, wages, job security, etc. and has been a frequent subject of analysis by economists and other social scientists. Following the methodology used by Mandl et al., 2015, we can state that these new forms of employment share one or more of the following characteristics:

- an employee-employer relationship different from the established bilateral employment relationship, as in the case of employment relationships involving multiple employers for a single employee, as in temporary agency work;
- work provided on a discontinuous or intermittent basis, or for a limited period of time, as in the case of fixed-term and casual work, rather than standard full-time open-ended contracts;
- networking and cooperation arrangements between self-employed, especially freelancers, that go beyond usual supply-chain relationships, sharing of premises and traditional project work.

All these features are described in opposition to a "normal" or "traditional" relationship between employer and employee. Although an official definition does not exist, the *Standard Employment Relationship* is generally understood as work that is full time, indefinite, and part of a subordinate and bilateral employment relationship.[1]

[1] On this definition see for instance: Deakin, 1990, Olsen and Kalleberg, 2004, Kalleberg and Hewison, 2013, ILO, 2016a Eurofound, 2017.

1.2 The rise of the Standard Employment Relationship

The expression Standard Employment Relationship does not appear in any legal text. Nonetheless, the idea of its existence is widespread and derives from the process of "contractualisation" of the employment relationship that began in Europe in the second half of the nineteenth century (ILO, 2016a). The process that brought about the standard employment relationship is complex and would take a whole dissertation to describe in detail; it is nevertheless useful to summarise it briefly in order to understand the rise of *non-standard employment relationships*.[2]

According to Deakin, 2002, employment contracts can be understood as governance mechanisms linking employers with the labour supply in a way that allows the management of long-term economic risks. In the first half of the twentieth century, the (now) familiar division between employees and self-employed emerged gradually in common and civil law systems (Deakin, 2005). Supiot, 1999, relates this phenomenon to the rise of the model of the welfare state. Under this framework, the work relationship had to balance the trade-off between economic dependence and social protection: the employee accepted to be subject to the managerial power of the firm in exchange for the implicit promise of economic security. The State, on the other hand, became an implicit third party to the employment contract, insuring the workforce against economic risk through the social insurance system, and using social security contributions and income tax to sustain the public provision of welfare services (Deakin, 2002). In the common and civil law systems, the employment contract became the legal device and the social parameter on which labour law was built (Veneziani, 2009). As a result, the further developments of the systems of social security systems came to assume that the employment relationship had to be subordinate, full-time and indefinite (ILO, 2016a).

According to Deakin, 2016, after the Second World War the rise of collective bargaining and "solidaristic forms of social insurance" made it necessary to shape the legal distinction between employment and self-employment. In this period the employment relationship was therefore defined as a way of balancing the managerial prerogative of directing work with an increased stability and continuity of work for the worker. On one hand firms started to have an incentive to invest in the skills of the workforce, something that could not be done when labour was provided independently as a service. On the other hand, workers began to invest in increasing their firm-specific skills, thanks to the relative stability of the employment relationship. This innovative way of looking at the relationship between firm and worker, coupled with the introduction of limited liability, gave rise to the "vertically integrated modern business enterprise" (Deakin and Wilkinson, 2005). Corazza and Razzolini, 2015, point out that several legal systems adapted to this process by drawing the boundaries of the legal concept of employer to coincide with the boundaries of the economic organisation in which the work is performed.

[2]To the best of my knowledge, the most complete work on this topic is Deakin and Wilkinson, 2005.

The subordinate employment relationship that was the result of these economic and social processes has been and still is central in the legal regulation of the labour market, although it is increasingly being pushed outside its core. At the time of industrial development, the labour contract linked an employer to an adult male working in his firm, who was required to perform a specific duty for an unspecified amount of time (Veneziani, 2009). Hence, both statutory law and collective bargaining were based on the assumption that a single activity would be carried out on the premises of the firm and in a single temporal sequence.

1.3 Challenges to the Standard Employment Relationship

Starting in from the 1970s, economic, social, and demographic transformations challenged the structure and dynamic of standard employment, making the previous assumptions largely obsolete. The economic transformations included the lower rate of growth that many developed countries started to experience with respect to the previous decade, an increase in international competition, imbalances in international trade, and counter inflationary policies (Cordova, 1986). These phenomena triggered an increase in the unemployment rate, that has favoured the growth of non-standard contracts in two ways. On one hand, the economy alone appeared incapable of maintaining 1960s levels of employment: governments were therefore forced to devise new means of creating jobs outside the standard wage employment model. On the other hand, workers who were unemployed or at risk of unemployment were more willing to accept precarious or unstable contracts. In this context, the standard employment relationship increasingly seemed to reflect a balance between labour demand and supply that belonged to the past (Veneziani, 2009).

In the same period, profound changes also occurred in the structure of employment, with a shift from a prevalence of the manufacturing sector to the service economy. The importance of the full-time wage employment model, which developed together with the industrial working class, was often unfit to meet the needs of the service economy (Cordova, 1986). The sustained pace of technological innovation, moreover, made it necessary to reorganise the production activities of the firm, further increasing employers' need for flexibility (Kalleberg, 2000). Governments often considered rigid labour markets to be an obstacle to firms' competitiveness and encouraged a transition to "flexible labour markets", in which non-permanent and non-full-time forms of employment are possible (Casey, Keep, and Mayhew, 1999). This process has required a progressive "de-regulation" of labour relations in most advanced economies and has led to the idea that stringent labour market rules are an obstacle to productivity and responsible for high levels of unemployment. Bosch, 2004, listed some of the main societal and economic changes that had started to undermine the Standard Employment Relationship at the end of the last century.

1.3.1 Flexibilisation of product markets

In the post-WW2 period, the strength of the SER was due to the fact that product markets were similarly structured. In the service sector, compliance to a standard working time was ensured by fixed opening hours. In the manufacturing industry, mass production allowed firms to respond to fluctuations in demand by holding stocks rather than adjusting working times.

On the contrary, mass production has now largely been moved to developing countries and in industrialised countries goods are mostly produced to order (Brettel et al., 2014). In the manufacturing sector, stocks of goods can therefore no longer mediate between production and demand for products: this role has been taken by working time flexibility (Bosch, 2004).

Furthermore, the structure of the service sector has changed, beginning to favour an increase in working time flexibility. Changes in the service sector include the deregulation of opening hours for many activities, and the rise of project-work in knowledge-intensive industries.

Finally, technological developments have provided substitutes for routine occupations, causing a polarisation of employment into low-skilled non-routine jobs (e.g. cleaners) and high-skilled non-routine jobs (e.g. engineers), as confirmed by Holmes and Mayhew, 2012, in the UK. Especially with regard to low-skilled workers, fluctuations in demand require that employers should be able to hire and fire them at the lowest possible cost: hence the need to deviate from the SER in terms of contract duration and the rise of contractual forms such as casual work and temporary agency work. Nevertheless, employers are increasingly dependent on skilled workers with firm-specific skills, and in times of crisis prefer to reduce their working time rather than fire them. This kind of internal flexibility has therefore contributed to the fall of the standard full-time employment model (Bosch, 2004).

1.3.2 Rising employment rates among women

In industrialised countries, female employment rose throughout the latter half of the twentieth century and the beginning of the new millennium. However, in most of these countries, views on work-family roles imply that women must combine paid work and domestic responsibilities (Gautié et al., 2010). Therefore when the number of working women increases without a change in institutions and social environment, we see an increase in non-standard employment relations such as temporary or part-time contracts (Bettio, Rubery, and Smith, 1996). The institutional and societal transformations that Bosch, 2004, mentions include adequate childcare infrastructure, elimination of the gender wage gap, and tax and social security systems offering incentives for non-employment or marginal employment.

1.3.3 Combining education and work

With the rise in the share of students combining study and employment (Gautié et al., 2010), many industries have adapted, offering them temporary

or on-call contracts. Atypical jobs have therefore increasingly become a standard phase in the careers of young people, particularly those enrolled in university.

1.3.4 Employment level

Bosch, 2004, argues that full employment and economic growth were the background for the advent of the SER, while high unemployment and slower economic growth have been fundamental factors in its dissolution. When unemployment is high, workers' bargaining power is low and firms can try to shift the burden of market risk onto their shoulders. Unemployed workers will therefore accept less-than-optimal work contracts. At the same time, access to non-standard forms employment has become less and less restricted since the 1990s, in response to the rise in the unemployment rate, as we have already stated. In many countries, the regulatory gap between different forms of employment combined with high unemployment levels due to economic downturns have therefore contributed to the success of non-standard employment.

1.4 Deviations from the Standard Employment model

As we have seen, demographic factors that have favoured the spread of non-standard employment include progressive feminisation of the workforce and the increase in the share of young workers. These job-seekers often have needs and preferences that do not resemble those of the traditional male family bread-winner. The change in attitudes towards work make the structured, subordinate and impersonal aspects of the standard employment relationship less and less appealing (Cordova, 1986). Following the scheme drawn by Veneziani, 2009, we describe five trends of deviation from the standard labour relationship that began to emerge in the late 1970s and 1980s.

1.4.1 The duration of contract

Although fixed-term contracts are an old institution, already envisaged by the Napoleonic Codes, in the 1950s and 1960s labour legislation tended to favour open-ended contracts. This trend was a way to guarantee the stability of the employment relationship, to avoid mass unemployment and allow post-war reconstruction of the economy. Fixed-term contracts became increasingly common in the 1980s in response to the increasing need for flexibility of the labour market, albeit often only for cases with "objective" or "practical" reasons. In the 1990s, however, these barriers were progressively lifted in many countries.

1.4.2 The duration of work

A reduction of working hours is a deviation from the standard full-time contract, although it is not incompatible with the "traditional" open-ended employment relationship. The reduction of the overall hours of worker performance

came about in response to transformations in workforce composition and production technologies. On one hand, the progressive increase in the participation of women and young people, and on the other hand, the introduction of computers allowed an increase in the volume of part-time work.

1.4.3 The personal availability to work

In the 1980s a further deviation from the SER was the introduction of jobs that were not continuous but alternating, intermittent or cyclic. Many non-standard jobs are based on the promise by the worker to perform a "potential task" in the future when the employer "calls" him. The worker must therefore change his or her approach to work-life balance and to the continuity of the tasks performed.

1.4.4 The triangular relationship

As stated above, the traditional employment contract is based on a bilateral relationship between a worker and an employer whose juridical identity is known. Since the early 1970s there has been an increase in socio-economic relationships of a triangular nature, including the worker, the employer, and a third party who receives the service, as in the case of temporary agency work.

1.4.5 The workplace

Thanks to the technological revolution and informatisation of many production processes, firms have increasingly been able to decentralise functions such as planning, research, supervision of accounts and know-how. Many activities of the productive cycle of the firm, that in the past would have been performed on its premises, are now often performed in other places. A good example is telework: through telecommunications, tasks can be performed inside or outside the firm.

1.5 The functions of the Standard Employment Relationship

The standard employment relationship plays a key role in our economic and social system; its function is not limited to providing social protection. Rubery, 2017, identifies the following eight different functions of the employment relationship. While non-standard employment contracts are not necessarily lacking these features, most of them do not have most of them.

1.5.1 Access to social protection

Social protection provides wage workers with income security in the transition between two jobs, or during periods of illness, disability, maternity and retirement. It also helps compensate for low earnings and provides access to

healthcare. Social protection schemes are usually financed partly by a contributory (social insurance) and partly by non-contributory (tax-financed) mechanisms. When they were designed, many social security systems were tailored to the Standard Employment Relationship.

The relationship between employment status and provision of social protection is critical for the life and security of workers. Some forms of social protection can be provided outside an employment relationship, while others, such as unemployment benefits, pensions and compensation of work-related injuries, are linked to employment. All these programmes, together with maternity and paternity leave, sick leave and so on, are essential components of a comprehensive social security system (ILO, 2016a). This is why social protection has often been argued to be a pillar of the employment model that emerged in the twentieth century (Leschke, 2007). As a result, access to these provisions may be difficult for workers in non-standard employment: in many countries coverage is less for this group, and for those who are eligible, benefit levels are often lower (Schmid and Wagner, 2017).

Coverage is less for non-standard workers because in many cases access to social security is conditional to minimum job tenure, earnings or hours (Matsaganis et al., 2016). Some temporary and part-time workers may be excluded from social security because they lack the job tenure or hours requirement. Casual workers and independent contractors (such as most workers employed in *gig economy* jobs) are usually excluded from social security provisions (OECD, 2015).

Social security benefits are often lower for eligible non-standard workers for a variety of reasons. First, non-standard workers have different contributory requirements with respect to standard workers. For instance enrolment in a benefit scheme is voluntary for non-standard workers in some countries. Second, non-standard workers may not be eligible for the main social security scheme, but for a side one, which is usually less generous. Third, being more exposed to career interruptions and lower life-time earnings, non-standard workers contribute less than standard ones, and therefore receive lower benefits (Buschoff and Protsch, 2008).

1.5.2 Employment and income security

The traditional full-time, open-ended subordinate employment model provides the worker with both employment and income security. According to the definition given by Wilthagen and Tros, 2004, *employment security* can be divided into two components: job security and employability security. Job security is the certainty of retaining a specific job with a specific employer, which derives directly from the open-endedness of the SER and the protection against unfair dismissal provided to standard workers. Employability security is the certainty of remaining in work over a long period of time, although not necessarily with the same employer.

Leschke and Schmid, 2006, point out that in many European countries labour market policies in the 1990s and early 2000s shifted their objective from ensuring job security to increasing employability security. The loosening

of regulations against unfair dismissals and the liberalisation of non-standard employment arrangements generated more flexibility in the labour market, increasing worker turn-over and allowing employers to employ more or fewer workers during the business cycle. At the same time, these policies are supposed to favour employability security, especially when atypical employment can be a stepping stone to market integration of marginalised workers. Nonetheless, as reported for example by Amable and Mayhew, 2011, in times of recession, countries where most workers benefit from stricter employment protection laws are those characterised by smaller increases in the unemployment rate with respect to countries with loose employment regulation.

The focus on "employability security" has often been criticised because of the effect that precarious employment has on workers. When the SER is no longer open-ended, workers are unable to plan in their everyday life in the long term or with regard to investment in their own capacity for work (Bosch, 2004). On one hand, workers in non-standard employment struggle to maintain a good work-life balance for several reasons (De Bruin and Dupuis, 2004): the boundaries between work and life are often blurred and the deadline-driven nature of many jobs increases work intensity. On the other hand, temporary workers do not have an incentive to invest in firm-specific skills or to commit to a firm on a long-term basis (Bardasi and Gornick, 2008). The lack of job security may also have health implications: for instance, Virtanen et al., 2002, found that workers perceiving their jobs as insecure were more likely to consider their health to be "bad", were more subject to chronic diseases, and reported higher levels of psychological distress.

The standard employment relationship also ensures *income security* in two major ways. First, non-standard workers are less likely to benefit from laws or collective agreements concerning minimum wages, aimed at providing a decent compensation for the work performed; an analysis on 17 OECD countries showed that all types of non-standard employment pay lower hourly wages and lead to lower annual earnings than do standard jobs, with hourly wages for temporary and part-time workers around 70% and 80% of the median hourly wages for standard workers s (OECD, 2015). Second, non-standard workers' incomes depend more heavily on the employer's discretion, so that the work schedule (and pay) can vary considerably and unpredictably from one period to another. As a result, temporary jobs are often also associated with lower earnings (Salverda and Mayhew, 2009). According to OECD, 2015, households whose members are in non-standard working arrangements are more likely to be at the lower end of the household income distribution and face a higher risk of poverty than other working households.

1.5.3 Equality of access

As observed by Rubery and Piasna, 2016: "employers are the gatekeepers to employment", because they determine who can access employment through their hiring, selection and retention strategies. Discrimination on the grounds of race, colour, sex, religion, political opinion, national extraction, age, social

origin or sexual orientation are prohibited by law in most countries.[3] These laws aim at ensuring equality and inclusiveness in the labour market, but they can often only be applied in the presence of an employment relationship. Self-employed and independent contractors can hardly prove that they have been discriminated against.

Furthermore, workers in non-standard employment can also experience discrimination on the grounds of their non-standard worker status: a major barrier to re-entry in employment for these individuals lies in the attitude of employers towards them. Non-linear careers and frequent spells of unemployment can often have a negative effect on worker employability and on their future wages (Gangl, 2006). This scarring effect can not only be found after an unemployment spell, but also after non-renewal of a temporary contract (Borland et al., 2002).

1.5.4 Fair treatment

Standard workers (at least in principle) benefit from regulations ensuring fair treatment throughout the employment hierarchy. They can apply to labour courts and tribunals for protection and redress if they endure unfair conditions. However, in many cases non-standard workers are excluded from fair treatment legislation (ILO, 2016a). This may happen because they are part of a multi-party employment relationship, in which the identity of the employer is uncertain, or because they are not strictly "employees", as in the case of disguised self-employment. Moreover, the position of weakness with respect to the employer of non-standard workers discourages recourse to labour courts in the case of unfair treatment, for fear of retaliation by the employer.

1.5.5 Human rights

Employers are generally also required to ensure respect for human rights, in terms of avoiding discrimination and providing acceptable conditions in the workplace. They have to ensure the safety and health of the worker. In principle, standard subordinate workers can refuse unsafe work; however, this may not be possible when the employment relationship is weak or when the worker performs his tasks in a workplace that is different from that of the principal employer.

Indeed precarious employment has often been associated with a higher risk of occupational injuries (Underhill and Quinlan, 2011). This outcome, according to several studies, can be imputed more to the lack of training and short tenure characterising non-standard work, than to differences in the tasks they perform (Benavides et al., 2006). Nonetheless, job insecurity over time has been linked to deterioration of mental health (Ferrie et al., 1995, Virtanen et al., 2002), and temporary workers appear to be more at risk of fatigue and chronic pain (Benavides et al., 2000).

[3] See the Discrimination (Employment and Occupation) Convention, 1958 (No. 111), https://www.ilo.org/dyn/normlex/en/f?p=NORMLEXPUB:12100:0::NO::P12100_ILO_CODE:C111

1.5.6 Voice

The employment relationship provides workers with the right to union representation. In this way, they can actively raise awareness of workplace safety issues and negotiate working conditions (including pay and working hours) through collective bargaining. This right is usually considered to be a pillar of modern democracies, allowing workers to establish social norms that influence wider social behaviours. Non-standard workers, however, are often excluded from union representation either because they are officially self-employed, or because the time they spend with the firm is brief (Heery et al., 2002). McGovern, Smeaton, and Hill, 2004, estimated that in 2000 only 1 in 5 non-standard workers in Britain were union members, compared to 1 in 3 workers in standard arrangements. They also concluded that workers lacking union representation were significantly more likely to experience substandard working conditions.

1.6 Non-standard employment today

In the last 10 years, the emergence of digital labour platforms has revolutionised the world of work. The term gig economy (or on-demand economy) has gained popularity to define work that is mediated through online web platforms (ILO, 2016b). These activities are in most cases characterised by a high level of marginality, short weekly hours and short employment duration (Eurofound and International Labour Office, 2017). Although it is hard to give a comprehensive definition of this phenomenon, when we talk about gig economy we usually refer to two main forms of work: *crowdwork* and *work on demand via apps*.

These forms of work, despite the differences, have an obvious feature in common. They are possible because of information technologies: in both cases the internet serves as match-maker between supply and demand. The minimal transaction costs and the rapidity with which job opportunities are offered and accepted imply that firms have access to a large number of potential workers. Conversely, workers can potentially do a gig and be paid at any time. This is why these jobs often go under the definition of smart-work.

The increasing number of workers doing gigs in the last decade makes it impossible for us to overlook this phenomenon. This section is therefore devoted to describing these forms of work, including the characteristics of gig economy workers and the opportunities and threats for those performing gigs. We do not contribute new results to the literature, but rather gather information from different sources to provide the completest possible picture of this phenomenon.

1.6.1 Crowdwork

What is now called *crowdwork* emerged more than a decade ago: Howe, 2006,) defined *crowdsourcing* as “the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined network of people in the form of an open call”. Nowadays, the term crowdwork

comprises working activities performed through online platforms that connect a large number of individuals and organisations on a global basis (Estellés-Arolas and González-Ladrón-De-Guevara, 2012). The kind of tasks performed through crowdwork are very different: from microtasks, quick and repetitive clerical activities that nonetheless require human judgement and cannot be performed by computers (for instance: tagging photos or completing surveys), to more complex jobs, such as the design of a logo, that can be outsourced to a *crowd* of individuals (Gadiraju et al., 2015a). Microtasks usually involve a *crowdworker* (the user performing the task on the platform, in exchange of a monetary reward) and a *requester* (a user that sets up the tasks on the platform and acts as tasks administrator), according to the definition given by Gadiraju et al., 2015b.

Since crowdwork is multifaceted and dynamic, a detailed comprehensive definition cannot be given. The fact that there are as many different business models as there are crowdsourcing platforms should be enough to understand why a precise definition of crowdwork cannot exist. Some crowdsourcing platforms only have the scope of matching two sides of a market by aggregating freelancer profiles and establishing a relationship with potential clients. Other platforms intervene to various extents in the working process. Either they verify and assess workers' profiles, or mediate payments, or set the conditions under which tasks must be performed (Potocka-Sionek, 2018).

Amazon Mechanical Turk is the most famous platform in the latter group. Since 2005, it outsources human intelligence tasks (HITs) to a large group of online workers (Stewart et al., 2015).HIT is the label given to the tasks on the platform which are single assignments an individual can complete and submit. A human intelligence task is usually a very simple and repetitive activity that is still too complicated to be performed by a computer algorithm (Potocka-Sionek, 2018), such as completing a survey. A single HIT can only be performed once, and if the result is approved by the requester, the worker is paid (Cheung et al., 2017). Hara et al., 2018 estimated the wage distribution of 2676 workers performing 3.8 million tasks on Amazon Mechanical Turk. They report a median hourly wage of approximately $2, with only 4% of the workforce receiving more than $7.5 per hour.[4]

While Amazon Mechanical Turk is considered to be the prototype of all crowdsourcing platforms, others have arisen in recent years, the most popular including Clickworker, UpWork and Google Image Labeler. Other platforms specialise in a sector, such as research and development (Innoget), marketing and design (CMNTY Corporation), creative co-creation (Quirky) and legal advice (UpCounsel). Others have been established by companies to involve their clients in the design of their product, as in the case of BMW Customer Innovation Lab, My Starbucks Idea and Dell IdeaStorm.

[4]Hourly wage is a misleading concept in this context. Workers are not paid per hour, they are paid according to the number of tasks they complete. Here "hourly wage" means "the average earnings of a crowdworker for one hour of work".

1.6.2 Work on demand via apps

Work on demand via apps is the updated version of traditional forms of work on demand. Activities that were common in the pre-gig economy (transport, cleaning, running errands, delivering goods and so on) are now channelled through apps where tasks are negotiated (Birgillito, 2018). The company managing the app selects the workforce and sets the standards of service (De Stefano, 2015). Work on demand and crowdwork share the feature that demand and supply are matched on online platforms. However, unlike crowdwork, jobs on demand are performed locally and offline.

The most popular apps span different sectors: transport (Uber, Lyft), food delivery (Deliveroo, Foodora, UberEats), home services (Taskrabbit). Uber, probably the best known of these services, is a "ridesharing" app that allows users to hail private cars for travel and uses online technologies to match passengers and drivers (who receive money for picking up rides). The app sets the fare according to demand, decides the share that goes to the driver, regulates the characteristics of the cars used, and provides evaluations of drivers and passengers (Cramer and Krueger, 2016). Foodora, a well-known food delivery app, works both as a marketplace for the food offered and as recruiter for deliverers. It also sets the requirements (smartphones and bikes equipped with a cargo rack) couriers must meet to perform their deliveries. An algorithm sorts deliveries among couriers according to the desired time of pick-up and the distance between the customer's house, the courier and the restaurant (Rauseo, 2018).

1.6.3 Gig economy workers, opportunities and threats

Table1.1 displays the shares of workers employed by online platforms in the European Union, according to different measures and studies, as gathered Eurofound, 2018.

A considerable part of these workers makes use of a platform or an app in their spare time, or as second job. Nevertheless, it is not uncommon to find workers who base their entire income on tasks in the gig economy, often combining different platforms and apps (ILO, 2018). These jobs are often perceived as an opportunity for workers who value the flexibility associated with self-employed status. The lack of a pre-determined working schedule enables workers to find job opportunities that perfectly match their other daily activities, such as studying, leisure and family-related tasks (De Stefano, 2015).

However, these jobs have many risks, especially for workers relying on the gig economy for their main or sole source of income. On the monetary side, the standard norms on minimum wages and social security are easily side-stepped, because workers are often regarded as independent contractors by the companies managing the apps or platforms. Gig economy workers do not have any bargaining power against these companies, which can modify their working conditions unilaterally or pay whenever they please (Eurofound, 2017).

According to Potocka-Sionek, 2018, digitalisation opened a gate through which employers can escape from employment-related obligations. De Stefano, 2015, cites the CEO of Crowdflower (a company engaging in crowdwork) to

Country	%	Unit of measure
Austria	19%	Population who has ever done platform work
Denmark	1%	Platform workers earning money at least once over the last 12 months
Finland	0.3%	Population aged 15–74 who had earned more than 25% of their income from work-related and non-work-related platform activities during the previous 12 months
Germany	1.8%	Population aged 15 and over registered as platform workers in January 2017
	12%	Population who has ever done platform work
Italy	22%	Population who has ever done platform work
Netherlands	9%	Population who has ever done platform work
Sweden	2.5%	Working-age population who performed platform work
	4.5%	Working-age population who looked for work on platforms
	10%	Population who has ever done platform work
United Kingdom	4%	Gig economy, performing tasks online, providing transport or delivering food or other goods at least once over the past 12 months
	4.4%	Gig economy, involving exchange of labour for money between individuals or companies via digital platforms that actively facilitate matching between providers and customers, on a short-term and payment-by-task basis

TABLE 1.1: Workers employed in the gig-economy in the EU. Shares of the workforce employed in the gig-economy in different EU countries. Source: Eurofound, 2018, see this publication for original references.

exemplify what being a gig-economy worker means: "Before the Internet, it would be really difficult to find someone, sit them down for ten minutes and get them to work for you, and then fire them after those ten minutes. But with technology, you can actually find them, pay them the tiny amount of money, and then get rid of them when you don't need them anymore."

The first major concern regards the employment status of gig-economy workers. According to the terms and conditions of each platform, workers can be classified as employees or independent contractors and therefore have very different rights (Eurofound, 2018). The distinction between employee and self-employed is made by verifying whether the platform only acts as matchmaker between clients and providers, or if it is one of the tools used to perform the service (Birgillito, 2018). An example of this dispute is the ruling of the Employment Tribunal of London (October 2016)) that classified Uber drivers as "workers" entitled to the legal minimum wage (Jamil, 2017)). In this case Uber's terms and conditions contained a contradiction: the service was described as a

simple network, while it stated that drivers using the app would enter into an agreement with a person whose identity they did not know, would undertake a journey to a destination decided by the client, and be paid by a third party. Based on this evidence the Employment Tribunal of London stated "[Uber's description of being a] mosaic of 30,000 small businesses linked by a common platform is faintly ridiculous" (as reported by Birgillito, 2018).

Workers who see their status of employee recognised can therefore claim the corresponding rights (the minimum wage in the case of the ruling reported above). Platforms, of course, have an incentive to describe their workers as autonomous in order to cut labour costs and increase profits (Leighton, 2016). They can also implement policies aimed at eluding union regulations, as in the case of Foodora in Italy. In October 2016, workers in Turin decided to take collective action by organising flash-mobs and calling for a boycott of the service in order to improve working conditions. In retaliation, Foodora disconnected them and prevented their access to the platform (Coccorese, 2016). However, the right of the riders to strike seems to be guaranteed by a previous ruling of the Italian Supreme Court, according to which "the right to strike (...) can be exercised whenever a provider of a service is in a weak position with respect to a counterpart" (Forlivesi, 2016).[5] Later six riders appealed to the Court of Turin claiming that they had been unfairly dismissed and asking for recognition of their status as employees. In January 2019 the Court ruled that Foodora riders are not subordinate employees, but they nevertheless have a right to the minimum wage established by collective bargaining in their economic sector (Prioschi, 2019).

Lack of income security is a further threat for gig economy workers. As we have seen, they are not paid by the hour but according to the number of "gigs" they perform. According to Eurofound, 2017, 90% of the tasks on Amazon Mechanical Turk are worth less than $0.10. As reported above, the average wage per one hour of work on the platform is just $2 (Hara et al., 2018). Moreover, Potocka-Sionek, 2018, reports that on Clickworker only 3% of European workers earn more than 20€ per week. According to Berg et al., 2018, many crowdworkers complain that their work can be unfairly rejected and therefore not remunerated. This is particularly worrisome in the case of creative work: if the work is rejected the worker is not paid but still loses the intellectual property of the creation, which goes to the requester of the activity.

Another risk for gig economy workers is that of "permanent availability", which blurs the boundaries between work and private life. Considering how poorly their tasks are paid, most live in "stand-by mode", meaning that they are always ready and willing for a work opportunity. This in turn leads to what has been defined as "technostress", a state of burnout caused by addiction to technology (Valenduc, 2017).

The fact that transactions occur virtually or with minimal human contact contributes to the creation of hidden human activities and "invisible workers" (Irani, 2015). This "invisibility" can be defined in two ways which have different consequences. First, the isolation and lack of recognition experienced by many crowdworkers has adverse effects on their well-being and mental health.

[5] Corte di Cassazione 29 June 1978, n. 3278, in FI, 1978, I, 1630.

Second, these workers may be "invisible" because they are not even recognised as "workers": not only in the sense that these jobs often escape labour regulations, but the worker is unlikely to be able to use the experience gained in the gig economy to move on to a more structured form of employment.

1.7 Conclusions

In this chapter, we introduced the topic of the present dissertation: the rise of non-standard forms of employment. Starting with the rise of the Standard Employment Relationship, we outlined the changes in the industrial labour market that brought about a decline in its importance. We listed the many functions that the SER has in protecting the workforce and promoting fair and inclusive labour markets. We explained the trends and deviations from the SER that have led to what we called non-standard forms of employment. Finally, we considered the rise of gig economy jobs, crowdwork and work on demand via apps, and the possible consequences for workers.

De Stefano, 2015, argues that extreme flexibility, shifting of risks to workers and income instability are not exclusive to gig economy jobs. These features have been present in the labour markets of industrialised countries for quite some time. The rise of working agreements such as zero-hour contracts and on-call jobs is another example of a progressive dismantling of the Standard Employment Relationship in favour of on-demand "pay-as-you-go" forms of work. This is why we can think of offline forms of non-standard employment, on which we focus in this dissertation, as having some similarities with gig economy jobs.

The present thesis addresses only three of the many issues raised by non-standard forms of employment. Although we focus mainly on "offline" forms of non-standard employment, we believe that the conclusions we draw and the problems we raise can easily be generalised to encompass the questions raised by gig economy jobs.

In Chapter 2, the reader will find an analysis of the wage differential between temporary and permanent workers in Italy. Starting from the end of the 1990s, fixed-term contracts and other forms of temporary employment have been progressively deregulated in Italy. As a result, the share of temporary workers over the total number of employees increased from 7.4% in 1996 to approximately 14% in 2012, the year under investigation in this analysis. According to the Italian National Statistical Institute (ISTAT), in the first half of 2019 the number of temporary workers in the Italian labour market overcame 3 million, corresponding to 17% of the total number of employees. Using microdata from the 2012 Survey on Income and Living conditions, we perform an Oaxaca-Blinder decomposition and a counterfactual quantile decomposition to understand how much of this gap can be attributed to differences in characteristics and differences in coefficients. The results suggest that the pay gap is positive and tends to be wider at the left tail of the income distribution. In the whole sample, this gap is mainly explained by differences in the distribution of personal characteristics of the two groups. However, when we focus on

less experienced and immigrant workers, we notice that the wage gap is fully explained by differences in coefficients associated with worker characteristics.

Chapter 3 deals with the topic of voucher work, often debated in Italy in the recent past. Characterised by very brief activities, few hours of work and a pay-as-you-go scheme, voucher work shares many characteristics with crowdwork and work on demand. This analysis provides an insight into the functioning of this extremely flexible working arrangement, used by more than 1.7 million workers in 2016 (Anastasia, Bombelli, and Maschio, 2016). Taking administrative data on vouchers issued in Tuscany between 2010 and 2017, we estimate the impact of a restrictive policy change that limits the spread of this instrument. To do so we first apply a sharp regression discontinuity design and then we calculate a difference-in-differences estimator to compare the behaviour of private employers to that of employers in the public sector.

In Chapter 4, we investigate the impact of telework on the mental well-being of workers. Although telework is not a recent phenomenon, modern technologies and the rise of smart-work mean that an increasing number of workers operate from home. Until few years ago the number of teleworkers in Italy was very small, just 372,000 individuals in 2015. However, several companies recently started to encourage their employee to adopt *smart working* solutions, including telework. As a result, the number of individuals working at least occasionally from reached 480,000 in 2018, with a 20% increase with respect to the previous year (Pizzin, 2018). In this chapter, we rely on a semi-parametric estimation of multivalued treatment effects to achieve three main objectives: 1) to investigate the characteristics of regular and occasional homeworkers; 2) to understand whether home-based teleworkers are more likely to suffer a deterioration in mental well-being due to time pressure or work overload; 3) to calculate the difference in usual hours of work and usual overtime between office-based workers, occasional home-based teleworkers and regular home-based teleworkers. The results suggest that occasional home-based workers are more likely to suffer from time pressure and work-overload, while regular home-based work is associated with longer working hours.

Chapter 2

The wage-gap between temporary and permanent workers

2.1 Introduction

Between the end of the 1980s and the early 2000s, several European countries reformed their labour markets by introducing or deregulating temporary employment. Temporary work arrangements, such as fixed-term contracts, were used to progressively increase labour market flexibility and to respond to a rise in the European unemployment rate in the 1990s (Picchio, 2008). In many industrialised countries, labour market reforms in the last three decades have challenged the traditional standard employment relationship and have introduced different atypical forms of employment. In Italy, for instance, temporary employment was an important component of employment growth in the 1990s (Barbieri and Sestito, 2008).

In this paper, the term temporary employment does not refer to a specific contract or working arrangement, but rather to all forms of non-standard employment of limited and pre-determined duration. Ceccato, Cimino, and Tronti, 2003, list the three main forms of temporary employment in Italy:

- *Fixed-term contract*, in which the duration of the working relationship is pre-determined by the employer and set at a certain date or conditioned by occurrence of a certain event;
- *Temporary agency work* performed by workers sent by the agency to the premises of a third-party customer firm;
- *Apprenticeship*, a training-related contract that should at least in principle lead to a permanent position when the worker is sufficiently trained.

The increasing share of temporary workers and its effect on labour market equilibria have been extensively debated by scholars. By increasing labour market flexibility, temporary jobs on one hand facilitate the transition from education to the first job and provide employers with an instrument to screen and test potential employees, enhancing the probabilities of successful pairing and therefore acting as a stepping stone towards permanent jobs (Booth, Francesconi, and Frank, 2002b, Autor and Houseman, 2010). Firms can also

exploit this instrument when faced with demand uncertainty, employing workers on a fixed-term basis (Graaf-Zijl, Berg, and Heyma, 2011). On the other hand, temporary workers face higher turnover, more frequent unemployment spells (Dolado, García-Serrano, and Jimeno, 2002), and greater earnings insecurity (Booth, Francesconi, and Frank, 2002a). Temporary jobs often come with little or no social security, lower levels of job satisfaction, fewer training opportunities and a more volatile working schedule (ILO, 2016b). In terms of consequences on the labour market, temporary jobs appear to have increased labour market segmentation in many European countries, leading to the creation of a dual system in which temporary workers may fail to make the transition to stable employment (Garibaldi and Taddei, 2013).

The purpose of this paper is to analyse the wage-gap between temporary and permanent workers in Italy. Econometric analysis is performed using the 2012 wave of the European Union Survey on Income and Living Conditions (EU-SILC).

The analysis is performed in two steps. The first step is an Oaxaca-Blinder decomposition of wage differentials, corrected for the bias arising from selection into employment (as suggested byNeuman and Oaxaca, 2004). The results show that permanent workers enjoy a large wage-gap. In the whole sample, this gap is explained by a combination of *endowment* and *coefficient effects*. However, for some workers, such as younger and non-EU ones, the gap is entirely due to differences in coefficients.

The second step is a conditional quantile decomposition, as proposed by Machado and Mata, 2005, and extended by Chernozhukov, Fernández-Val, and Melly, 2013. This method makes it possible to decompose the wage-gap at different quantiles of the wage distribution, in order to obtain deeper insights than the traditional Oaxaca-Blinder decomposition on the mean wage difference. The results for the whole sample show a U-shaped wage-gap, with a larger difference in extreme quantiles. Moreover, the role of the *endowment effect* in explaining this gap tends to be larger at the right tail of the wage distribution, whereas that of the *coefficient effect* tends to be larger at the left tail.

This research aims to contribute in two ways to the literature on wage differentials between temporary and permanent workers. First it analyses labour market outcomes of Italian temporary workers in 2012, the year in which their number was highest in the recent past. It does so both in absolute terms and with respect to the number of permanent workers. Second, it focuses on the wage-gaps experienced by different groups of temporary and permanent workers, showing that for them, the conclusions drawn for the whole sample do not always hold.

The paper is organised as follows. The empirical literature on labour market outcomes of temporary workers is summarised in Section 2. Section 3 provides a timeline of the growth of temporary employment in Italy. Section 4 describes the data and reports descriptive statistics. Section 5 describes the model specification and Section 6 presents the results. Conclusions follow.

2.2 The literature

As briefly noted in the previous section, the literature on temporary employment has diverging views concerning its consequences on the labour market and on the careers of the workers involved. It has been argued that temporary jobs may provide workers with opportunities to acquire experience, establish contacts in the labour market, and signal their abilities. Moreover, temporary jobs allow the inclusion in the labour market of workers that may not otherwise have been able to find a job.

One of the main issues analysed by scholars has been whether temporary jobs are a *dead end* or a *stepping stone* towards more stable jobs. Given that most studies find that temporary workers often face poorer working conditions than permanent ones (ILO, 2016b), it is crucial to assess whether they have an easier access to open-ended contracts than unemployed individuals. For instance, Graaf-Zijl, Berg, and Heyma, 2011, showed that temporary jobs unambiguously shorten unemployment duration in the Netherlands, increasing the transition rate of the unemployed to permanent jobs. Booth, Francesconi, and Frank, 2002a, acknowledged that in the UK temporary workers receive less training, are less satisfied by their job, and are not as paid as permanent workers. However, they also found a springboard effect of fixed-term contracts towards more stable jobs. In Italy, Gagliarducci, 2005, found that the length of the first temporary contract positively influences the likelihood of transitioning to an open-ended contract. Ichino, Mealli, and Nannicini, 2008, showed that temporary agency jobs can be an effective stepping stone towards permanent employment. Temporary agency jobs have been taken into consideration also by Autor and Houseman, 2010, who found no positive effect of these contracts on the probability of attaining a permanent contract in the US.

A second widely discussed issue, and the object of this analysis, is the pay gap between temporary and permanent workers, with most studies finding that more stable jobs are also associated to higher wages. Let us take into consideration the international empirical evidence on the matter. Segal and Sullivan, 1998, used administrative data drawn from the unemployment insurance system of the state of Washington and estimated a wage penalty of 10% for temporary workers in the service industry. Gustafsson, Kenjoh, and Wetzels, 2001, found that fixed-term workers were earning less than permanent workers in Britain, Netherlands and Sweden in 1998. Booth, Francesconi, and Frank, 2002a, and Booth, Francesconi, and Frank, 2002b, estimated a wage penalty of approximately 17% and 7% respectively for men, and 14% and 11% respectively for women holding temporary jobs in the UK. Hagen, 2002, considered workers in the Federal Republic of Germany and accounted for the possibility of selection bias using Heckman, 1976, dummy endogenous variable (DEV) model: results showed that temporary jobs paid wages approximately 26% lower than permanent ones.

Davia and Hernanz, 2004, investigated the wage differential in Spain, trying to find which workers' characteristics determine the gap. They replicated an Oaxaca-Blinder decomposition, accounting for selection into the labour force, using first the European Community Household Panel and then the Structure

of Earnings Survey. In both cases results showed that the gap was entirely explained by differences in workers' characteristics rather than differences in the rewards of those characteristics.

In Australia, Lass and Wooden, 2017, applied an unconditional quantile regression with fixed effects to analyse the wage gap over the entire wage distribution. They concluded that low paid fixed-term workers suffered a wage loss, while high-paid fixed-term workers benefited from a wage premium. Moreover, temporary agency workers usually received a wage premium.

Focusing our attention on the case of Italian workers, we find several works that contributed to the estimation of the temporary/permanent wage-gap. Picchio, 2006, estimated a Mincerian-type wage equation, augmented with a dummy variable accounting for temporary/permanent status of the worker, using the 2002 wave of the Survey of Italian Households' Income and Wealth. He controlled for endogeneity of the contract choice (using IV and Heckman's DEV model) and for the classical sample selection bias; results showed that temporary workers were consistently worse paid than permanent ones.

Rossetti and Tanda, 2007, used the European Community Household panel and considered the period 1995-2001. Results from both an OLS with fixed effect and an IV estimation showed that the negative wage differential was always present in the period under consideration. However, they noticed that the gap tended to reduce over time. They explained this result in the following way: the bargaining power of permanent workers (which was high at the beginning of the period, as shown by the larger wage gap) tended to reduce as fixed-term contracts began to spread.

Bosio, 2009, used the 2006 wave of the Survey of Italian Households' Income and Wealth and examined differences in the wage gap between temporary and permanent workers along the wage distribution, applying a quantile regression model. Then, he disentangled the endowments and coefficients effects in the explanation of wage differentials using an extension of the traditional Oaxaca-Blinder decomposition. Results showed evidence of a *sticky-floor effect*, i.e. a wider wage gap at the bottom of the distribution. Moreover, he detected the presence of a wider coefficients-effect in the left tail of the wage distribution and he interpreted it as a sort of discrimination in low-wage jobs for fixed term workers.

Santangelo, 2011, analysed several European countries, including Italy, using the 2007 wave of the EU-SILC. Her results, based on the quantile treatment effect method, highlighted that in the pooled sample of European countries the wage discrimination for temporary workers decreased over the wage distribution (from 13.4% in the 10th percentile to 7% in the 90th). In explaining this gap for Italy, she detected the presence of strong discrimination against temporary workers only in the left tail of the wage distribution.

Comi and Grasseni, 2012, focused on Italy and other eight European countries, using the 2006 wave of the EU-SILC. Results from a quantile regression show that the wage gap tends, in all the countries, to be wider at the bottom and narrower at the top of the distribution. Moreover, using the methodology by Machado and Mata, 2005,, they decomposed the wage gap and found evidence of a "discrimination effect" along the wage distribution in all the countries but

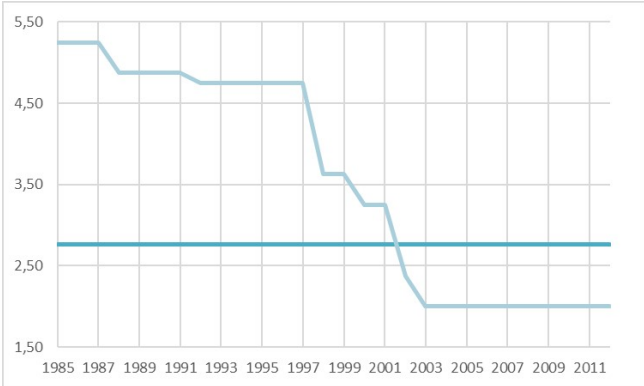

FIGURE 2.1: OECD indicators of employment protection in Italy. The darker line represents the strictness of the regulation on individual dismissals for permanent workers. The lighter line represents measures of strictness of regulation on the use of fixed-term contracts. *Source: OECD.stat*

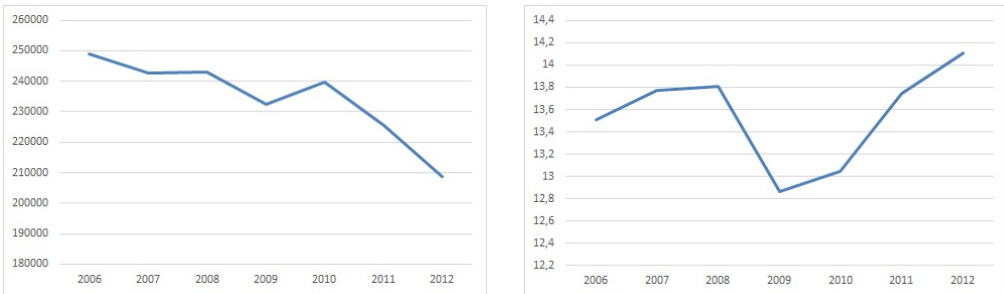

FIGURE 2.2: Permanent and temporary workers in Italy. Number of employed individuals in Italy between 2006 and 2012 (left), and share of temporary workers on the total number number of employees (right). *Source: LFS, own calculations*

more so in Italy and other countries where employment protection legislation is stronger.

2.3 Temporary employment in the Italian labour market

As shown by Figure2.1, in Italy the level of protection against individual dismissals of workers on open-ended contracts remained constant between 1985 and 2012. In the same period, a sequence of reforms of fixed-term contracts significantly loosened their regulation while introducing new typologies of atypical jobs.

Fixed-term contracts were introduced in Italy in 1962 by Law 230/62. For almost four decades they could only be used in a limited number of situations (e.g.: seasonal occupations, temporary replacement of workers in maternity or sick leave, etc.), which were referred to as *objective reasons* in the law. A fixed-term contract, moreover, could only be renewed once. Because of this strict

regulation, temporary jobs were not widespread in Italy: in 1996 temporary workers only accounted for 7.4% of the active population (Tompson, 2009).

The first major de-regulation of fixed-term contracts came in 1997 with Law 196/97, also known as the *Treu Law*. The main objective of the provision was to tackle the problem of the rising unemployment rate, especially in the Southern regions, by increasing labour market flexibility (Petrini, 1995). As a matter of fact, the unsatisfactory performance of the Italian labour market was then attributed to a level of employment protection considered to be excessive with respect to other European countries (Piazza and Myant, 2016).

One of the main provisions of the *Treu Law* was the introduction of temporary work agencies. It also eased the regulation of apprenticeships, work-training contracts, on-the-job training, and encouraged the use of part-time contracts. Moreover, sanctions against the violation of the fixed-term contracts discipline were reduced (Alberti, 2017). The reform, therefore, provided great incentives for firms to hire on a temporary basis.

In 2003, the Biagi Law narrowed once again the list of possible objective reasons for a fixed term job and limited the duration of temporary agency work. Nevertheless, it introduced new forms of atypical working arrangements, including project work: a fixed-term employment relation in which the employer and the employee work to achieve a common project. In the following years, it was often the case that these contracts served as disguised fixed-term jobs with lower social security contributions, no sick leave, and no unemployment benefits (Tiraboschi, 2005).

The consequence of these changes in the regulation is that in the first decade of the XIX century, the phenomenon of temporary employment became increasingly relevant in Italy. As shown by the left panel of Figure2.2, between 2006 and 2012, in the sample the absolute number of employed individuals decreased sharply because of the global financial crisis. In the same period, however, the share of temporary workers over the total number of employees was increasing (Figure2.2, right panel). The only reversal of this trend can be seen in 2008, when the first impact of the crisis led to massive lay-offs of precarious workers. However, after 2009 their share over the total number of employees resumed the previous trend and exceeded 14% in 2012.

2.4 Data and structure of the sample

The empirical analysis has been carried out using the 2012 wave of the European Union Survey on Income and Living Condition (SILC). EU-SILC is a rotational panel survey designed to provide information on economic and living conditions of private households and their members.

After restricting the analysis to households residing in Italy, the sample size is 40,287 individuals in the reference year. Out of these, 32,383 are in employment, 24,169 of which are wage employees. Among the group of employees, 3,983 describe themselves as temporary workers. We restricted our analysis to temporary and permanent employees, thus removing self-employed individuals. Furthermore, we limited the analysis to individuals aged between 16 and

65 and we ended up with of 17,867 observations. To perform a wage decomposition analysis, we need a variable assigning each observation to one of the groups that are object of the comparison. The variable grouping individuals refers to the type of contract and is T_i, a dummy equal to 0 if the individual has an open-ended contract, and equal to 1 if he or she has a temporary contract. More precisely, the interviewer required to indicate whether the main job of the respondent had a limited or unlimited duration. In the sample, we have 14,721 permanent and 3,148 temporary workers.

The dependent variable, W_i, is a measure of the hourly wage, constructed using the information provided by EU-SILC on monthly earnings and the number of hours usually worked per week. The variable "gross monthly earnings" (Y_i) refers to earnings deriving from an employee's main job before tax and social insurance contribution are deducted. It includes usual paid overtime, but excludes income from investments-assets, savings, stocks and shares. Supplementary payments (13th or 14th month payments and the like) are accounted for on a monthly basis. The number of hours usually worked per week (H_i) refers only to the main job and includes all extra hours (paid or unpaid) which the person normally works. The dependent variable is thus constructed as follows:

$$W_i = \ln \frac{Y_i}{H_i \times 4} \tag{2.1}$$

Figure2.3 shows the kernel density estimates of W_i for temporary and permanent workers. Descriptive statistics referring to the covariates are summarised in Table2.1 and Table2.2.

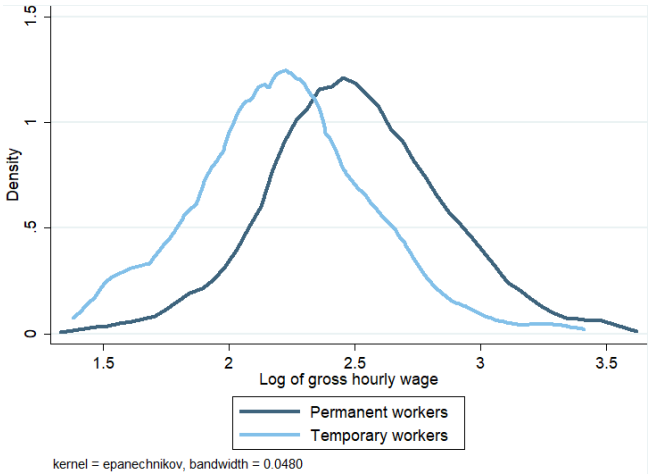

FIGURE 2.3: Kernel densities of log hourly wage.
Kernel densities of log of hourly wage for permanent workers (dark blue) and temporary workers (light blue). *Source: EU-SILC, own calculations.*

	Whole Sample	T_0	T_1	**Difference**
Hourly wage	12. 863	13.289	9.620	3.669***
Sex: Male	0.500	0.518	0.412	0.106***
Age	45.145	46.638	38.158	8.480***
Labour market experience	19.977	21.777	11.557	10.219***
Region: North West	0.251	0.269	0.168	0.100***
Region: North East	0.251	0.257	0.222	0.035***
Region: Centre	0.249	0.253	0.231	0.022***
Region: South	0.249	0.221	0.378	-0.157***
Citizenship: Italian	0.946	0.951	0.922	0.029***
Citizenship: European	0.019	0.017	0.026	-0.009***
Citizenship: Extra EU	0.035	0.032	0.051	-0.019***
Educ.: Low	0.352	0.344	0.388	-0.044***
Educ.: Medium	0.484	0.488	0.464	0.024**
Educ.: High	0.164	0.168	0.149	0.019***
Number of observations:	17867	14721	3146	

TABLE 2.1: Individual-level covariates.
Shares and averages of individual covariates in the whole sample and in each group defined by Ti. In the last column the difference between the last categories and its significance (*=10%, **=5%, ***=1%). *Source: EU-SILC, own calculations.*

2.5 Methodologies

2.5.1 Selectivity-corrected Oaxaca Blinder decomposition

The first step of our analysis consists in a decomposition of the mean earnings distribution, applying an extension of the traditional Oaxaca-Blinder (Oaxaca, 1973, Blinder, 1973) decomposition method, generalised by Oaxaca and Ransom (Oaxaca and Ransom, 1994, and Oaxaca and Ransom, 1999).[1] This procedure divides the wage differential between two groups into a part that is explained by group differences (i.e. by the different characteristics of the individuals belonging to each group, such as level of education or age) and an unexplained part that is often used as a measure of discrimination but, more properly, measures whether the same individual characteristics are rewarded in a different way in the two groups.

The decomposition method is based on the estimation of two wage equations, one for each group. However, in presence of sample selection, OLS estimation of wage equations can yield biased and inconsistent estimators. Since wages are only observed for people who are participating in the labour force, a selection problem may arise. For this reason, it is common in labour research to include in the wage equation a correction for sample selection bias, based on the procedure by Heckman, 1979, and Heckman, 1976. The consequences of combining Oaxaca-Blinder decomposition and Heckman sample selection correction are illustrated by Neuman and Oaxaca, 2004.

Let the following equations identify the employment and wage functions of an individual i belonging to group j:

[1]The STATA package *oaxaca* has been used for this estimation.

	Whole Sample	T_0	T_1	Difference
Occup.: High skills	0.353	0.172	0.131	0.041***
Occup.: Medium skills	0.483	0.492	0.442	0.050***
Occup.: Low skills	0.353	0.337	0.428	-0.091***
Sector: Manufacturing	0.249	0.255	0.203	0.052***
Sector: Construction	0.054	0.051	0.073	-0.22***
Sector: Trade	0.131	0.125	0.178	-0.053***
Sector: Hospitality	0.053	0.055	0.038	0.018***
Sector: IT	0.027	0.028	0.018	0.010***
Sector: Financial serv.	0.044	0.048	0.013	0.035***
Sector: Professional act.	0.088	0.083	0.128	-0.046***
Sector: P.A., defence	0.098	0.104	0.055	0.049***
Sector: Education	0.100	0.096	0.125	-0.029***
Sector: Health services	0.097	0.101	0.074	0.027***
Sector: Other	0.059	0.054	0.094	-0.040***
Firm size: Very large	0.386	0.404	0.250	0.154***
Firm size: Large	0.194	0.193	0.195	-0.002
Firm size: Medium	0.140	0.137	0.160	-0.023***
Firm size: Small	0.281	0.266	0.396	-0.130
Supervisory position: yes	0.189	0.217	0.059	0.158***
Number of observations:	17867	14721	3146	

TABLE 2.2: Job-level covariates.
Shares and averages of job-level covariates in the whole sample and in each group defined by Ti. In the last column the difference between the last categories and its significance (*=10%, **=5%, ***=1%). *Source: EU-SILC, own calculations.*

$$Z^*_{ij} = Y'_{ij}\gamma_j + \epsilon_{ij} \tag{2.2}$$

$$W_{ij} = X'_{ij}\beta_j + u_{ij} \tag{2.3}$$

Z^*_{ij} the latent variable associated with employment status; Y'_{ij} is a vector containing variables that determine the employment status; W_{ij} is the log of the hourly wage as defined in the previous section; X'_{ij} is a vector of determinants of wages; γ_j and β_j are the vectors of parameters; ϵ_{ij} and u_{ij} are i.i.d. and follow a bivariate normal distribution $(0,0,\sigma_{j\epsilon},\sigma_{ju},\rho_j)$. The probability that an individual i is employed is:

$$Prob\left(Z^*_{ij} > 0\right) = Prob\left(\epsilon_{ij} > -Y'_{ij}\right) = \Phi\left(Y'_{ij}\right) \tag{2.4}$$

With $\Phi(.)$ indicating the standard normal cumulative distribution function when the variance of ϵ_{ij} is normalised to 1. Only those with $Z^*_{ij} > 0$ are in employment, hence only for them we observe a wage:

$$\begin{aligned} \mathbb{E}\left(W_{ij} \,\middle|\, Z^*_{ij} > 0\right) &= X'_{ij}\,\beta_j + E\left(u_{ij} \,\middle|\, \epsilon_{ij} > -Y'_{ij}\gamma_j\right) \\ &= X'_{ij}\beta_j + \theta_j\lambda_{ij} \end{aligned} \tag{2.5}$$

In the last term, $\theta_j = \rho_j\sigma_{ju}$ and $\lambda_{ij} = \frac{\phi\left(Y'_{ij}\gamma_j\right)}{\Phi\left(Y'_{ij}\gamma_j\right)}$, with $\phi(.)$ representing the

standard normal probability density function. Therefore, the wage equation can be estimated as:

$$\left(W_{ij} \,\middle|\, Z^*_{ij} > 0 \right) = X'_{ij}\beta_j + \theta_j \lambda_{ij} + error \tag{2.6}$$

Moving on to the estimation of the wage discrimination between temporary and permanent employees, we can begin by adopting the wage structure of permanent workers as the non-discriminatory one. The Heckman procedure estimates the parameters in the last equation separately for each group and the Oaxaca-Blinder decomposition corrected for sample selection bias can be expressed as:

$$\bar{W}_p - \bar{W}_t = \left(\bar{X}_p - \bar{X}_t\right)' \widehat{\beta_p} + \bar{X}'_t \left(\widehat{\beta_p} - \widehat{\beta}_t\right) + \left(\widehat{\theta_p}\widehat{\lambda_p} - \widehat{\theta}_t \widehat{\lambda}_t\right) \tag{2.7}$$

Where $\bar{W}$ is the predicted mean log wage, $\bar{X}$ is the mean vector of covariates determining wage, $\hat{\beta}$ is the vector of estimated coefficients, $\hat{\theta}$ is an estimate of $\rho\sigma_u$ and $\hat{\lambda}$ is an estimate of the mean Inverse Mill's Ratio (IMR); the subscripts p and t indicate the group of permanent workers and the group of temporary workers respectively. The last equation can be divided in three parts:

$$G = E + C + S \tag{2.8}$$

Where $G \equiv \bar{W}_p - \bar{W}_t$ represents the mean outcome difference expressed as the differences in the linear prediction at the group specific means of the regressors. The first summand:

$$E \equiv \left(\bar{X}_p - \bar{X}_t\right)' \widehat{\beta_p} \tag{2.9}$$

expresses the part of the differential G that is due to group differences in the predictors. This is usually defined the endowments effect. The second component:

$$C \equiv \bar{X}'_t \left(\widehat{\beta_p} - \widehat{\beta}_t\right) \tag{2.10}$$

measures the contribution of differences in the coefficients (including the intercept). This coefficients effect is usually interpreted as the differences in the reward of personal characteristics in each group. Finally:

$$S \equiv \widehat{\theta_p}\widehat{\lambda_p} - \widehat{\theta}_t \widehat{\lambda}_t \tag{2.11}$$

expresses the selectivity bias correction. The most straightforward way to account for this term in the decomposition is to deduct it from the overall differential and then apply the standard decomposition formulas to the adjusted differential:

$$G - S = E + C \tag{2.12}$$

In this way, on the right-hand side we are left with the familiar Oaxaca-Blinder decomposition term and on the left-hand side we have the selectivity corrected wage differential. This approach has been followed in the seminal

works by Duncan and Leigh, 1980, and Reimers, 1983, and suggested by Jann, 2008. In this specification of the Oaxaca-Blinder decomposition we have assumed that the non-discriminatory wage structure is the one associated with permanent workers. The implication is that the wages of permanent workers are taken as correctly related to their productivity. The assumption is strong but reasonable, given that we find that the wage gap is in favour of permanent workers. Moreover, this assumption is the standard one in the literature. However, to make sure that our results are robust to different specifications of the model, we replicate the same decomposition using the coefficients associated to the pooled sample as non-discriminatory wage structure. The model thus becomes:

$$\bar{W}_p - \bar{W}_t = \left(\bar{X}_p - \bar{X}_t\right)' \widehat{\beta_q} + \bar{X}_p' \left(\widehat{\beta_p} - \widehat{\beta_q}\right) + \bar{X}_t' \left(\widehat{\beta_t} - \widehat{\beta_q}\right) \tag{2.13}$$

Where $\widehat{\beta_q}$ represents the vector of coefficients associated to the pooled regression.

2.5.2 Quantile counterfactual decomposition

The Oaxaca-Blinder decomposition has been extensively used in the past to disentangle endowments and coefficients effects in presence of a wage gap. However, its main limitation is that it compares average wages and does not account for wage differences across the wage distribution. In order to analyse the wage gap between temporary and permanent workers across the wage distribution we can resort to quantile counterfactual decomposition methods. The technique applied in this paper has been proposed by Machado and Mata, 2005, and extended by Chernozhukov, Fernández-Val, and Melly, 2013.[2] In this framework, earnings at a certain quantile are decomposed for individuals in the two groups who share the same characteristics (Sohn, 2015).

Consider the following conditional distribution functions:

$$F_{W_t|X_t}(W|\ X);\ F_{W_p|X_p}(W|\ X) \tag{2.14}$$

Describing the stochastic assignment of wages W to workers with characteristics X, respectively for temporary and permanent workers. Let $F_{W(p|\ p)}$ and $F_{W(t|\ t)}$ represent the observed distribution functions of wages for permanent and temporary workers, and $F_{W(t|\ p)}$ the counterfactual distribution function of wages received by temporary workers, had they faced the wage schedule of permanent ones:

$$F_{W(t|\ p)} = \int_{\chi_p} F_{W_t|X_t}(W|\ X)\, dF_{X_p}(x) \tag{2.15}$$

This distribution does not arise from the observed data, but it is derived by integrating the conditional distribution of wages for temporary workers with respect to the distribution of characteristics of permanent workers; χ_p represents the support of permanent worker's characteristics. In this case permanent workers are called *reference group*, and temporary workers *counterfactual*

[2]The STATA package *cdeco* has been used for this estimation.

group. The difference in observed wage distributions between permanent and temporary workers can be decomposed in the following way:

$$F_{W(p|p)} - F_{W(t|t)} = (F_{W(p|p)} - F_{W(t|p)}) - (F_{W(t|p)} - F_{W(t|t)}) \tag{2.16}$$

This decomposition can be interpreted analogously to the Oaxaca-Blinder one in the following way. On the right-hand side of the equation, the first term in brackets represents the difference due to the wage structure (the *coefficient effect*, in the Oaxaca-Blinder framework) and the second term represents the difference due to different characteristics (the *endowment effect*, in the Oaxaca-Blinder framework).

2.6 Results

We began by using a probit model to estimate the probability of being a temporary or permanent wage earner. This enables us to calculate the Inverse Mill's Ratios, $\hat{\lambda}_p$ and $\hat{\lambda}_t$, needed to estimate the selectivity-corrected Oaxaca-Blinder decomposition. The results of this probit model are reported in Table2.3 and indicate that being a man, being older, being Italian, and having university-level education all increase the probability of being in employment. On the contrary, coming from the South or from rural areas, being unemployed in the previous year and having a chronic medical condition all decrease the chance of being an employee. For women, being married or in a long-term relationship are also found to be negatively related to the chances of being an employee. For women, being married or in a long-term relationship are also found to be negatively related to the chances of being in employment. Other variables, such as having sources of income other than the labour market (from rental of properties or capital investments), are not significant predictors of our dependent variable.

Table2.4 shows the results of a linear regression on hourly wage. We enter the covariates in the Oaxaca-Blinder decomposition and use them as conditioning set in the conditional quantile decomposition. Individual level variables include sex and age (and their squares). We also include three possible citizenships: Italian, other European, non-European. A variable for area of residence is included with the following categories: north-west, north-east, centre and south.[3] The educational variable divides workers into three groups: those with primary or lower secondary education, those with upper secondary education, and those with tertiary or post-tertiary education. Occupation is divided into three bands: high-skill, medium-skill and low-skill.[4] A dummy for managerial or supervisory role is included. We also include the size of the firm where the

[3]North-west: Valle d'Aosta, Piemonte, Lombardia, Liguria. North-east: Autonomous Province of Trento, Autonomous Province of Bolzano, Veneto, Friuli-Venezia Giulia, Emilia-Romagna. Centre: Toscana, Umbria, Marche, Lazio, Abruzzo. South and islands: Molise, Puglia, Basilicata, Campania, Calabria, Sicilia, Sardegna.

[4]High-skill occupations: managers and professionals. Medium-skill occupations: technicians, clerks, services and sales. Low-skill occupations: plant and machine operators, elementary occupations.

	Coefficient	(S.E.)
Sex: male	0.186***	(0.042)
Age	0.334***	(0.007)
Age^2	-0.004***	(0.000)
Region (reference: North-West)		
North-East	0.093**	(0.034)
Centre	0.042	(0.034)
South	-0.142***	(0.034)
Degree of urbanisation (reference: City)		
Town	-0.038	(0.027)
Rural area	-0.125***	(0.033)
In a consensual union	0.099**	(0.016)
Female and in a consensual union	-0.690***	(0.052)
Citizenship (reference: EU country other than Italy)		
Italy	0.269**	(0.085)
Non-EU	0.062	(0.104)
Level of education (reference: primary and lower secondary)		
Upper secondary	0.450***	(0.027)
Tertiary	0.778***	(0.039)
Months of unemployment in the previous year	-0.196***	(0.004)
Has a chronic condition	-0.191***	(0.031)
Rental income	0.000	(0.000)
Financial income	0.000	(0.000)
Number of observations:	17,867	
LR χ^2 (18):	8030.23	
Pseudo R^2:	0.3642	

TABLE 2.3: Probit estimation for the probability of being a wage employee.
Results have been used to calculate the Inverse Mill's Ratios. $***p < 0.01, **p < 0.05, *p < 0.1$ *Source: EU-SILC, own calculations.*

worker is employed: very small (less than 10 employees), small (11-19 employees), medium (20-49 employees), large (more than 50 employees). Finally, a variable accounting for years of experience in the labour market is included, together with its square.[5]

Table2.5 reports the results of the Oaxaca Blinder decompositions on the sample containing all workers employed in Italy. Unadjusted results are in the upper panel, those corrected for sample selection in the lower panel. The rows *Group 1* and *Group 2* report the estimated W_{ij}. The row *Difference* indicates the mean outcome difference $G \equiv \bar{W}_p - \bar{W}_t$ in the unadjusted case, and the selectivity corrected mean outcome difference $G - S$ in the adjusted case. The

[5]This set of variables is different from the set used in the probit equation (see Table 2). In particular, we excluded: being married or in a relationship, unemployed status in previous year, chronic medical condition and sources of income different from job. With respect to the probit equation, we added: type of occupation, economic sector, size of firm, managerial position and labour market experience. We therefore meet the exclusion restriction needed for identification of the model in the Oaxaca-Blinder framework

	Coefficient	**(S.E.)**
Sex: male	0.1103***	(0.0062)
Age	0.0113***	(0.0031)
Age^2	-0.0001**	(0.000)
Region (reference: North-West)		
North-East	0.0007	(0.0081)
Centre	-0.0624***	(0.0081)
South	-0.1467***	(0.0087)
Citizenship (reference: EU country other than Italy)		
Italy	0.1043***	(0.0214)
Non-EU	0.0025	(0.0258)
Level of education (reference: tertiary)		
Upper secondary	-0.1545***	(.0086)
Primary or lower secondary	-0.2586***	(0.0109)
Occupation (reference: high-skilled)		
Medium-skilled	-0.1508***	(0.0087)
Low-skilled	-0.2664***	(0.0107)
Firm size (reference: very small)		
Small	0.0686***	(0.0096)
Medium	0.1033***	(0.0088)
Large	0.1519***	(0.0076)
Supervisory role	0.1468***	(0.0076)
Experience	0.0164***	(0.0016)
$Experience^2$	-0.0002***	(0.000)
Temporary contract	-0.1468***	(0.0097)
Number of observations:	11,493	
F(19, 11,473):	437.74	
Adjusted R^2:	0.4193	

TABLE 2.4: OLS wage equation.
Linear regression of our covariates on hourly wage for workers in our sample. $***p < 0.01, **p < 0.05, *p < 0.1$ *Source: EU-SILC, own calculations*.

rows *Explained* and *Unexplained* give the part of that difference due to the *endowments effect (E)* and the *coefficients effect (C)*. The first column of the table reports the results obtained when the wage structure of permanent workers is taken as reference, whereas the second column indicates the results obtained from the pooled regression.

The selectivity-corrected decomposition reported in the lower panel of Table 3 estimates a large and statistically significant wage gap, amounting to a 0.3717 difference between the log of the wage of a permanent and the log of the wage of a temporary workers. In other terms, a temporary worker's average wage is 31% lower than the average permanent worker's wage. The result is consistent with that obtained when the pooled sample is taken as reference group. From the average contribution of endowment and coefficient effects, 17% and 20% respectively, we conclude that observable differences between temporary and permanent workers explain less than half the wage-gap. The presence of a large average wage penalty for temporary workers is consistent with the findings of previous studies on the Italian labour market (for instance: Picchio,

	OB decomposition Permanent = reference	OB decomposition Pooled = reference
Overall		
Group 1 (Permanent)	2.4819*** (0.0049)	2.4819*** (0.0049)
Group 2 (Temporary)	2.1781*** (0.0137)	2.1781*** (0.0137)
Difference	0.3038*** (0.0145)	0.3038*** (0.0145)
Adjusted		
Group 1 (Permanent)	2.5000*** (0.0069)	2.5000*** (0.0069)
Group 2 (Temporary)	2.1282*** (0.0347)	2.1282*** (0.0347)
Difference	0.3717*** (0.0354)	0.3717*** (0.0354)
Explained	0.1727*** (0.0102)	0.1683*** (0.0099)
Unexplained	0.1989*** (0.0349)	0.2035*** (0.0348)
N. of obs.	17,867	

TABLE 2.5: OB decomposition in the whole sample. Oaxaca-Blinder decompositions of wage differentials in the whole sample. Permanent workers used as reference in the left column and pooled sample used as reference in the right column. Standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1. *Source: EU-SILC, own calculations.*

2006, and Rossetti and Tanda, 2007).Moreover, our result that a considerable part of the wage-gap can be attributed to different rewards for similar worker characteristics is consistent, for example, with Santangelo, 2011, and Comi and Grasseni, 2012.

We proceed by applying the same method to sub-groups of workers, to investigate whether the wage-gap is wider or narrower for specific profiles of workers. We begin with male workers (Table2.6, left panel). The adjusted decomposition for this group shows a significantly larger wage difference than that calculated for the whole sample: 39%. Only 20% of this gap can be attributed to different worker characteristics. Consequently, 30% of the gap can be interpreted as a wage premium granted to permanent employees based solely on their contract.

Unlike the result obtained for male workers, the wage difference between female temporary and permanent workers is smaller than that calculated on the whole sample. It amounts to approximately 21.8% (Table2.6, right panel) and is explained by an almost even composition of endowments and coefficients effects (13.3% and 11.3% respectively).

Table2.7 shows the results of adjusted decomposition on workers under and over 30 years. The average wage gap is significant in both groups; however, it is considerably larger for younger workers (31.9% vs 26.2%). Moreover, the gap appears to be explained by completely different factors. The wage differential between older temporary and permanent workers is almost evenly decomposed between the explained and unexplained component, in similar proportions to those found in the whole sample (Table2.5). On the contrary, the wage penalty

	OB decomposition Men	OB decomposition Women
Overall		
Group 1 (Permanent)	2.5145*** (0.0063)	2.4393*** (0.0076)
Group 2 (Temporary)	2.1635*** (0.0175)	2.1925*** (0.0205)
Difference	0.3510*** (0.0187)	0.2468*** (0.0218)
Adjusted		
Group 1 (Permanent)	2.5383*** (0.0107)	2.4510*** (0.0010)
Group 2 (Temporary)	2.0372*** (0.0449)	2.2050*** (0.0588)
Difference	0.5012*** (0.0461)	0.2459*** (0.0596)
Explained	0.1957*** (0.0133)	0.1331*** 0.0159
Unexplained	0.3054*** (0.0457)	0.1128* (0.0590)
N. of obs.	8,926	8,941

TABLE 2.6: OB decomposition by gender.
Oaxaca-Blinder decompositions of wage differentials by gender: men are on the left panel and women on the right one. Standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1. *Source: EU-SILC, own calculations*.

suffered by younger temporary workers is almost entirely explained by differences in reward of their characteristics (35%).

The last two sub-groups of the population considered were: workers coming from the European Union and non-European workers. Table2.8 shows the decompositions for these two categories. On the left side we find Italian and European workers, whose decomposition results are similar to those obtained for the whole sample. Conversely, the wage-gap between temporary and permanent non-European workers is considerably smaller (19.4%) but appears to be entirely explained by differences in coefficients. In this case, the role of endowment differences is not statistically significant.

To sum up, the results of the selectivity-corrected Oaxaca-Blinder decomposition suggest that in the whole sample and all the sub-groups of workers considered, temporary workers suffer a wage penalty with respect to permanent workers. The largest temporary wage-gap in relative terms is that associated with temporary and permanent male workers. The unexplained proportion of this gap, namely the proportion coming from differences in rewards for similar characteristics, varies in different subgroups. In fact, almost the entire temporary wage-gap associated with younger and non-European workers can be attributed to the unexplained component.

Further insights come from the results of the conditional quantile decompositions. Table2.9 reports the results on the whole sample. These results are calculated at different deciles of the wage distributions, excluding the first and the last because the standard asymptotic does not apply to the extreme tails of

	OB decomposition Age ≤ 30	OB decomposition Age > 30
Overall		
Group 1 (Permanent)	2.2478*** (0.0134)	2.5047*** (0.0051)
Group 2 (Temporary)	2.0745*** (0.020)	2.2340*** (0.0168)
Difference	0.1732*** (0.0258)	0.2707*** (0.0176)
Adjusted		
Group 1 (Permanent)	2.2828*** (0.0318)	2.5274*** (0.0075)
Group 2 (Temporary)	1.8984*** (0.0902)	2.2238*** (0.0356)
Difference	0.3844*** (0.0957)	0.3037*** (0.0364)
Explained	0.0342** (0.0160)	0.1401*** (0.0118)
Unexplained	0.3503*** (0. 0946)	0.1635*** (0.0355)
N. of obs.	2,172	15,695

TABLE 2.7: OB decomposition by age.
Oaxaca-Blinder decompositions of wage differentials by age: workers younger than 30 are on the left panel and workers older than 30 on the right one. Standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1. *Source: EU-SILC, own calculations*.

the distribution. The temporary wage penalty is approximately 31% for workers in the lowest decile of the wage distribution. However, the temporary wage-gap decreases rapidly along the distribution and maintains a value between 26 and 27% up to the last decile. These results are best viewed graphically in Figure2.4. The unexplained component follows a similar pattern to that of the whole wage-gap: wider near the left tail, it reaches its minimum around the 4th decile and remains steady afterwards. In line with this result, the role of endowments becomes relatively more relevant as we move to the right of the plot and explains approximately two thirds of the wage-gap in the highest deciles.

Bootstrap inference on the conditional quantile decomposition is reported in Table2.10. The results indicate that we can reject the null hypothesis of "no difference between observed distributions" (the wage distributions for permanent and temporary workers). Thus we can confidently state that the wage-gap is significant in every decile of the wage distribution. We also reject the null hypothesis of "no effect of characteristics" and "no effect of coefficients". We can therefore say that the wage-gap is the result of both components.

Table2.11 reports the conditional quantile decomposition calculated on male workers only. The decomposition of the gap along the wage distribution shows a U-shaped pattern: the largest penalty is suffered by male workers at the tails of the wage distribution (Figure2.5, left panel). Another observation is that the temporary wage-gap associated with men varies not only in size across the distribution, but also in composition. Low-wage workers are associated with a larger unexplained component. On the contrary, the temporary wage gap on the right side of the wage distribution appears to be mostly generated by differences in endowments. After the 5th decile, the temporary wage-gap and the endowment effect both increase monotonically: at higher wages, the differences

	OB decomposition IT/EU	OB decomposition Non EU
Overall		
Group 1 (Permanent)	2.499*** (0.0049)	2.2205*** (0.0214)
Group 2 (Temporary)	2.1819*** (0.0142)	2.1417*** (0.0431)
Difference	0.3175*** (0.0151)	0.0788 (0.0481)
Adjusted		
Group 1 (Permanent)	2.5166*** (0.0071)	2.2569*** (0.0404)
Group 2 (Temporary)	2.1316*** (0.0374)	2.0401*** (0.0946)
Difference	0.3850*** (0.0381)	0.2167** (0.1029)
Explained	0.1817*** (0.0106)	-0.0086 (0.0364)
Unexplained	0.2032*** (0.0375)	0.2254** (0.1051)
N. of obs.	17,222	632

TABLE 2.8: OB decomposition by citizenship.
Oaxaca-Blinder decompositions of wage differentials by citizenship: Italian and EU workers are on the left panel and non-EU workers on the right one. Standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1. *Source: EU-SILC, own calculations.*

between temporary and permanent workers play a larger role in explaining the wage-gap than at the other tail of the distribution.

Female temporary workers receive a 28.6% lower wage at the left tail of the wage distribution and a 20.5% lower wage at the right tail (Table2.12). This differential decreases monotonically along the wage distribution (Figure2.5, right panel), showing that low-earning women are those most affected by the wage penalty associated with temporary employment. The unexplained component is also wider at the bottom of the distribution and rapidly decreases until, at the right tail of the wage distribution, the difference in wages is explained mostly by differences in observable characteristics. The results from the whole population and the separate analyses of men and women therefore suggest that differences in the reward of labour market characteristics generate a large wage-gap between low-paid temporary and permanent workers.

At the left tail of the wage distribution, a temporary worker under 30 years earns on average 22.7% less than a permanent worker in the same wage bracket (Table2.13). The temporary wage-gap is only 0.07% at the top deciles. For this subgroup of the population, the temporary wage-gap appears to decrease monotonically along the wage distribution (Figure2.6, left panel). As we saw from the results of the adjusted average decomposition, most of this wage-gap can be attributed to the coefficient effect.

Temporary workers without European citizenship earn 17.3% less than their permanent counterparts in the lowest decile of the wage distribution (Table2.14 and Figure2.6, right panel). This figure reaches 0.07%, its lowest value, in the 7th decile. The wage penalty suffered by non-European temporary workers is due solely to the unexplained component of the wage gap.

Quantile	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 7$	$\tau = 8$	$\tau = 9$
Total effect:	0.3717	0.3267	0.3075	0.3038	0.3035	0.3062	0.3099	0.3145	0.3203
	(0.021)	(0.016)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.019)
Endowment effect:	0.1828	0.1837	0.1829	0.1833	0.1831	0.1848	0.1879	0.1911	0.1979
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Coefficients effect:	0.1889	0.1429	0.1246	0.1205	0.1204	0.1219	0.1214	0.1233	0.1223
	(0.020)	(0.015)	(0.013)	(0.011)	(0.011)	(0.011)	(0.010)	(0.012)	(0.017)

Number of observations in the reference group: 10,149
Number of observations in the counterfactual group: 1,344

TABLE 2.9: CQ decomposition in the whole sample. Counterfactual quantile decomposition of wage differentials in the whole sample. Pointwise standard errors in parenthesis. *Source: EU-SILC, own calculations.*

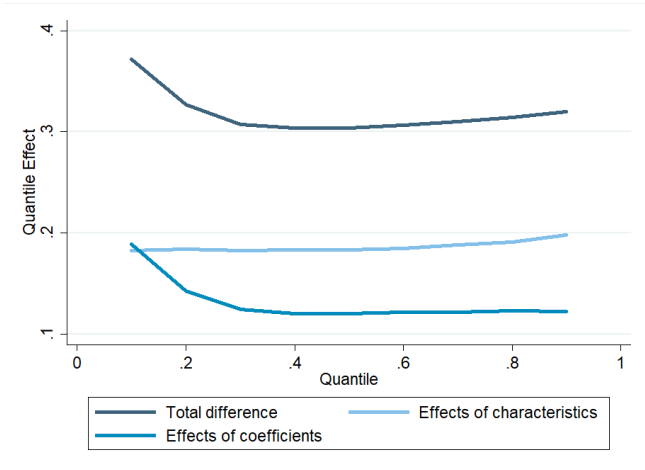

FIGURE 2.4: CQ decomposition in the whole sample. Counterfactual quantile decomposition of wage differential in the whole sample. *Source: EU-SILC, own calculations*.

2.7 Discussion

The results reported in the previous sections afford three major conclusions. First, in the whole sample and all subgroups of the population, and over the whole wage distribution, the difference between the wages of permanent and temporary workers is always positive. This means that all types of temporary workers suffer a wage penalty regardless of their level of earnings. Second, the temporary wage-gap is wider at the left tail of the wage distribution for all subgroups of the population. Third, the unexplained component of the wage-gap, which derives from different rewards for similar characteristics, is always significant in explaining the wage difference between permanent and temporary employees.

The first explanation for the temporary wage penalty comes from our results which show that the temporary wage-gap for the whole population and in most subgroups is characterised by a significant composition effect. This means that permanent and temporary workers are often different in observable ways and this contributes to wage differences. For instance, according to Table2.1,

Null Hypothesis	p-values KS Statistic	CMS Statistic
Correct specification of the parametric model 0	0.7	0.7
Correct specification of the parametric model 0	0.3	0.7
No difference between the distributions: QE(tau)=0	0	0
No effect of characteristics: QE(tau)=0	0	0
No effect of coefficients: QE(tau)=0	0	0

TABLE 2.10: Bootstrap inference on CQ process.
Source: EU-SILC, own calculations.

Quantile	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 7$	$\tau = 8$	$\tau = 9$
Total effect:	0.3944	0.3487	0.3346	0.3316	0.3347	0.3435	0.3574	0.3782	0.4008
	(0.026)	(0.016)	(0.010)	(0.014)	(0.016)	(0.015)	(0.012)	(0.010)	(0.017)
Endowment effect:	0.1805	0.1849	0.1882	0.1906	0.1968	0.2051	0.2165	0.2302	0.2506
	(0.015)	(0.013)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)	(0.014)
Coefficients effect:	0.2138	0.1638	0.1464	0.1410	0.1378	0.1383	0.1409	0.1479	0.1501
	(0.033)	(0.021)	(0.014)	(0.012)	(0.016)	(0.017)	(0.015)	(0.014)	(0.023)

Number of observations in the reference group: 5,589
Number of observations in the counterfactual group: 648

TABLE 2.11: CQ decomposition for men.
Counterfactual quantile decomposition of wage differentials for women. Pointwise standard errors in parenthesis. *Source: EU-SILC, own calculations.*

among temporary workers there are relatively more workers employed in low-skill occupations, younger workers, and workers hired by smaller firms, three characteristics that are often associated with lower wages (as shown by the results reported by Table2.5).

Nevertheless, the role of the unexplained component of the wage-gap is significant in all subgroups of the populations. This means that there is a wage premium granted to permanent workers based solely on their contract, regardless of the observable characteristics we considered. In the literature we can find several reasons why temporary workers may receive wages lower than those of permanent workers.

Rebitzer and Taylor, 1991, have shown that in a dual labour market where jobs are difficult to monitor and demand is uncertain, firms choose to hire a mix of permanent and temporary workers and pay the former a higher wage, even when the two groups are perfect substitutes in production. The authors' hypothesis of demand uncertainty is particularly fitting, since the present analysis is based on data from 2012, when the Italian economy was still suffering under the global financial crisis. The effect reported by Rebitzer and Taylor, 1991, has been partially confirmed by Daniel and Sofer, 1998,whose results show a positive relationship between good working conditions and wages (i.e. higher wages for permanent workers) when workers are highly unionised. As a matter of fact, despite the difficulties faced by trade unions all over the world

Quantile	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 7$	$\tau = 8$	$\tau = 9$
Total effect:	0.3371	0.2971	0.2768	0.2702	0.2663	0.2633	0.2528	0.2473	0.2303
	(0.020)	(0.017)	(0.017)	(0.015)	(0.018)	(0.017)	(0.016)	(0.018)	(0.018)
Endowment effect:	0.1760	0.1739	0.1707	0.1679	0.1634	0.1577	0.1514	0.1427	0.1330
	(0.017)	(0.015)	(0.012)	(0.011)	(0.009)	(0.009)	(0.010)	(0.012)	(0.015)
Coefficients effect:	0.1612	0.1233	0.1062	0.1028	0.1030	0.1056	0.1015	0.1047	0.0973
	(0.028)	(0.022)	(0.017)	(0.014)	(0.016)	(0.015)	(0.011)	(0.011)	(0.013)

Number of observations in the reference group: 4,560
Number of observations in the counterfactual group: 696

TABLE 2.12: CQ decomposition for women. Counterfactual quantile decomposition of wage differentials for women. Pointwise standard errors in parenthesis.*Source: EU-SILC, own calculations.*

Quantile	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 7$	$\tau = 8$	$\tau = 9$
Total effect:	0.2584	0.1992	0.1687	0.1517	0.1383	0.1278	0.1171	0.1014	0.079
	(0.032)	(0.023)	(0.014)	(0.009)	(0.012)	(0.013)	(0.018)	(0.024)	(0.034)
Endowment effect:	0.0469	0.0424	0.0351	0.0257	0.0192	0.0194	0.0176	0.0188	0.0284
	(0.023)	(0.021)	(0.019)	(0.015)	(0.016)	(0.016)	(0.017)	(0.017)	(0.018)
Coefficients effect:	0.2115	0.1569	0.1337	0.1259	0.1191	0.1084	0.0994	0.0825	0.0515
	(0.046)	(0.031)	(0.022)	(0.014)	(0.012)	(0.012)	(0.014)	(0.014)	(0.021)

Number of observations in the reference group: 825
Number of observations in the counterfactual group: 476

TABLE 2.13: CQ decomposition for younger workers. Counterfactual quantile decomposition of wage differentials for workers aged less than 30. Pointwise standard errors in parenthesis. *Source: EU-SILC, own calculations.*

Quantile	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 7$	$\tau = 8$	$\tau = 9$
Total effect:	0.1894	0.1179	0.0988	0.1079	0.1123	0.0721	0.0723	0.0774	0.1182
	(0.096)	(0.079)	(0.065)	(0.046)	(0.049)	(0.059)	(0.040)	(0.046)	(0.083)
Endowment effect:	-0.0056	-0.0198	-0.0104	-0.0082	-0.0123	-0.0058	-0.0091	-0.0122	-0.0173
	(0.048)	(0.041)	(0.039)	(0.012)	(0.032)	(0.031)	(0.031)	(0.031)	(0.036)
Coefficients effect:	0.1950	0.1378	0.1091	0.1161	0.1246	0.0779	0.0814	0.0896	0.1355
	(0.104)	(0.083)	(0.071)	(0.054)	(0.053)	(0.064)	(0.047)	(0.054)	(0.084)

Number of observations in the reference group: 344
Number of observations in the counterfactual group: 74

TABLE 2.14: CQ decomposition for non-European workers. Counterfactual quantile decomposition of wage differentials for workers who are not citizens of the EU. Pointwise standard errors in parenthesis. *Source: EU-SILC, own calculations.*

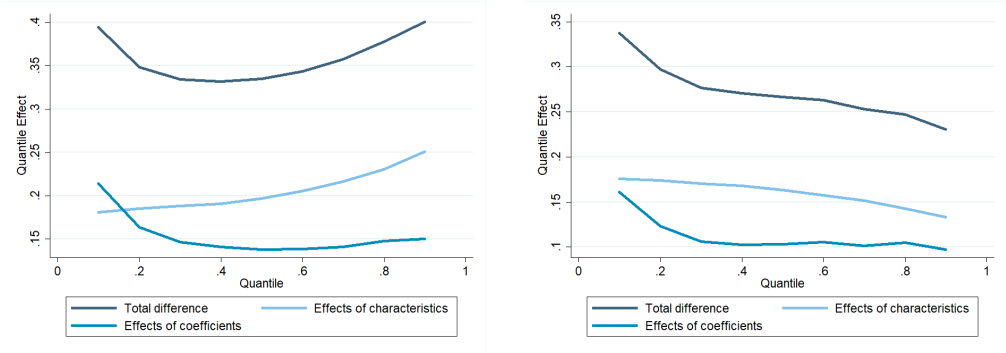

FIGURE 2.5: CQ decomposition by gender.
Quantile decomposition of wage differential for men (left) and women (right). *Source: EU-SILC, own calculations*.

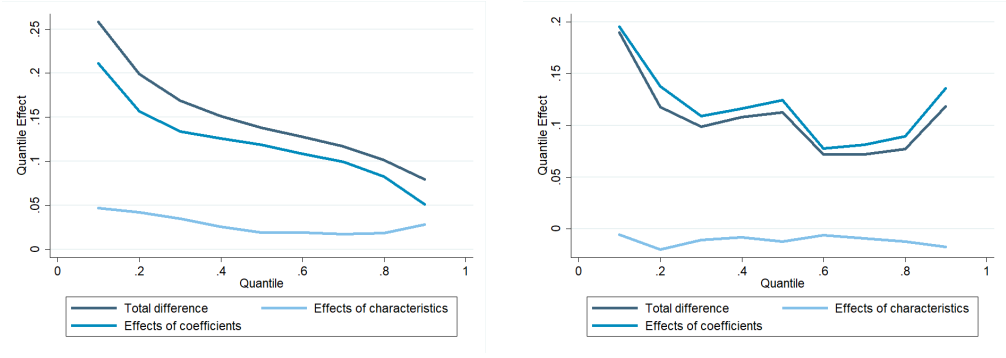

FIGURE 2.6: CQ decomposition by age and citizenship.
Quantile decomposition of wage differential for younger workers (left) and non-European workers (right). *Source: EU-SILC, own calculations*.

in recent decades, Italian trade unions proved to be important actors in economic and political life during the global economic crisis and are considered to be more solid that in similar countries (Regalia and Regini, 2018, Leonardi, 2017).

Another explanation for the wage differential relates to the above-mentioned role of temporary contracts as probationary periods. If the employer thinks that the worker meets his needs in terms of productivity and job performance, then the worker will later be hired on a permanent basis. Loh, 1994, pointed out that a probationary contract posted by an employer may attract workers with good abilities who are confident about transitioning to a permanent job. The probationary contract is associated with a lower wage, but higher wages are promised on renewal of the contract. The lower entry wage is compensated by higher future wages if the worker's performance is appraised positively by the employer. Furthermore, Güell, 2000, argues that if the temporary contract is used as a probationary period, there is no need for the firm to use wages as an incentive to increase worker effort and reduce shirking, as they do with permanent workers in the standard efficiency wage framework (Shapiro and Stiglitz, 1984).

A further explanation is related to the increase in labour market flexibility

that Italy has experienced since the end of the 1990s. According to Bentolila and Dolado, 1994, increases in labour market flexibility are often increases in flexibility at the margin, affecting certain groups of workers and not the whole workforce. According to these authors, when unions are dominated by insiders (permanent workers, in our context), then the presence of outsiders (temporary workers) can only increase the bargaining power and wages of insiders. Permanent workers therefore pursue their own interest in wage bargaining, disregarding the interests of temporary workers who are considered less important because of their weaker attachment to the firm.

As argued in the introduction, several studies since the 1980s have blamed labour market rigidities, such as employment protection legislation and long-duration unemployment benefits, for the high unemployment rates in European countries like Germany, France and Italy (Mason, Mayhew, and Osborne, 2008). As a result, increasing labour market flexibility has been an objective of many national policies in industrialised countries since the 1990s (Schömann, 2014), and the rise of temporary employment has been one of the consequences. As argued by Rubery and Piasna, 2016, employment of workers on different contracts not fully related to their productivity can cause problems and may put groups of workers at risk of exclusion. Workers who are at a disadvantage may be more vulnerable to pressure from employers and this can result in lower wages.

Rubery and Piasna, 2016, also showed that in several European countries (including Italy), temporary workers are much more at risk of in-work poverty than permanent ones. This is consistent with our observation that the temporary wage-gap tends to be wider among lower paid workers. According to Salverda and Mayhew, 2009, the incidence of low pay in a country is strictly linked to inclusion of all workers in collective bargaining agreements and to universal application of minimum wage legislation, when present. They argue that a tool to fight low pay is labour market "inclusiveness", i.e. the existence of formal or informal mechanisms to extend working conditions negotiated by workers with strong bargaining power to workers with less bargaining power. Although the conclusions by Salverda and Mayhew, 2009, were drawn considering pay in the whole labour force, and not just the temporary population, we can easily extend them to our case. A possible explanation for the temporary wage-gap can be found looking at how wage-setting institutions work in Italy.

Italy lacks a statutory universal minimum wage, although different wage floors have been set by collective bargaining in all industrial sectors (Bellavista, 2014). Several scholars have pointed out that this system prevents universal coverage of workers and may generate wage-gaps between protected and not protected low paid workers. For instance, Garnero, Kampelmann, and Rycx, 2014, calculated that sectoral minimum wages in Italy are very close to the national median wage, a figure that can only be explained if we assume that a significant part of the working population is not covered by the minimum wage. This happens when the employer is not obliged to comply with sectoral collectively bargained contracts, as when he or she hires a temporary worker. The lack of a universal minimum wage may therefore explain the higher temporary wage-gap at the left tail of the wage distribution for all groups of workers.

As reported by Picchio, 2006, the remuneration of temporary workers should in principle be the same as that of permanent workers, by virtue of the non-discrimination principle recognised in the Italian legislation. However, the different degree of participation of temporary and permanent workers in firm life was invoked by the Court of Ravenna (2002) to rule that there is no absolute principle dictating equity of treatment of these two groups of workers. Wage discrimination of temporary workers is therefore possible in the Italian institutional framework and this helps explain why a wage-gap is observed throughout the wage distribution.

On this basis, we conclude that a possible explanation for the width of the unexplained component of the temporary wage-gap in Italy depends on the institutions regulating wage setting and wage bargaining. Increasing the flexibility of the labour market has resulted in an increase in the number of workers employed with atypical contracts and therefore with weaker attachment to the firm. These workers, whose bargaining power and representation in unions are less than those of permanent workers, suffer a wage penalty that is only partly related to their observable characteristics. This happens both because they are excluded from sectoral minimum wages that apply to comparable permanent workers, and because the temporary wage-gap is not considered wage discrimination. A policy maker wishing to close the unexplained component of the temporary wage-gap should therefore probably start by increasing the "inclusiveness" of labour market institutions. In this way, even workers with less bargaining power could benefit from minimum wage coverage and non-discriminatory wage setting, despite the increase in flexibility.

When we observe the results of the subgroups of the population, younger and non-European workers stand out because their temporary wage-gap can be attributed entirely to the unexplained component. For workers under 30 this may happen because, unlike workers over 30, they can be hired with apprenticeship contracts. Unfortunately, the data did not allow us to exclude apprentices, but we know that they are excluded from the pool of workers over 30 (whose results are similar to those of the whole sample). Apprenticeship contracts, which are used to screen and train workers, can therefore explain the size of the coefficient effect on the temporary wage-gap associated with younger workers. According to Leombruni, Razzolini, and Serti, 2019, new entrants in the labour market have a weak bargaining position in times of high unemployment. This may explain the lack of endowment effect in the temporary wage-gap of younger workers: because of their weak position, comparatively few get hired with permanent contracts, but those who eventually do receive a wage premium.

We can therefore say that groups that may have more difficult access to the labour market, like younger workers (who may have less experience, or may simply find it difficult to be hired in a time of recession) and immigrant workers (who may experience discrimination or entry barriers like linguistic and cultural differences), face a sort of bottleneck. Almost irrespective of their characteristics, they are more likely to end up in temporary jobs and to earn less. However, those who manage to find a permanent job receive a wage premium.

2.8 Conclusions

We have use survey data to assess if, and to what extent, temporary workers suffered a wage penalty in 2012 in Italy. To do so, we first applied an Oaxaca-Blinder decomposition (accounting for selection bias) on the difference between the average wages paid by temporary and permanent jobs. Then, we applied a conditional quantile decomposition, as proposed by Chernozhukov, Fernández-Val, and Melly, 2013, to decompose the temporary-permanent wage-gap in different quantiles of the earnings distribution.

Results from both methodologies are consistent in identifying in the whole population a large wage penalty for temporary workers as a result of a combination of *endowments* and *coefficients effects*. When we disentangle the magnitude of this gap along the wage distribution, we realise that low-paid temporary workers suffer the largest wage penalty. Our findings suggest, moreover, that, among higher paid workers, the effect of coefficients tends to be less relevant in explaining the gap.

We have tried to explain the relevance of the unexplained component by observing that the wage penalty may be a result of the process of flexibilisation of the labour market started in Italy during the 1990's. Temporary workers have less bargaining power than permanent ones and are also less represented inside trade unions. Their weaker attachment to the firm and decreased bargaining power may result in a lack of coverage of employment protection legislation and, therefore, in lower wages.

When we focus our attention on sub-samples of the population, we notice several deviations from these trends. The gap calculated for male workers, for instance, is significantly larger than the one calculated for women and it does not decrease at higher wages. On the contrary, it exhibits a U-shape and is narrower for male workers situated in the 4th and 5th decile of the wage distribution.

Moreover, the wage-penalties associated to younger workers and migrant workers from outside the European Union tend to be explained almost exclusively from differences in coefficients. This result holds both in the Oaxaca-Blinder and in the counterfactual quantile decomposition framework. A possible explanation can be found by considering that these two groups of workers face more barriers to the entry in the labour market. For this reason, comparatively few of men eventually get hired into a permanent job, but those who do receive a wage premium when it happens.

Chapter 3

The spread of voucher work in Tuscany

3.1 Introduction

In 2016, the impact of *subsidiary employment*[1] on the national labour market was the object of an intense public debate in Italy. Often referred to as voucher work, when it was introduced subsidiary employment intended to emulate the French *cheques services (CES)* (Sansoni, 2009). It was, indeed, meant to provide families and small businesses with a flexible arrangment to regulate occasional or seasonal activities which are often hidden in the shadow economy (Pala, 2014). Subsidiary employment was just one example of the rise of alternative contractual arrangements in Europe and other western countries, albeit an example with rather extreme characteristics. Somewhat similar examples include British zero-hour contracts and German mini-jobs. Nevertheless, subsidiary employment had unique characteristics in the Italian experience.

As will be clearer in the following sections, the main feature of subsidiary employment was that the workers' payment was based on the exchange of (at first physical, later electronic) cheques named "vouchers" with a pre-determined value. Employers (firms, families and public authorities) could hire occasional workers for short-termed activities (as short as one single hour) and pay them using one or more vouchers. Between 2008 and 2017 subsidiary employment became an increasingly popular phenomenon, to the point where several policy analysts and trade unionists urged the government to act in order to protect workers' rights from what seemed like a threat to job security and to the Standard Employment Relationship. In 2016, therefore, voucher regulation was tightened and subsequently, in April 2017, subsidiary employment was abolished.

The purpose of our analysis is to assess the impact of the reform of voucher work enforced in October 2016. This reform introduced an additional, small, organisational cost on the use of this instrument for firms only (therefore not for families and public authorities). The scope of the reform, as will be explained in Section 3.2, was twofold. First, it was meant to make the use of vouchers less convenient in case of a continuous relationship between employer and worker (and, therefore, encourage the use of other, more structured, forms of employment). Second, the intention of the legislator was to prevent vouchers from

[1] Literal translation of Lavoro accessorio

being used in a fraudulent way from employers to avoid sanctions in case they hired a worker without a regular employment contract.

We want to understand whether the implementation of the October 2016 reform has had an impact on the number of vouchers used in the following months. Our hypothesis is that a rather small reduction in the flexibility of the instrument might have had a negative effect on its spread, causing the number of vouchers used after October 2016 to plunge with respect to the past. To do so, we first estimate the impact of this reform using Sharp Regression Discontinuity analysis. We employ the local linear regression framework proposed by Porter, 2003, and extended by, among others, Imbens and Kalyanaraman, 2012, and Calonico, Cattaneo, and Titiunik, 2014. We then provide alternative results by resorting to at a Difference-in-differences estimator and showing that the number of vouchers used by private decreased significantly with respect to the number of vouchers used by public authorities (that were not subject to the new regulation). We use three data sources. The core database comprises administrative records of vouchers sold and used in the region of Tuscany, and was collected by the National Social Security Institute (INPS). The Registro Asia and the Comunicazioni Obbligatorie are ancillary administrative sources that have been matched to the core source in order to add information on the users (organizations) and the workers.

The contribution of our research is twofold. First, it delves deep in the analysis of subsidiary employment, a contractual development that has been the object of rather scant research. Second, it tries to understand the impact of introducing a small rigidity on the functioning of a very flexible contractual arrangement. From this point of view, we argue that our findings may be relevant to investigate the functioning of similar atypical working relations.

This chapter is organised as follows. Section 2 and 3 summarise the evolution of the regulation of subsidiary employment and its spread throughout the Italian economy. Section 4 and 5 describe the data and the methodologies used, respectively. In section 6 we present our main findings. Conclusions follow.

3.2 The evolution of the regulation

Subsidiary employment was introduced in Italy in 2003, as part of the broad reform of contractual arrangements that goes under the name of *Biagi Law* (Law 276/2003). The regulation of subsidiary employment based its use on the exchange of vouchers as means of payment for the workers' services. The possibility to resort to subsidiary employment was limited to *casual* and *ancillary* activities "performed by individuals at risk of social exclusion, not participating in the labour market, or about to leave it".[2]

The purpose of subsidiary employment was to provide a viable alternative to informal employment for a set of activities often confined in the shadow economy, while favouring the inclusion of peripheral and marginalised workers (Politiche Sociali, 2016). The activities in question included: housework and

[2]Law 276/2003, art. 70.

care work, private tuitions, small-scale gardening and cleaning, and the organisation of events. The pool of eligible workers was limited to the long-term unemployed, housewives, retirees, and non-EU migrants with regular residency permit. Hours of work were limited to 30 per month and earnings to €3,000 per year.

Initially, the price of a voucher was set at €7.5 gross, 5.8 of which accrued to the worker net of tax and social security, while the remainder was divided between a small operating fee collected by the National Social Security Institute, employers' contributions to a special pension fund, and an occupational hazard insurance scheme. Hence, from the beginning social security costs were set to be much lower than for any other type of contract in Italy. The same was true for benefits, since voucher recipients could not claim any benefit other than the insurance payment in case of accidents, and a very small pension income. From the start, therefore, Italian law set subsidiary employment as something clearly apart from anything like a standard labour contract.

Although the regulation for vouchers was introduced in 2003, they actually began to circulate only in 2008 (Guglielmo and Lippolis, 2012). Thereafter, the scheme was repeatedly revised, and the most consequential changes were enforced at different dates between 2008 and 2015. Firstly, the range of admissible activities was expanded until eventually encompassing the entire economy, with a few specific exceptions within agriculture (INPS, 2016). Secondly, the possibility of becoming a subsidiary worker was progressively extended, from marginalised individuals to almost anyone, including full-time employees and self-employed workers wishing to supplement their earnings. The group of employers was extended to include families, entrepreneurs, professionals, not-for-profit organisations, and even public authorities. Thirdly, the price per voucher was set at €10 gross (€7.5 for the worker). Total earnings were also capped higher: in 2017 each worker could cash vouchers for up to €2,000, net, per year, from a single employer and up to €7,000, net, per year, from all his or her employers combined (Natali, 2016).

Moreover, the purchase of voucher was progressively made easier. In 2008 vouchers could only be sold by the local office of the National Social Security Institute. Then, other resellers such as tobacconists and post offices were authorised. Finally, from 2016 vouchers could also be purchased online.

The consequence of this progressive deregulation has been an unprecedented spread of subsidiary employment across the whole economy, as will be illustrated in the following section. This phenomenon prompted critiques and warnings from economists, trade unionists, and policy analysists fearing that vouchers were becoming a threat to workers' rights and job security. Many people feared that what was supposed to be an almost niche instrument was becoming the "new frontier of precarious employment", as Tito Boeri[3] warned in May 2015.[4]

Nevertheless, as will be clearer in the next section, vouchers represented a marginal source of income for most subsidiary workers. This evidence is hard to reconcile with the pervasive diffusion of vouchers in the Italian labour

[3]Economist and president of the National Social Security Institute.

[4]As reported by the newspaper La Repubblica on 29 May 2015.

market. An explanation that has often been mentioned in the public debate is the possibility that vouchers were used in a fraudulent way to conceal irregular employment relations (Pala, 2014, and Schiavone, 2016).

Hiring workers in the shadow economy in Italy is a widespread practice (De Gregorio and Giordano, 2015), and voucher were supposed to provide a viable alternative for casual activities usually paid over-the-counter. Nevertheless, for some years vouchers may have had the opposite result of favouring informal employment. The reason is that employers could pay fewer vouchers than the hours they contracted. Moreover, they could pay workers over-the-counter as a rule and hold a certain number of vouchers to be exhibited in the event of an inspection or when a worker injured himself or herself and needed insurance coverage. This was possible because vouchers were traced by the National Social Security Institute only after the working activity had been performed. Employers, as a matter of fact, had to register on the National Social Security Institute website each voucher by providing information on themselves, the workers, and the activity (including the time and place where it was performed). However, this registration could be done in the 30 days after the activity had been performed (Carosielli, 2016). With this system suppose an injury occurred to an informal worker in the employer's premise, after the event the employer could declare that the worker was a subsidiary worker. Therefore, the worker would benefit from the insurance coverage granted by the voucher and the employer would be safe from sanctions.

In the attempt to slow down the exponential growth of subsidiary employment, existing regulation was amended in October 2016 making the tracking of voucher almost instantaneous. From that date,[5] mandatory communications concerning vouchers had to be made via text message or e-mail to the National Social Security Institute at least one hour before actual work was performed. Non-compliance would result in fines ranging from €400 to €2,400 for each non-declared worker. After that date the fraudulent use of vouchers was claimed to have substantially reduced (Baroni, 2017).

Nevertheless, the criticism to subsidiary employment did not halt and in the following months the debate escalated to the point where CGIL (Confederazione Generale Italiana del Lavoro), the largest trade union in Italy, threatened to insert a bill abolishing subsidiary employment in an upcoming referendum on labour reforms (CGIL, 2017). To avoid a potential political defeat in the referendum, in April 2017 the government decided to repeal the regulation on subsidiary employment and to abolish this working arrangement from January 2018 (IlPost, 2017).

3.3 The spread of Subsidiary Employment

During the period of progressive deregulation, vouchers became increasingly popular. As noted above, the growth was exponential between 2008 and 2016, whether it was by the number of vouchers sold or by the number of workers involved. If we qualify as recipients all those who cashed at least one

[5] Law 185/2016, art. 1.

voucher in the reference year, their number grew from almost 25,000 in 2008 to almost 1.8 million in 2016 (Figure3.1, left panel). During the same period, the number of vouchers sold grew from about half a million to more than 134 million (Figure3.1, right panel).[6]

In the period under consideration, the use of vouchers spread across sectors but, contrarily to what is often claimed, households remained peripherally involved (Anastasia, Bombelli, and Maschio, 2016). This appears surprising given that in Italy most of the care activities for the elderly and the children are managed within the family (Bettio and Mazzotta, 2011), nevertheless an explanation could be that vouchers are not "cheap" enough with respect to alternative means of payment of domestic work (Bettio and Mazzon, 2017).

In 2015 the number of employers had doubled with respect to 2013, exceeding 473,000 units. About two thirds of them were firms operating in the secondary and tertiary sector, with the largest share accruing to tourism and manufacturing. Only 15% of all employers were families, while employers operating in agriculture accounted for less than 4%. In 2015, moreover, the average number of recipients per employer was 3.5. Nevertheless, only 3% of all employers were hiring more than five workers over the course of one year.

Despite a downward trend, the turn-over of recipients remained high in 2016. Year after year, new entrants (or re-entrants) were and remained the majority (Figure3.2, left panel). The percentage of voucher workers not having performed subsidiary employment in the previous year followed a decreasing trend since 2003, but always stayed above 50%. This figure reflects the fast spreading of vouchers in the period under consideration. However, it can also be interpreted as showing that for most recipients, subsidiary employment largely represented a temporary condition lasting less than one year.

Despite the pace of growth in sales, until 2016 the average number of vouchers per workers per year was roughly stable at between 60 and 70 (Figure3.2, right panel). This suggests that most work spells on vouchers tended to be short, sometimes even a few hours in the whole year.

Earnings per recipient were also low, consistently with the low number of vouchers per head. In 2015, annual average earnings ranged from €554 for the youngest recipients to €700 for the oldest ones (Table3.1). Moreover, in 2015 more than three-fifths of all recipients totalled less than €500 each and more then one in seven recipients cashed less than five vouchers over the course of the year (Table3.2).

In the region of Tuscany,[7] more than 27 million vouchers were sold between 2008 and 2016, corresponding to 7% of the total amount sold in the whole country (INPS, 2017). Following the same pattern witnessed at national level, the

[6]Figures concerning the evolution of subsidiary employment at a national level, as presented in this section, are mainly drawn from two source. The first is the "basic figures" published by the National Social Security Institute (INPS, 2017), updated at December 2016 but providing very minimal information limited to voucher sales. The second is the paper by Anastasia, Bombelli, and Maschio, 2016, the most comprehensive work published so far on vouchers, including many descriptive statistics and updated at December 2015. The figures presented in this section have always been drawn from the most updated source.

[7]Unless differently specified, the figures referring to the region of Tuscany are own calculations performed on the database used for this analysis, explained in the following section.

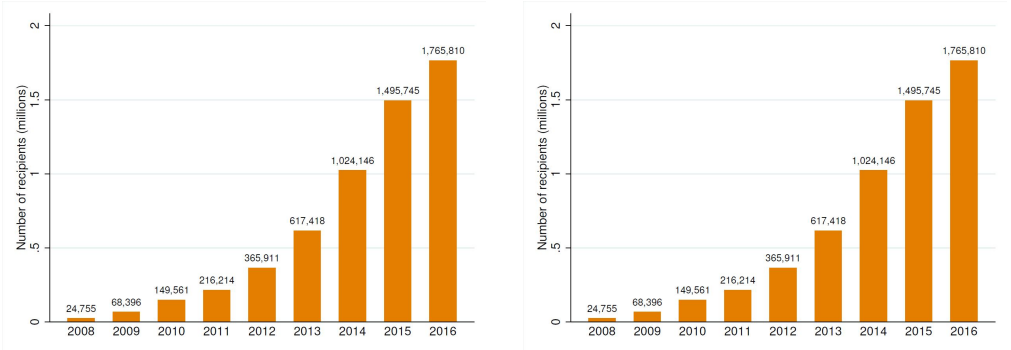

FIGURE 3.1: The spread of voucher work (1).
Number of voucher workers per year (left) and total number of vouchers sold (right). *Source: INPS, 2017*

number of hours of work paid with vouchers has been growing in the whole period, reaching 7.3 million in 2016.

Moreover, the number of recipients and employers also grew in the period under consideration, although it followed a seasonal pattern. Figure3.3 shows seasonal peaks and troughs over the course of one year: in all the three years reported, we see that a peak during summer is followed by a fall in winter. This seasonal pattern is consistent with the important role that activities related to tourism, travelling and lodging played for the growth of vouchers in Tuscany (Figure3.4, left panel), but also elsewhere in Italy. The right panel in Figure3.4 shows the main economic sectors in which voucher employers operated.[8] More than half of them are hotels, restaurants, or other firms operating in hospitality. Consistently with what is shown by national data, manufacturing and trade should feature among the most important branches that resorted to vouchers.

Figure3.5 shows the number of vouchers used (i.e. the number of hours contracted) in Tuscany in 2014, 2015 and 2016. As noted above, the number of vouchers grew year after year. However, we can see that in the last months of 2016 the growth slowed down and eventually the trend reversed with respect to the same period in the previous years. In the months of November and December 2016 the number of vouchers used has been even lower than in the same months of 2015. At a first glance, therefore, the picture seems to suggest that the policy introduced in October 2016 slowed down the increase in voucher sales.

3.4 The data

The main dataset we used to perform this analysis has been provided by the National Social Security Institute. It includes a record of the vouchers sold

[8]It is important to note that there is a difference between voucher activity and sector of the voucher employer. While the first refers to the kind of job that a subsidiary worker performs, the latter refers to the core business of the employer. For instance: a voucher used to pay a subsidiary worker hired by a manufacturing firm to clean its premises would be associated to the activity *gardening and cleaning* and to the economic sector *manufacturing*.

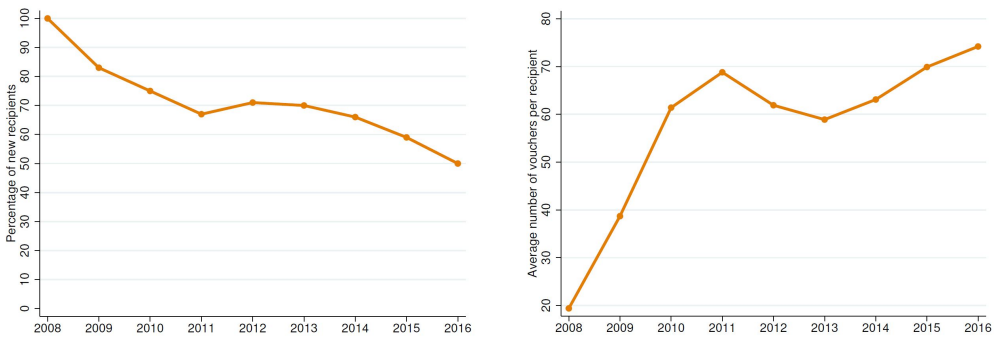

FIGURE 3.2: The spread of voucher work (2).
Percentage of new voucher workers per year (left) and average number of vouchers per year (right). *Source: INPS, 2017*

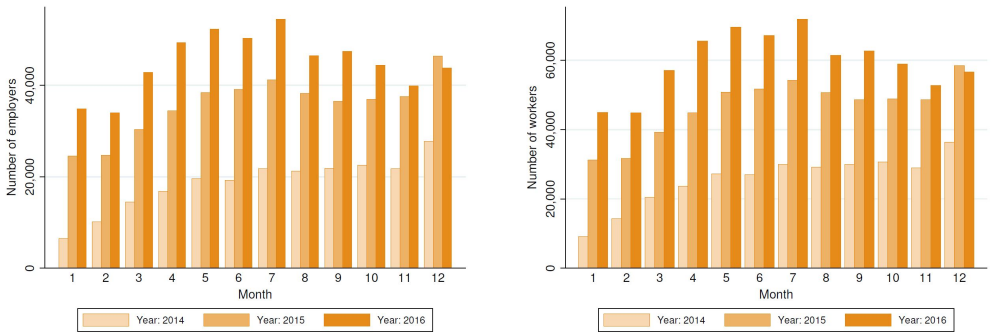

FIGURE 3.3: The spread of voucher work (3).
Number of voucher employers (left) and workers (right) by month and year in Tuscany. *Source: INPS, 2017*

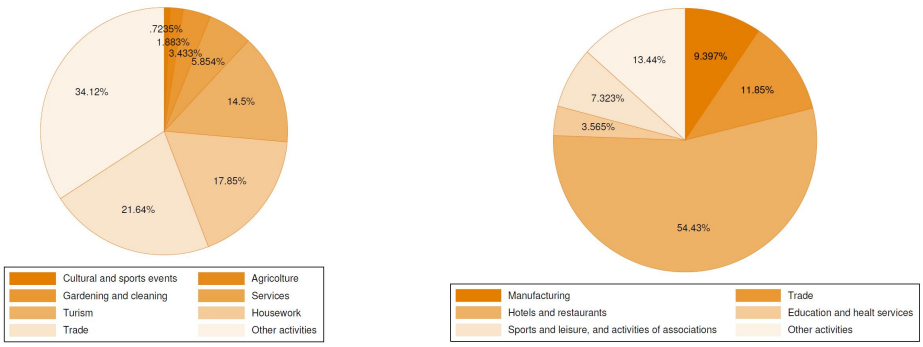

FIGURE 3.4: The spread of voucher work (4).
Main activities performed by voucher workers (left) and main economic sectors of voucher employers (right). *Source: INPS, 2017*

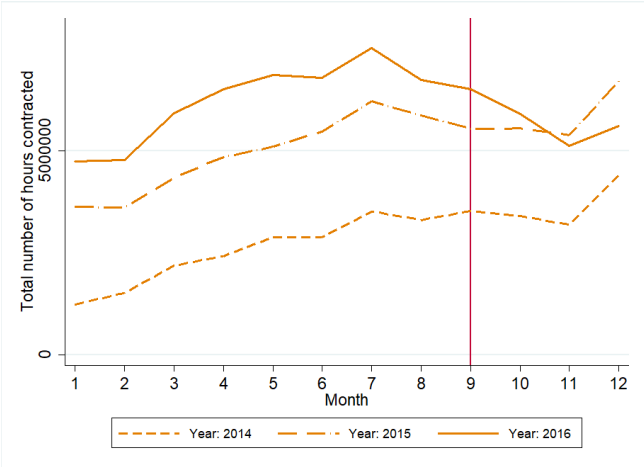

FIGURE 3.5: The spread of voucher work (5).
Number of hours contracted with vouchers in Tuscany by month and year. *Source: INPS, own calculations.*

Age	Number of recipients	%	Average annual earnings per recipient (€)
<25	431,613	31.0	554
26-59	849,968	61.0	660
60-65	57,483	4.1	762
>65	53,842	3.9	700

TABLE 3.1: Annual earnings of voucher recipients.
Source: Politiche Sociali, 2016

and used in the region of Tuscany between 2010 and 2017. Each observation corresponds to a single 'activity' which can consist of more than one voucher. For each entry, the database records the type of activity performed and the sector of the employer as well as information on workers like gender, age, and the Italian province or the foreign country of birth. Finally, for each entry the source reports the dates in which the vouchers were sold and cashed, and the dates in which the activity began and ended, together with the province where the voucher was sold.

This database was matched with two additional sources. The first database is derived from *Registro Asia*, which records Italian corporations with at least one employee, is managed by the National Social Security Institute, and was last updated in 2014. The Registro includes details on the firms' location, sector, number of employees, and revenues.

The second database is drawn from Comunicazioni Obbligatorie, a large administrative source gathering communications by firms concerning the transactions entailed by every contract they sign or terminate. Using this record, each voucher workers is matched to his or her working history preceding or following his or her last subsidiary employment activity. Variables include the workers' tasks, the type of contract, the reason of termination of each job, and the employment branch.

Number of vouchers cashed	Number of recipients	%
1-5	232,348	13.2
6-10	200,885	11.4
11-25	315,812	17.9
26-55	327,754	18.6
56-100	250,350	14.1
101-200	246,628	13.9
>200	191,933	10.9
Total	1,765,710	100

TABLE 3.2: Number of recipients by number of vouchers cashed..
Source: INPS, 2017

3.5 Methodologies

3.5.1 Regression discontinuity

A popular way of identifying causal effects of a binary intervention of treatment is the regression discontinuity design (RD) (Lee and Lemieux, 2010). RD applies to situations in which individuals are sorted between treated and non-treated based on whether their value for a certain variable falls above or below a given threshold (Jacob et al., 2012).

Let $Y_i(0)$ and $Y_i(1)$ denote the outcome variable for individual i in absence and in presence of treatment, respectively. Ideally, we would like to calculate: $Y_i(1) - Y_i(0)$, but we never observe both realisations at the same time for the same individual. If $I_i \in (0,1)$ is an indicator function representing the absence or presence of treatment, the observed outcome can be written as:

$$Y_i = (1 - I_i) \times Y_i(0) + I_i \times Y_i(1) \tag{3.1}$$

In a sharp regression discontinuity design (SRD), like the one used in this analysis, the assignment I_i is a deterministic function of one of the covariates, Z_i:

$$I_i = 1\{Z_i \geq c\} \tag{3.2}$$

The variable Z_i is called forcing variable, the value c is called cut-off. All individuals with a value of Z_i larger than c will be assigned to the treatment group. Thus, in SRD, the probability of receiving treatment, $Pr(I = 1 \mid Z = z)$, jumps from 0 to 1 in correspondence of the cut-off value c. In SRD the conditional expectation of the outcome Y_i given Z_i (Imbens and Lemieux, 2008):

$$\lim_{z \downarrow c} \mathbb{E}[Y_i \mid Z_i = z] - \lim_{z \uparrow c} \mathbb{E}[Y_i | Z_i = z] \tag{3.3}$$

is interpreted as the average causal effect of the treatment at the cut-off point c:

$$\tau^{SRD} = \mathbb{E}[Y_i(1) - Y_i(0) \mid Z_i = c] \tag{3.4}$$

Therefore, in the SRD framework, the treatment effect τ^{SRD} is the distance between $\mathbb{E}[Y_i(1)|\ Z_i = z]$ and $\mathbb{E}[Y_i(0)|\ Z_i = z]$ calculated at $z = c$. The estimation of τ^{SRD} requires the approximation of an unknown regression function before computing the treatment effect. In general, an unknown function can be approximated by a polynomial of some order. However, this strategy does not perform well when estimating a value at a boundary point, as in the case of SRD (Porter, 2003). Our analysis, therefore, will exploit the estimation of a local polynomial in a neighbourhood of the cut-off c.[9] More specifically, using only observations close to c, two local linear regressions are estimated, for control and treated units respectively. The observations used are in a range between $c-h$ and $c+h$, where h is called "bandwidth". Within the bandwidth, a kernel function $K(\bullet)$ is used to weight observations according to their distance from the cut-off.

The procedure can be summarised as follows. On each side of the cut-off we fit a weighted least squares regression of the outcome Y_i on a constant and $(Z_i - c)$, $(Z_i - c)^2$, ..., $(Z_i - c)^p$, where p is the chosen order the polynomial. Each observation is weighted by a kernel function, $K = \frac{(Z_i - c)}{h}$, assigning non-negative weight to each observation proportionally to its distance from c. For observations in the treatment group, i.e. for observations with $Z_i \geq c$, we estimate the intercept $\hat{\mu}_+ = E[Y_i(1)|Z_i = c]$ from:

$$\hat{Y}_i = \hat{\mu}_+ + \hat{\beta}_{+,1}(Z_i - c) + ... + \hat{\beta}_{+,p}(Z_i - c)^p \tag{3.5}$$

Finally, the treatment effect is calculated as point estimate: $\hat{\tau}^{SRD} = \hat{\mu}_+ - \hat{\mu}_-$.

To perform this estimation, we must choose: a polynomial order p, a bandwidth h, and a Kernel function $K(\bullet)$. In choosing the order of the polynomial one must weight the fact that increasing p leads both to improved accuracy of the approximation against the fact that it also leads to higher variability of the treatment effect estimator. For this reason, a local linear RD estimator is often the best choice, hence $p = 1$ (Cattaneo, 2018).

The optimal bandwidth must be chosen considering the so-called "bias-variance trade-off": a smaller h reduces the misspecification error of the local polynomial approximation, at the cost of reducing the number of observations available. The most common way to balance this trade-off is to minimise the mean square error (MSE) of τ^{SRD}, given the chosen p and Kernel function, as proposed by Imbens and Kalyanaraman, 2012.

Two popular Kernel functions uniform and triangular, respectively. A uniform kernel function assigns equal weight to each observation between $c-h$ and $c+h$, formally: $K(u) = 1$ in the support ($|u| \leq 1$). A triangular kernel function, often recommended with an MSE-optimal bandwidth, is defined as $K(u) = (1 - |u|)$ in the support ($|u| \leq 1$). In the next section we will present results using both functions.

In a local linear regression framework, like the one just described, there are three main approaches to inference: conventional, bias-corrected, and robust

[9]The Stata package adopted is: *rdrobust*.

(Calonico, Cattaneo, and Titiunik, 2014). When the bandwidth choice is MSE-optimal, the approximate large-sample distribution of the SRD point estimator is:

$$\frac{\hat{\tau}^{SRD} - \tau^{SRD} - \mathscr{B}}{\sqrt{\mathscr{V}}} \sim \mathscr{N}(0,1) \tag{3.6}$$

Where $\mathscr{B}$ is the asymptotic misspecification bias of the SRD local polynomial estimator of order p, and $\mathscr{V}$ its asymptotic variance. Formally, therefore, the asymptotic 95% confidence interval for τ^{SRD} is:

$$CI = \left[\left(\hat{\tau}^{SRD} - \mathscr{B}\right) \pm 1.96\sqrt{\mathscr{V}}\right] \tag{3.7}$$

The first approach to the calculation of this confidence interval is to adopt *conventional* OLS inference and ignore the bias term $\mathscr{B}$:

$$CI_C = \left[\hat{\tau}^{SRD} \pm 1.96\sqrt{\mathscr{V}}\right] \tag{3.8}$$

This confidence interval should be chosen only when it is reasonably certain that the polynomial gives an exact approximation of the underlying functions $\mathbb{E}[Y_i(1)|\ Z_i]$ and $\mathbb{E}[Y_i(0)|\ Z_i]$. Conversely, if misspecification bias is non-negligible, all inference will be incorrect.

A *bias-corrected* approach uses the bias estimator $\hat{\mathscr{B}}$ to centre the confidence interval at the bias-corrected point estimate:

$$CI_{BC} = \left[\left(\hat{\tau}^{SRD} - \hat{\mathscr{B}}\right) \pm 1.96\sqrt{\mathscr{V}}\right] \tag{3.9}$$

The estimation of $\hat{\mathscr{B}}$ requires a local polynomial of order $q = p+1$ (or higher) and another bandwidth, usually denoted b. This second bandwidth is chosen in order to minimize the ratio between h and b: $\rho = \frac{h}{b} \to 0$. This confidence interval results in valid inference when the MSE-optimal h is used.

The *robust* approach exploits the same bias estimator $\hat{\mathscr{B}}$, but is also based on the calculation of a different (and larger) asymptotic variance term $\mathscr{V}_R$. This term incorporates the contribution given by the bias estimation to the conventional OLS variance $\mathscr{V}$. The robust confidence interval obtained is valid when the MSE-optimal bandwidth is selected:

$$CI_R = \left[\left(\hat{\tau}^{SRD} - \hat{\mathscr{B}}\right) \pm 1.96\sqrt{\mathscr{V}_R}\right] \tag{3.10}$$

A more detailed analysis on the derivation of these confidence intervals can be found in Calonico, Cattaneo, and Titiunik, 2014, and Cattaneo, 2018. In summary, the main difference between these approaches is that the conventional confidence interval CI_c is centred at the point estimator τ^{SRD} and ignores the presence of the misspecification bias. The bias-corrected confidence interval CI_{BC} and the robust confidence interval CI_R are centred at the bias-corrected point estimator $\tau^{SRD} - \hat{\mathscr{B}}$. However, only CI_R incorporates a standard error $\sqrt{\mathscr{V}_R}$ that accounts for the variability introduced in the bias correction step.

With the analysis that follows we intend to assess the impact on the use of vouchers of the introduction of the October 2016 regulation. To do so we

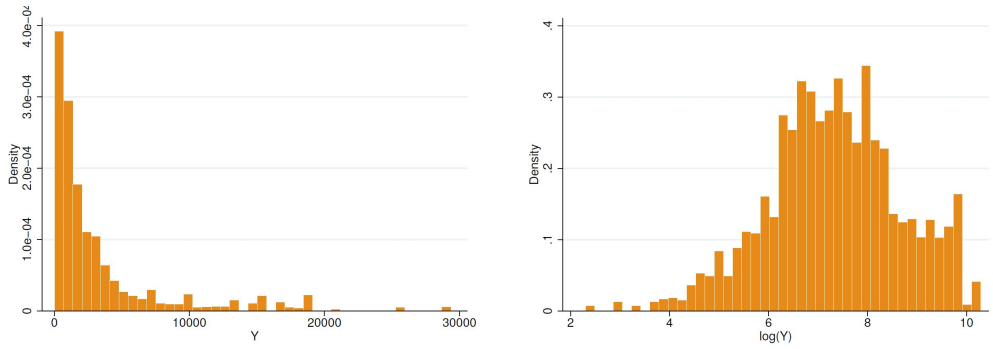

FIGURE 3.6: Distribution of the dependent variable.
Distribution of Y_I (left) and $log(Y_i)$ (right). *Source: INPS, own calculations.*

will apply the SRD framework in presence of time as a forcing variable, as illustrated by Hausman and Rapson, 2018. A similar methodology has been applied, for instance, by De Paola, Scoppa, and Falcone, 2013, and Anderson, 2014. The treatment variable, therefore, will be set at 1 after 8th October 2016 and 0 before (the regulation was enforced on October the 8th). Since that date falls on the 40th week of 2016 we will have:

$$I_i = \begin{cases} 1 \text{ if week} > 40 \\ 0 \text{ if week} \leq 40 \end{cases} \tag{3.11}$$

The choice of the outcome variable offers two options . We could choose the number of vouchers purchased by each employer or, alternatively, the number of hours contracted in a specific week. An important discriminant for this choice is the fact that the government had expressed its willingness to tighten the regulation on vouchers in the summer of 2016, a few months before implementation. Hence voucher purchases might have decreased in anticipation of this change of policy even before October 2016. More so since many employers, according to our data, used to buy large amounts of vouchers at the beginning of the month or of the season and used a few of them day by day. In contrast, there is no clear cut reason why the number of hours contracted should have changed in anticipation of the law. Even those employers using vouchers in a fraudulent way are likely to have continued business-as-usual for as long as possible, and to have changed their behaviour only when forced to do so. Our dependent variable is the (log of) the number of vouchers used by a single employer in one week[10]. The distribution of the variable is set out inn Figure3.6.

3.5.2 Difference-in-differences

SRD analysis is a powerful instrument in estimating a causal relation, however it does not provide us with any clue concerning the reason why that causal relation operates. To make an example, suppose we obtain a significant and negative result for $\hat{\tau}^{SRD}$: this would mean that in consequence of the reform

[10]Which, in principle, should be equivalent to the number of hours contracted by that employer

the number of vouchers used significantly decreased. This effect that could, in turn, be interpreted as the success of the reform in curbing the fraudulent use of subsidiary employment. However, this same finding could also be interpreted less optimistically, i.e. as the negative impact of an additional organisational cost (even if small) had a negative effect on the use of an instrument whose success was due to its flexibility. To provide further insight on this problem we decided to replicate the estimation applying the difference-in-differences (DiD) framework.

The basic set-up for a DiD estimator refers to two groups in a population are observed for two time periods (Athey and Imbens, 2006, Lechner, 2011). In the second period, one group is exposed to a new regime that is the object of the evaluation. The reason to apply DiD derives from the concern that comparing different groups at the same point in time entails a potential source of bias, because the groups may differ systematically in unobserved ways. Furthermore, the comparison of the same group at different points in time is potentially biased because other changes may occur over time (Imbens and Wooldridge, 2009).

Let individual i belong to a group, $G_i \in \{0,1\}$ (where group 1 is the treatment group), and be observed in two time periods $T_i \in \{0,1\}$. Let the outcome variable be Y_i, while the observed data are the triple (Y_i, G_i, T_i).

Using the same notation as before, let $Y_i(0)$ denote the potential outcome for individual i if he or she does not receive the treatment, and let $Y_i(1)$ be the potential outcome for the same individual if he or she receives the treatment. Let $I_i = G_i \times T_i$ be the indicator function for treatment status. The realised (or observed) outcome for individual i is:

$$Y_i = Y_i(0) \times (1 - I_i) + Y_i(1) \times I_i \tag{3.12}$$

In the standard DiD model the outcome for individual i in absence of intervention satisfies:

$$Y_i(0) = \alpha + \beta T_i + \gamma G_i + \epsilon_i \tag{3.13}$$

The parameter β measures the impact of the time component. The parameter γ represents a group-specific, time-invariant, component. The last term $\epsilon_i \perp (G_i, T_i)$ is an error term accounting for unobservable individual characteristics. The standard DiD estimand is:

$$\begin{aligned} \tau^{DiD} = &\{\mathbb{E}[Y_i \mid G_i = 1,\ T_i = 1] - \mathbb{E}[Y_i \mid G_i = 1,\ T_i = 0]\} \\ &- \{\mathbb{E}[Y_i \mid G_i = 0,\ T_i = 1] - \mathbb{E}[Y_i \mid G_i = 0,\ T_i = 0]\} \end{aligned} \tag{3.14}$$

The interpretation of τ^{DiD} depends on assumptions about how outcomes are generated in the presence of the intervention. It is often assumed that the treatment effect is constant across individuals, so that $Y_i(1) - Y_i(0) = \tau$. Combining this restriction with the standard DiD model for the outcome without intervention leads to a model for the realised outcome:

$$Y_i(0) = \alpha + \beta T_i + \gamma G_i + \tau I_i + \epsilon_i \tag{3.15}$$

More generally, the effect of the intervention may vary across individuals. Then, the standard DiD estimand gives the average effect of the intervention on the treatment group. τ can be estimated using Ordinary Least Squares:

$$\hat{\tau} = \bar{Y_{11}} - \bar{Y_{10}} - \left(\bar{Y_{01}} - \bar{Y_{00}}\right) \tag{3.16}$$

To understand how this is derived, let N_{gt} be the number of observations in period t and group g:

$$N_{gt} = \sum_{i=1}^{N} 1_{G_i=g,T_i=t} \tag{3.17}$$

Then, the average outcome in period t and group g is:

$$\bar{Y}_{gt} = \frac{1}{N_{gt}} \sum_{i|G_i=g,T_i=t} Y_i \tag{3.18}$$

The model can be generalised in presence of covariates. If X_i is observed for unit i we have:

$$Y_i = \alpha + \beta T_i + \gamma G_i + \tau I_i + \delta X_i + \epsilon_i \tag{3.19}$$

In this case we require ϵ_i to be independent from both the time/group dummies and the covariates. OLS can again be used for this estimation.

To apply this framework to the present analysis we need to begin by identifying in our data the triple (Y_i, G_i, T_i) and a set of covariates X_i. Given that our aim is to assess the impact of the regulation enforced in October 2016, we can identify a pre-treatment period going from January 2015 to September 2016 and a post-treatment period going from October to December 2016.

As in the SRD analysis, the outcome variable is the log of the number of vouchers used by each employer (per month, in this case), while the allocation of observations into treatment and control groups is less straight-forward. In standard applications, a control group would include employers who were not affected by the regulation and had no incentive to change their behaviour as voucher purchasers. However, the legislation under analysis was enforced at national level and applied to all employers, leaving the control group potentially empty. A way to overcome this problem is to take private and public employers as representing the treatment and control group, respectively. The reason is the following. Given that the law was approved mainly to prevent vouchers being (mis)used to hide informal employment relations, and given that public authorities cannot resort to informal employment, the latter should not have been affected by the 2016 reform (at least in principle). Given that the public sector was an important employer of subsidiary workers, the control group is relatively large with respect to the treatment group.

A major assumption in the difference-in-differences framework is that treatment and control groups must show a parallel trend in outcome in the pre-intervention period. If this occurs then we can assume that in the absence of treatment the difference between the outcomes of the two groups would have remained constant over time (Athey and Imbens, 2006). Figure3.7 compares the trend in voucher use by employers in the private sector and employers in

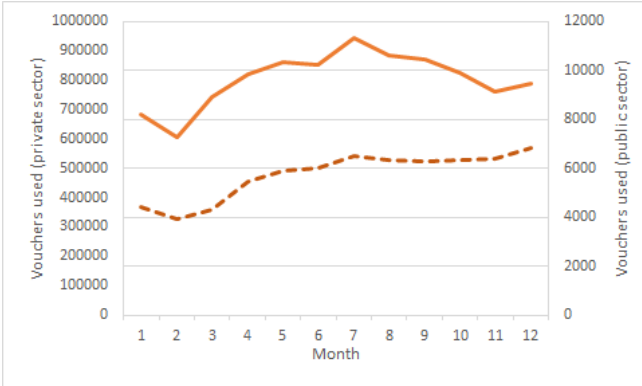

FIGURE 3.7: The spread of voucher work (6).
Total number of hours contracted with vouchers in Tuscany in 2016 by employers in the private sector (solid line) and employers in the public sector (dotted line). *Source: INPS, own calculations.*

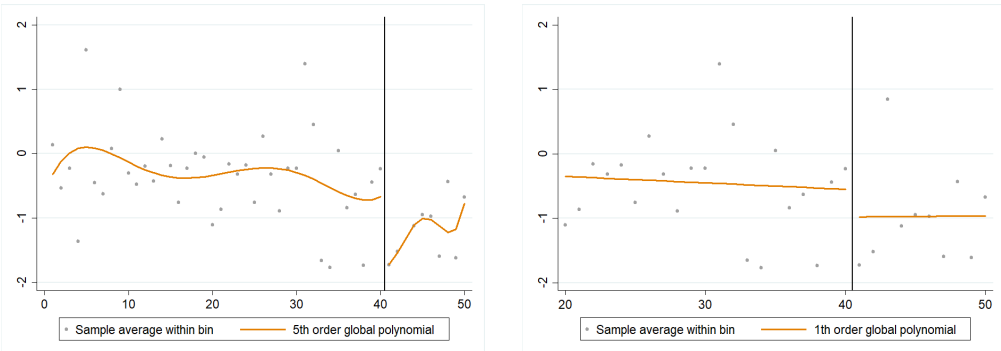

FIGURE 3.8: RD: number of vouchers used.
5th order global polynomial and distribution of de-seasonalised Y over time (left) and linear regression and distribution of de-seasonalised Y over time in a neighbourhood of c (right). *Source: INPS, own calculations.*

the public sector, in the year under consideration. As we can see, the two trends appeared similar until our treatment date, when the number of vouchers used in the private sectors started to decrease more rapidly than the number vouchers used by public authorities. From the visual inspection of Figure3.7 we can conclude that parallel trend assumption is not violated in this context and that the application of difference-in-differences estimation is supported by our data.

3.6 Results

A convenient property of RD is that it allows a clear graphical representation. On the left panel of Figure3.8 we show the plot of the de-seasonalised dependent variable against time together with the predicted values from a fifth order global polynomial trend estimated separately on each side of c. The right panel of Figure3.8, conversely, reports the plot of the de-seasonalised dependent variable interpolated by a local linear regression in a neighbourhood of c.

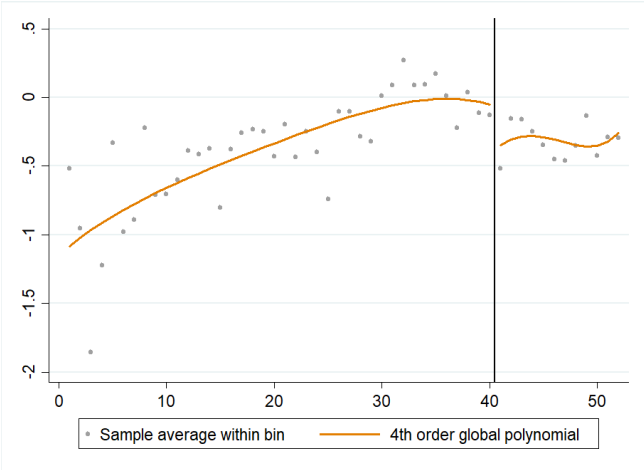

FIGURE 3.9: RD: ratio between vouchers used and employees. 4th order global polynomial and distribution of the ratio between the number of vouchers and the number of employees over time. *Source: INPS, own calculations.*

Cut-off c=41	*Left of c*	*Right of c*			Dependent variable:	$Log(Y_i)$
Number of observations:	1,262	2,354			Number of observations:	69,032
Order of local polynomial:	1	1			NN matches:	3
Order of bias:	2	2			BW tipe:	CCT
Bandwidth:	1.446	1.446			Kernel type:	Uniform
Method	*Coeff.*	*S.E.*	Z	$P > \|Z\|$	*95% C.I.*	
Conventional	-0.12019	0.02712	-4.432	0.000	-0.1733	-0.0670
Bias-corrected	-0.1265	0.02712	-4.663	0.000	-0.1797	-0.0733
Robust	-0.1265	0.03775	-3.355	0.001	-0.2005	-0.0525

TABLE 3.3: Local linear RD, uniform kernel. Local linear regression results with uniform Kernel function. *Source: INPS(2017), own calculations.*

Cut-off c=41	*Left of c*	*Right of c*			Dependent variable:	$Log(Y_i)$
Number of observations:	2,636	3,620			Number of observations:	69,032
Order of local polynomial:	1	1			NN matches:	3
Order of bias:	2	2			BW tipe:	CCT
Bandwidth:	2.552	2.552			Kernel type:	Triangular
Method	*Coeff.*	*S.E.*	Z	$P > \|Z\|$	*95% C.I.*	
Conventional	-0.15766	0.06724	-2.332	0.019	-0.2894	-0.0259
Bias-corrected	-0.18534	0.06724	-2.754	0.006	-0.3171	-0.0535
Robust	-0.18534	0.09497	-1.924	0.051	-0.3715	0.0008

TABLE 3.4: Local linear RD, triangular kernel. Local linear regression results with triangular Kernel function. *Source: INPS(2017), own calculations.*

Cut-off c=41	*Left of c*	*Right of c*			Dependent variable:	$Log(Y_i/A_i)$
Number of observations:	654	571			Number of observations:	13,867
Order of local polynomial:	1	1			NN matches:	3
Order of bias:	2	2			BW tipe:	CCT
Bandwidth:	2.591	2.591			Kernel type:	Triangular
Method	*Coeff.*	*S.E.*	Z	$P > \|Z\|$	*95% C.I.*	
Conventional	-0.50622	0.21027	-2.498	0.016	-0.9183	-0.0940
Bias-corrected	-0.57844	0.21027	-2.721	0.006	-0.9906	-0.16631
Robust	-0.57844	0.26310	-2.232	0.028	-1.0941	-0.0628

TABLE 3.5: Local linear RD, triangular kernel.
Local linear regression for the ratio between number of vouchers and number of employees. *Source: INPS(2017) and RegistroAsia(2014), own calculations.*

Number of observations: 20854			
	Before	*After*	
Control	345	110	455
Treated	17485	2914	20399
	17830	3024	

Outcome variable	$log(Y_i)$	*S.E.*	$\|t\|$	$P > \|t\|$
Before				
-Control	5.765			
-Treated	5.939			
Diff (T-C)	0.174	0.060	2.90	0.004***
After				
-Control	5.776			
-Treated	5.643			
Diff (T-C)	-0.133	0.119	1.12	0.263
Diff-in-diff	-0.307	0.132	2.32	0.020**

R-square: 0.11
*Means and standard errors estimated by linear regression
**Robust standard errors
**Inference: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

TABLE 3.6: DiD estimation.
Difference-in-differences treatment effect estimation with covariates, OLS regression with robust standard errors. *Source: INPS(2017) and ComunicazioniObbligatorie(2017), own calculations.*

In both pictures we can detect the presence of a negative jump in correspondence of the vertical line set at the date of implementation of the reform.

Table3.3 and Table3.4 show the estimation of $\hat{\tau}^{SRD}$ resulting from a local linear approximation with uniform and triangular kernel functions respectively. When we apply a uniform weighting, we estimate a reduction in the number of vouchers used of approximately 12.6%. It is interesting to note that this result and its significance are essentially the same regardless of the method used to calculate the confidence interval.

Using a triangular kernel, we estimate a negative effect of 18.5%. This result is statistically significant also when the bias-corrected and robust approaches to inference are used. Considering that the triangular kernel is the most appropriate weighting when using a MSE-optimal bandwidth, we can effectively say that this is the most accurate estimation of $\hat{\tau}^{SRD}$ and, therefore, of the impact of the restrictive regulation on the overall number of vouchers used.

Figure3.9 reports the plot against time and the 4th order global polynomial approximation of the ratio between the average number of vouchers used per week by a single employer and the number of workers that he or she employed on voucher. To do this, we matched or data on voucher with the sample drawn from Registro Asia. The advantage was more information about the single firm, the disadvantage a reduction in the number of observations down to 13,867. Table 4 reports the results from the local linear approximation around the cut-off for this alternative dependent variable. We obtain a negative and significant $\hat{\tau}^{SRD}$, indicating a decrease in the ratio after the introduction of the reform. This decrease may have been due to a reduction in the number of vouchers used per employer, per week, or an increase in the average number of workers hired on voucher. The first possibility confirms what we found earlier using the number of vouchers actually used as dependent variable. The second possibility hints at the fact that the small organisational cost introduced by the new law may have been big enough to crowd out smaller firms, those with less resources to devote to bureaucratic activities. If this were true, it is possible that the contribution of vouchers in bringing out of the shadow economy many short-term and marginal employment relations was frustrated. These activities probably went back the previous over-the-counter payment.

In order to better understand the behaviour of the employers of subsidiary workers after the introduction of the reform let us move on to the DiD estimation which we carried out by estimating the following equation:

$$log(Y_i) = \alpha + \beta T_i + \gamma G_i + \tau I_i + \delta\prime_1 M_i + \delta\prime_2 X_i + \epsilon_i \tag{3.20}$$

where $log(Y_i)$ is the logarithm of the number of vouchers used by a certain employer in one month. T_i and G_i are the time and treatment dummies, and I_i is the indicator function. M_i is a dummy variable accounting for the month of the observation, hence for seasonality. Finally, X_i is a set of covariates controlling for the type of activity performed by the worker and the economic sector of the employer. The results are reported in Table3.6.

The DiD estimator is significant at the conventional 5% level. It is negative and shows that in the post treatment period the number of vouchers used in

H0: q=0 (serially uncorrelated)			
HA: s.c. present at range specified			
Lags	*Chi2*	*df*	*p-value*
1	0.013	1	0.9092
2	0.264	2	0.8842
3	0.392	3	0.9418
4	3.897	4	0.4201
5	4.646	5	0.4606

TABLE 3.7: Robustness check 1: autocorrelation.
Test for serial autocorrelation in the dependent variable. *Source: INPS(2017), own calculations*.

the private sector decreased with respect to the number of vouchers used by public authorities.

To summarize, the combined findings from the RD and the DID estimations yield a rather detailed picture of the behaviour of voucher users after the enforcement of the reform under examination. As we already noted, the objective of the reform was to prevent the fraudulent use of subsidiary employment to cover over-the-counter employment relations. The preventative measure implemented by the legislator was instantaneous tracking of vouchers, which can be viewed as a relatively small organisational cost. In response the number of vouchers actually used plunged almost immediately. The estimated fall is statistically significantly with respect to the pre-reform period. We also found a significant decrease in the ratio between hours contracted by means of vouchers and the number of employees of the firm using vouchers . This can be interpreted as a combination of the reduction in the number of vouchers used by all employer, and the crowding-out of smaller firms due to the additional organisational cost imposed by the reform. Finally, the DiD analysis shows that the number of vouchers used plunged more for private employers than for public ones, which suggests, in turn, that the reform may have effectively curbed the fraudulent use of the instrument.

3.7 Robustness checks

In the Method section we explained how Regression Discontinuity design works and stated that we would use a similar, yet not identical, framework in which the forcing variable is time. Although Regression Discontinuity in Time is analytically analogous to traditional cross-sectional RD, it has some conceptual differences. Hausman and Rapson, 2018, list the major differences between the two types of Regression Discontinuity and explain how to deal with the sources of bias that can arise in the RDiT framework.

Cut-off c=41	*Left of c*	*Right of c*			Dependent variable:	$Log(Y_i)$
Number of observations:	493	583			Number of observations:	13,867
Order of local polynomial:	1	1			NN matches:	3
Order of bias:	2	2			BW tipe:	CCT
Bandwidth:	6.878	6.878			Kernel type:	Triangular
Method	*Coeff.*	*S.E.*	Z	$P > \|Z\|$	*95% C.I.*	
Conventional	0.01471	0.14064	0.1046	0.917	-0.2609	0.2904
Bias-corrected	-0.01265	0.14064	-0.0899	0.928	-0.2883	0.2630
Robust	-0.01265	0.17716	-0.0714	0.943	-0.3599	0.3345

TABLE 3.8: Robustness check 2: different dependent variable (1). Local linear regression for the average number of wage employees of each firm. *Source: INPS(2017) and RegistroAsia(2014), own calculations*

Cut-off c=41	*Left of c*	*Right of c*			Dependent variable:	$Log(Y_i)$
Number of observations:	329	397			Number of observations:	13,867
Order of local polynomial:	1	1			NN matches:	3
Order of bias:	2	2			BW tipe:	CCT
Bandwidth:	6.860	6.860			Kernel type:	Triangular
Method	*Coeff.*	*S.E.*	Z	$P > \|Z\|$	*95% C.I.*	
Conventional	0.05894	0.25864	0.227	0.820	-0.4479	0.5658
Bias-corrected	0.05202	0.25864	0.201	0.841	-0.4548	0.5589
Robust	0.05202	0.3575	0.1455	0.884	-0.6486	0.7527

TABLE 3.9: Robustness check 2: different dependent variable (2). Local linear regression for the average number of days between voucher purchase and beginning of activity. *Source: INPS(2017) and RegistroAsia(2014), own calculations*

Cut-off c=40						
Method	*Coeff.*	*S.E.*	Z	$P > \|Z\|$	*95% C.I.*	
Conventional	-0.00544	0.03973	0.131	0.891	-0.0724	0.0832
Bias-corrected	-0.02796	0.03973	0.702	0.482	-0.0499	0.1058
Robust	-0.02796	0.05148	0.541	0.587	-0.0729	0.1288
Cut-off c=43						
Method	*Coeff.*	*S.E.*	Z	$P > \|Z\|$	*95% C.I.*	
Conventional	0.04564	0.06128	0.745	0.456	-0.07447	0.16574
Bias-corrected	0.03412	0.06128	0.557	0.578	-0.08599	0.15422
Robust	0.03412	0.08813	0.387	0.699	-0.13862	0.20685

TABLE 3.10: Robustness check 3: different cutpoints. Local linear regression results at different cutpoints. Triangular Kernel function. *Source: INPS(2017), own calculations*.

	2nd order GP BW: 5 weeks	3rd order GP BW: 5 weeks	2nd order GP BW: 10 weeks	3rd order GP BW: 10 weeks
Estimated T.E.	-0.1004**	-0.1750**	-0.1159***	-0.1060**
(S.E.)	(0.03207)	(0.0689)	(0.0280)	0.0399
Number of observations:	39,817		74,633	

TABLE 3.11: Robustness check 4: different specifications. Results with Global Polynomial approximation approach with covariates and manually chosen bandwidths. Covariates included: province where the voucher was sold, activity performed by the worker, sector of the employer. Standard errors in parentheses; $***p < 0.001, **p < 0.005, *p < 0.01$ *Source: INPS(2017), own calculations*.

3.7.1 Autoregressive properties

A possible pitfall of RDiT is that the time-series component of the data may exhibit serial dependence. If the residuals show serial dependence, then the standard errors should reflect it. We used the STATA command *rdrobust* that automatically constructs robust standard errors that reflect this problem and provide correct inference. Conversely, if the dependent variable shows autoregressive behaviour, this affects the estimation of short- and long-run treatment effects. Since in our study we only considered a short-run effect in a relatively narrow neighbourhood of the threshold, any autoregressive behaviour of our dependent variable should not be a problem. Nevertheless, it is useful to test for autoregressive behaviour, and if the result is positive, include the lagged dependent variable as covariate in the equation.

We therefore tested our dependent variable for serial correlation using a test proposed by Cumby and Huizinga, 1992,[11] We included a five-weeks lag. At 1% significance level we were unable to reject the null hypothesis of lack of serial correlation in any of the lags. Table3.7 reports the results of the test. In every lag we reject the null hypothesis of presence of serial correlation.

3.7.2 Unobservables correlated with time

In the setting of RD in time, unobservable confounders may be correlated with the running variable and have a discontinuous impact on outcome. A problem of most RDiT studies is little or no cross-sectional variation, which arises for instance when analysing changes in time of a single cross-sectional unit. Researchers often try to increase their sample size by expanding the time window around the cut-off, however when this approach is chosen, the larger the time span considered, the higher the chance that unobservable confounders can lead to overfitting of the global polynomial. We argue that possible bias due to unobservable confounders is not a problem in our study for two reasons. First, our bandwidth is much smaller than those employed in many other RDiT

[11] Implemented for Stata by Baum and Schaffer, 2013, with the command *actest*.

studies[12]. Second, we chose a local-linear approximation instead of a higher order polynomial, a context in which overfitting is not a concern.

3.7.3 Sorting and strategic behaviour

In a cross-sectional RD setting, sorting behaviour occurs when individuals strategically place themselves on either side of the cut-off in order to be affected or unaffected by a policy. To rule out selection in or out of treatment, researchers can employ a density test such as the one proposed by McCrary, 2008. When time is the running variable, however, it is not possible to test for strategic behaviour around the threshold. These tests are used to check for discontinuities in the conditional density of the running variable. Since time has a uniform density, the tests are logically irrelevant.

As noted in Section 5, we chose the number of vouchers used by employers per week as dependent variable. We did so because while the number of vouchers sold might have decreased in anticipation of the new policy, there is no reason why the number of hours contracted might have changed before application of the law. Employers probably continued business-as-usual for as long as possible, only changing their behaviour when forced to do so. This is why we can assume that sorting behaviour is unlikely in our dataset. In this situation, sorting could occur in two ways: first by significantly limiting the number of vouchers used before implementation of the policy. As we have seen, there is no reason why a voucher employer should do this. The other possible sorting behaviour could occur if an employer who bought vouchers in bulk at the beginning of the month or season, decided to use them all before implementation of the new regulation. An employer might do this if he feared he would be effectively unable to employ voucher workers under the new regime. We do not think this occurred since there are no substantial peaks in voucher use in the weeks immediately preceding the implementation of the regulation.

Nevertheless, we tested for discontinuities in other variables of our dataset at the threshold, and for discontinuities in the outcome variable at other thresholds.

The first alternative outcome variable that we consider is the number of regular employees hired by firms employing voucher workers (G). The variable is the same as the one we used as denominator when we investigated the behaviour of the ratio of number of vouchers used to employees in a firm around the cut-off. As shown in Table3.8 reports, there is no discontinuity in the average number of employees in the firms of our sample, thus suggesting that sorting behaviour does not influence our dataset.

A second alternative outcome variable is the number of days between purchase of the voucher and the beginning of voucher activity (D). As noted above, a possible sorting behaviour could be increased use of vouchers just before implementation of the new law to get rid of them before the regulation on their

[12]To cite some examples: Davis, 2008, investigated the effect of a driving restriction on pollution levels in Mexico City using an 8-year window around the cut-off date; Auffhammer and Kellogg, 2011, estimated the impact of gasoline regulations in the US on ozone pollution using a 365 days bandwidth around treatment date.

use becomes too difficult to comply with. This is possible because we observed that most voucher purchasers bought a packet of vouchers at the beginning of the month or season. Table3.9 shows the results of the RD on the average number of days between voucher purchase and the start of activity. We do not find evidence of any change in the trend around the threshold, which suggests that this type of sorting did not occur.

Table3.10 shows the results of the same linear approximation, with MSE-optimal bandwidth and triangular kernel, at different cut-off values. The results indicate that immediately before and immediately after the reform there was no significant jump in the number of vouchers used.

3.7.4 Robustness to different specifications

Table3.11 reports the results obtained by different specifications of our model. Instead of a locally linear regression with parametrically chosen bandwidth, we adopted two global polynomial specifications (2nd and 3rd order) and different manually selected bandwidths (5 weeks and 10 weeks).

The arbitrary choice of bandwidth is discouraged by most of the RD literature because it does not ensure balancing of the "bias-variance trade-off" (Imbens and Kalyanaraman, 2012). As noted in Section 3, this trade-off arises because a smaller bandwidth reduces the misspecification error while at the same time reducing the number of observations available. In this case, a larger bandwidth should improve linear approximation of our function by the global polynomial. Again, as with the locally linear regression, the treatment effect is calculated on both sides of the same threshold and is not supposed to indicate the trend in voucher use in time.

We included controls in the regression for: province where voucher was sold, type of activity performed by voucher worker and economic sector of firm. The four results agree on the estimation of a negative and statistically significant treatment effect, although the magnitude of the treatment effect differs between approaches. The 3th order global polynomial with 5-week bandwidth estimates a treatment effect of 17.5%, closer to that estimated by locally linear regression with triangular kernel. All other approaches estimate a treatment effect between 10% and 12%, closer to the results of the locally linear regression with linear kernel.

The use of global polynomials is discouraged for several reasons, the main one being that the results are extremely sensitive to arbitrary choice of the order of polynomial approximation (Gelman and Imbens, 2018). The results presented here are therefore not alternative to those in Table3.3 and Table3.3. Their purpose was only to show that the global polynomial approach leads to results of the same order of magnitude as the local regression approach.

3.8 Conclusions

Subsidiary employment has often been indicated as an extreme form of flexibilisation of the labour market. To better understand this phenomenon, we

used administrative data collected by the Italian National Social Security Institute on vouchers used between 2014 and 2017. We applied a regression discontinuity and a difference-in-differences analysis to assess the impact of the introduction of a small organisational cost on the use of vouchers after October 2016.

Our finds afford three main conclusions. First, the number of vouchers used decreased substantially after the introduction of the reform. Second, the composition of employers possibly changed in favour of bigger firms/organisations since smaller firms may have lacked the resources to bear the additional cost imposed by the reform. Third, the number of vouchers used by private firms decreased more than the number of vouchers used by public authorities, suggesting that in many cases private firms had used these vouchers to conceal the employment of informal workers.

The main drawback of RD and DiD analyses is that they often lack external validity. In this case, for example, our results are only valid for subsidiary employment at a point in time and in just one region of Italy. Nevertheless, we believe that a few general conclusions can be drawn from our results, and from the Italian experience of subsidiary work in general. The first is that atypical forms of employment and informal work are often linked. Both these arrangements are profitable when an employment relation is either very short, or lasts few hours each week or each month. For this reason, traditional arrangements (even those that do not correspond to the standard employment relation, such as part-time or temporary work) are unfit to address marginal employment opportunities. If, then, it is both efficient and desirable to device regulations that pull marginal jobs out the shadow economy, the Italian experience shows that to obtain a significant pull-out effect employers must be offered an arrangement as flexible as informality, and the pre-reform Italian vouchers ensured such flexibility. However, the pulling out effect was only partial in the Italian case since fraudulent use was a non-negligible component of the growth of vouchers before the reform was implemented. Any attempt to reduce or qualify flexibility in order to reduce fraude should, however, be weighed against the risk of discouraging from use those firms/organisations that are more prone to resort to shadow labour, namely smaller concerns in the Italian context.

Chapter 4

The impact of working from home on mental well-being: an analysis of time pressure and work overload among Italian teleworkers

4.1 Introduction

Since the 1970s, technological developments (such as the introduction of personal computers) and the transition to a largely knowledge-based economy have enabled an increasing number of individuals to work outside factories and office buildings. Virtual "invisible" workers working digitally anywhere are now likely to become more and more common. Firms are promoting *new ways of working* that may be independent of time and place (Popma, 2013).

Work outside the employer's premises is usually referred to as "telework". According to the broad definition of Nilles, 1994,), telework is a form of work that entails spending some portion of the working time away from conventional workplaces and communicating by means of computer-based technologies. Of course, current technologies are even more sophisticated than those imagined by Nilles in 1994, however this definition still captures the fundamental characteristics of telework: it is based outside traditional office space and uses information and communication technologies. The Telework, 2002, defines telework as "a form of organising and performing work, using information technology, in the context of an employment contract/relationship, where work, which could also be performed at the employer's premises, is carried out away from those premises on a regular basis". [1]

As we show in the remainder of this analysis, the characteristics of telework and teleworkers have changed with the introduction of new technologies and ways of doing business. In particular, most of the places where telework is now conducted are different from those of 20 or 40 years ago. Nevertheless, one place has remained constant over this period: workers' homes.

[1]Framework Agreement on Telework, July 16 2002, EU agreement between ETUC, UNICE/UEAPME and CEEP.

Working from home is believed to have several positive effects on worker wellbeing and on the community. It often allows a better work-life balance, it increases the worker's perception of autonomy and flexibility and it cuts commuting time and therefore decreases transport-related emissions and traffic congestion in metropolitan areas. Nevertheless, working at home can blur the division between work and family life, generating tensions and fatigue. The constant use of digital technologies may make it difficult to find personal time away from work.

This study examines the phenomenon of working from home and the consequences it may have on the mental well-being of Italian teleworkers. The analysis is performed in three steps. First, we divided the population of workers into three groups (office-based workers, occasional home-based teleworkers, regular home-based teleworkers) and investigated their characteristics using a multinomial logit model. Second, we applied the semi-parametric estimation of multivalued treatment effects proposed by Cattaneo, 2010, to determine which workers are more likely to experience time pressure and severe work overload. Finally, we used the same method to calculate between-group differences in the usual number of hours worked and the usual number of hours of paid overtime. We used data on Italian workers from the 2013 EU Labour Force Survey *ad-hoc* module on "accidents at work and other work-related health problems", together with the standard EU-LFS cross-sectional national dataset.

The results show that the occasional and regular home-based teleworker groups comprise individuals with different profiles and characteristics. While occasional homeworkers are more likely to report work-related stress, regular homeworkers are associated with longer weekly working hours than occasional homeworkers and office-based workers.

This research builds on the existing literature on telework in two ways. First, it studies the personal and job-related characteristics of Italian home-based workers, since in the last few years this phenomenon has expanded as never before. Second, it offers insights into the mental health-related issues associated with telework.

Section 2 gives a picture of the evolution of telework in recent decades. Section 3 summarises the literature on the characteristics of teleworkers and the factors leading people to choose telework. Section 4 analyses the literature on the positive and negative consequences of working from home on individuals. Section 5 presents the data and characteristics of the sample and Section 6 shows the results of analysis. Section 7 summarises and discusses our main findings.

4.2 The development of telework

Working from home is not a recent trend: Popma, 2013, argues that the origins of this phenomenon date back to the 19th century. The term *Verlagssystem* (or *putting-out system*) indicates the decentralised production system adopted by European textile firms of that time: at that time, the manufacturer would provide raw materials and machineries for the worker to weave at home (Berg, Hudson, and Sonenscher, 2002).

According to Nilles, 1988, modern home-based telework was born in the 1970s in California, when large tech companies like Yahoo promoted the idea of working from home with the help of information and communication technologies (ICTs). Forty years later, *new* ICTs (smartphones, tablet computers and so on) have contributed to the evolution of the concept of telework (Craipeau, 2010) and enabled a revolution of traditional office work.

In the 1980s personal computers and telephones allowed the decentralisation of part of the workplace inside the employees' homes. Nowadays, laptops, smartphones, and the accessibility of the Internet allow many workers to perform their tasks anywhere. Messenger and Gschwind, 2016, identify three key phases in the history of telework: *Home Office*, *Mobile Office*, and *Virtual Office*.

The first phase, the *Home Office*, began during the 1970s, when large companies based in the United States (especially in California) were putting a lot of effort in overcoming two major issues affecting wide metropolitan areas: long commuting times for their employees, and the increasing cost per square meter of office space. The emergence of ICTs enabled the relocation of certain activities outside the employers' premises and closer to (or into) the employees' homes. This phenomenon was defined by :Nilles, 1975, "telecommuting network" or, in short, "telework".

Between the end of the 1980s and the beginning of the 1990s, a further push to telework was given by the replacement of traditional forms of correspondence with the electronic mail (Wellman, 1996). In this period, telework was widely perceived as a deep revolution in the world of work, with many early studies enthusiastically listing the possible benefits of working from home in terms of reduced pollution (Olson, 1982), greater community stability (Daniels, 1987), and the rise of new industries (Toffler, 1980) and of new family structures (Kraut, 1989). Given the potential positive effects of telework on society, several public authorities in the US started to encourage their employees to work from home. For instance, the Government of the United States launched an experimental programme in 1990 to increase the number of federal teleworkers (Di Martino and Wirth, 1990).

The second phase in the history of telework, the *Mobile Office*, spans through the 1990s and the 2000s thanks to the rapid evolution of ICTs. Smaller, cheaper and lighter devices like notebooks and mobile phones transformed the home office into a mobile one: employees could work not just from home, but from anywhere they wanted (Bailey and Kurland, 2002). Nevertheless, the main distinction between these two phases is that "traditional" home-based teleworkers were mainly clerical workers across all industries, while during the 1990s the group of "new" teleworkers was almost exclusively composed by managers and professionals in marketing and finance industries (Messenger and Gschwind, 2016). In this period, therefore, the two modes of teleworking coexisted and involved different profiles of workers.

At the same time, governments reacted to the ongoing debates on the potential negative effects of telework by approving legislations to regulate working times, working conditions and occupational safety of teleworkers. The most notable example of this trend is the 2002 *EU Framework Agreement on Telework*, introducing several key principles for telework regulation. According to

this agreement, the European Union protected the voluntary nature of telework for both the employee and the employer and guaranteed that teleworkers enjoyed the same rights as comparable office-based workers, including in terms of workload, access to training, and performance standards.

In the 2010s with the spread of contemporary ICTs, smartphones and tablet computers, the latest phase in the history of telework begun. These devices broke down the barrier between information technology and communication technology, and allowed remote access to information: they enabled "cloud-based work", in which files and applications are stored and shared by a network of computers and servers accessible on the internet. The *Mobile Office* was flexible, but all information had to be carried around in order to be accessible at all times. The *Virtual Office*, on the contrary, is possible because information is stored in "clouds" accessible by tiny and cheap devices like smartphones and tablets: any task can be completed within a miniscule time frame just in the palm of one's hand. This is only recently starting to rise questions concerning the consequences of telework in terms of work intensification, managerial control, and the balance between work and private life (Pyöriä, 2011). The risk for teleworkers is that the "omnipresence" of internet and connectivity has made work itself omnipresent (Messenger and Gschwind, 2016).

In the last decade, the rise of crowdwork has given new popularity to a more traditional concept of telework. *Crowdwork* can be defined as working activities performed through online platforms that connect a large number of organisations and individuals on a global basis. Tasks are performed in the cyberspace, thus there is no need for personal contact between the worker and the employer, or between the worker and the client/user of the service provided (ILO, 2018). Most crowdworkers can find the job, be employed, and carry on their activities directly from their own homes (Kovács, 2017). In the Home Office and the Mobile Office eras, the tasks performed by teleworkers were linked to offline activities, albeit performed more efficiently and from remote thanks to ICTs. In the era of crowdwork, activities are completely digital, and providers and clients are connected only through online platforms. The lack of personal contact and the complete digitalisation of the tasks has led to an increase in the percentage of individuals working from home in certain countries (Holts, 2018). In addition, Barrio and Zekic, 2017, report that the possibility of working from home is one of the reasons of the spread of crowdwork as if the two phenomena are complementary to some extent. Among European countries, crowdwork is particularly relevant in Italy: according to the recent study published by Huws et al., 2017, approximately 22% of the Italian working population has performed some sort of crowdwork, working virtually from their own homes via an online platform.

A recent study published by Eurofound, 2017, refers to the phenomenon of working outside the office as T/ICTM (telework/ICT mobile work), and highlights the increase in the share of teleworkers since the beginning of the 21st century in many developed countries. Consistently, Popma, 2013, reports that in 2007 7% of all EU workers worked outside the employer's premises at least for one quarter of their time; by 2012 this figure had reached 25%. In France, for example, the proportion of home-based teleworkers has risen from 7% to

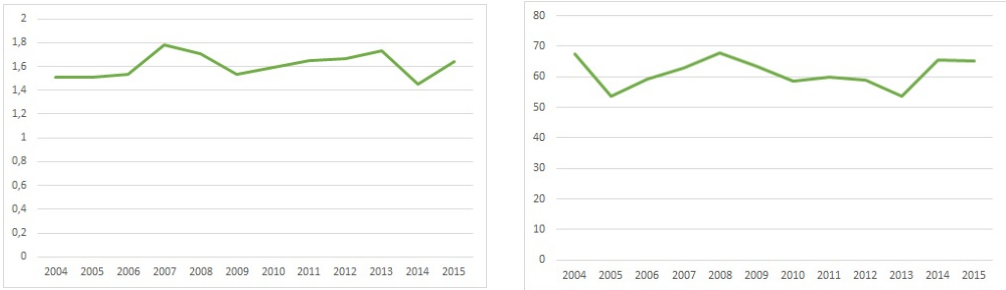

FIGURE 4.1: Spread of home-based telework in Italy. Percentage of home-based teleworkers on the workforce (left) and percentage of regular home-based teleworkers on all homeworkers (right). *Source: EU-LFS, own calculations.*

12.4% of the workforce between 2007 and 2012 (Greenworking, 2012). Vilhelmson and Thulin, 2016, report that, according to survey data, in Sweden in 2012 almost one quarter of the population with commuting-based jobs regularly performed some kind of telework, compared to one-tenth in 2006 and one-twentieth in 1999.

Nevertheless, the incidence of telework is very low in other countries. In the United States, as reported by Lister, 2011, only 2.3% of the workforce consider their home as their primary workplace, even if 45% of the working population hold a job that is suitable for telework. Similarly, in Germany 40% of the jobs are compatible with telework, nevertheless only 12% of all employees work at least occasionally from home (Eurofound and International Labour Office, 2017).

Evidence concerning the phenomenon of home-based telework be found using the data available to us, the European Labour Force Survey spanning from 2004 to 2015. The left panel in Figure4.1 shows that, in the period under consideration, the percentage of home-based teleworkers fluctuated between 1.4% and 1.8%, corresponding to approximately 372,000 individuals in 2015. [2] The majority of these (about 60% according to the right panel in Figure4.1) worked from home on a regular basis, meaning for more than 50% of the time they spent at work.

In the last few years, however, we have witnessed in Italy to the rise of a new attitude towards telework, thanks to the popularisation of *smart working*, defined as "an employment relationship in which the employees perform their working activities partly inside and partly outside of the employer's premises". [3] Vodafone has been one of the first companies to encourage this phenomenon in 2014, with the result that 3500 of its employees could work from home at

[2]The report by Eurofound and International Labour Office, 2017, based on data from the 2015 European Working Conditions Survey, shows that Italy is the European country where telework is less spread. According to them, only 7% of the Italian workforce in 2015 worked outside the office at least occasionally. Note that the differences in the figures resulting from different sources is just a matter of definition of the variable. While the Eurofound and ILO report provides a figure for all employees who work at least occasionally outside the office (at home, while travelling, in a different office space), the LFS dataset only reports home-based telework, i.e. employees working at least occasionally from their home.

[3]Law 81/2017.

least once a week in 2017. In 2014 Intesa-SanPaolo too signed an agreement with trade unions and introduced a *smart working* option for 8000 employees. In 2007 Enel, one of the largest Italian corporations, started a successful experimental programme involving 7000 employees who could work from home once a week, in order to improve the workers' flexibility, autonomy and work-life balance. Other large corporations have introduced similar agreements in 2017, including Barilla, Ferrovie dello Stato Italiane, and Unicredit (Tucci, 2017).

This rise in the number of teleworkers has triggered the introduction of Law 81/2017, regulating the phenomenon of *smart working* in Italy and encouraging the introduction of more flexible working arrangements in public authorities. The objective of this reform was to extend the use of telework to at least 10% of public employees and some experimental projects have involved the Autonomous Province of Trento, the municipalities of Milano, Genova, and Torino, the Office of the Prime Minister, and the Ministry of Economy and Finance (Mochi Sismondi, 2018). As a result, the number of smart workers in Italy reached 480,000 in 2018, with a 20% increase with respect to 2017, according to the Italian Observatory on Smart Working (Pizzin, 2018).

4.3 Factors affecting telework adoption

As noted in the previous paragraph, telework adoption has been uneven across countries in the last decades. The prediction of early researchers on the field that "the new production system could shift millions of jobs out of the factories and offices into (...) the home" (Toffler, 1980) has largely been disattended all over the world (Hynes, 2014). According to Scott, 2012, the reason is that the mere technological progress cannot be the only driver of telework: the decision to pursue telework, by managers and employees, is far more complex. To investigate the observed trends in telework adoption we need to understand its constraining/enabling factors: Vilhelmson and Thulin, 2016, propose to group them in four families: work-related factors, personal factors, technological factors, geographical factors.

4.3.1 Work-related factors

Work-related factors are certainly the most crucial in influencing the likelihood that an employee will be able to work away from the office. Work-related factors include manager willingness to coordinate work from the office and from other places, the level of trust between managers and employees, workplace interaction needs, and the availability of office space and equipment at home.

According to Di Martino and Wirth, 1990, managerial approval of telework is possible when managers supervise the output (results of the work) rather than the input (working time and effort) . This is best done when managers facilitate decentralisation by enhancing communication with teleworkers and increasing trust, loyalty, and employee responsibility. Pyöriä, 2011, argues that the need to evaluate output of teleworkers rather than processes is linked with the rise of performance-based pay schemes in several companies.

Kaplan et al., 2017, investigate the factors underlying managerial resistance towards telework in the US. They concluded that the decision to allow telework varies considerably between-managers and within-managers. "Between-managers" because each manager has a different view on telework and is not always willing to coordinate workers in different locations. "Within-managers" because a manager's decision on telework depends on the conscientiousness and trustworthiness of the specific worker involved.

Besides personal considerations on the worker, managers evaluate the possibility to allow telework also based on the tasks performed. Highly interdependent tasks, that necessitate more frequent communication among employees, often are best performed if they all work side to side, to achieve better coordination (Golden, 2007). Moreover, moving outside the office those tasks that are more difficult to monitor via phone or computer may increase the burden for managers (Kaplan et al., 2017). For this reason, several studies suggest that certain tasks lend themselves to telework more than others; it is the case, for instance, of administrative tasks, writing, accounting, management of information, software and web design, computer graphics (Tremblay, 2002). Nevertheless, when the decision to telework is taken by the employee, idiosyncratic traits of individual jobs, rather than general job characteristics, are more likely to be taken into consideration (Bailey and Kurland, 2002). In other words, based on first-hand knowledge of their own job, employees choose to telework only when they think that their tasks can be effectively performed also outside the office.

4.3.2 Personal factors

It is generally agreed that gender, professional status, income and education are all relevant in determining whether an individual will telework (Hjorthol, 2006). Nonetheless, research has yielded mixed results regarding how and to what extent these characteristics are associated with telework adoption (Vilhelmson and Thulin, 2016).

Di Martino and Wirth, 1990, included working time flexibility among the possible advantages of teleworking. According to them, certain individuals may find in working from home the flexibility they need in order to balance their family responsibilities (or their lifestyle) with their job. On this matter, Bailey and Kurland, 2002, provocatively states that most studies on telework have tried to answer the unspoken question: "do women chose to telework so that they might work and provide childcare simultaneously?". Telework may help individuals improve their work-life balance by significantly reducing commuting time. Furthermore, working outside the office may be especially appealing for those who struggle to be productive in crowded environments and enjoy the autonomy and peace of their home.

Telework, moreover, may be a way of further integrating people with disabilities in the workplace (Baker, Moon, and Ward, 2006). Individuals with disabilities often face considerable challenges when entering the labour market due to barriers related to transportation, mobility limitation, lack of support services in the workplace, and fatigue imposed by medical complications

(Schopp, 2004; Bricout, 2004). Therefore, disabled workers may benefit from the flexible schedule granted by home-based work (Linden, 2014).

Felstead et al., 2001, sketched two possible portraits of the average teleworker. On the one hand, an unskilled woman exploited by her employer, performing tedious tasks at home for a low and erratic wage in order to be able to meet all her care responsibilities. On the other hand, a well-educated individual (more likely to be a man) with high wage, whose high-skill profession requires him to work away from the office from time to time. Despite having been drawn on observations of workers in the 1990s, this dichotomy has recently been confirmed by several studies. For example, the report by Eurofound and International Labour Office, 2017, collecting the results of different national analyses. The latter suggests that, when looking only at home-based telework, in several European countries there is a larger proportion of women working from home on a regular basis and a larger proportion of men doing occasional home-based work. Therefore, the report concludes that in Europe women tend to perform more home-based telework than men, as a strategy to combine work and care responsibilities.

4.3.3 Technological factors

ICTs are usually considered a precondition to telework, without technology the number of tasks that could be performed remotely would be much smaller. Nonetheless, technological advancements alone have proved to be insufficient in triggering telework adoption. Several studies have shown that, while ICTs are a precondition for working outside the office, they alone are not the drivers of the decision to telework (Haddon and Brynin, 2005). This has been confirmed by the fact that the huge increase in Internet access which occurred in the early 2000s did not generate a corresponding increase in the diffusion of telework (Vilhelmson and Thulin, 2016). Nevertheless, some exceptions exist: Neirotti, 2013, report that the increase in the number of teleworkers observed in one region of Italy (Piemonte) between 2005 and 2009 was attributable to the diffusion of portable devices allowing “mobile work”. Eurofound and International Labour Office, 2017, suggest that telework became more feasible for many Swedish workers after 2005 because of the increased portability, interactivity, and media richness of new ICTs.

To sum up, it is difficult to draw a definite conclusion on the relationship between technological advancement and telework. It appears that, in certain contexts, enabling technologies induce some office-based employees to telework. Nevertheless, the choice to telework also depends on personal and job-related factors: when these conditions are not favourable, technological advancement alone cannot trigger an increase in telework diffusion.

A different technology-related issue, underlined by Pyöriä, 2011, is linked with data security protection, that may be difficult in the context of telework. Access control and encryption are crucial data protection systems in many firms and these procedures often suffer problems related to human carelessness. This risk of data breach increases exponentially if data flows involve the employees’ personal computers, and not just the company’s network. Therefore,

organisations willing to allow telework need to adopt technologies that guarantee a high-standard data security policy, which can be particularly costly in small and medium firms (Clear, 2007).

4.3.4 Geographical factors

One of the original motivations for the rise of telework in the 1970s was the possibility of reducing commuting time and costs, as noted in the previous section. Telework, indeed, offers flexibility as far as location of work is concerned and allows people to work potentially very far away from their offices. By being able to reduce or eliminate commuting trips, telework could cause a reduction of traffic congestion levels in metropolitan areas and a decrease of transport-related emissions (Silva and Melo, 2018).

Moreover, since they do not need to commute, teleworkers would be able to live far from the city and help the development and repopulation of rural areas (Grimes, 2000, Simpson, 2003). Telework, in fact, can be a tool to create employment in isolated areas and reduce regional imbalances (Di Martino and Wirth, 1990). Nevertheless, it has been noted that telework is much more common in urban and suburban areas than in rural or remote areas (Pyöriä, 2011). This happens partly because the employers that are more likely to allow telework are concentrated in cities and because most teleworkers spend at least one day per week in the office (Pérez, 2002). The link between commuting time and propensity to telework, therefore, is not as strong as early adopters would have expected (Andreev, Salomon, and Pliskin, 2010), hinting that the relation between household location, office location and teleworking decision is complex and difficult to sort out (Vilhelmson and Thulin, 2016).

4.4 Psychological well-being of workers

Despite the efforts of the scientific community, there are no clear conclusions concerning the impact of telework on the emotional experience and psychological well-being of individuals. The general assumption is that home-based teleworkers benefit from increased flexibility and autonomy, higher job satisfaction, improved work-life balance, and more productive working hours; nevertheless, some drawbacks of telework have been identified: a detrimental effect on teamwork and co-operation between workers, reduced opportunities for social interaction, feeling of social isolation, increase in work-life conflict (Boell, Cecez-Kecmanovic, and Campbell, 2016). The general conclusion is that which of these factors will predominate largely depends on the individual traits and attitudes of the worker.

Gajendran and Harrison, 2007, drew a framework to look at the possible positive or negative effects of telework on the worker's life. According to them, the impact of working from home on several individual outcomes (such as: job satisfaction and performance) is mediated by three factors: perceived autonomy, work-family balance, relationship quality. Perceived autonomy is considered to be higher for teleworkers: not only because they are physically removed from direct visual supervision, but also thanks to the increased control over the

schedule of daily activities. Moreover, working from home allows control over several aspects of the environment that can enhance productivity: temperature, decoration, lighting, music, and so on, thus contributing to an increased perception of flexibility and discretion.

The work-family consequences of telecommuting are less straightforward. Work-family conflict can generate stress and anxiety because of the blurredness of the boundaries between the two spheres, arising because both dimensions occupy the same space and potentially the same time. In this context it may even become problematic for the home-based teleworker to disengage from work, leading to further time-based conflict and increased stress. Nevertheless, work-family balance may benefit from a more flexible synchronisation of work and leisure or family time. When the timing of work is in the employee's control, time-based conflict can be reduced by scheduling work time in order to meet the needs of other family members.

The reduction of face-to-face interaction associated to telework is generally believed to degrade interpersonal relationships for the individuals involved. Working from home, in fact, usually changes the frequency, the quality, and the modality of interactions with co-workers. Spending a lot of time in physical proximity with other individuals makes strong, positive, deep connections easier to develop and maintain. The lack of this daily experience may generate in the teleworker a sense of isolation, while the spatial distance from his or her peers can translate into psychological distance and reduction in the commitment towards the organisation. The relationship with managers too can be altered by the lack of face-to-face interaction. As immediate feedback and affective signals (like facial expressions) are not an available way of communicating, managers can find it difficult to monitor work and maintain a positive office environment.

Anderson, Kaplan, and Vega, 2015, collected data from 702 employees from a large US federal agency and concluded that the relationship between work environment, individual personality traits, and well-being is complex and difficult to grasp. In general, they noted that telework would increase significantly the well-being of most individuals. Nevertheless, workers with specific personal characteristics (for example rumination and low-openness) would exacerbate the negative aspect of the reduced social contact associated with telework. According to their conclusions, therefore, managers and organisations should carefully consider individual personalities before allowing their employees to work from home. Moreover, managers should put extra effort in encouraging social connections between co-workers at home and in the office.

Wilton, 2011, interviewed the employees of a large secondary education institution in Canada and conducted a qualitative analysis on the relation between telework and social interactions. Many subjects reported among the costs of telework the lack of face-to-face contact with others, both for work purposes and for social interaction. For what concerns social interactions, respondents mentioned that working from home entails a risk of isolating themselves, and expressed their worry to miss opportunities for human contact (going for lunch with friends, meeting new people, and so on). Furthermore, the lack of

support from one's colleagues can make problem solving more difficult. Feedback on one's work, moreover, may be more difficult to communicate without face-to-face interaction.

The effect of social interactions has been studied also by Windeler, 2017. They interviewed 500 employees of a large financial service firm in the US and found that part-time telework can be a useful tool in alleviating work exhaustion generated by intense interpersonal interaction. In their framework, social interaction, although certainly beneficial and necessary, can consume energy and diminish cognitive resources in the workplace. Employees who could telework once or twice per week experienced it as a break from social interactions and a way to achieve greater control over their allocation of time.

The relationship between home-based telework and family life is one of the most studied areas in telework literature. Spending at least part of the working time in the house can be helpful for dual-earner couples struggling to cope with personal/family demands (Bae and Kim, 2016). Research has shown that working from home enables increased autonomy in the scheduling of daily activities, in order to combine paid work, housework, childcare and leisure (Sullivan, 2001). Nevertheless, home-based workers are more likely than office workers to mix paid employment with childcare or domestic work during the conventional business hours, thus, they are often forced to work early in the morning or late at night (Hill, Ferris, and Märtinson, 2003).

Hill, Hawkins, and Miller, 1996, interviewed the employees of a large US corporation and examined the spillovers between family life and telework, focusing on two aspects: quality of family relationships and ability to complete household chores. Both these aspects are generally believed to be enhanced by telework. Family relationships can benefit from more frequent interactions between family members. Nevertheless, blurring the barrier between work and family may increase stress and make conflicts more frequent. Furthermore, overlapping household chores with paid employment can improve the teleworker's experience and save time for leisure, provided that household tasks do not absorb all the energies.

Hill, Hawkins, and Miller, 1996, report that the results of their interviews were mixed. Most teleworkers stated that working from home had a positive influence on their personal and family life. Nevertheless, home-based workers were not more likely to report that they had enough time for family life than their counterparts in the office. Moreover, certain respondents reported that balancing family time and work became increasingly difficult since they started working at home, forcing them to work longer hours or at unconventional times. The influence of telework on household chores, on the other hand, has been reported as positive by the great majority of the respondents, especially by parents of preschool-aged children who benefited from more flexibility in the management of child care.

The role of household chores in the choice of teleworking has been taken into consideration also by Sullivan, 2001. They interviewed 14 home-based teleworkers and their co-residents, to explore to what extent the flexibility granted by telework can perpetuate traditional work and family roles of men

and women. Respondents reported that the two main motivations for choosing to work from home were: domestic reasons (e.g.: childcare) and individual reasons, with childcare being the main motivation for women, but not for men. Overall, they noticed that family commitments were much more marginal in the decision-making of male teleworkers. Most of the teleworkers and co-residents, moreover, reported that the distribution of household chores did not change after the decision to work at home, regardless of whether the teleworker was the man or the woman. Therefore, Sullivan and Lewis concluded that home-based telework for women and men is a very different experience. Women especially valued the possibility to fulfil their domestic responsibilities without leaving aside their career prospects. Men, on the other hand, benefited from the increase flexibility of telework that allowed them to spend more time with other family members, as well as "help" their partners with domestic chores.

A gender difference in the perception of telework has been reported also by Bae and Kim, 2016. They relied on the 2013 US Federal Employee Viewpoint Survey to evaluate the impact of the adoption of a telework programme by the employer on job satisfaction. Their results show that female workers had the lowest levels of job satisfaction when their employer adopted telework, but they could not utilize the programme. Thus, they showed higher expectations than men from the possibility of working from home.

Standen, 1999, recognised the deep connection between work-family balance and psychological well-being. They argued that working from home may entail a loss of variety in social connections, preventing the access to material, psychological, and social resources to minimize family conflict. Therefore, they suggested that the fit between the worker and the home work environment should be improved by selection procedures, training, and counselling programs. Managers, moreover, should be aware of the link between improved performance and well-being, which results from adequate support of the worker at home and in the workplace.

Mann, 2003, identified the possible causes of psychological distress in teleworkers. Among the problems associated to telework they mentioned social isolation due to the lack of interactions, *presenteeism* due to the tendency to work longer hours or even when sick, career marginalisation due to the limited visibility and lack of office information networks. They implemented two studies: a qualitative interview aimed at evaluating the emotional impact of working away from the office, and quantitative questionnaire comparing stress and health symptoms of office-workers and home-workers. They concluded that homeworkers are more likely to report negative emotions such as loneliness, irritation, worry, and guilt than office-based workers. This translated into higher levels of emotional ill health for those working from home.

Golden, 2007, studied the impact of telework in a completely different perspective. He interviewed 240 educated professional employees in a large high-tech company to investigate whether the prevalence of teleworkers in an office influenced the performance and the satisfaction of non-teleworkers. He concluded that a higher prevalence of teleworkers is negatively associated with job-satisfaction of their co-workers. Furthermore, he found a negative association between satisfaction with co-workers and turnover intentions. Therefore,

he concluded that perceptions of injustice may be particularly strong among the colleagues of teleworkers, considering that they might suffer from decreased flexibility and increased workload.

4.5 Data and sample

We used cross-sectional microlevel data from the 2013 wave of the European Labour Force Survey (LFS), including the ad-hoc module on "accidents at work and other work-related health problems". The LFS is a large household sample survey providing data on labour participation of people aged 15 and over as well as persons outside the labour force. We selected data for Italy, where the survey is conducted by the National Statistical Institute (ISTAT) and coordinated by Eurostat.

Almost every year the LFS is supplemented with an *ad-hoc module*, in order to provide users with statistics on specific topics concerning the labour market. In 2013 the chosen topic was "accidents at work and other work-related problems". The aim of this ad-hoc module is to know whether an individual has had an accident at work in the previous 12 months that resulted in a physical injury, as well as whether the individual is exposed to mental well-being risk factors in the workplace.

In 2013 the database comprised 153,317 individuals, 51,690 of which were in employed. We focus our attention only on wage employees, aged between 22 and 67. Therefore, we ended up with a sample of 36,186 observations.

The data allows a distinction between three types of workers, according to the variable "homewk" that measures the intensity of home-based telework. Individuals are asked how frequently they had the chance to work from home in their main job: usually (more than 50% of their working time), sometimes (less than 50% of their working time), or never. In our sample 321 workers stated that they usually worked from home, 309 sometimes worked from home, while the great majority (35,531 individuals) never worked from home.

The remaining of this section lists the other relevant variables to our analysis. Their distribution in the two major categories (non-teleworkers and at least occasional home-based teleworkers) are reported in Table4.1. Table4.2, moreover, reports the differences in distribution of these variables between occasional and usual home-based teleworkers.

We begin by listing personal characteristics. In our sample we have 17,036 women and 19,150 men. Table4.1 shows that there is no significant difference in their proportions among home-based and office-based workers. Nevertheless, in Table4.2 we notice that women account for a much larger share (61%) of usual home-based teleworkers.

The variable "age" has been divided in 5 band: younger than 27 (7.72% of the sample), aged between 28 and 37 (25.03% of the sample), aged between 38 and 47 (34.8% of the sample), aged between 48 and 57 (28.39% of the sample), and older than 57 (4.05% of the sample). Observing the distribution of these categories in Table4.1 and Table4.2 we can conclude that younger workers tend to be over-represented among office-based workers. On the contrary, working from home becomes more and more common as workers get older.

	Home-based telework		
	No	**Yes**	**Difference**
Sex: male	0.532	0.513	0.019
Age:<= 27	0.121	0.087	0.034***
Age: 28-37	0.239	0.211	0.028*
Age: 38-47	0.332	0.328	0.004
Age: 48-57	0.270	0.312	-0.042**
Age: >57	0.038	0.062	-0.024***
Education level: University	0.178	0.395	-0.216***
Education level: Upper secondary	0.329	0.206	0.123***
Education level: Lower secondary	0.493	0.399	0.093***
Occupation: High skills	0.314	0.580	-0.267***
Occupation: Medium skills	0.466	0.326	0.140***
Occupation: Low skills	0.221	0.094	0.127***
Sector: ICT services	0.126	0.164	-0.037***
Degree of urbanisation: City	0.277	0.317	-0.039**
Degree of urbanisation: Town	0.424	0.412	0.013
Degree of urbanisation: Rural area	0.298	0.271	0.027
Region: North West	0.295	0.297	-0.002
Region: North East	0.242	0.238	0.004
Region: Centre	0.189	0.229	-0.040**
Region: South and Islands	0.274	0.237	0.037**
Contract: Part-time	0.193	0.128	0.065***
Firm size: small	0.308	0.206	0.103***
Firm size: medium	0.160	0.237	-0.078***
Firm size: large	0.218	0.195	0.023
Firm size: very large	0.314	0.362	-0.048**
Tenure (months)	148.505	167.844	-19.339***
Marital status: married	0.099	0.092	0.007
Marital status: divorced	0.306	0.267	0.039**
Marital status: single	0.596	0.641	-0.046**
At least one child younger than 14	0.367	0.362	0.005
Number of observations	37,331	641	

TABLE 4.1: Descriptive statistics, office-based workers and homeworkers.
Shares and averages of covariates for office-based workers and home-based workers (occasional and regular). In the last column the difference between the two categories and its significance; $***p < 0.001, **p < 0.005, *p < 0.01$. *Source: EU-LFS, own calculations.*

	Homework intensity		
	Occasional	**Regular**	**Difference**
Sex: male	0.617	0.422	0.195***
Age:<=27	0.117	0.062	0.055**
Age: 28-37	0.240	0.185	0.055*
Age: 38-47	0.319	0.329	-0.011
Age: 48-57	0.266	0.360	-0.094***
Age: >57	0.058	0.065	-0.006
Education level: University	0.301	0.477	-0.176***
Education level: Upper secondary	0.266	0.148	0.118***
Education level: Lower secondary	0.433	0.375	0.057
Occupation: High skills	0.482	0.677	-0.195***
Occupation: Medium skills	0.398	0.251	0.147***
Occupation: Low skills	0.120	0.072	0.048**
Sector: ICT services	0.181	0.135	0.046
Degree of urbanisation: City	0.319	0.311	0.008
Degree of urbanisation: Town	0.38	360.428	-0.045
Degree of urbanisation: Rural area	0.298	0.262	0.037
Region: North West	0.289	0.296	-0.007
Region: North East	0.227	0.255	-0.028
Region: Centre	0.195	0.2596	-0.064**
Region: South and Islands	0.289	0.190	0.099***
Contract: Part-time	0.135	0.120	0.015
Firm size: small	0.178	0.240	-0.062*
Firm size: medium	0.342	0.129	0.213***
Firm size: large	0.251	0.154	0.098***
Firm size: very large	0.228	0.477	-0.249***
Tenure (months)	161.237	171.117	-9.880***
Marital status: married	0.056	0.123	-0.068***
Marital status: divorced	0.295	0.234	0.061*
Marital status: single	0.649	0.643	0.006
At least one child younger than 14	0.386	0.335	0.051
Number of observations	342	325	

TABLE 4.2: Descriptive statistics, occasional and regular home-workers.
Shares and averages of covariates for occasional home-based teleworkers and regular home-based teleworkers . In the last column the difference between the two categories and its significance; $***p < 0.001, **p < 0.005, *p < 0.01$. *Source: EU-LFS, own calculations.*

The level of education represents a relevant difference between the two groups of workers. We divide our variable in three groups: high (graduate and post-graduate), medium (upper secondary), and low (lower secondary) level of education. Observing the results from Table4.1 and Table4.2, we notice that home-based teleworkers (especially those who do it for most of their working time) are much more likely to hold a graduate or post-graduate diploma than other workers.

As we have mentioned in Section 3, geographical factors may be relevant in the individual choice to telework. Here we analyse two geographical variables: macro-region of the place of work, and degree of urbanisation of the area where the worker lives. The macro regions identified are: North-West, North-East, Centre, and South-Islands. [4] Observing the regional distribution of office-based and home-based workers we see that in the former group workers from the South are under-represented, while workers from the Centre are over-represented. As far as the degree of urbanisation is concerned, individuals living in metropolitan areas appear relatively more frequently among home-based workers than among office-based workers.

Employees with high-skilled occupations are also more represented in this group, with respect to those with medium or low-skilled occupations. Moreover, a larger share of home-workers comprises those employed in the ICT services sector. [5] Employees of large corporations represent a bigger share of home-based workers than office-based workers (37% vs 32%). The opposite is true for employee of very small firms (20% of at least occasional home-based workers and 30% of office-based workers). Furthermore, office-based workers include a larger share of part-timers with respect to home-based ones (19% and 12% respectively).

The variable "tenure" indicates the number of months the workers has worked for the current employer. From Table4.1 and Table4.2 we can conclude that both occasional and regular home-based workers are associated with longer job tenures than office-based workers. This is consistent with the results reported in the previous sections concerning the link between employee's trustworthiness and the managerial decision to allow telework.

The last set of workers' characteristics that we consider deals with the composition of the family. We include the marriage status (single, married, divorced) and the number of children in the household. What we notice from Table4.1 is that married individuals are over-represented among home-based workers.

Another relevant set of variables for our analysis is the number of hours worked. Here we consider two measures: number of hours usually worked per

[4] Grouped in the standard way, according to the definition of ISTAT. North-West: Valle d'Aosta, Piemonte, Lombardia, Liguria. North-East: Autonomous Province of Trento, Autonomous Province of Bolzano, Friuli - Venezia Giulia, Veneto, Emilia - Romagna. Centre: Toscana, Umbria, Marche, Lazio. South-Islands: Abruzzo, Molise, Puglia, Basilicata, Campania, Calabria, Sicilia, Sardegna.

[5] ICT services correspond to groups J-K-L-M-N in the one-digit Nace Rev. 2 classification: "information and communications", "financial and insurance activities", "real estate activities", "professional, scientific and technical activities", "administrative and support service activities".

week and the number of hours of paid overtime. From Table4.1 we can observe that home-based workers have a higher average value for both variables than office-based workers, while there is no statistical difference between usual and occasional home-based teleworkers (Table4.1). This result apparently contradicts the fairness perception reported by Golden, 2007. Nevertheless, the two results are not incompatible. A possible reason for the difference is that the two results are based on analyses of different countries. Moreover, another explanation may be the fact that office-based workers may have a distorted perception concerning the number of hours worked by their home-based colleagues.

4.6 Methodology

To perform our analysis and obtain the average treatment effect (ATE) of being an occasional or regular home-based teleworker on our dependent variables the main methodology we are going to employ is the *multivalued treatment effect estimation under conditional independence*, proposed by Cattaneo, 2010.

To explain its functioning, let us begin with a random cross-sectional sample of a population of n individuals. Each individual $i = 1,\ldots,n$ is assigned a non-binary treatment j out of a set of $J+1$ possible treatments ($j = 0,\ 1,\ \ldots,\ J$). Let us define y_i as the outcome variable of interest, $\mathbf{x}_i$ as a set of observable covariates, and w_i as a variable denoting the treatment level administered. Therefore, for each i we can observe the random vector $\mathbf{z}_i = \left(y_i, w_i, \mathbf{x}_i'\right)'$. Let us now introduce an indicator variable $d_i(j) = 1(w_i = j)$, which takes value 1 if j is the administered treatment and 0 otherwise.

As seen, y_i denotes the observed outcome. Now let $y_i(j)$ denote the $J+1$ potential outcomes for each treatment level j. Therefore, the observed outcome variable is given by the following expression:

$$y_i = d_i(0)y_i(0) + d_i(1)y_i(1) + \ldots + d_i(J)y_i(J) \tag{4.1}$$

he distribution of each $y_i(j)$ is the distribution of the outcome variable that would occur if individuals were given treatment level j: it is the potential outcome distribution of treatment level j. The potential outcome distributions are marginal distributions with respect to the set covariates $\mathbf{x}_i$. Of course, only one of the $J+1$ outcomes can be observed for each individual, because a single individual cannot be treated twice at the same time. For this reason, the observed y are draws from a distribution of $y(j)$ conditional on $w = j$.

To identify the unconditional distribution of y_j we need to introduce the assumption of ignorability. This assumption is a combination of two propositions: selection on observables and overlap. Selection on observables implies that the distribution of each potential outcome $y(j)$ is independent of the random treatment $d(j)$, conditional on $\mathbf{x}$: [6]

$$y(j) \perp d(j) | \mathbf{x} \tag{4.2}$$

[6]This assumption is standard in the literature and we are not going to discuss it here in details. For further reference see, for example, Imbens, 2004.

Overlap assumption says that for every possible value of $\mathbf{x}$ in the population, the probability that someone with that covariate pattern could be assigned to each treatment level is strictly positive. Formally:

$$0 < p_{min} < p_j(x), \text{ with } p_j(x) = P(w = j|x) \tag{4.3}$$

Now let $F_{y(j)}(y)$ be the distribution function of the potential outcome $y(j)$. The $J+1$ means of the potential outcome distribution are summarised by the vector $\mathbf{m} = (m_0, m_1, \ldots, m_J)'$, where $m_j = \mathbb{E}[y(j)] = \int y\, dF_{y(j)}(y)$. Intuitively, if the potential outcome distributions $F_{y(j)}(y)$ are identifiable from observable data, then so are the population parameters m_j, because they are just means of $F_{y(j)}(y)$ for each j.

Ignorability assumption implies that for each treatment level j:

$$F_{y(j)}(y) = \mathbb{E}[F_{y(j)|\mathbf{x}}(y\,|\,\mathbf{x})] = \mathbb{E}[F_y(y\,|\,\mathbf{x}, w = j)] \tag{4.4}$$

Where $F_y(y\,|\,\mathbf{x}, w = j)$ represents the distributional function of $y\,|\,\mathbf{x}, w = j$, which is identifiable from the data. Thus $\mathbf{m}_j$ is observable from the data under regularity conditions.

Cattaneo, 2010 proposes two estimators for the multivalued treatment effect: the inverse probability of treatment estimator (IPWE) and the efficient influence function estimator (EIFE). For a more detailed explanation of both estimators we advise the reader to refer to Cattaneo, 2010. Here, we will only derive the functional form of the EIFE, the estimator used to obtain the results in the following section. The EIFE approach is more complex with respect to the IPWE, because it involves the estimation of more non-parametric functions. Nevertheless, as will be clearer later on the EIFE enjoys several robustness properties.

Consider the following function:

$$e_j(\mathbf{x}_i; m_j) = \mathbb{E}[y_i(j) - m_j\,|\,\mathbf{x}_i] = \mathbb{E}(y_i - m_i\,|\,\mathbf{x}_i, w_i = j) \tag{4.5}$$

These conditional expectations can be estimated using observed data. Let $p_j(\mathbf{x})$ be the conditional probability functions for each j, the EIFE is then constructed using the following moment conditions for the mean of the jth potential outcome:

$$\mathbb{E}[\,\Psi_{EIF}\{\mathbf{z}_i; m_j; p_j(\mathbf{x}); e_j(.; m)\}\,] = 0 \tag{4.6}$$

with:

$$\Psi_{EIF}\{\mathbf{z}_i; m_j; p_j(\mathbf{x}); e_j(.; m_j)\} = \frac{d_i(y_i - m_j)}{p_j(\mathbf{x}_i)} - \frac{e_j(\mathbf{x}_j; m_j)}{p_j(\mathbf{x}_i)}\{d_i(j) - p_j(\mathbf{x}_i)\} \tag{4.7}$$

By replacing expectations with sample averages and unknown functions with (parametric or non-parametric) appropriate estimators, we obtain the estimates for the means of the potential outcome distributions, $\hat{m}_{EIF,j}$, such that:

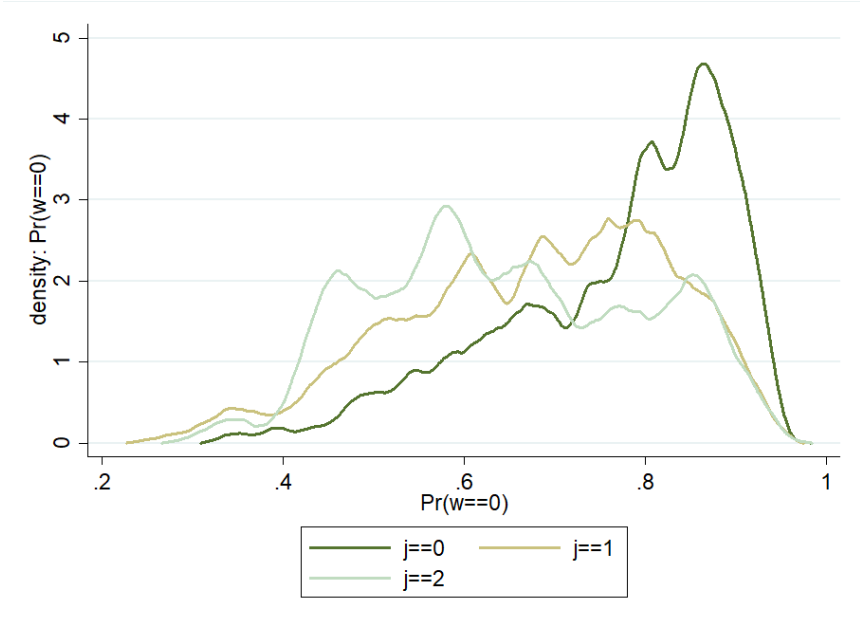

FIGURE 4.2: Conditional densities (1).
Conditional densities for probability of treatment level 0 (no homework). *Source: EU-LFS, own calculations.*

$$\frac{1}{2}\sum_{i=1}^{n}\Psi_{EIF}\{\mathbf{z}_i;\hat{m}_{EIF,j};\hat{p}_j(\mathbf{x}_i);\hat{e}_j(.,\hat{m}_{EIF,j})\}=0 \tag{4.8}$$

Under standard regularity conditions, this estimator is consistent, asymptotically normal, and semiparametric efficient when nonparametric estimators are used to approximate the unknown functions. To have further details on the construction of the variance-covariance matrix estimator we refer to Cattaneo, Drukker, and Holland, 2013. [7] The construction of a joint VCE allows joint inference on the means of the potential outcome distributions. The difference in means of potential outcomes is the most common measure of treatment effect and the one used in the following Section.

4.7 Empirical analysis

We begin by modelling the probability of being an occasional or regular home-based teleworker in 2013 against the set of covariates described in the previous section. The dependent variable takes value 1 if the individual works from home from time to time, 2 if he or she works from home often, and zero otherwise. As the dependent variable is not binary, we use a multinomial logistic regression.

The results reported in the left part of Table4.3 partially confirm the observations in Section 5. As we can see, gender is significant in determining propensity to work from home. However, male workers are more likely to work from home occasionally, while female workers are more likely to do so regularly.

[7] See, in particular, Section 7 of the cited paper.

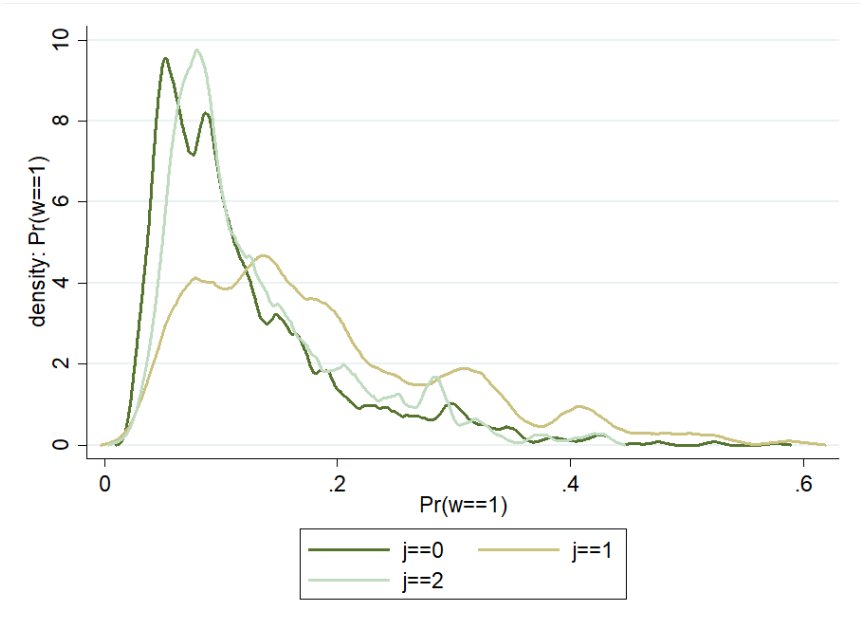

FIGURE 4.3: Conditional densities (2).
Conditional densities for probability of treatment level 1 (occasional homework). *Source: EU-LFS, own calculations.*

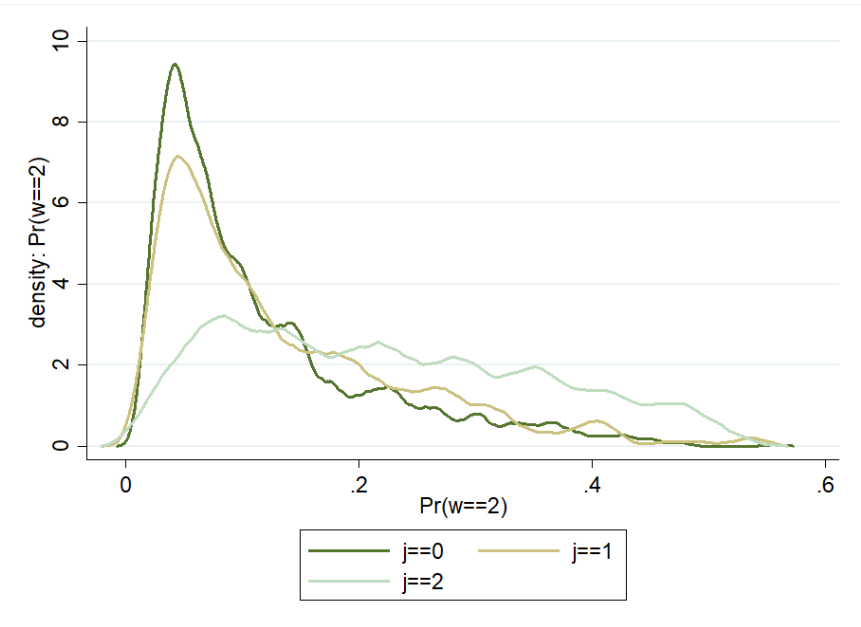

FIGURE 4.4: Conditional densities (3).
Conditional densities for probability of treatment level 2 (regular homework). *Source: EU-LFS, own calculations.*

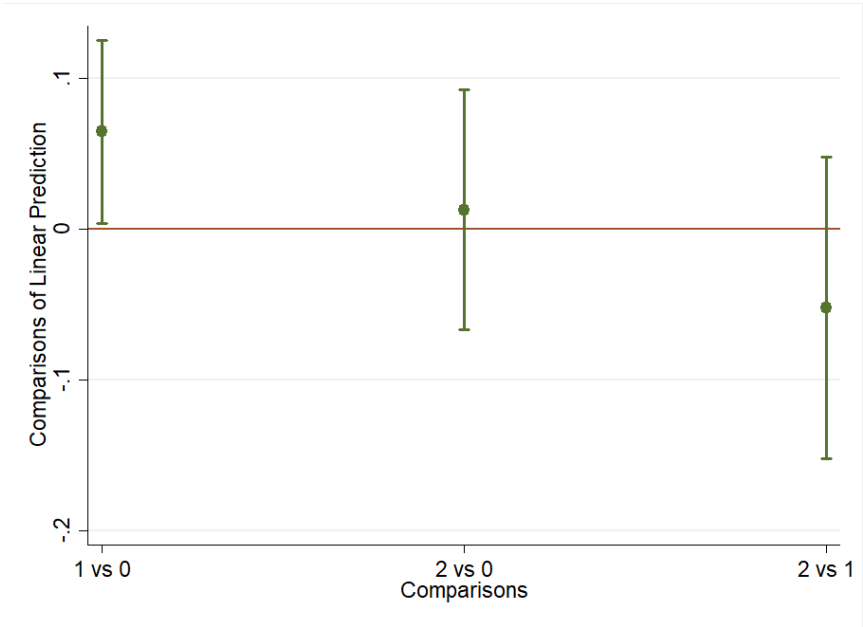

FIGURE 4.5: Pairwise comparisons of adjusted predictions (1). Pairwise comparisons of adjusted predictions of exposure to time pressure or work overload for each group, with 95% confidence intervals. *Source: EU-LFS, own calculations.*

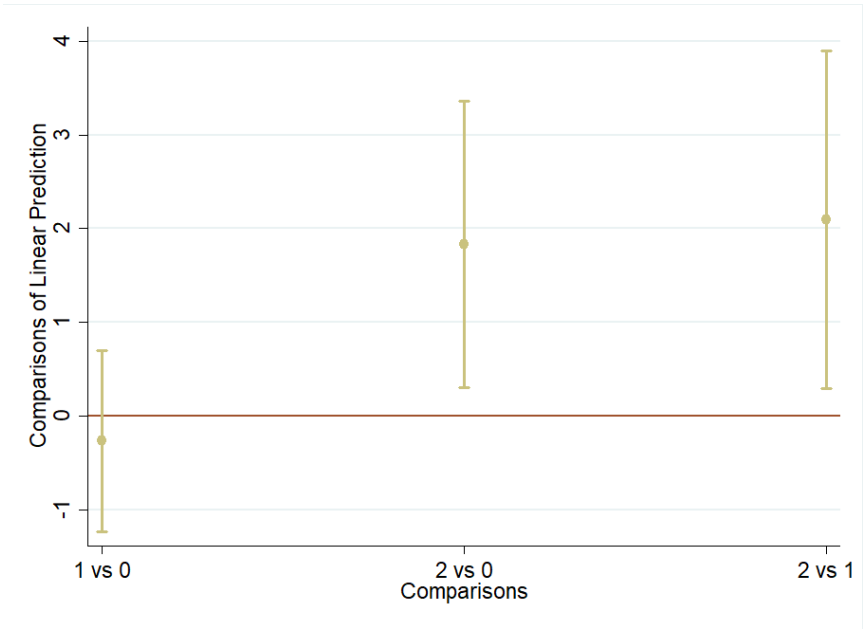

FIGURE 4.6: Pairwise comparisons of adjusted predictions (1). Pairwise comparisons of adjusted predictions of usual number of hours worked per week for each group, with 95% confidence intervals. *Source: EU-LFS, own calculations.*

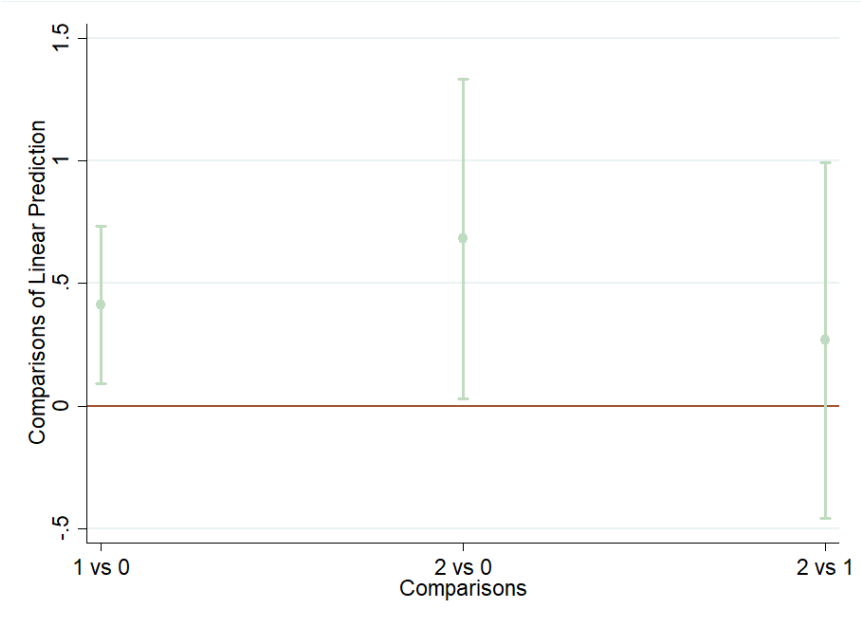

FIGURE 4.7: Pairwise comparisons of adjusted predictions (1). Pairwise comparison of adjusted predictions of usual number of hours of paid overtime per week for each group, with 95% confidence intervals. *Source: EU-LFS, own calculations.*

This observation appears to confirm the sketch made by Felstead et al., 2001, of the two possible types of home-based teleworkers: a woman who predominantly works at home to balance her job and care responsibilities, and a man who works outside the office from time to time.

Older individuals are much more likely to be regular home-based teleworkers than younger persons. Nevertheless, we do not observe any significant age difference between occasional home-based teleworkers and the reference group. As expected, lower levels of education significantly reduce the probability of working from home, both occasionally and regularly, with respect to having graduate or post graduate qualifications. Furthermore, low-skilled workers are associated with a lower likelihood of home-based telework than high- and medium-skilled workers. Workers employed in the advanced services sector are much more likely to work from home occasionally, but not regularly.

The variable accounting for degree of urbanisation is not significant. However, workers based in the north and centre of Italy are the most likely to be working regularly from home. Furthermore, workers employed in medium-sized firms are more likely to be able to work from home occasionally than others. Among family variables, only being married (with respect to divorced or single) is shown to increase the probability of working regularly from home.

In partial contradiction to the view maintained by Felstead et al., 2001, we can imagine two profiles of home-based teleworkers. The first is a worker who although predominantly office-based, teleworks from time to time. He is most likely male and employed in the advanced services sector. He is often high-skilled with university qualifications. The second profile is a married woman who regularly works from home. Like her counterpart, she is skilled and has

university-level education; she also most likely lives in the centre or north of Italy and is employed full-time.

Proceeding to our main research question, we investigate whether home-based teleworkers are more likely to suffer from mental risks associated with "severe time pressure and work overload", as defined by the EU-LFS 2013 ad-hoc module on "accidents at work and other work-related health problems". The dependent variable, *mentrisk* takes value 1 if the worker was exposed (in his or her main job, and in the current reference period) to psychological distress generated by work overload or excessive time pressure.

As stated above, according for instance to Mann, 2003, the work schedule of teleworkers is likely to lead to a deterioration of their mental health for at least three reasons. The first is *presenteeism*: home based workers often feel unable to take time off from work during sickness or for other personal reasons. The second reason is lack of support: home-based workers are often left alone to deal with problems related to their tasks. This is particularly true in case of technical support for personal computers, which can significantly slow down an office-based worker, but for the home-based worker may result in a catastrophic loss of time. The third reason, already explored in Section 4, is the blurring of boundaries between work and family: since the worker can often be distracted during normal business hours, he or she may choose to work at unusual times (very early in the morning or late at night). These and other reasons are likely to generate issues related to time-constraints and the feeling of being overloaded with work. These feelings may threaten the worker's mental health.

Being a home-based worker is not a random event: as we have seen it is influenced by a complex array of personal, job-related, technological and geographical factors. We therefore cannot simply compare non teleworkers with occasional and regular home-based teleworkers. This is why we estimate telework mean treatment effects using the multivalued treatment procedure proposed in Cattaneo, 2010. This procedure minimises the impact of observables in the selection of treatment status. As explained above, our treatment is divided into three states: 0 (no home-based telework), 1 (occasional home-based telework), 2 (regular home-based telework).

Multivalued treatment effects are constructed by contrasting the parameters of the distribution of the outcome variable (exposure to mental risk factors related to time pressure and work overload) under each level of treatment. The "potential outcome distributions" are identified from the observed data under the standard unconfoundedness and common-support assumptions.

We begin by using a multinomial logit model to predict the probability of treatment level conditional on a set of covariates. We select the best model using the *bfit* command on Stata, as suggested by Cattaneo, Drukker, and Holland, 2013. In this way, among all the variables used in the model reported in the left panel of Table4.3 we can select the combination that minimises the AIC. Table4.3 shows the resulting model, a linear polynomial containing most of the variables used in Table3 (only the family-related variables are excluded). We can now proceed to the estimation of the predicted probability of each treatment status.

Figure4.2 Figure4.3 and Figure4.4 report the overlap plots of the predicted probabilities (using the methodology suggested by Busso, DiNardo, and McCrary, 2014). For each treatment level, an overlap plot depicts the estimated density of the predicted probabilities for that treatment level, conditional on the set of variables contained in the multinomial logit model reported in Table4.3. As we can see, the predicted probabilities are sufficiently different from 0 and 1, and the overlap suffices to satisfy the common-support hypothesis. Since this condition holds, the semiparametric estimator that we calculate can also be expected to perform well in finite samples.

Having calculated the predicted probability of treatment status, we estimate a model for our dependent variable: mental health risk. In the same way as before, we let the command bfit select the best (AIC-minimising) linear-probability model for our binary outcome. The resulting model (Table4.4), contains a mix of personal, job-related and family-related variables, along with the number of hours usually worked per week. qtttt

From the results of the linear probability model reported in Table4.4, we observe that male and younger workers are relatively less likely to experience work-related time pressure and other stress factors that may affect their mental wellbeing. On the contrary, being a skilled worker and having a supervisory role increases the probability of suffering time pressure and work overload. Finally, as expected, longer working hours appear to be detrimental to mental wellbeing.

After calculating our predicted probabilities of treatment status and selecting our outcome model, we estimate the potential-outcome distributions. [8] The output in the upper panel of Table4.5 indicates that the mean of the potential-outcome distribution is highest for treatment level 1 (occasional home-based telework). The lower panel in Table4.6 represents the estimated average treatment effect of moving between all pairwise combinations of groups. The result is better explained in Figure4.5, that shows pairwise comparisons of adjusted predictions of average treatment effects with 95% confidence intervals. We immediately notice that the only statistically significant treatment effect is the one we obtain comparing group 0 (no telework) and group 1 (occasional telework). We conclude that individuals in our sample who work from home from time to time are significantly more likely to report a perception of stress, time pressure or work overload than individuals working only from the office or regular home-based workers.

To investigate the reasons for this result we use the same method to estimate the difference in the number of hours usually worked and the number of hours of paid overtime per week, between groups.[9] Table4.7 and Table4.8 show the mean of the potential-outcome distributions (upper panels) and the estimated average treatment effects (lower panels). Table4.7, combined with Figure4.6indicates that there is no significant difference between the average number of hours usually worked per week between office-based workers and

[8] We use the Stata command *poparms*, proposed by Cattaneo, Drukker, and Holland, 2013.

[9] Again, we use the *bfit* command to select the best-fitting regression models for the variables *hwusual* (usual number of hours worked per week) and *hwpover* (usual paid overtime per week). Results of the linear regressions are reported in Table4.6.

occasional home-based teleworkers. In contrast, regular home-based teleworkers tend to work significantly more than all other groups: 1.8 hours more than other home-based teleworkers, and 2 hours more than office-based workers. Table4.8 and Figure4.7, moreover, show that office-based workers do significantly less overtime than workers in the other groups. With respect to an office-based worker, an occasional teleworker does on average 0.41 hours (i.e. 24 minutes) more overtime per week, while the figure increases to 0.68 hours (40 minutes) for a regular home-based worker.

	Homework intensity		**Homework intensity**	
	Occasional	**Regular**	**Occasional**	**Regular**
	Coeff. (S.E.)	**Coeff. (S.E.)**	**Coeff. (S.E.)**	**Coeff. (S.E.)**
Sex: male	0.328***	-0.331***	0.349***	-0.340***
	(0.125)	(0.121)	(0.124)	(0.120)
Age (reference: >57)				
<27	-0.224	-0.982***	-0.190	-1.215***
	(0.353)	(0.377)	(0.328)	(0.354)
28-37	-0.366	-0.810***	-0.305	-0.965***
	(0.307)	(0.298)	(0.290)	(0.282)
38-47	-0.346	-0.440	-0.295	-0.549**
	(0.281)	(0.267)	(0.267)	(0.255)
48-57	-0.403	-0.147	-0.390	-0.168
	(0.261)	(0.243)	(0.260)	(0.242)
Education level (reference: university)				
Upper secondary	-0.423**	-0.952***	-0.424**	-0.932***
	(0.197)	(0.210)	(0.196)	(0.210)
Lower secondary	-0.543***	-0.830***	-0.546***	-0.817***
	(0.151)	(0.139)	(0.151)	(0.139)
Occupation type (reference: high skills)				
Medium skills	-0.331**	-0.935***	-0.337**	-0.936***
	(0.149)	(0.159)	(0.149)	(0.159)
Low skills	-0.893***	-1.367***	-0.902***	-1.357***
	(0.222)	(0.253)	(0.222)	(0.253)
ICT services	0.429***	-0.020	0.430***	-0.025
	(0.149)	(0.170)	(0.142)	(0.171)
Degree of urbanisation (reference: rural area)				
City	0.151	-0.125	0.145	-0.127
	(0.151)	(0.153)	(0.151)	(0.153)
Town	-0.050	-0.000	-0.048	0.003
	(0.144)	(0.142)	(0.143)	(0.142)
Region (reference: South and Islands)				
North West	0.003	0.448***	-0.011	0.440***
	(0.152)	(0.169)	(0.151)	(0.169)

North East	-0.157	0.554***	-0.171	0.543***
	(0.167)	(0.171)	(0.167)	(0.174)
Centre	0.036	0.739***	0.024	0.732***
	(0.168)	(0.173)	(0.167)	(0.173)
Part-time contract	-0.068	-0.357*	-0.061	-0.354*
	(0.178)	(0.184)	(0.178)	(0.183)
Firm size (reference: small)				
Medium	1.293***	-0.248	-0.100	-0.020
	(0.173)	(0.200)	(0.193)	(0.160)
Large	0.520***	-0.506***	1.200***	-0.266
	(0.190)	(0.193)	(0.156)	(0.181)
Very large	0.095	0.022	0.429**	-0.528***
	(0.194)	(0.160)	(0.166)	(0.167)
Tenure	0.001	-0.001*	0.001	-0.001*
	(0.001)	(0.0006)	(0.001)	(0.000)
Marital status (reference: single)				
Divorced	-0.299	0.263	-	-
	(0.272)	(0.222)	-	-
Married	0.039	0.294*	-	-
	(0.164)	(0.166)	-	-
Presence of children	0.061	-0.167	-	-
	(0.145)	(0.146)	-	-
Number of observations:	37,221		37,221	
Log likelihood:	-3362.6738		-3365.7422	
Pseudo R2:	0.0641		0.0632	

TABLE 4.3: Multinomial logit results for the probability of being occasional or regular homeworker vs office-based worker (base outcome). Left: whole model; right: variables chosen to minimise the AIC. Results report coefficients and standard errors in parenthesis; $***p < 0.01, **p < 0.05, *p < 0.1$. *Source: EU-LFS, own calculations.*

	Coefficient (S.E.)
Sex: male	0.347
	(0.257)
Age (reference: >57)	
<27	-0.045
	(0.583)
28-37	-0.199
	(0.509)

38-47	-0.278
	(0.477)
48-57	0.042
	(0.467)
Occupation type (reference: high skills)	
Medium skills	-0.437
	(0.289)
Low skills	-0.641**
	(0.309)
ICT services	0.464
	(0.330)
Degree of urbanisation (reference: rural area)	
City	0.342
	(0.275)
Town	0.272
	(0.252)
Part time contract	-0.632*
	(0.348)
Temporary contr.	0.181
	(0.260)
Supervisory role	-0.724**
	(0.299)
Marital status (reference: married)	
Divorced	-0.331
	(0.418)
Single	0.157
	(0.299)
Presence of older relatives in the household	-0.139
	(0.343)
Presence of children in the household	0.406
	(0.251)
Usual hours of work	0.053
	(0.033)
Number of observations:	37,221
Log likelihood:	-20084.883
Pseudo R2:	0.0305

TABLE 4.4: Multinomial logistic regression for the probability of reporting time pressure or work overload vs not reporting it (base outcome). Results report coefficients and standard errors in parenthesis; $***p < 0.01, **p < 0.05, *p < 0.1$. *Source: EU-LFS, own calculations.*

	Coefficient	Analytic S.E.	95% C.I.	
Treatment 0 (no homework)	0.2435	0.0022	0.2391	0.2479
Treatment 1 (occasional homework)	0.3083	0.0309	0.2478	0.3689
Treatment 2 (regular homework)	0.2565	0.0406	0.1768	0.3361
	Contrast	**Delta-method S.E.**	**95% C.I.**	
1 vs 0	0.0648	0.0309	0.0041	0.1255
2 vs 0	0.0129	0.0407	-0.0668	0.0927
2 vs 1	-0.0518	0.0510	-0.1519	0.0481

TABLE 4.5: Multivalued T.E. results (1)
Upper panel: estimated means for the linear probability of reporting time pressure and work overload for each of the three potential treatments. Lower panel: estimated treatment effects and their confidence interval for all pairwise comparisons of treatment groups. Source: EU-LFS, own calculations.

	Dependent variable	
	Usual hours	Usual paid overtime
	Coefficient (S.E.)	Coefficient (S.E.)
Sex: male	2.128***	0.119***
	(0.139)	(0.015)
Age (reference:>57)		
<27	0.821*	0.082*
	(0.458)	(0.043)
28-37	0.293	0.116**
	(0.445)	(0.039)
38-47	0.393	0.050
	(0.437)	(0.037)
48-57	0.512	0.045
	(0.449)	(0.038)
Occupation type (reference: high skills)		
Medium skills	3.015***	0.022
	(0.173)	(0.017)
Low skills	1.636***	0.037*
	(0.198)	(0.020)
ICT services	0.841***	0.017
	(0.196)	(0.020)

Region of work (reference: South and Islands)		
North West	0.301*	0.135***
	(0.172)	(0.018)
North East	0.342*	0.136***
	(0.181)	(0.019)
Centre	-0.205	0.132***
	(0.193)	(0.021)
Temporary contract	-0.817***	-0.022
	(0.151)	(0.022)
Supervisory role	0.882***	0.062***
	(0.172)	(0.017)
Firm size (reference: small)		
Medium	0.295	-0.103***
	(0.189)	(0.019)
Large	-0.244	-0.056**
	(0.217)	(0.021)
Very large	-0.199	-0.056**
	(0.208)	(0.019)
Tenure	-0.019***	-0.001*
	(0.004)	(0.000)
$Tenure^2$	0.000	0.000
	(0.000)	(0.000)
Interaction terms		
Sex*Tenure	0.004**	-
	(0.002)	-
Age(<27)*Tenure	0.013	-
	(0.008)	-
Age(28-37)*Tenure	0.016***	-
	(0.005)	-
Age(38-47)*Tenure	0.008*	-
	(0.004)	-
Age(48-57)*Tenure	0.002	-
	(0.004)	-
Medium Skills*Tenure	-0.012***	-
	(0.002)	-
Medium Skills*($Tenure^2$)	0.001***	-
	(0.000)	-
Low skills*Tenure	-0.003	-
	(0.003)	-
Low skills*($Tenure^2$)	0.001***	-
	(0.000)	-
NorthWest*Tenure	0.010***	-
	(0.002)	-
NorthWest*($Tenure^2$)	-0.001***	-
	(0.000)	-
NorthEast*Tenure	0.010***	-

	(0.002)	-
NorthEast*($Tenure^2$)	-0.001***	-
	(0.000)	-
Centre*Tenure	0.012***	-
	(0.002)	-
Centre*($Tenure^2$)	-0.001***	-
	(0.000)	-
Temporary*Tenure	-0.010***	-
	(0.003)	-
Temporary*($Tenure^2$)	0.001***	-
	(0.000)	-
Number of observations:	37,005	36,673
Adj R-squared:	0.5789	0.0065

TABLE 4.6: Linear regression for the number of usual hours worked per week (left) and usual hours of paid overtime per week (right). Results report coefficients and standard errors in parenthesis; $***p < 0.01, **p < 0.05, *p < 0.1$. *Source: EU-LFS, own calculations.*

	Coefficient	**Analytic S.E.**	**95% C.I.**	
Treatment 0 (no homework)	35.1085	0.0486	35.0132	35.2038
Treatment 1 (occasional homework)	34.7597	0.4751	33.8283	35.6909
Treatment 2 (regular homework)	36.9373	0.8098	35.3501	38.5245
	Contrast	**Delta-method S.E.**	**95% C.I.**	
1 vs 0	-0.3488	0.4750	-1.2798	0.5821
2 vs 0	1.8287	0.8097	0.2417	3.4157
2 vs 1	2.1776	0.9377	0.3397	3.9154

TABLE 4.7: Multivalued T.E. results (2).
Upper panel: estimated means for the usual number of hours worked per week for each of the three potential treatments. Lower panel: estimated treatment effects and their confidence interval for all pairwise comparisons of treatment groups. Source: EU-LFS, own calculations.

	Coefficient	Analytic S.E.	95% C.I.	
Treatment 0 (no homework)	0.1694	0.0066	0.1564	0.1824
Treatment 1 (occasional homework)	0.5192	0.1639	0.1980	0.8404
Treatment 2 (regular homework)	0.8089	0.3427	0.1372	1.4805
	Contrast	**Delta-method S.E.**	**95% C.I.**	
1 vs 0	0.3498	0.1639	0.0883	0.6712
2 vs 0	0.6395	0.3427	0.0223	1.3912
2 vs 1	-0.2897	0.3798	-0.4547	0.9940

TABLE 4.8: Multivalued T.E. results (3). Upper panel: estimated means for the usual number of hours of paid overtime per week for each of the three potential treatments. Lower panel: estimated treatment effects and their confidence interval for all pairwise comparisons of treatment groups. Source: EU-LFS, own calculations.

4.8 Conclusions and discussion

We used cross-sectional data from the 2013 EU Labour Force Survey, as well as the ad-hoc module on worker health and wellbeing, to investigate the impact of working from home on mental health. In particular, we linked mental health outcomes to the perception of time pressure and work overload reported by workers. To do so, we estimated multivalued treatment effects according to the method proposed by Cattaneo, 2010. Our main results can be summarised in three points.

First, occasional home-based teleworkers are different from regular home-based teleworkers. We divided our sample into three groups: those who always work from the office, those who work from home for less than 50% of their working time, and those who work from home for more than 50% of their working time. Our results show that the average occasional home-based worker is a high-skilled male employed in the advanced services sector, whereas most regular home-based workers are married women with higher educational degrees who live in central or northern Italy. This result is partially coherent with that proposed by Felstead et al., 2001, and Sullivan, 2001. According to these authors, regular home based telework is preferred by women who see it as a way of balancing their career with household and care tasks.

Second, occasional home-based workers are the most likely to suffer from deteriorated mental health due to time-pressure or severe work overload, whereas regular home-based workers and office-based workers report similar lower levels of distress. There can be several explanations for this apparently contradictory result. Workers who are home-based for most of their time may organise their life around telework more efficiently than those who do so only from time

to time. Balancing worktime between the office and home may therefore be a bigger struggle for occasional home-based workers. On one hand, they work at the office too frequently to enjoy the perception of autonomy and discretion shared by most teleworkers. On the other, they do not work enough from home to be able to manage the complex overlap of work and family life.

Third, when we compare the number of hours worked per week across our three groups of employees, we realise that those working longer hours are regular home-based workers. They score higher than any other group in both measures: usual number of hours worked per week, and usual number of hours of paid overtime. This result is not surprising in the light of the conclusions drawn by Mann, 2003, on presenteeism for home-based workers. Since their effort is harder for managers to monitor, home-based workers feel that they must work more, and are less keen on taking time off for sick leave and other reasons. Norms usually associated with the traditional workplace (for instance: visibility, presence, trust, availability) still matter outside the traditional workplace (Sewell, 2015), so workers still need to signal their effort and to do so they work longer. Moreover, occasional home-based workers may telework in order to supplement normal working hours outside the employer's premises. This explanation is consistent with both our main results: occasional home-based workers do more overtime than office-based workers, and they are more likely than all other groups to report fatigue and stress.

We showed that the flexibility of telework is potentially linked to the number of hours worked: working from home creates the possibility for more flexible, and longer, working hours. ICTs have increased the capacity of workers to perform their tasks regardless of their location and this may lead to *presenteeism* and an inability of the worker to switch-off from his or her job: as noted by Messenger and Gschwind, 2016,), the "omnipresence" of the internet may have made work "omnipresent". Furthermore, most home-based workers work the hours they would have spent commuting to the office (as shown by Lasfargue and Fauconnier, 2015). Other reasons for longer working hours may include: working during weekends, taking more frequent breaks to run errands or deal with household tasks, failure to self-monitor when it comes to deciding one's schedule (Eurofound and International Labour Office, 2017).

Based on our findings, at least two aspects have been identified that can pose a risk for the teleworker's wellbeing: longer working hours (especially for regular home-based workers), and higher levels of work-related stress and fatigue (for occasional home-based workers). From a policy perspective, addressing these issues is critical considering the recent spread of smart-work and other forms of home-based work in Italy. Italian Law 81/2017, like the Telework, 2002, grants home-based workers the same rights as office-based workers in terms of number of working hours and protection against work-related accidents. Nevertheless, application of these principles is not straightforward and monitoring home-based workers may be difficult for employers. Moreover, in the context of crowdwork, the blurred distinction between employees and self-employed may imply that workers lack support from their managers and colleagues regarding how to organise their work and their daily schedule.

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