Long-run effects of health shocks in a highly regulated labour market

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Abstract: Based on administrative data covering employment, social security and hospital record histories, we investigate the effect of acute cardiovascular health shocks resulting in unplanned hospitalisation, on blue collars' long-term labour outcomes in Italy. The Italian institutional setting, characterised by a highly regulated labour market and high job protection, is different from that of countries - mainly Nordic and Anglo-Saxon - covered in previous studies. We apply matching and parametric regression techniques to remove possible bias arising from observable and time-invariant unobservable confounders. Results point at sizeable and persistent reductions in employment and labour income, while hours and wage adjustments appear limited. Whereas a relatively generous social insurance system might compensate the earnings loss, our findings question the appropriateness of existing labour inclusion policies.

Keywords: health shocks, employment, labour market institutions, administrative data
JEL codes: I10, J22, J24, J31, C14

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1 Introduction

Fostering the labour market inclusion of older and unhealthy workers is indeed a daunting task among those appearing in the economic policy agenda of many countries. While social security sustainability calls for extending working lives as a policy priority, this comes at the cost of an increased chance for older workers to experience health deteriorations. Policy makers are thus compelled to face complex choices, trading-off the provision of incentives to remain active, and the protection that motivates social insurance institutions.

In such scenario, empirical evidence on how workers' labour market performance is affected after a health deterioration experienced in a particular institutional setting, is crucial for shaping the policy agenda. Insights on the issues at stake represent a primary step for identifying the kind of policy interventions that could be recommended. Indeed, existing evidence has produced so far a relative consensus on the existence of a detrimental effect (Currie and Madrian, 1999) of health shocks on labour and other socioeconomic outcomes: first and foremost, labour market participation (Jones et al, 2019; Au et al, 2005; García Gòmez et al., 2010; Bradley et al, 2013), but also hours worked (Moran et al, 2011; Cai et al, 2014), labour income (Flores et al., 2019; García Gòmez and Lopez Nicolas, 2006; Halla and Zweimüller, 2013; Moller Dano, 2005), and even wealth, due to increased health expenditures (Dobkin et al., 2018; Wu, 2003).

However, a recurrent limitation of this literature, and to its potential for informing policy design, is that results are typically confined to a short time horizon. Except for a few cases providing evidence for up to 6 years (García Gòmez et al. 2013; Moller Dano, 2005 and Moran 2011), the bulk of works covers about one to three years after the health shock occurrence, due to reasons involving a combination of data availability and identification strategy credibility[1]. In this way though, the picture remains pretty partial. On the one hand, a thorough assessment of the adverse socioeconomic consequences of health deteriorations should account for possibly cumulative detrimental effects arising over time. For example, a labour market exit observed in the short term, and intended to be temporary because meant to foster health recovery, could become permanent in the longer run, particularly in rigid labour market settings offering more limited opportunities of re-entry to older 'outsiders'. On the other hand, a return to employment or a recovery in earnings could emerge only in the medium to long run, through health improvements or the development of different forms of disability-specific human capital. For example Charles (2003) finds, in the US, the immediate reduction in earnings to be then followed by a recovery, evident since the first two post-onset years.

No less important than the timeframe, for policy design purposes, comes devoting attention to the peculiarity of the institutional setting (Arpaia and Mourre, 2012; Holmlund, 2014) where the empirical evidence is drawn. Recent comparative evidence from European countries has

[1] Credible identification strategies generally rely on observing information on previous labour and health histories, which then results in a reduced observational window for analysing the post-shock outcomes dynamic.

shown that labour responses to the same health shock can vary substantially across heterogeneous labour market, social insurance and healthcare system settings. Both García Gòmez (2011) and Trevisan and Zantomio (2016) found, in the short term, stronger employment contractions (following a health shock) in Nordic countries[2], characterised by more generous disability benefits (both in terms of access rates and replacement income) and high job mobility, in comparison to other European countries.

Actually, institutional differences represent a precious source of identification for the role played by particular policy instruments or institutional features. In this respect, the bulk of existing works have been produced on Anglo-Saxon countries (e.g. Jones et al, 2019; Dobkin et al, 2018; Moran et al, 2011; Au et al., 2005; Coile, 2004; García Gońez et al., 2010; Zucchelli et al., 2010), Nordic countries, (e.g. Datta Gupta et al 2011; Lundborg et al., 2015; Moller Dano, 2005; Heinesen et al, 2013; Maczulskij and Bockerman, 2019), and the Netherlands (García Gońez et al., 2013). Such pattern reflects these countries' more generous availability of appropriate data sources, which have sometimes allowed exploring subgroups responses (by gender, or education, see e.g. Moller Dano, 2005; Lundborg et al., 2015; Heinesen et al, 2013), also useful to draw policy inference. However, in comparative terms (OECD, 2014; OECD, 2016; EC, 1999; EC, 2009), these countries generally feature high job mobility[3] and a more limited role for job protection legislation (such as obligations for firms to employ a mandatory quota of disabled workers). This partial view casts doubts on the obtained results' robustness to different institutional environments, such as Southern European countries, generally[4] featuring highly regulated labour markets, typically resulting in comparatively low labour flow indicators (EC, 2009; OECD, 2016); and therefore questions the appropriateness of possibly extending the potential policy recommendations drawn there, to these other settings.

This work offers a contribution towards these limitations of an otherwise undoubtedly developed stream of literature, by measuring the effect of health shocks on labour outcomes until up to 9 years later, in Italy, a country characterised by a highly regulated labour market and high job protection by European standards, as explained in Section 2. In more detail, we study the outcomes of blue-collar male workers, aged 18 to 64 years old, hit by acute forms of cardiovascular diseases (CVD) between 2003 and 2005, namely myocardial infarction (ischemic heart disease) and stroke (a cerebrovascular disease), which typically result in an unplanned hospitalisation (Braunwald et al., 2015).

Multiple reasons underpin the choice of focussing on these CVD shocks. On the one hand, there is policy interest. CVDs represent a source of major human and economic cost in

[2]Followed by the UK, in Trevisan and Zantomio (2016) (while UK is not covered in García Gòmez 2011) a country featuring less generous disability benefits than Nordic countries but a tight labour market, in comparative terms.

[3]With the notable exception of the Netherlands, featuring comparatively low hiring rates: in 2006 the hiring rate for older workers (ages 55-64: measured as the number of employees with job tenure of less than one year as a percentage of total employees) was 1.7 (against an OECD average of 9.2).

[4]One exception though is Spain, featuring high hiring rates (in 2006 the hiring rate for older workers was 7.7, while the same indicator was 4.0 for Italy- against an OECD average of 9.2). For evidence on the consequences of health shocks in Spain, see García Gońez and Lopez Nicolas (2006).

developed countries (Wilkins et.al., 2017)[5]. Over the past 25 years, the incidence of CVD cases has increased in most European countries, including Italy[6]. In 2015, the incidence of myocardial infarction was 2,968,582 among males and 2,784,341 among females; while new cases of stroke were 675,872 among males and 879,493 among females. Data on the crude prevalence for the same year depict an impressive situation: more than 85 million people across Europe were living with CVDs[7], myocardial infarction representing one of the most prevalent conditions, with corresponding costs estimated in about €59 billion a year. The cost of stroke was estimated in €45 billion per year. While CVDs are among the leading causes of death in developed countries, survival rates have remarkably improved over the past decades[8]. Upon survival, these types of health deteriorations often lead to serious physical and mental impairments limiting most daily-life activities and also work-capabilities.

Besides policy interest, the choice of focussing on CVD shocks relates to the endogeneity challenge that plagues empirical research on the relationship between health and labour (Haan and Myck, 2009; Cai, 2010). Grossman (1972) seminal contribution, based on Becker (1964), introduced a model of health production where people are endowed with a depreciable stock of health capital, restorable with additional investment. While additional economic resources may increase health through such investment, the health stock enhances socioeconomic outcomes through extended working times and higher earnings. At the empirical level, the main resulting implication is that health must be treated as endogenous, with respect to labour (Currie and Mandrian (1999)), or in other words, identification of health effects is to be based on exogenous sources of variation in health[9]. As pointed out by Smith (1999), particular forms of major health shocks might represent a source of unexpected variation in health: indeed, although people may anticipate to some extent the onset of a certain illness, or their underlying risk, the actual realisation and its timing come as unexpected. Previous authors (Smith, 1999, 2005; Coile, 2004; Datta Gupta et al., 2011; Trevisan et al., 2016; Jones et al., 2019; Bradley et al., 2013) have studied the consequences of selected subgroups of major health shocks, which typically included CVD shocks, cancer and lung diseases. The advantage of selecting only acute CVD conditions, such as myocardial infarction and stroke for identification purposes, relates to their local time-specific onset (Braunwald et al., 2015), in contrast to other health condition, whose onset is hardly referable to a specific point in time.

Studying the labour outcomes consequences of CVD shocks in the Italian institutional

[5]Both direct health costs, productivity loss and informal care costs are considered in the total estimated cost.

[6]In Europe, new CVD cases were 4,467,489 (5,013,645) among males (females) in 1990 compared with 5,441,564 (5,842,358) new cases in 2015, showing a percentage increase of 21% (16%). In Italy there were 293,767 (300,865) new cases among males (females) in 1990 compared to 359,888 (371,869) cases in 2015.

[7]The more than 30 million of CVD cases among males (34 million for females) in 1990 have increased to more than 41 million cases (44 million for females) in 2015. Age-standardised prevalence rates show instead a decline over the 25 years period in Europe, for both genders.

[8]For men in particular, CVD diseases represent the most common cause of death under 65 years old (31%) in Europe (compared to about 22% of deaths related to cancer). For women aged below 65 years old, CVD shocks are the second largest cause of death (26%), after cancer (35%).

[9]For example, Moller-Dano(2005) and Halla et al. (2013) consider respectively accidents occurred on the way to and from work, road accidents in general; García Gośmez et al. (2013) and Lindeboom et al. (2016) consider unplanned hospitalisations.

context is possible thanks to a unique opportunity in the national panorama, the availability of a new administrative dataset, WHIP&Health, described in more detail in Section 3.2. WHIP&Health covers the work and social security histories of a 7% random sample drawn from the Italian Social Security (INPS) archives from 1990 to 2012, which are linked to individuals' hospital discharge records from all private and public hospitals, between 2001 and 2012. The availability of administrative data on acute CVD shock hospitalisations allows overcoming several measurement error challenges typically encountered when approaching the subject using survey data, spanning from recall and justification biases, to pure filling errors (Jackle and Himmler, 2010; Benitez-Silva et al., 2004; Baker et al., 2004).

While the topic areas covered by WHIP&Health, as generally by other administrative data, remain limited in scope with respect to survey data, the wide time window covered gives the opportunity to exploit a very long record of labour market and social insurance information, up to 15 years before the health shock occurrence. Conditioning on such a long history of health, labour and social insurance variables, we assume the conditional probability for a worker to experience a CVD health shock or not, at a particular point in time, to be as good as random. Also, by conditioning on lagged outcomes, we remove the bias stemming from time invariant unobservables, on top of time varying observables. Following Jones et al. (2019), the identification strategy detailed in Section 3.1 is implemented through a combination of Coarsened Exact Matching and Entropy Balancing matching procedures, followed by parametric estimation of the Average Treatment effect on the Treated (ATT) for employment, labour activity (including also self-employment and atypical work), the probability of working full, rather than part-time, annual labour income and hourly wage.

Results, presented in Section 4, reveal that, in the current Italian institutional setting, acute CVD shocks cause a significant and sizeable reduction in employment. The probability of exiting employment one year after the shock is increased of one third, with respect to its baseline value. The dynamic pattern over the nine years past the shock shows an employment reduction that peaks three years past the shock, and displays only a minor recovery thereafter. After nine years, the drop in employment reaches a value that, in terms of relative size, is four times larger than the effect observed in the first year. Moreover, loss of employment is not compensated by increased chances of transition to other forms of work, i.e. self-employment or atypical work. The shock-induced loss of employment entails a substantial income loss, also persisting up to nine years after, and amounting to more than 10% of the counterfactual value since the first year past the shock. For those who maintain employment, no significant adjustment in terms of working hours emerges in the short run. The probability of working full- versus part-time registers a slight reduction between two and five years after the health event, driven by individuals hit by stroke, but the effect substantially fades for workers remaining active after then, up to nine years past the shock. Wage dynamics after the shock reveal a small negative effect of health shocks, arising from lower wage growth, with respect to the counterfactual. Interestingly, a systematic gradient in the size of the effect by firm size emerges, consistent with the higher employment protection legally granted to workers in large firms. Overall, results suggest that, in a highly regulated institutional setting like the Italian labour market, there appears to be limited scope for workers to flexibly adjust working times on the one side, and for employers to adjust the wage of lower productivity workers, on the other. This might force some workers, who would have preferred to remain active under a reduced working time and/or under adjusted wages, to withdraw from the labour force; and at the same time, might favor the dismissal of less healthy workers: in both cases with remarkable labour income losses to be borne. Such evidence questions the appropriateness of existing labour inclusion policies for unhealthy workers, besides their income opportunities.

2 Institutional background

When looking at comparative labour market institutions indicators over the period covered by our study (1990-2012), the Italian labor market emerges as highly regulated one. The value of the *Strictness of Employment Protection*[10] OECD indicator (ranging 0 to 5) for Italy scores 2.76 (in the period 1990-end 2011, decreasing to 2.68 in 2012), a value close to other Southern European countries (e.g. Greece, 2.8) but much higher than for Anglo-Saxon countries (e.g. UK, 1.1) and for OECD countries as a whole (2.08, in 2012).

In Italy, employment protection has historically been particularly high for workers on open-ended contracts in medium and large companies (i.e. firms with more than 15 employees). Their dismissal was in facts not allowed[11] during most of the time period we study. Legal safeguards[12] have been later reduced, since 2011; in more detail, the 2012 'Monti-Fornero' reform introduced the possibility of dismissal for economic reasons, significantly lowering firing restrictions previously applying to medium and large companies. Employees in small firms (i.e. up to 15 employees, a widespread case in the Italian productive panorama, also in comparison with all the other OECD countries)[13] or under fixed term-contracts (which remain relatively marginal in comparative terms, particularly for older workers, more exposed to health shocks)[14] have historically, and throughout the period we consider, relied on remarkably lower levels of employment protection.

High regulation, in comparative terms, emerges also from the OECD *Trade unions and Collective Bargaining* indicators. The *Collective bargaining coverage* rate is 80 percent for Italy (years 1998-2016), similarly to Spain, Portugal and Greece before the crisis, against an OECD average of 33 percent. Although a legal minimum wage does not exist in the country, it is de facto otherwise set through collective bargaining agreements on a sector-by-sector basis. In comparative terms, the compensation structure emerges as particularly rigid: in facts, Italy stands out as having a completely different profile for lifecycle trajectories of hourly wages than other countries (Contini, 2009). Strikingly, for many years, Italy has been the only European country where remuneration was

[10] Referring to individual dismissals in regular contracts.

[11] Reinstatement of the worker was the sanction the employer was subject to in case of unlawful dismissal.

[12] Based on Article 18 of the Workers' Statute (Law No. 300 of May 20, 1970). In 2011, an attempt to circumvent article 18 was introduced by the Berlusconi government (Law 148, September 2011, art. 8). This law allowed for collective agreements at the plant or local level ("proximity agreements") to derogate from national collective agreements and the law in various matters, including the possibility to permit compensation in lieu of reinstatement in case of unlawful dismissal in larger firms' apparently even if acting against the guidelines issued by peak-level unions (Berton et.al., 2012). The application of article 8 Law 148 was limited due to the fear of a massive number of lawsuits triggered by the unions. The Fornero-Monti reform of employment law, which came into force in July 2012, rewrote in total article 18 of the Workers' Statute, providing different regulations for different types of dismissal. Its most relevant novelty concerns the possibility for a firm with more than 15 employees to dismiss workers for economic reasons. In this type of dismissal, the employee cannot claim his job back and has only right to an indemnity ranging from 12 to 24 months of salary, the sum being decided by a court. The Fornero-Monti reform thus lessened the restrictions to firing In Italy significantly.

[13] Italy is the second leading OECD country by number of micro-businesses (319k firms with 0 to 9 persons employed) preceded only by Turkey, while is third by number of small size business (40k firms with 10-19 persons employed) preceded only by the US (OECD, 2017). Micro-businesses represented 95% of all Italian firms in 2015 (all sectors), while firms with 10-49 employees an additional 4.1% (ISTAT, 2017).

[14] According to OECD (2016), the incidence of temporary work for those aged 55-64 was 6.4 per cent in 2006, decreasing to 5.8 in 2016, against corresponding OECD figures amounting to 8.9 and 7.9 respectively.

not declining at older ages[15] because, as long as open-ended contracts were prevailing, particularly in large firms, wages were linked to seniority until retirement[16]. This type of wage adjustment contributes to shaping a highly regulated market, where firms can hardly adjust working hours, require overtime work, make workers redundant, and no firm level negotiations generally occur (Contini, 2019). More in detail, Devicienti et al. (2007) provide evidence of a sizeable amount of downward wage rigidity in Italy, with a prevalence of real over nominal rigidity.

High downward wage rigidity might result in frictions that increase labor mobility and workers reallocations (see Devicienti et.al., 2007, using WHIP data for the period 1985-1999). Indeed, although highly regulated, the Italian labor market has been characterised by hiring rate and labor turnover indicators that during the 1980s and the 1990s were middle-way between central European and Anglo-Saxon countries (OECD 1994, Contini, 2019). More recently, in the years 2002-2007 (covered by European Commission (2009)), Italy is found among the bottom positions in terms of hiring, separations and turnover (European Commission,2009). More disaggregated statistics on labor mobility in the country can be found in Contini (2019), based on Italian administrative data for the period 1991-2012[17]. Interestingly, the hiring rate in small firms is about 50 percent, declining to a value of 25 percent for firms with more than 200 employees, where stricter employment protection legislation applies.

The incidence of part-time contracts has been increasing at a fast pace during the last two decades; this increase has led Italy to register, in 2018, a higher incidence of part time (18.8%) than the average OECD countries[18]. However, the majority of part time in the country is involuntary: in 2018, the share of voluntary part-timers as a % of total employment was 6.9% (the residual 11.9% being involuntary). Moreover, the share of voluntary part time is even lower if one focuses on males (1.5%), slightly increasing for older males (aged 55 to 64: 3.1%). These are astonishing figures if compared with the corresponding OECD values, where the share of voluntary part-timers in total employment is equal to 13.4% (all ages, both genders), 7.5% (males, all ages), and 7.1% (older males) (OECD, 2019). Also, evidence from Eurostat (2019) revels that prevalence of part-time contracts, among male workers aged 45 or older and suffering health-related limitations, is only 12%, a figure that places Italy in penultimate position among EU28 countries.

In case of sickness, blue collar workers are entitled to paid sickness leave, which is granted for a maximum of 180 days (about six months) per calendar year. Combining the public benefit rate with further compensations obtained through collective bargaining agreements results in a full

[15]Whereas in Nordic countries and the UK wages peak at around 45 years old, and then start decreasing, in Italy wages continue to increase until 60 years old.

[16]After 1991, Italy experienced a trend of declining union power and increasing role of local wage setting. Nevertheless, the influence of local wage bargaining has always been modest. Devicienti et.al. (2007) report a wage drift of about 1 percent.

[17]Based on WHIP data (note that the frequency of WHIP is monthly: therefore, indicators of labor mobility cannot be compared with the European Commission ones, based on EU-LFS, which is quarterly). Open-ended contracts appear characterised by separation rates regularly greater than association rates; for these contracts, the value of labor turnover has been constant over time around a value of 25 percent, implying a surprisingly low average length of open-ended contracts of 4 years.

[18]In Italy, the incidence of part-time on the total employment was 11.7 percent in 2000, to reach a value of 18.8 percent in 2018. The corresponding values for the OECD are 13.9% and 16.5%.

replacement rate[19]. After 180 days, if work is not resumed, the employer may rescind the contract.

Still, further protection against health-related income risk is offered though two types of welfare schemes targeted at disabled workers. The first is a temporary disability benefit (*assegno ordinario di invaliditá*) in case of certified mental or physical impairment leading to a reduction in working capacity by at least two-thirds. The entitlement lasts three years, and, upon medical screening, can be renewed for up to three times, until it becomes permanent. Noticeably, the temporary disability benefit is compatible with working activity; and while being earnings-tested, the earnings-related reduction applies to high income levels[20]. The second disability-related benefit is a very generous permanent disability pension (*pensione di inabilitá*) paid to claimants who, after medical screening, result in permanent and total impossibility of performing any kind of work activity[21]. This payment is incompatible with any type of paid work.

[19]By law, the benefit is equal to 50% of the average daily earnings for the first 20 days and to 66.66% of it for the following days. The first three days ('periodo di carenza') are not paid. Generally, however, collective bargaining agreements provide a more generous coverage, with benefits raised up to 100 percent of the remuneration and extended to the first three days of sickness.

[20]The benefit is reduced by 25% (50%) when labour income is greater than four (five) times the minimum pension (i.e. €26676,52 or €33.345,65 in 2019).

[21]Additional requirements to claim these benefits are five years of enrolment to Social Security and at least three years of contributions in the previous five.

3 Empirical Approach

3.1 Identification strategy

Ideally, the causal effect of health deterioration on labour would be measured as the difference in individual labour outcome $Y_{i,t}$ observed for individual i at time t, simultaneously in two states of the world. In the first, the CVD shock event T occurs for individual i at time $\bar{t}$ ($T_{i,\bar{t}} = 1$), yielding outcome $Y^1_{i,t}$; in the other, for the same individual, it does not ($T_{i,\bar{t}} = 0$), yielding outcome $Y^0_{i,t}$. In that case, we could estimate the average treatment effects on the treated (i.e. on individuals' hit by the CVD shock) $ATT_{\bar{t}+\nu}$ at time $\bar{t}+\nu$, i.e. ν years after the CVD shock, as:

$$E[Y^1_{i,\bar{t}+\nu} - Y^0_{i,\bar{t}+\nu}|T_{i,\bar{t}} = 1] = E[Y^1_{i,\bar{t}+\nu}|T_{i,\bar{t}} = 1] - E[Y^0_{i,\bar{t}+\nu}|T_{i,\bar{t}} = 1]$$

In practice though, an individual will only experience - and be observed - in one state, implying that the two potential health states ($T_{i,\bar{t}} = 1$,$T_{i,\bar{t}} = 0$), and the corresponding labour outcomes ($Y^0_{i,t}$, $Y^1_{i,t}$) are never simultaneously observed. The potential outcome approach tackles the evaluation problem modelling the counterfactual unobserved outcome under the assumption of unconfoundedness, or conditional independence (Rosembaum and Rubin, 1983). In our context, the assumption can be formulated as:

$$(Y^0_{i,t}, Y^1_{i,t}) \perp T_{i,\bar{t}}|(W_i, X_{i,\bar{t}-s}) \qquad s = 1...S$$

where W_i represents the individual time invariant characteristics, and $X_{i,\bar{t}-s}$ the time varying ones, including labour, social insurance and health histories, observed s years before the shock, up to past time S. Under unconfoundedness, conditioning on the observables W_i and $X_{i,\bar{t}-s}$ makes both potential outcomes independent w.r.t the treatment status, and the conditional probability of experiencing an acute CVD shock in $\bar{t}$, as good as random. The assumption would be violated if unobservables systematically differed between individuals experiencing the $T_{i,\bar{t}} = 0$ and those experiencing the $T_{i,\bar{t}} = 1$ states. Therefore, while untestable, its credibility crucially relies on the scope of the available data, a point to which we come back in the following section, after presenting our data in more detail. A second assumption for identification requires some overlap in the distribution of observables W_i and $X_{i,\bar{t}-s}$ between individuals experiencing, and not experiencing, the health shock, so that for both, the conditional treatment probability is:

$$0 < pr(T_{i,\bar{t}} = 1|W_i = w, X_{i,\bar{t}-s} = x) < 1$$

Under both assumptions, i.e. under strong ignorability (Rosenbaum and Rubin, 1983), the $ATT_{\bar{t}+\nu}$ at time $\bar{t}+\nu$, i.e. ν years after the CVD shock, denoted by $\tau_{\bar{t}+\nu}$, is identified as:

$$\tau_{\bar{t}+\nu} \equiv E[Y^1_{i,\bar{t}+\nu} - Y^0_{i,\bar{t}+\nu}|W_i = w, X_{i,\bar{t}-s} = x]$$

$$\equiv E[Y^1_{i,\bar{t}+\nu}|W_i = w, X_{i,\bar{t}-s} = x] - E[Y^0_{i,\bar{t}+\nu}|W_i = w, X_{i,\bar{t}-s} = x]$$

3.2 Data, sample selection and research design implementation

WHIP&Health is an administrative dataset that combines the work and social insurance histories with the health histories of a 7% random sample of workers covered by the Italian Social Security System (INPS) i.e. all private sector workers, excluding agriculture.

The first component, i.e. the Work Histories Italian Panel (WHIP), spanning from 1990 to 2012[22], is a rich employer-employee database collecting detailed information for each employment contract (e.g. qualification, sector of activity, firm, firm dimension, labour income). Further information available includes other types of working spells (i.e. self-employment or atypical work), and non-working spells, such as unemployment. Information on a variety of social security programmes is also available. Information on death is generally not available (except for deaths occurring during hospitalisation, captured in the health component).

The health component is drawn from the hospital discharge records (or SDO i.e. *Schede di dimissione ospedaliera*) registry maintained by the Italian Ministry of Health and collects information on all types of hospitalisations occurred between 2001 and 2014. Variables include the main and the secondary diagnoses, accordingly to the ICD codes (ICD-IX), the year and month of hospitalisation and the type of dismissal (which allows identifying death occurred in the hospital). We identify unplanned hospitalisations related to an acute CVD shock onset (ischemic, codes: ICD-IX 410-414; or cerebrovascular, codes: ICD-IX 430-434 and 436-437) which does not result in death, before reaching or while staying at the hospital. Figure 1 clarifies the time window covered respectively by the labour and social insurance (WHIP), and health (SDO) components of WHIP&Health, and how these are exploited to implement the research design.

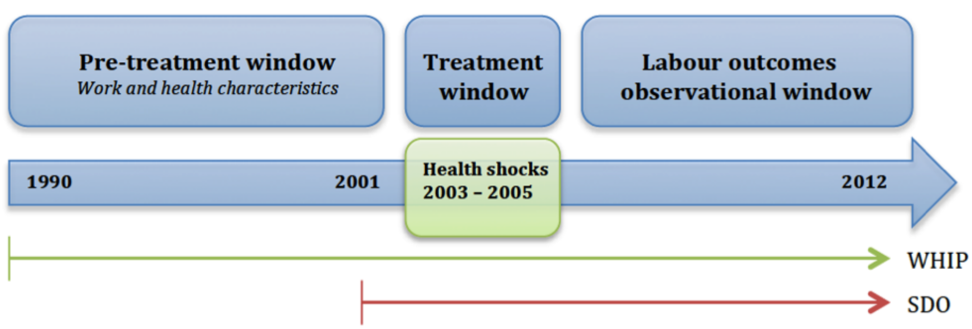

Figure 1: Dataset time coverage and related identification strategy

For the unconfoundedness assumption to be credible, one needs to observe as much previous labour and health history information as possible: therefore, the identification strategy requires a sizeable time widow for observing pre-shock characteristics. On the other hand though, the research question is centred around the chance of evaluating the effect of a health shock in the longer

[22] Previous years would also be available, from 1985, but useless for our purposes due to lower coverage and high frequency of missing information.

term. Trading-off the two, we place the treatment time window of CVD shocks occurrence in the years 2003-2005. This allows observing up to s=15 years of previous labour and social insurance history (i.e. for individuals experiencing the CVD shock in 2005, with WHIP available variables dating back to 1990), and up to ν=9 years of labour outcomes past the health shock onset year (i.e. for individuals experiencing the CVD shock in 2003, with WHIP available variables dating back to 1990).

The sample for analysis includes male individuals who, in any year between 2003 and 2005, were observed in employment as blue-collars, and aged 18-64 years old. The first two restrictions reflect limitations of the underlying WHIP data with respect our identification strategy needs. In more detail, for women, besides lack of reliable information on fertility, the scope of available information on history would be significantly reduced due to their more discontinuous employment patterns, and lack of corresponding information in WHIP (which captures only job or social security spells). The exclusion of white-collar workers is motivated by lack of information on their sickness leave, which is not captured in WHIP (while it is, in the case of blue collars). Sickness leave represents a crucial confounder that allows capturing health-related information for up to 15 previous years, with the SDO time frame being limited to up to 4 years prior the CVD shock occurrence. Because of unobserved heterogeneity concerns, we further restrict the sample to those who had not experienced an acute CVD shock in 2001 and 2002 i.e. the two years before the treatment observational window, and to individuals who could claim four previous years of employment since 1990. We further drop cases with missing or inconsistent information on relevant variables.

The resulting working sample consists of 326,337 individuals: among them, 1,629 experience an acute CVD shock between 2003 and 2005 (i.e. 506 in 2003, 556 in 2004 and 567 in 2005) and represent the 'treated' subsample. While they might potentially experience recurrent CVD events within the treatment window, we consider the first shock observed within the 2003-2005 window as the reference shock. In line with the national and international trends[23], most cases involve an myocardial infarctions (76,98%), and about one in four (23,02%) are cerebrovascular diseases. The subsample of those who do not experience any acute CVD shock between 2003 and 2005, amounts to 324,708 individuals.

Table 1 describes the full set of variables that we exploit to credibly implement the identification strategy outlined in section 3.1: besides basic demographics and health history variables, they include a strikingly rich battery of retrospective labour and social security history information, reconstructing the workers' past for up to 15 previous years. We derive multiple summary indicator of labour market trajectories, as well as time-and job-specific characteristics for previous employments, aiming at substantially reducing the potential influence of time-varying unobservables, captured to

[23]Wilkins E, Wilson L, Wickramasinghe K, Bhatnagar P, Leal J, Luengo-Fernandez R, Burns R, Rayner M, Townsend N (2017). European Cardiovascular Disease Statistics 2017. European Heart Network, Brussels.

the extent they are correlated with observed confounders. Notably, we also include time-specific lagged outcomes, which allow removing any bias that would stem from time-invariant unobservables (O'Neill et al., 2016). Indeed unobserved heterogeneity concerns might arise, for example, from lack of available information on genetic or behavioural risk factors (e.g. smoking, eating habits, physical activity) correlated with labour market outcomes. However our results would not be invalidated, if, besides genetic invariance over time, the above mentioned behaviours are deemed as pretty stable over time (in which case their effect would be purged via lagged outcomes inclusion). Full descriptive statistics for our working sample are reported in Appendix, Table A1.

Table 1: Variables description

Variable Name	**Description**
Time and demographic characteristics	
Year	Year (of CVD shock, for the treated)
Age	Age (when the CVD shock occurs, for the treated)
Abirth_north	Area of birth (north)
Abirth_center	Area of birth (center)
Abirth_south&Isl.	Area of birth (south or islands)
Abirth_abroad	Area of birth (abroad)
Country_underdev	Equal to 1 if the person comes from an underdeveloped country
Health History	
Hosp_cvd_cum	Equal to 1 if the person ever had a hospitalisation for cardiovascular diseases until (t-1)
Days_cvd_cum	Number of days spent in hospitals for a cardiovascular shock until ($\bar{t}$-1)
Hosp_other_cum	Equal to 1 if the person ever had a hospitalisation for other diseases until ($\bar{t}$-1)
Days_other_cum	Number of days spent in hospitals for other type of diseases until ($\bar{t}$-1)
Hosp_other_($\bar{t}$-1)	Number of hospitalisations for other types of diseases in ($\bar{t}$-1)
Days_other_($\bar{t}$-1)	Number of days spent in hospitals for other types of diseases in ($\bar{t}$-1)
Inv_benefit_cum	Equal to 1 if the person ever received ordinary invalidity benefits until ($\bar{t}$-1)
Sick_leave_cum	Number of weeks in sick leave until ($\bar{t}$-1)
Labour History	
Work_active_cum	Number of years the person is observed as employee, self-employed or atypical worker, until (t-1)
Nemployee_cum	Number of contracts as employee until ($\bar{t}$-1)
Rate_employee_cum	Percentage of years as an employee over the total observed as a worker, until ($\bar{t}$-1)
Jobloss_cum	Number of involuntary job losses experienced until ($\bar{t}$-1)
New_firm_cum	Number of firms changed until ($\bar{t}$-1)
Nblue_collar_cum	Number of contracts as blue-collar until ($\bar{t}$-1)
Nwhite_collar_cum	Number of contracts as white-collar until ($\bar{t}$-1)
Nmanager_cum	Number of contracts as manager until ($\bar{t}$-1)
Rate_perm_cum	Percentage of permanent contracts on the total as an employee until ($\bar{t}$-1)
Rate_fullt_cum	Percentage of full-time contracts and the total as an employee until ($\bar{t}$-1)
Ever_CIG	Equal to 1 if the person ever been in "cassa integrazione guadagni" until ($\bar{t}$-1)
Nunempl_cum	Number of unemployment benefits received until ($\bar{t}$-1)
Unempl_($\bar{t}$-1)	Equal to 1 if the person received unemployment benefits in ($\bar{t}$-1)
Rate_selfempl_cum	Percentage of years as self-employed over the total observed as a worker until ($\bar{t}$-1)
Days_self_cum	Total number of days as self-employed until ($\bar{t}$-1)
Rate_atypical_cum	Percentage of years as atypical worker over the total observed as a worker until ($\bar{t}$-1)
N_atypical_cum	Total number of contracts as atypical worker until ($\bar{t}$-1)
Characteristics of the last (pre-shock) job as employee	
Dist_last1_employee	Distance between the treatment year and the last job as employee as if (t-1)
Dist_last2_employee	Distance between the treatment year and the second previous job as employee as if ($\bar{t}$-1)
Dist_last3_employee	Distance between the treatment year and the third previous job as employee as if ($\bar{t}$-1)
Dist_last4_employee	Distance between the treatment year and the fourth previous job as employee as if ($\bar{t}$-1)
Last_sick_leave	Number of weeks in sick leave corresponding to the last job as employee as if ($\bar{t}$-1)
Last_weeks_paid	Number of paid weeks corresponding to the last job as employee as if ($\bar{t}$-1)
Last_fix_term	Equal to 1 if the person is in a permanent contract during the last job as employee as if ($\bar{t}$-1)
Last_jtenure	Number of years under the same employer up until the last job as employee as if ($\bar{t}$-1)
Last_awork_north	Area of work (north) of the last job as employee as if ($\bar{t}$-1)
Last_awork_center	Area of work (center) of the last job as employee as if ($\bar{t}$-1)
Last_awork_south&Isl.	Area of work (south or islands) of the last job as employee as if ($\bar{t}$-1)
Last_awork_abroad	Area of work (abroad) of the last job as employee as if ($\bar{t}$-1)
Last_apprentice	Job qualification (apprentice) of the last job as employee as if ($\bar{t}$-1)
Last_bluecollar	Job qualification (blue-collar) of the last job as employee as if ($\bar{t}$-1)
Last_whitecollar	Job qualification (white-collar) of the last job as employee as if ($\bar{t}$-1)
Last_manager	Job qualification (manager) of the last job as employee as if ($\bar{t}$-1)
Last_director	Job qualification (director) of the last job as employee as if ($\bar{t}$-1)
Last_firm_015	Firm dimension (between 0 and 15 employees) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_firm_16250	Firm dimension (between 16 and 250 employees) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_firm_250	Firm dimension (more than 250 employees) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_sec_agriculture	Sector of activity (agriculture) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_sec_manufac	Sector of activity (manufacturing) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_sec_construc	Sector of activity (construction) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_sec_extraction	Sector of activity (mineral extraction) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_sec_energy	Sector of activity (energy) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_sec_trade	Sector of activity (trade) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_sec_foodservices	Sector of activity (food and hotel services) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_sec_transports	Sector of activity (transports) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_sec_finance	Sector of activity (finance services) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_sec_realestate	Sector of activity (real estate services) corresponding to the last job as employee as if ($\bar{t}$-1)
Last_public	Sector of activity (public services) corresponding to the last job as employee as if ($\bar{t}$-1)

(continue)

Variable Name	Description
Lagged outcomes	
Last1_lab_income	Annual earnings of the last job as employee as if ($\bar{t}$-1)
Last2_lab_income	Annual earnings of the second previous job as employee as if ($\bar{t}$-2)
Last3_lab_income	Annual earnings of the third previous job as employee as if ($\bar{t}$-3)
Last4_lab_income	Annual earnings of the fourth previous job as employee as if ($\bar{t}$-4)
Last1_hwage	Hourly wage of the last job as employee as if ($\bar{t}$-1)
Last2_hwage	Hourly wage of the second previous job as employee as if ($\bar{t}$-2)
Last3_hwage	Hourly wage of the third previous job as employee as if ($\bar{t}$-3)
Last4_hwage	Hourly wage of the fourth previous job as employee as if ($\bar{t}$-4)
Last1_fulltime	Equal to 1 if the person is full-time employed in the last job as employee as if ($\bar{t}$-1)
Last2_fulltime	Equal to 1 if the person is full-time employed in the second previous job as employee as if ($\bar{t}$-2)
Last3_fulltime	Equal to 1 if the person is full-time employed in the third previous job as employee as if ($\bar{t}$-3)
Last4_fulltime	Equal to 1 if the person is full-time employed in the fourth previous job as employee as if ($\bar{t}$-4)
Last1_LMP	Equal to 1 if the person is an employee, self-employed or an atypical worker in $\bar{t}$-1
Last2_LMP	Equal to 1 if the person is an employee, self-employed or an atypical worker in $\bar{t}$-2
Last3_LMP	Equal to 1 if the person is an employee, self-employed or an atypical worker in $\bar{t}$-3
Last4_LMP	Equal to 1 if the person is an employee, self-employed or an atypical worker in $\bar{t}$-4

3.3 Implementation

Before any compositional adjustment, the distribution of characteristics varies remarkably between treated and control individuals (visible in Table 2, first and second columns), revealing selection in experiencing CVD shocks. Individuals who experience an acute CVD shock are on average older, with poorer previous health outcomes (e.g. more frequent previous hospitalisations and for longer periods, higher receipt of invalidity benefits and sickness leave take-up etc.) and significant differences in labour market outcomes, possibly related to their different age distribution, with respect to control individuals. In the spirit of Ho et al. (2007), we compute ATTs combining preprocessing procedures, aimed at balancing the distribution of covariates between treated and control individuals over a common support, with parametric estimation on the preprocessed samples (via OLS and Probit for continuous and binary outcomes respectively), thus obtaining ATTs that are robust to model misspecification[24].

[24]This two-step approach is regarded as doubly robust as consistency only requires that either the parametric or the non-parametric component is consistently estimated (Ho et al., 2007).

Table 2: Pre and post matching covariates balance

	Pre-matching				Post-matching			
	Mean				Mean			
	Treated (1629)	Controls (769174 obs.)	%bias	p-value	Treated (1596)	Controls (294862 obs.)	%bias	p-value
Year	2004	2004	1.7	0.503	2004	2004	0.0	1.000
Age	50.73	39.77	127.9	0.000	50.68	50.68	0.0	0.998
Abirth_north	0.271	0.359	23.4	0.000	0.273	0.273	0.0	1.000
Abirth_center	0.142	0.133	2.6	0.284	0.142	0.142	0.0	1.000
Abirth_south&Isl.	0.508	0.354	31.3	0.000	0.507	0.507	0.0	1.000
Abirth_abroad	0.079	0.154	-23.4	0.000	0.078	0.078	0.0	1.000
Country_underdev	0.073	0.139	-21.5	0.000	0.072	0.072	0.0	1.000
Hosp_cvd_cum	0.037	0.001	26.6	0.000	0.024	0.024	0.0	1.000
Days_cvd_cum	0.409	0.012	19.3	0.000	0.282	0.282	0.0	1.000
Hosp_other_cum	0.311	0.190	28.2	0.000	0.308	0.308	0.0	1.000
Days_other_cum	2.814	1.303	22.3	0.000	2.766	2.766	0.0	1.000
Hosp_other_($\bar{t}$-1)	0.207	0.096	21.6	0.000	0.204	0.204	0.0	1.000
Days_other_($\bar{t}$-1)	0.993	0.440	14.7	0.000	0.979	0.979	0.0	1.000
Inv_benefit_cum	0.077	0.007	35.5	0.000	0.068	0.068	0.0	1.000
Sick_leave_cum	19.28	10.70	38.9	0.000	19.10	19.10	0.0	0.999
Work_active_cum	12.37	10.99	43.0	0.000	12.41	12.41	0.0	0.998
Nemployee_cum	14.23	13.2	25.2	0.000	14.27	14.27	0.0	0.999
Rate_employee_cum	97.01	97.90	-8.9	0.000	96.98	96.98	0.0	1.000
Jobloss_cum	0.312	0.324	-1.8	0.476	0.315	0.315	0.0	1.000
New_firm_cum	2.843	2.937	-3.7	0.120	2.847	2.847	0.0	1.000
Nblue_collar_cum	12.78	10.84	43.8	0.000	12.82	12.82	0.0	0.998
Nwhite_collar_cum	0.281	0.261	1.5	0.523	0.271	0.271	0.0	0.999
Nmanager_cum	0.001	0.002	-1.0	0.753	0.001	0.001	0.0	0.992
Rate_perm_cum	94.88	89.86	28.1	0.000	95.11	95.11	0.0	0.998
Rate_fullt_cum	96.39	96.55	-1.1	0.636	96.64	96.64	0.0	1.000
Ever_CIG	0.384	0.335	10.2	0.000	0.385	0.385	0.0	0.999
Nunempl_cum	0.393	0.381	1.1	0.646	0.384	0.384	0.0	1.000
Unempl_($\bar{t}$-1)	0.039	0.059	-9.5	0.000	0.039	0.039	0.0	0.999
Rate_selfempl_cum	3.699	2.596	9.1	0.000	3.749	3.748	0.0	1.000
Days_self_cum	165.5	130.6	5.9	0.013	168.4	168.4	0.0	1.000
Rate_atypical_cum	0.403	0.632	-6.1	0.030	0.374	0.374	0.0	1.000
N_atypical_cum	0.050	0.062	-2.6	0.307	0.046	0.046	0.0	1.000
Dist_last1_employee	1.044	1.056	-3.3	0.205	1.036	1.036	0.0	1.000
Dist_last2_employee	2.141	2.153	-1.4	0.580	2.130	2.130	0.0	1.000
Dist_last3_employee	3.261	3.267	-0.6	0.816	3.249	3.249	0.0	1.000
Dist_last4_employee	4.391	4.413	-1.6	0.536	4.375	4.375	0.0	1.000
Last_sick_leave	2.202	1.156	23.4	0.000	2.167	2.167	0.0	1.000
Last_weeks_paid	47.57	45.95	14.5	0.000	47.65	47.65	0.0	0.999
Last_fix_term	0.041	0.081	-16.9	0.000	0.036	0.036	0.0	0.997
Last_jtenure	8.911	6.621	34.9	0.000	8.952	8.952	0.0	0.999
Last_awork_north	0.484	0.568	-16.8	0.000	0.482	0.482	0.0	1.000
Last_awork_center	0.179	0.176	0.8	0.735	0.182	0.182	-0.0	1.000
Last_awork_south&Isl.	0.336	0.256	17.8	0.000	0.336	0.336	0.0	1.000
Last_awork_abroad	0	0.002	-2.2	0.539	0	0	.	.
Last_apprentice	0.001	0.017	-17.3	0.000	0	$3.6e^{(-05)}$	-0.2	0.810
Last_bluecollar	0.994	0.976	15.3	0.000	0.996	0.996	0.1	0.986
Last_whitecollar	0.005	0.007	-3.1	0.247	0.004	0.004	0.0	1.000
Last_manager	0	$6.0e^{(-05)}$	-1.1	0.755	0	$3.3e^{(-06)}$	-0.1	0.942
Last_director	0	$3.1e^{(-05)}$	-0.8	0.822	0	$1.1e^{(-06)}$	0.0	0.966
Last_firm_015	0.297	0.368	-15.2	0.000	0.298	0.298	0.0	0.999
Last_firm16250	0.431	0.414	3.4	0.175	0.431	0.431	0.0	1.000
Last_firm_250	0.273	0.218	12.8	0.000	0.271	0.271	0.0	1.000

(continue)

	Pre-matching				Post-matching			
	Mean				Mean			
	Treated (1629)	Controls (769174 obs.)	%bias	p-value	Treated (1596)	Controls (294862 obs.)	%bias	p-value
Last_sec_agriculture	0.001	0.0004	1.1	0.626	0.001	0.001	0.0	1.000
Last_sec_manufac	0.416	0.493	-15.5	0.000	0.420	0.420	0.0	1.000
Last_sec_construc	0.169	0.172	-0.7	0.784	0.170	0.170	0.0	1.000
Last_sec_extraction	0.008	0.005	3.4	0.128	0.008	0.008	0.0	1.000
Last_sec_energy	0.018	0.011	6.0	0.006	0.019	0.019	0.0	1.000
Last_sec_trade	0.069	0.101	-11.5	0.000	0.068	0.068	0.0	1.000
Last_sec_foodservices	0.043	0.046	-1.6	0.531	0.043	0.043	0.0	1.000
Last_sec_transports	0.144	0.088	17.6	0.000	0.143	0.143	0.0	1.000
Last_sec_finance	0.123	0.076	15.7	0.000	0.119	0.119	0.0	1.000
Last_sec_realestate	0.006	0.003	3.8	0.069	0.006	0.006	0.0	1.000
Last_public	0.004	0.005	-1.7	0.516	0.003	0.003	0.0	1.000
Last1_lab_income	22310	20835	14.1	0.000	22429	22429	0.0	1.000
Last2_lab_income	21822	20344	14.1	0.000	21922	21922	0.0	1.000
Last3_lab_income	21491	19851	15.0	0.000	21620	21619	0.0	0.999
Last4_lab_income	21222	19002	20.2	0.000	21337	21337	0.0	1.000
Last1_hwage	11.83	11.34	9.2	0.002	11.85	11.85	0.0	1.000
Last2_hwage	11.69	11.14	9.9	0.001	11.72	11.72	0.0	1.000
Last3_hwage	11.65	10.98	9.0	0.005	11.67	11.67	0.0	1.000
Last4_hwage	11.56	10.82	6.9	0.044	11.61	11.61	0.0	1.000
Last1_fulltime	0.950	0.962	-6.0	0.009	0.956	0.956	0.0	1.000
Last2_fulltime	0.952	0.965	-6.7	0.004	0.956	0.956	0.0	1.000
Last3_fulltime	0.956	0.965	-4.7	0.046	0.961	0.961	0.0	1.000
Last4_fulltime	0.956	0.965	-4.3	0.069	0.960	0.960	0.0	1.000
Last1_LMP	0.981	0.976	3.2	0.219	0.984	0.984	0.0	0.999
Last2_LMP	0.964	0.964	0.0	0.985	0.966	0.966	0.0	1.000
Last3_LMP	0.949	0.953	-1.7	0.495	0.950	0.950	0.0	1.000
Last4_LMP	0.934	0.936	-0.8	0.746	0.937	0.937	0.0	1.000

Following Jones et al. (2019), the distributional adjustments are implemented in two steps: coarsened exact matching (CEM) (Iacus et al., 2011) along a set of basic confounders, and entropy balancing matching (EB) (Hainmueller, 2012; Hainmueller and Xu, 2013) on the full set of observed potential confounders. CEM performs an exact matching between treated and control individuals based on coarsened variables values. The advantage, with respect to other matching procedures, is that CEM reduces the imbalance in selected variables, while implementing common support on these, without affecting the balancing in other variables (as other procedures, such as propensity score matching, might instead entail, trading-off the balance obtainable for different variables), while also accounting for variables' interactions and nonlinearities. In practice, the CEM algorithm stratifies the sample by subsets of coarsened variables values (or exact variable values, in the case of dichotomous variables, or if no coarsening is applied) of selected variables. Individuals falling in strata lacking at least one treated and one control are dropped, while retained individuals are attributed a weight accounting for the different number of treated and control individuals retained in each matched stratum. The greater the number of variables involved, and the finer the coarsening applied to non-dichotomous variables, the higher the loss of cases for which no exact matching is found.

We implement CEM on uncoarsened variable values, which results in an exact matching on: age, year, the distance (in years) from the previous time the individual was observed as employee[25], whether the individual had a past experience of acute CVD shock[26], whether working in a part-time or full-time contract, and whether under a fixed-term or open-ended contract as of $\bar{t}$-1. Two further variables included are instead coarsened: firm size (0-15/16-250/250+ employees) as of $\bar{t}$-1; and region of work, coarsened to a geographical area indicator (north-east, north-west, centre, south and islands). Job-specific variables are included as of $\bar{t}$-1, rather than as of the year of shock occurrence, to avoid the chance of introducing post-treatment bias, which would arise if they were themselves affected by the shock, a possibility that we cannot rule out for year $\bar{t}$. It is worth noting though that in the 89% of treated cases and the 88% of control cases, the employer does not change between $\bar{t}$-1 and $\bar{t}$.

Out of the 17,349 strata obtained, only 961 are retained. However, this corresponds to a loss of only 33 treated individuals, paired with a striking reduction in the number of control individuals (about the 60%). The ratio of #potential control/#treated individuals is reduced from 472 controls for every treated pre-CEM to 185 controls for every treated post-CEM (Table A2 in Appendix). To remove imbalances remaining in the larger set of potential confounders observed, we further apply EB matching on the CEM-retained samples of treated and control individuals. The EB procedure reweights observations so that the covariate distributions satisfy a set of specified moment conditions (Hainmueller et al., 2012), imposing ex-ante a desired level of sample moment adjustment. We impose, as usually chosen, a first moment condition on the extended set of variables, obtaining a remarkable overlap, as visible in the right panel of Table 2 (and Table A.3 in Appendix for further moments). In the preprocessed samples, the bias, measured as standardised percentage difference in means between treated and matched controls, is strikingly reduced to zero for all variables, with a few exceptions, where it anyway does not exceed a -0.2.

Indeed, lack of bias in observables does not address the chance of potential remaining bias stemming from unobservables, in particular time- varying unobservables (as potential bias from the time invariant ones is tackled through the inclusion of lagged outcomes), which would invalidate our identification strategy. However, while we cannot entirely rule out the chance of this particular source of bias, it is reassuring to observe in Figure 2 the post-preprocessing sample means for each labour outcome $Y^1_{i,t}$ and $Y^0_{i,t}$, over the years before the shock for the treated and matched controls. If time-varying unobservable were actually playing a role as confounders, that would presumably emerge in detectable differences in pre-shock outcomes between treated and successfully matched controls. Instead, no such difference is detectable in the four years before $\bar{t}$, i.e. the year of shock occurrence. On the contrary, average outcomes for the two groups diverge since $\bar{t}$+1 in terms of employment and probability of full-time work; or even since $\bar{t}$ in the case of annual employment

[25]In the 97.9% of cases, this corresponds to the previous year. For the other, including this variables allows then comparing individuals with lagged outcomes referable to the same past calendar year.

[26]Which would be captured in the available SDO data, i.e. since 2001.

income and hourly wages, signalling an immediate adjustment in the first months past the shock[27].

We finally proceed by estimating parametric models (OLS and probit according to the continuous or binary nature of outcome), to obtain the ATTs (measured by coefficients and marginal effects for the treatment indicator respectively) reported in the following results section[28]. With respect to taking a simple difference in outcomes sample means on the post-preprocessing treated and control samples (anyway visible in Figure 2 for each outcome, for the shock year $\bar{t}$ and the following years), the parametric estimation controls for any possibly remaining imbalance in the larger set of all included covariates' distribution.

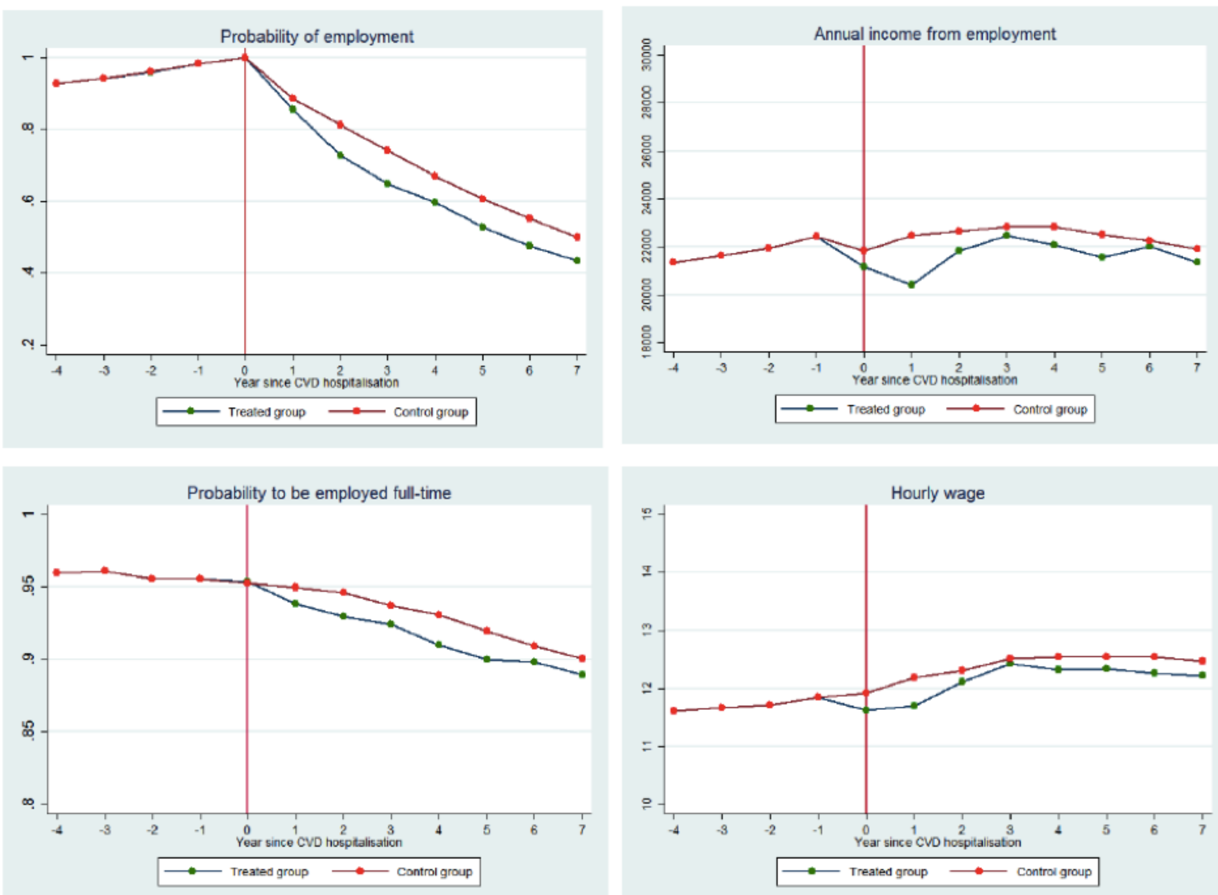

Figure 2: Sample means for labour outcomes, by treatment status, after CEM and EB adjustments
Source: WHIP&HEALTH. Notes: Control group sample means are computed on successfully matched controls only. Continuous lines connect time-specific sample means.

[27]In Figure 2, continuous lines connect time-specific sample means. It would be incorrect though to interpret figures on earnings and wages as revealing a drop in outcomes for the treated since before the shock occurs; the apparent drop rather results from the treated outcome means in $\bar{t}$, which averages months before and months after the shock occurrence, being lower than in $\bar{t}$-1.

[28]The following regression model has been applied:

$$Y_{\bar{t}+\nu} = \alpha_0 + \alpha_1 T_{i,\bar{t}} + \beta_1' \mathbf{W}_i + \beta_2' \mathbf{X}_{i,\bar{t}-s} + \epsilon_{i,\bar{t}}$$

where ν goes from 1 to 7 (up to 9 in the longer term analysis), $T_{i,\bar{t}}$ is a dummy variable representing the treatment group, $\mathbf{W}_i$ indicates the individual time-invariant characteristics, while $\mathbf{X}_{i,\bar{t}-s}$ includes time-varying labour, social insurance and health histories variables, observed s years before the shock.

4 Results

4.1 Labour market outcomes

Table 3 reports the estimated ATTs ($\tau_{\bar{t}+\nu}$) for the probability of employment (i.e. working as an employee) and unconditional annual income from employment, together with the relative size effect, computed as the percentage ratio of each ATT $\tau_{\bar{t}+\nu}$ to the mean of the corresponding counterfactual outcome $Y^0_{i,\bar{t}+\nu}$ in matched controls sample. Estimated ATTs and corresponding 95% confidence intervals on these outcomes are also depicted in Figures 3-4.

Table 3: Employment-related unconditional outcome: ATT and Relative Effect

	Probability of Employment		**Annual income from employment**	
Time	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
$\bar{t}$	-	-	-693.2***	-3.17
Rob. SE.	-	-	(202.4)	
N .treated	-	-	1.594	
$\bar{t}$ +1	-0.030***	-3.35	-2540.4***	-12.8
Rob. SE.	(0.009)		(278.7)	
N. treated	1596		1.596	
$\bar{t}$+2	-0.085***	-10.41	-2584.9***	-14.11
Rob. SE.	(0.011)		(303.8)	
N. treated	1596		1.596	
$\bar{t}$+3	-0.093***	-12.59	-2337.4***	-13.9
Rob. SE.	(0.011)		(311.6)	
N. treated	1596		1.596	
$\bar{t}$+4	-0.076***	-11.38	-2195.9***	-14.4
Rob. SE.	(0.012)		(317.5)	
N. treated	1596		1.596	
$\bar{t}$+5	-0.080***	-13.17	-2229.7***	-16.4
Rob. SE.	(0.012)		(310.3)	
N. treated	1596		1.596	
$\bar{t}$+6	-0.078***	-13.90	-1761.6***	-14.5
Rob. SE.	(0.000)		(305.5)	
N. treated	1596		1.596	
$\bar{t}$+7	-0.068***	-13.60	-1665.6***	-12.9
Rob. SE.	(0.011)		(291.6)	
N. treated	1596		1.596	

Source: WHIP&Health
Notes: marginal effects are reported for the Probability of employment (ATTs); by sample selection all individuals are employed in $\bar{t}$, thus the probability of employment in that year is 1 by construction.

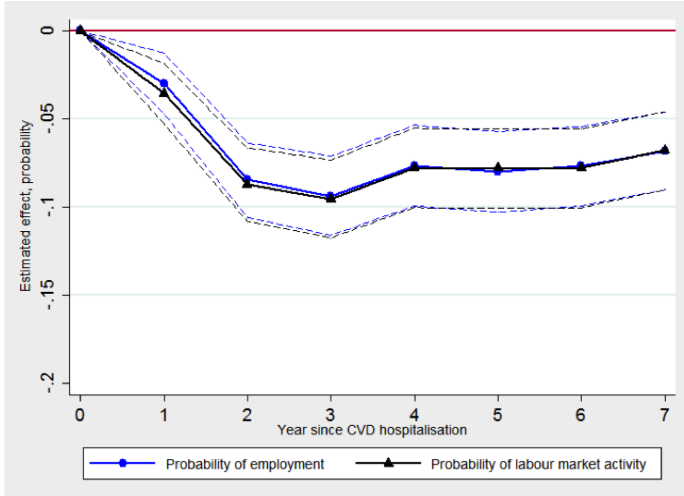

Figure 3: ATTs by year since CVD hospitalization: employment and labour market activity
Source: WHIP&Health. **Notes**: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported; by sample selection all individuals are employed in the year of the shock, thus the ATT is set to 0 in that year

In the Italian institutional setting, experiencing a CVD shock entails a remarkable reduction in blue-collar workers' employment probability, a results which is line with previous studies conducted in other countries[29]. Here, the employment probability reduction amounts to about -3 percentage points in the year immediately after the shock, but increases, and persists, over the following years. Actually, loss of employment peaks three years after the shock, reaching -9.3 percentage points, and displays only a very minor recovery thereafter. Seven years later, the consequence of having experienced a CVD shock amounts to a -6.8 percentage points lower probability of employment, thus reaching in the longer term a value that is almost twice the short-term (i.e. $\bar{t}$+1) effect. It is worth emphasising how, in terms of relative size effect, i.e. w.r.t. the average counterfactual outcome, the size of employment probability reduction exceeds 10 per cent from $\bar{t}$+2 onwards, reaching 13 per cent in $\bar{t}$+7.

In line with the majority of previous literature, loss of employment bears a substantial and immediate (i.e. since the shock year) loss of income from employment. But also, our longer-term analysis reveals how persistent this loss is, amounting, in any of the seven years past the shock, to more than 12 per cent of the earnings those blue collars would have obtained in the absence of the shock, up to a relative effect of about 13% in $\bar{t}$+7. The peak in earnings loss arises in the very short term (i.e. $\bar{t}$+1), plausibly in relation to the take-up of sickness leave, which is only partially covered

[29]Note that a potential threat for our findings may arise due to selective mortality. The estimated ATT for the probability of employment and of labor market activity might be potentially biased upward if the probability to die is higher among the treated than among the controls. Remember that we are not in the condition to identify exits due to death. In the introduction, we outlined that CVD are among the leading causes of death in developed countries, including Italy. A sizeable quota - amounting to 30-40% - of fatal events in the age range 35-64 occur right after the symptoms start and before reaching the hospital (Ministry of Health, 2010). Furthermore, we are able to select into the analysis survivors after the period of hospitalisation. The Italian Ministry of Health (2017) reports that the 30-days mortality rate for myocardial infarctions is equal to 8.3%, while the 1-year mortality is equal to 10.2%, only 1.9 percent higher. This means that after the first month from the health shock, the probability to die is rather low. Based on these data and considerations, we believe that the mortality-based selectivity issue does not sizeably bias our findings.

by the employer (the remaining replacement being granted trough public transfers).

Table 4: Labour activity and transition to self-employment/atypical work: ATT and Relative Effects

Time	**Probability of labour market activity** $\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	**Probability of working as self-employed/atypical worker** $\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
t	-	-	-	-
Rob. SE	-	-	-	-
N. treated	-	-	-	-
$t+1$	-0.036***	-4.02	-0.009***	-45.48
Rob. SE	(0.009)		(0.002)	
N. treated	1.596		1.596	
$t+2$	-0.087***	-10.5	-0.002	-8.14
Rob. SE	(0.011)		(0.004)	
N. treated	1.596		1.596	
$t+3$	-0.095***	-12.5	-0.003	-11.40
Rob. SE	(0.011)		(0.004)	
N. treated	1.596		1.596	
$t+4$	-0.078***	-11.3	-0.003	-9.20
Rob. SE	(0.011)		(0.004)	
N. treated	1.596		1.596	
$t+5$	-0.078***	-12.3	-0.002	-6.97
Rob. SE	(0.012)		(0.004)	
N. treated	1.596		1.596	
$t+6$	-0.078***	-13.5	-0.005	-13.83
Rob. SE	(0.011)		(0.004)	
N. treated	1.596		1.596	
$t+7$	-0.068***	-12.9	-0.002	-6.38
Rob. SE	(0.011)		(0.004)	
N. treated	1.596		1.596	

Source: WHIP&Health
Notes: marginal effects are reported for the Probability of labour market activity and for the Probability of working as self-employed/atypical worker (ATTs); by sample selection all individuals are employed in $\bar{t}$, thus the probability of labour market activity in that year is 1 by construction, and for the same reason the probability of working as self-employment/atypical work is 0.

In Table 4, we consider a wider concept of labour market activity, which includes, beside employment, possible transitions to other forms of labour supply, i.e. self-employment or atypical work. In the year after the shock, the size of the negative ATT for labour market activity (Table 4, first column) is even larger than for employment (Table 3, first column), which is explained by a shock-induced reduction in the probability of switching from employment to other forms of labour, at least in the short term (Table 4, right-hand panel). This finding might appear at odds with the argument that individuals might be "pushed" into self-employment by lack of opportunities or perspectives as employees (see e.g. Blanchflower and Oswald, 1998). In this literature, some studies identify health-related limitations to work ability as a main driver of switches to self-employment; and a higher quota of disable persons among the self-employed, better able to accommodate their own condition (see, e.g., Zissimopoulos and Karoly, 2005). However, in the Italian institutional context, our finding can be plausibly explained by the short-run health-related protection granted under employment (i.e. sickness leave paid for six months, allowing to stop working while maintaining the contract, and the option to resume that work later on). Such employment-related protection plausibly lowers the incentive to switch to other forms of work, which, although possibly more flexible, grant lower income protection. In the following years though, the ATTs on employment and labour market activity are roughly comparable in size, consistently with the evidence of no significant response in the probability of switching to self-employment or atypical work from $\bar{t}+2$ onwards.

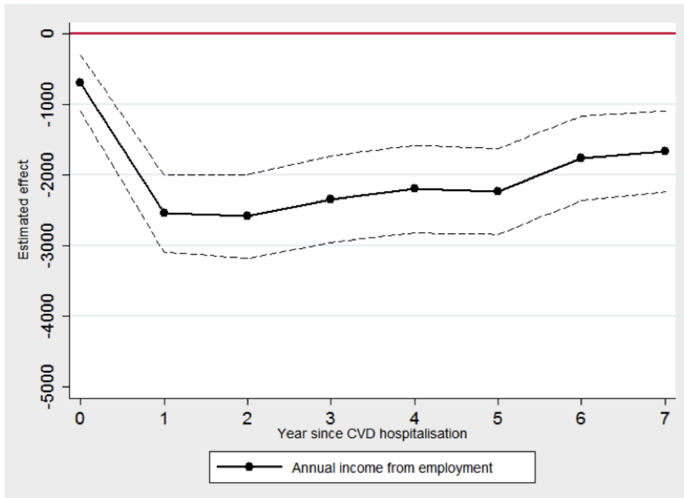

Figure 4: ATTs by year since CVD hospitalization: (unconditional) annual income from employment
Source: WHIP&Health. **Notes**: ATTs: point estimates (connected line) and 95% confidence intervals (dashed lines).

Table 5: Conditional employment-related outcomes: ATT and Relative Effect

Time	**Annual income from employment**		**Probability to be employed full-time**		**Hourly wage**		**Probability of working with the same employer as in $\bar{t}$**	
	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
$\bar{t}$	-693.2***	-3.17	0.003	0.32	-0.295***	-2.48	-	-
Rob. SE.	(202.4)		(0.005)		(0.099)	-	-	-
N. Treated	1,594		1,594		1,594	-	-	-
$\bar{t}$+1	-2138.1***	-9.50	-0.007	-0.74	-0.551***	-4.52	0.019**	2.18
Rob. SE.	(255.6)		(0.006)		(0.119)		(0.008)	
N. Treated	1.349		1.349		1349		1361	
$\bar{t}$+2	-1081.9***	-4.76	-0.015**	-1.59	-0.297**	-2.41	0.004	0.49
Rob. SE.	(273.9)		(0.007)		(0.116)		(0.015)	
N. Treated	1.144		1.144		1.144		1152	
$\bar{t}$+3	-606.8**	-2.64	-0.011	-1.17	-0.198	-1.58	-0.014	1.96
Rob. SE.	(283.5)		(0.008)		(0.129)		(0.014)	
N. Treated	1.020		1.020		1.020		1031	
$\bar{t}$+4	-860.4**	-3.75	-0.017*	-1.83	-0.274**	-2.18	-0.022	-3.43
Rob. SE.	(322.1)		(0.009)		(0.124)		(0.015)	
N. Treated	932		932		932		945	
$\bar{t}$+5	-983.3***	-4.33	-0.016*	-1.74	-0.281*	-2.24	0.003	0.48
Rob. SE.	(345.5)		(0.010)		(0.146)		(0.016)	
N. Treated	826		826		826		840	
$\bar{t}$+6	-528.6	-2.35	-0.007	-0.77	-0.356**	-2.83	-0.008	-1.50
Rob. SE.	(362.7)		(0.011)		(0.145)		(0.017)	
N. Treated	749		749		749		756	
$\bar{t}$+7	-742.6*	-3.35	-0.005	-0.56	-0.323**	-2.59	-0.001	-0.23
Rob. SE.	(348.9)		(0.012)		(0.158)		(0.018)	
N. Treated	675		675		675		685	

Source: WHIP&Health
Notes: marginal effects are reported for the Probability to be employed full-time and for the Probability of working with the same employer as in $\bar{t}$ (ATTs); the probability of working with the same employer in that year is 1 by construction.

Table 5 and Figures 5 to 8 report the estimated ATTs (and corresponding relative size effects) for outcomes observed conditionally on remaining in employment: in more detail, we consider annual income from employment, the probability to be employed full- (versus part-) time, hourly wage[30] and the probability of working with the same employer as in $\bar{t}$ (the year of the shock). The blue-collar workers that continue employment after a CVD shock still bear a significant loss in earnings, again with a peak in $\bar{t}$+1 plausibly related to the take-up of sickness leave. In relative terms, the loss amounts to about -9 per cent in the first year; later, while reduced in size (up to -3% in $\bar{t}$+7), it remains significant throughout the longer run (see also Figure 5). Clearly, exit from employment explains the quantitative difference observable between the relative effect measured on unconditional (Table 3) and conditional (Table 5) earnings. Further columns in Table 5 contribute to shed some light on the possible channels explaining why a reduction in earnings might occur despite remaining employed. First, we consider the possibility of an adjustment in working times. The probability of switching from full- to part-time is substantially unaltered (see also Figure 6) with respect to what would have happened in the absence of the CVD shock. In a few years only

[30] We compute hourly wages combining information on labour income, paid weeks and the working time (part-time or full-time). We do not observe the number of hours worked in the WHIP data. However, we do recover the distribution of hours worked for male blue-collar workers from the EU-QLFS data. We do find that this distribution is highly concentrated around two mass points: 20 hours for part timers and 40 hours for full time workers (with no dispersion in the latter case, consistently with legal provisions). When computing the hourly wage, we attribute 20 hours of work to part time contracts and 40 hours to full time contracts. It is worth noticing that 94,34% of all annual prevalent contracts in our data are full-time.

($\bar{t}$+2,$\bar{t}$+4,$\bar{t}$+5) the ATT of full- (versus part-) time employment is significant and negative, yet pretty small in size: the relative effect in those years does not exceeds the two percentage points.

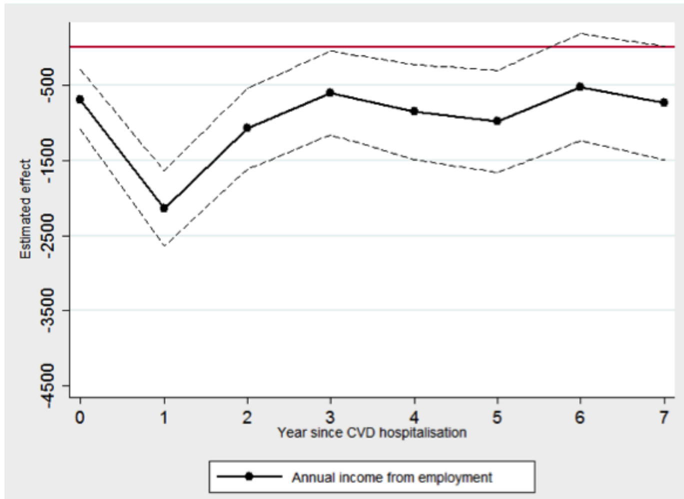

Figure 5: ATTs by year since CVD hospitalisation: (conditional) annual income from employment
Source: WHIP&Health. Notes: ATTs: point estimates (connected line) and 95% confidence intervals (dashed lines)

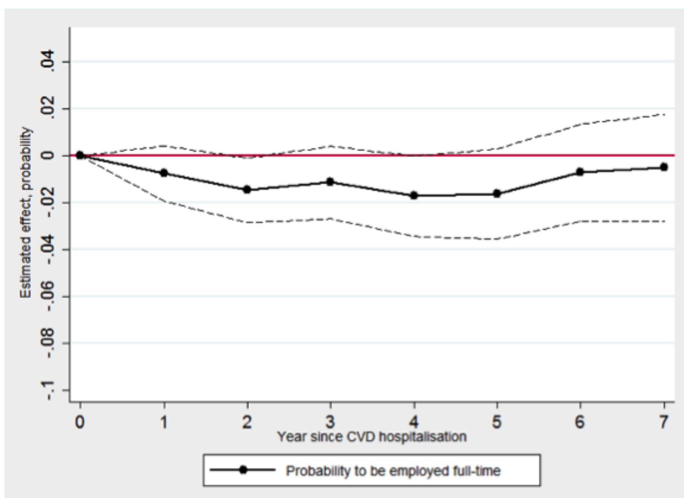

Figure 6: ATTs by year since CVD hospitalisation: probability of full- (versus part-) time
Source: WHIP&Health. Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

Second, we investigate hourly wage adjustments (see also Figure 7). Hourly wage shows negative and significant ATTs. In relative terms, the magnitude is low, ranging from less than 2% to 4% in the first year past the shock. The later wage dynamics observed for individuals in the treatment and control groups reveal, consistently with a downward wage rigidity scenario, that the negative effect is mostly to be traced to a lower nominal growth experienced by individuals' hit by the CVD shock, with respect to matched controls.

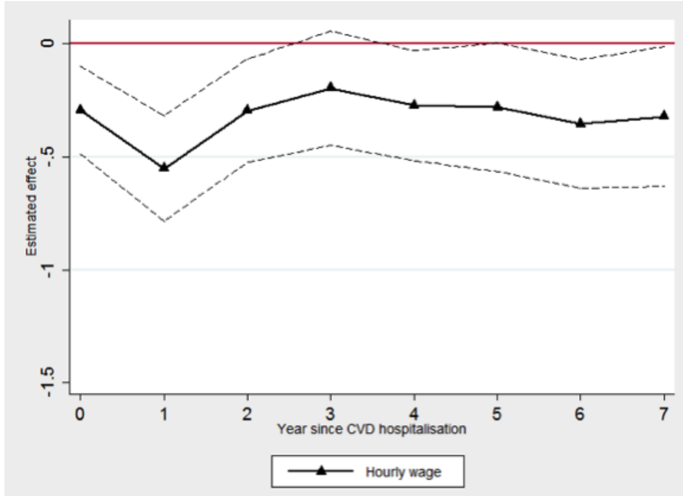

Figure 7: ATTs by year since CVD hospitalisation: hourly wage
Source: WHIP&HEALTH. Notes: ATTs: point estimates (connected line) and 95% confidence intervals (dashed lines).

A further mechanism through which labour income losses might occur entails transitions to other jobs (with a different employer), motivated by the search for tasks more suited to accommodate disability, acceptable even under a lower pay. Interestingly, the probability of working with the same employer as at the time of the shock registers a significant, yet small, increase only in $\bar{t}+1$ (see also Figure 8). The timing of this increase matches that observed for the reduction in transitions to self-employment or atypical work (Table 4), and correspond to the time when sickness protection is being granted under employment. However, in the following years, transitions to other jobs do not appear as an adjustment channel actually pursued by Italian blue-collar workers.

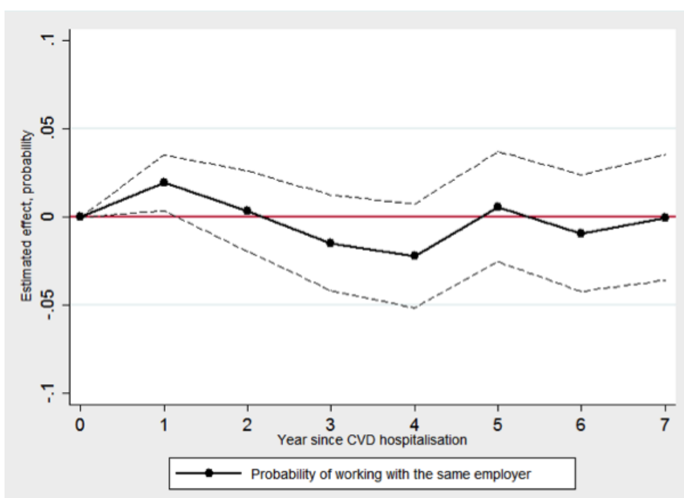

Figure 8: ATTs by year since CVD hospitalisation: (conditional) probability of working with the same employer as in $\bar{t}$
Source: WHIP&HEALTH. Notes: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

4.2 The long(er) run

Table 6 reports the relative effects of the probability of employment and unconditional annual earnings in the (even) longer run, i.e. up to $\bar{t}$+8 and $\bar{t}$+9, which can be estimated only on workers hit by CVD shocks occurred respectively in 2003-2004 and 2003 (corresponding ATTs are shown in Appendix Table A4). To enhance comparability across results obtained from these restricted subsamples, in the first two columns we repeat results reported in Table 3, obtained on the full treatment sample covering also the CVD shocks experienced in 2005.

Exploiting the two subsamples for which long-run outcomes can be observed, columns 3-4 illustrate results extended up to $\bar{t}$+8, while columns 5-6 reports results extended up to $\bar{t}$+9. Notice that only in the latter case a one-to-one relationship between distance from the shock and calendar year can be established: in more detail, $\bar{t}$+8 corresponds to the calendar year 2011 and $\bar{t}$+9 to the calendar year 2012. Overall, results highlight the long-term effect persistence for both outcomes.

It is interesting to note how the effects in $\bar{t}$+9 deviate somehow from those registered in previous years/periods: the relative reduction in employment probability jumps to -22% (from a value of -14% in 2011). Similarly, annual earnings suddenly drop, in relative size effect terms, from -22% to -29%. While we cannot entirely rule out the chance of effect dynamics specific to the ninth year past the shock, the 2012 evidence nicely fits the important legislated changes outlined in section 2, namely the Monti-Fornero reform of labour law (and partly the September 2011 Berlusconi reform) which significantly reduced firing restrictions in medium and large firms.

Table 6: Long(er) term unconditional employment-related outcomes: Relative Effect

Time	*CVD shock experienced in 2003/2004/2005*		*CVD shock experienced in 2003/2004*		*CVD shock experienced in 2003*	
	Probability of employment	**Annual income from employment**	**Probability of employment**	**Annual income from employment**	**Probability of employment**	**Annual income from employment**
$\bar{t}$	-	-3.17***	-	-4.34***	-	-5.94***
N. treated	-	1594	-	1042	-	503
$\bar{t}$+1	-3.35***	-12.8***	-4.41***	-13,43***	-4.59**	-14.88***
N. treated	1596	1956	1043	1043	503	503
$\bar{t}$+2	-10.41***	-14.11***	-10.95***	-14.07***	-9.86***	-15.93***
N. treated	1596	1956	1043	1043	503	503
$\bar{t}$+3	-12.59***	-13.9***	-13.10***	-14.18***	-15.25***	-14.16***
N. treated	1596	1956	1043	1043	503	503
$\bar{t}$+4	-11.38***	-14.4***	-12.18***	-14.60***	-14.04***	-16.87***
N. treated	1596	1956	1043	1043	503	503
$\bar{t}$+5	-13.17***	-16.4***	-13.15***	-16.56***	-11.29***	-18.38***
N. treated	1596	1956	1043	1043	503	503
$\bar{t}$+6	-13.90***	-14.5***	-12.67***	-14.81***	-12.06***	-17.76***
N. treated	1596	1956	1043	1043	503	503
$\bar{t}$+7	-13.60***	-12.9***	-13.35***	-15.08***	-12.76***	-18.80***
N. treated	1596	1956	1043	1043	503	503
$\bar{t}$+8	-	-	-12.54***	-16.52***	-13.95***	-21.82***
N. treated	-	-	1043	1043	503	503
$\bar{t}$+9	-	-	-	-	-21.86***	-28.56***
N. treated	-	-	-	-	503	503

Source: WHIP&Health
Notes: Relative effects are reported (corresponding ATT are reported in Table A4); by sample selection all individuals are employed in $\bar{t}$, thus the probability of employment in that year is 1 by construction.

4.3 Heterogeneity: age, CVD shock type, firm size

In this section, we explore effect heterogeneity along three dimensions: workers' age, type of CVD shock, and firm dimension. A priori, age might be expected to affect findings, both in terms of size and time trend. Older individuals might be less attached to the labour market in the light of their higher chances of exploiting available routes of permanent exit from the labour market, such as early-retirement or disability pensions. Besides, in a model of health capital formation, investments in health-specific human capital fostering labour recovery may be more attractive for by that younger individuals, given expected earnings-related returns over a longer time horizon (Charles, 2003). Table 7 reports results for employment and unconditional earnings, distinguishing workers aged 52 (i.e. the median sample age at the time of the shock) or younger, from workers older than 52. Consistently with previous studies conducted in other countries (see e.g. Jones et al., 2019) older workers' shock-induced loss, both in employment and in unconditional earnings, is substantially higher than younger workers'. In the short term, the relative size effects for older workers, in both outcomes, is at least twice the one observed for younger workers. A similar age gradient (i.e. a relative effect for older workers more than doubling that for younger workers) is visible in Table 8 for conditional outcomes in the short term. In the longer run, apparent gradients for conditional outcomes are to be interpreted with caution, as reflecting also the higher chances of previous employment exit suffered by older workers.

Next, in Table 9, we consider the specific type of CVD shock experienced, distinguishing myocardial infarction from stroke, which often turns out as a more severe condition, possibly leading to stronger impairment to work[31]. Indeed, we find stroke to bring about a much stronger reduction in the probability of employment than myocardial infarction, systematically over time: for instance, the relative effect in $\bar{t}+3$ amounts to -21 per cent for the former and -8 per cent for the latter. For both CVD conditions, the shock-induced loss of employment is persistent over time. Similar findings are obtained for other labor market outcomes in the short term; again, longer terms gradients on outcomes measured conditional on being employed will also reflect the higher chances of previous exit suffered in case of stroke, and for this reason are to be interpreted with caution. Bearing this limitation in mind, results - presented in Table 10 - for the probability of working full- (versus part-) time suggest that the small but significant result previously obtained on the full sample (in Table 5) for $\bar{t}+4$ and $\bar{t}+5$ is mostly attributable to individuals hit by stroke.

The third type of heterogeneity we investigate, novel in this literature to our knowledge, concerns firm size just before the shock onset. Firm size is of particular policy interest in the light of the differing extent of employment protection granted in the country, and related hiring rates (to give a figure, based on Contini (2009): 50 percent in small firms, declining to a value of 25

[31] Shock severity has an a priori undefined effect on preference for leisure/work. In fact, a more severe shock may, on the one hand, increase the value of leisure as a consequence of an expected lowered life expectancy; on the other hand, it may reduce its value by limiting the possibility of performing or enjoying leisure activities.

percent for firms with more than 200 employees). Also, because organisational practices fostering disabled workers' inclusion, for example workplace training, disability accommodation, reallocation to different tasks or branches, increase with firm size (see e.g. Bassanini et al., 2007). Table 11 shows ATTs for employment probability and unconditional earnings, distinguishing firms with a) up to 15 employees; b) from 16 to 250 employees; c) with more than 250 employees[32].The shock-induced reduction in employment is particularly evident in small firms, with a relative effect increasing over time from -9.7 per cent in $\bar{t}+1$ up to -23 per cent in $\bar{t}+7$. Indeed, firms with up to 15 employees are those not subject to the Worker's Statute[33], thus bearing a cost, for firing workers under open-ended contracts, which is much lower than for larger firms[34]. At the same time, within-firm reallocations are very difficult to implement in small firms.

The reduction in the employment probability following a CVD shock is systematically smaller in medium-big firms; even smaller in firms with 250+ employees, where actually no significant reduction takes place, before two years past the shock. A qualitatively similar gradient emerges when looking at annual earnings (unconditional, see Table 11; conditional, see Table 12). The ATTs for the conditional probability of being employed full- (versus part-) time is never significant in small firms. Results for hourly wage by firm size, reported in Table 13, display a clear negative association between firm dimension and the size of differential wage adjustment, suggesting that most of the effect reported in Table 5 for the full sample occurs in smaller firms, featuring larger scope for firm-level bargaining.

Finally, we report in Appendix (Tables A5 and A6) results obtained from heterogeneity analyses for labour activity, by the type of contract (open-ended versus fixed-term) and hours worked (part- versus full-time) just before the shock onset. In both cases, the sample numbers for one subgroup (fixed-term contracts and part-time contracts respectively) is definitely low, given the limited sample prevalence of such types, with a consequent possible loss of significance. Bearing this limitation in mind, results visible in Table A5 are consistent with the lower protection granted to blue collar workers hired under fixed term contracts, visible since the short run. The fact that, in Table A6, no significant reduction in labour activity is ever experienced by part-timers, as opposed to full-timers, appears suggestive of a role for reduced working times in facilitating labour inclusion.

[32]The sample distribution of firm size emerging from Table 11 (and shown in Table 2) is very different from that reported in footnote 13, which provides evidence of a very high percentage of micro and small firms. This is because WHIP&Health offers a sample representative of workers, rather than firms, thus over representing larger firms.

[33]See section 2, footnote 12.

[34]The effects of a differential workers' protection on the probability to exit employment is confirmed when disaggregating the sample according to the worker' contract type. Table A5 illustrates that workers with a fixed-term contract have a much higher probability to exit employment in the short run (i.e. until t+3) than workers with a permanent job. The effect for fixed-term jobs is so striking to emerge even in a sample of constituted of about 55 observations.

Table 7: Unconditional employment-related outcomes by age group: ATT and Relative Effect

Time	*Age* $\leq$ *Median (52)* Probability of employment		*Age* $\leq$ *Median (52)* Annual income from employment		*Age* $>$ *Median (52)* Probability of employment		*Age* $>$ *Median (52)* Annual income from employment	
	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
$\bar{t}$	-	-	-392.1	-1.75	-	-	-1082.5***	-5.11
Rob. SE.	-	-	(261.0)		-	-	(304.2)	
N. treated	-	-	870		-	-	724	
$\bar{t}$+1	-0.015*	-1.62	-1965.3***	-8.98	-0.047***	-5.73	60974	-18.76
Rob. SE.	(0.009)		(347.9)		(0.015)		(425.2)	
N. treated	871		871		725		725	
$\bar{t}$+2	-0.058***	-6.39	-2036.0***	-9.46	-0.119***	-17.10	-3324.6	-22.91
Rob. SE.	(0.012)		(378.1)		(0.018)		(450.2)	
N. treated	871		871		725		725	
$\bar{t}$+3	-0.072***	-8.11	-2121.8***	-9.98	-0.119***	-20.78	-2667.1***	-23.02
Rob. SE.	(0.013)		(396.9)		(0.018)		(437.3)	
N. treated	871		871		725		725	
$\bar{t}$+4	-0.072***	-8.44	-2296.9***	-11.22	-0.080***	-17.54	-1820.3***	-24.08
Rob. SE.	(0.014)		(426.0)		(0.018)		(361.3)	
N. treated	871		871		725		725	
$\bar{t}$+5	-0.079***	-9.68	-2637.1***	-13.65	-0.081***	-22.34	-941.9**	-27.08
Rob. SE.	(0.015)		(437.3)		(0.016)		(333.8)	
N. treated	871		871		725		725	
$\bar{t}$+6	-0.089***	-11.52	-2516.2***	-13.87	-0.063***	-21.84	-941.9**	-18.63
Rob. SE.	(0.016)		(444.9)		(0.015)		(333.8)	
N. treated	871		871		725		725	
$\bar{t}$+7	-0.090***	-12.37	-2465.4***	-14.73	-0.046***	-19.72	-786.6**	-20.73
Rob. SE.	(0.016)		(441.4)		(0.014)		(287.9)	
N. treated	871		871		725		725	

Source: WHIP&Health
Notes: marginal effects are reported for the Probability of employment (ATTs); by sample selection all individuals are employed in $\bar{t}$, thus the Probability of employment in that year is 1 by construction.

Table 8: Conditional employment-related outcomes by age group: ATT and Relative Effect

	Age ≤ Median (52)						*Age > Median (52)*					
	Probability to be employed full-time		**Annual income from employment**		**Hourly wage**		**Probability to be employed full-time**		**Annual income from employment**		**Hourly wage**	
Time	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$		
$\bar{t}$	0.002	0.21	-392.1	-1.75	-0.246**	-2.07	0.008	0.85	-1082.5***	-5.11	-0.383**	-3.21
Rob. SE.	(0.006)		(261.0)		(0.116)		(0.008)		(304.2)		(0.163)	
N. treated	852		870		870		724		724		724	
$\bar{t}$+1	-0.009	-0.94	-1553.29**	-6.65	-0.453***	-3.70	-0.003	-0.32	-3074.3***	-14.41	-0.775***	-6.38
Rob. SE.	(0.007)		(314.1)		(0.141)		(0.010)		(408.5)		(0.197)	
N. treated	795		795		795		554		554		554	
$\bar{t}$+2	-0.009	-0.94	-837.6**	-3.54	-0.345**	-2.78	-0.023*	-2.48	-1708.6***	-8.07	-0.313	-2.57
Rob. SE.	(0.007)		(334.5)		(0.134)		(0.014)		(450.3)		(0.206)	
N. treated	734		734		734		410		410		410	
$\bar{t}$+3	-0.013	-1.36	-673.7**	-2.79	-0.202	-1.60	-0.004	-0.44	-659.5	-3.18	-0.268	-2.19
Rob. SE.	(0.008)		(339.7)		(0.143)		(0.016)		(480.9)		(0.252)	
N. treated	701		701		701		319		319		319	
$\bar{t}$+4	-0.014	-1.47	-769.6**	-3.18	-0.191	-1.50	-0.030	–3.40	-1375.6**	-6.81	-0.527**	-4.35
Rob. SE.	(0.009)		(375.3)		(0.142)		(0.021)		(596.0)		(0.236)	
N. treated	667		667		667		265		265		265	
$\bar{t}$+5	-0.017*	-1.80	-1110.2**	-4.61	-0.280*	-2.19	-0.018	-2.12	-975.2	-5.12	-0.336	-2.83
Rob. SE.	(0.009)		(391.6)		(0.157)		(0.026)		(713.3)		(0.329)	
N. treated	627		627		627		199		199		199	
$\bar{t}$+6	-0.014	-1.49	-882.1**	-3.71	-0.290*	-2.26	0.013	1.60	295.7	1.63	-0.703**	-6.02
Rob. SE.	(0.010)		(403.0)		(0.161)		(0.029)		(783.8)		(0.310)	
N. treated	586		586		586		199		199		199	
$\bar{t}$+7	-0.008	-0.86	-1060.9**	-4.52	-0.305*	-2.39	0.004	0.51	72.11	0.42	-0.473	-4.15
Rob. SE.	(0.011)		(413.2)		(0.175)		(0.034)		(930.6)		(0.363)	
N. treated	544		544		544		131		131		131	

Source: WHIP&Health
Notes: marginal effects are reported for the Probability to be employed full-time.

Table 9: Unconditional employment-related outcomes by type of CVD shock: ATT and Relative Effect

	Ischemic heart diseases (ICD-9: 410-414)				*Cerebrovascular diseases (ICD-9: 430-434/436-437)*			
	Probability of employment		**Annual income from employment**		**Probability of employment**		**Annual income from employment**	
Time	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
t	-	-	-658.3**	-3.01	-	-	-817.0**	-0.07
Rob. SE	-	-	(232.1)		-	-	(394.2)	
N. treated	-	-	1225		-	-	369	
t+1	-0.014	-1.62	-2032.8***	-10.21	-0.087***	-5.73	-4269.4***	-21.45
Rob. SE	(0.009)		(312.5)		(0.020)		(569.9)	
N. treated	1227		1.227		369		369	
t+2	-0.062***	-6.39	-2008.7***	-10.97	-0.164***	-17.10	-4578.2***	-24.99
Rob. SE	(0.012)		(342.4)		(0.024)		(614.9)	
N. treated	1227		1.227		369		369	
t+3	-0.065***	-8.11	-1632.9***	-9.70	-0.189***	-20.78	-4740.2***	-28.14
Rob. SE	(0.013)		(353.3)		(0.025)		(612.8)	
N. treated	1227		1.227		369		369	
t+4	-0.056***	-8.44	-1642.1***	-10.79	-0.146***	-17.54	-4084.7***	-26.84
Rob. SE	(0.013)		(361.9)		(0.024)		(617.6)	
N. treated	1227		1.227		369		369	
t+5	-0.060***	-9.68	-1798.9***	-13.26	-0.151***	-22.34	-3709.1***	-27.35
Rob. SE	(0.013)		(354.2)		(0.023)		(605.2)	
N. treated	1227		1.227		369		369	
t+6	-0.058***	-11.52	-1438.8***	-11.83	-0.143***	-21.84	-2877.8***	-23.66
Rob. SE	(0.013)		(348.7)		(0.023)		(599.0)	
N. treated	1227		1.227		369		369	
t+7	-0.052***	-12.37	-1417.5***	-13.10	-0.124***	-19.72	-2523.1***	-23.32
Rob. SE	(0.013)		(332.6)		(0.022)		(578.2)	
N. treated	1227		1.227		369		369	

Source: WHIP&Health
Notes: marginal effects are reported for the Probability of employment (ATTs); by sample selection all individuals are employed in $\bar{t}$, thus the Probability of employment in that year is 1 by construction.

Table 10: Conditional employment-related outcomes by type of CVD shock: ATT and Relative Effect

	Ischemic heart diseases (ICD-9: 410-414)						*Cerebrovascular diseases (ICD-9: 430-434/436-437)*					
	Probability to be employed full-time		**Annual income from employment**		**Hourly wage**		**Probability to be employed full-time**		**Annual income from employment**		**Hourly wage**	
Time	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$		
$\bar{t}$	0.008	0.84	-658.3**	-3.01	-0.266**	-2.23	-0.011	-1.15	-817.0**	-0.07	-0.397**	-3.33
Rob. SE.	(0.005)		(232.1)		(0.115)		(0.011)		(394.2)		(0.179)	
N. treated	1225		1225		1225		369		369		369	
$\bar{t}+1$	-0.003	-0.32	-1974.9***	-8.78	-0.655***	-5.37	-0.022	-2.32	-2784.9***	-12.38	-0.197	-1.62
Rob. SE.	(0.006)		(287.7)		(0.129)		(0.136)		(535.9)		(0.276)	
N. treated	1060		1060		1060		289		289		289	
$\bar{t}+2$	-0.012	-1.27	-1003.9***	-4.42	-0.286**	-2.32	-0.022	-2.33	-1464.2**	-6.45	-0.367	-2.92
Rob. SE.	(0.008)		(307.9)		(0.129)		(0.015)		(575.9)		(0.250)	
N. treated	905		905		905		239		239		239	
$\bar{t}+3$	-0.008	-0.85	-519.6	-2.26	-0.205	-1.64	-0.018	-1.92	-992.7*	-4.32	-0.216	-1.73
Rob. SE.	(0.009)		(319.0)		(0.145)		(0.017)		(584.6)		(0.244)	
N. treated	813		813		813		207		207		207	
$\bar{t}+4$	-0.008	-0.86	-818.2**	-3.56	-0.267*	-2.13	-0.054**	-5.81	-1085.9	-4.73	-0.317	-2.53
Rob. SE.	(0.009)		(365.0)		(0.139)		(0.022)		(664.5)		(0.258)	
N. treated	737		737		737		195		195		195	
$\bar{t}+5$	-0.010	-1.09	-971.6**	-4.28	-0.311*	-2.48	-0.046*	-5.00	-1031.4	-4.54	-0.166	-1.32
Rob. SE.	(0.011)		(389.1)		(0.162)		(0.024)		(729.6)		(0.312)	
N. treated	652		652		652		174		174		174	
$\bar{t}+6$	0.001	0.11	-581.3	-2.59	-0.385**	-3.07	-0.040	-4.40	-401.6	-1.79	-0.231	-1.84
Rob. SE.	(0.011)		(408.9)		(0.160)		(0.027)		(760.3)		(0.321)	
N. treated	587		587		587		162		162		162	
$\bar{t}+7$	-0.002	-0.22	-674.3	-3.05	-0.280	-2.25	-0.017	-1.89	-1051.4	-4.75	-0.474	-3.80
Rob. SE.	(0.013)		(435.1)		(0.178)		(0.026)		(807.2)		(0.331)	
N. treated	524		524		524		151		151		151	

Source: WHIP&Health
Notes: marginal effects are reported for the Probability to be employed full-time (ATTs).

Table 11: Unconditional employment-related outcomes by firm dimension: ATT and Relative Effect

	Probability of employment						**Annual income from employment**					
	0-15 employees		*16-250 employees*		*250+ employees*		*0-15 employees*		*16-250 employees*		*250+ employees*	
	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
$\bar{t}$	-	-	-	-	-	-	-813.9**	-4.57	-390.6	-1.79	-1008.7**	-3.84
Rob. SE.	-	-	-	-	-	-	(308.3)		(301.7)		(409.2)	
N. treated	-	-	-	-	-	-	475		687		432	
$\bar{t}$+1	-0.084***	-9.71	-0.021*	-2.37	0.018	2.04	-3607.5***	-22.58	-2099.9***	-10.39	-2002.4***	-8.44
Rob. SE.	(0.018)		(0.012)		(0.014)		(423.4)		(406.8)		(592.1)	
N. treated	476		688		432		476		688		432	
$\bar{t}$+2	-0.133***	-16.84	-0.083***	-9.96	-0.034*	-4.28	-3556.1***	-24.26	-2354.6***	-12.53	-1766.8**	-8.18
Rob. SE.	(0.021)		(0.015)		(0.019)		(444.8)		(442.8)		(662.8)	
N. treated	476		688		432		476		688		432	
$\bar{t}$+3	-0.136***	-18.66	-0.093***	-12.27	-0.049**	-6.69	-2947.6***	-21.65	-2387.4***	-13.74	-1624.8**	-8,31
Rob. SE.	(0.021)		(0.017)		(0.021)		(444.3)		(447.8)		(701.9)	
N. treated	476		688		432		476		688		432	
$\bar{t}$+4	-0.107***	-16.21	-0.077***	-11.06	-0.040*	-6.26	-2708.4***	-21.82	-2486.9***	-15.66	-1154.0	-6.69
Rob. SE.	(0.021)		(0.017)		(0.021)		(442.9)		(459.4)		(701.2)	
N. treated	476		688		432		476		688		432	
$\bar{t}$+5	-0.119***	-19.82	-0.078***	-12.39	-0.045**	-7.91	-2801.6***	-25.16	-2414.9***	-17.01	-1316.2*	-8.65
Rob. SE.	(0.021)		(0.017)		(0.021)		(442.7)		(456.8)		(687.2)	
N. treated	476		688		432		476		688		432	
$\bar{t}$+6	-0.122***	-22.37	-0.075***	-13.00	-0.033	-6.46	-2443.8***	-24.46	-1584.4***	-13.37	-1265.8*	-9.35
Rob. SE.	(0.021)		(0.017)		(0.020)		(439.7)		(454.9)		(668.9)	
N. treated	476		688		432		476		688		432	
$\bar{t}$+7	-0.114***	-22.89	-0.053***	-10.20	-0.044**	-9.61	-2102.1***	-23.81	-1418.9***	-12.31	-1550.4*	-13.04
Rob. SE.	(0.020)		(0.017)		(0.020)		(418.7)		(435.0)		(635.6)	
N. treated	476		688		432		476		688		432	

Source: WHIP&Health

Notes: marginal effects are reported for the Probability of employment (ATTs); by sample selection all individuals are employed in $\bar{t}$, thus the Probability of employment in that year is 1 by construction.

Table 12: Conditional employment-related outcomes by firm dimension: ATT and Relative Effect

	Probability to be employed full-time						**Annual income from employment**					
	0-15 employees		*16-250 employees*		*250+ employees*		*0-15 employees*		*16-250 employees*		*250+ employees*	
	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
t	0.007	0.75	0.0002	0.02	0.009	0.94	-813.9**	-4.57	-390.6	-1.79	-1008.7**	-3.84
Rob. SE.	(0.010)		(0.007)		(0.006)		(308.3)		(301.7)		(409.2)	
N. treated	475		687		432		475		687		432	
t+1	-0.017	-1.83	-0.010	-1.04	0.012*	1.27	-2411.7***	-13.08	-1879.4***	-8.36	-2328.4***	-8.64
Rob. SE.	(0.013)		(0.008)		(0.007)		(392.9)		(372.3)		(526.3)	
N. treated	369		599		381		369		599		381	
t+2	-0.025	-2.70	-0.020**	-2.08	0.009	0.95	-1733.2***	-9.32	-889.7**	-3.92	-917.6*	-3.37
Rob. SE.	(0.016)		(0.010)		(0.008)		(438.1)		(390.1)		(539.7)	
N. treated	312		508		324		312		508		324	
t+3	-0.001	-0.11	-0.025**	-2.62	0.011	1.17	-859.6**	-4.59	-895.7**	-3.88	-278.9	-1.02
Rob. SE.	(0.016)		(0.012)		(0.010)		(417.1)		(397.6)		(609.8)	
N. treated	282		456		282		282		456		282	
t+4	-0.015	-1.66	-0.029**	-3.06	0.001	0.11	-1390.9***	-7.38	-1418.6***	-6.14	252.5	0.92
Rob. SE.	(0.018)		(0.013)		(0.014)		(450.5)		(459.1)		(695.8)	
N. treated	263		420		249		263		420		249	
t+5	-0.013	-1.47	-0.027*	-2.87	0.0005	0.05	-1324.5**	-7.11	-1131.1**	-4.96	-481.9	-1.76
Rob. SE.	(0.020)		(0.014)		(0.015)		(484.7)		(493.2)		(737.7)	
N. treated	232		370		224		232		370		224	
t+6	-0.003	-0.34	-0.025	-2.70	0.011	1.20	-765.8	-4.16	-399.3	-1.77	-643.7	-2.37
Rob. SE.	(0.022)		(0.016)		(0.015)		(555.2)		(512.8)		(789.6)	
N. treated	204		346		199		204		346		199	
t+7	-0.004	-0.47	-0.013	-1.42	0.006	0.65	-938.5	-5.24	-826.6	-3.69	-658.8	-2.46
Rob. SE.	(0.024)		(0.016)		(0.017)		(598.9)		(528.9)		(822.8)	
N. treated	185		321		169		185		321		169	

Source: WHIP&Health
Notes: marginal effects are reported for the Probability to be employed full-time (ATTs).

Table 13: Conditional employment-related outcomes by firm dimension: ATT and Relative Effect

	Hourly Wage					
	0-15 employees		*16-250 employees*		*250+ employees*	
	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
t	-0.291*	-2.81	-0.256*	-2.17	-0.320	-2.31
Rob. SE.	(0.148)		(0.141)		(0.213)	
N. treated	475		687		432	
t+1	-0.699***	-6.57	-0.451**	-3.76	-0.631**	-4.45
Rob. SE.	(0.192)		(0.164)		(0.247)	
N. treated	369		599		381	
t+2	-0.731***	-6.80	-0.104	-0.86	-0.259	-1.81
Rob. SE.	(0.181)		(0.156)		(0.237)	
N. treated	312		508		324	
t+3	-0.343	-3.13	-0.242	-1.96	-0.164	-1.13
Rob. SE.	(0.208)		(0.169)		(0.273)	
N. treated	282		456		282	
t+4	-0.463**	-4.23	-0.354**	-2.85	-0.115	-0.79
Rob. SE.	(0.175)		(0.171)		(0.260)	
N. treated	263		420		249	
t+5	-0.292	-2.66	-0.474**	-3.81	-0.092	-0.63
Rob. SE.	(0.238)		(0.193)		(0.310)	
N. treated	232		370		224	
t+6	-0.768***	-6.98	-0.394**	-3.16	-0.101	-0.69
Rob. SE.	(0.200)		(0.195)		(0.318)	
N. treated	204		346		199	
t+7	-0.635***	-5.80	-0.474**	-3.80	0.178	1.24
Rob. SE.	(0.197)		(0.205)		(0.395)	
N. treated	185		321		169	

Source: WHIP&Health

5 Discussion and Conclusions

The findings reported in the previous sections offer a novel representation of the long-term consequences of acute CVD shocks in a highly regulated labour market, featuring strong downward wage rigidity. In the Italian case, the onset of acute health conditions suffered by blue-collar workers results in frictions that find little scope for adjustment along the hours or wage margins. The bulk of response emerges instead along the extensive margin, in terms of a sizeable and persistent employment loss. It is important to stress how employment exit happens in a setting where low hiring rates hamper later return to work. Indeed, among those who leave employment within the first year past the shock, we observe only the 16 per cent to resume employment within the following three years. Relatedly, transitions to possibly less demanding jobs do not generally offer a viable route of adjustment in the medium to long-term, suggesting that employment exit might likely become an absorbing state. Indeed, our long-term analysis has clarified that loss of employment persists for at least nine years past the health shock, and presumably thereafter.

Should we be concerned about the consequences? On the one hand, loss of employment entails a loss of market earnings. Arguably, in Italy, a relatively generous social insurance system compensates such earnings loss: substantial renewable or permanent disability-related transfers are granted to workers satisfying mild contributory conditions. Yet, in the face of such protection, there are further losses entailed. Besides the fiscal cost of the public transfer programmes used to replace market earnings, losing employment means losing social inclusion opportunities. Several studies in psychology have related work activity to wellbeing through self-esteem, motivation, sense of purpose, and social interactions (e.g. Spelten et al., 2002; Hackett et al., 2012; Vestling et al., 2013), while clinical studies use return to work as indicative of recovery after a major health shock (Daniel et al., 2009; Trygged et al., 2011).

In practice, remaining at work might actually be problematic for individuals experiencing severe health deteriorations, particularly if they cannot reduce working times, not even when prepared to accept a remuneration adjustment reflecting lower productivity. In this respect, a first policy recommendation, viable even in the short-term, would be providing public incentives for firms to agree on voluntary (on the employee side) part-time work, as a way to reconcile working activity with health related limitations (Devicienti et al., 2015). Currently, in the country, firms rather avoid offering part-time options, because entailing lower productivity (e.g. in relation to the fixed cost of hiring each worker) and ultimately higher costs, in a setting where there is no chance of compensating them through wage adjustments (Devicienti et al., 2015). Acting on the wage mobility side appears a less viable option, at least in the short term, given the extensive role played by collective bargaining in the country.

The evidence we offer is subject to several potential limitations. To begin with, it concerns only a segment of the labour force, i.e. blue-collar workers, although the one presumably more exposed to the risk of experiencing work-ability limitations as generally employed in more physically demanding tasks. Second, it only concerns individuals hit by acute CVD conditions, while also several other types of health deteriorations might affect workers. Moreover, while using administrative data presents major advantages, it also entails drawbacks. The limited coverage of relevant topic areas has hampered the scope for further heterogeneity analyses, and limited the range of observed confounders we could exploit for identification. Last, but not least, lack of information on later mortality implies exposure to bias possibly stemming from selective mortality.

Bearing these limitations in mind, the novel evidence produced, for the labour effects of health shocks over the longer term in a highly regulated institutional setting, will hopefully contribute to inform policy design on the timely and challenging issue of disabled workers' social inclusion.

References

[1] Au, D. W. H. Crossley, T. F. Schellhorn, M. (2005). The effect of health changes and long-term health on the work activity of older Canadians Health Economics. Quantitative Studies in Economics and Population Research Reports 397, McMaster University.

[2] Arpaia, A. and Mourre, G. (2012). Institutions and performance in European labor markets: taking a fresh look at the evidence. Journal of Economic Surveys 26: 1? 41.

[3] Baker, M., Stabile, M., Deri, C. (2004). What Do Self-Reported, Objective, Measures of Health Measure?, Journal of Human Resources, 39(4): 1067-1093.

[4] Bassanini A, Booth A, Brunello G, De Paola M, Leuven E (2007). Workplace training in Europe. In: Brunello G, Garibaldi P, Wasmer E (eds) Education and training in Europe. Oxford University Press, Oxford, pp 8?13

[5] Becker G.S. (1964). Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education. (3rd Edition), NBER Books, National Bureau of Economic Research, Inc, number beck94-1.

[6] Benitez-Silva, H., Buchinsky, M., Man Chan, H., Cheidvasser, S. , Rust, J. (2004). How large is the bias in self reported disability?, Journal of Applied Econometrics, 19(4): 649-670.

[7] Berton F., Richiardi, M., Sacchi S. (2012). The Political Economy of Work Security And Flexibility: Italy In Comparative Perspective. The Policy Press, University of Bristol.

[8] Blanchflower, D.G., Oswald, A.J. (1998). What makes an entrepreneur? Journal of Labor Economics 16 (1), 26?60.

[9] Bradley, C.J., D. Neumark, H.L., Barkowski, S. (2013). Does employer provided health insurance contraint labour supply adjustments to health shocks? New evidence on women diagnosed with Breast cancer. Journal of Health Economics, 32(5): 833-849.

[10] Braunwald, E., Mann, D. L., Zipes, D. P., Libby, P., Bonow, R. O. (2015). Braunwald's heart disease: a textbook of cardiovascular medicine. Philadelphia, PA: Elsevier/Saunders.

[11] Cai, L. (2010). The relationship between health and labour force participation: Evidence from a panel data simultaneous equation model. Labour Economics, 17(1): 77-90.

[12] Cai, L., Mavromaras, K. Oguzoglu, U. (2014). The effects of Health and Health Shocks on Hours Worked. Health Economics, 23(5): 516-528.

[13] Charles, K. (2003). The longitudinal structure of earnings losses among work-limited disabled workers. Journal of Human Resources. 38 (3), 618-646.

[14] Coile, C. (2004). Health Shocks and Couples' Labour Supply Decisions. NBER Working Paper No. 10810.

[15] Contini, B. (2019), Dai "lavori usa e getta" al Jobs Act. Aracne editrice, Roma.

[16] Currie, J., Madrian, B.C. (1999). Health, Health Insurance and the Labor Market, in Handbook of Labor Economics vol. 3C, ed. Orley Ashenfelter and David Card, 3309-3416. New York: Elsevier Science.

[17] Daniel, K., Wolfe, C.D., Busch, M.A., McKevitt, C., (2009) What are the social consequences of stroke for working-aged adults? A systematic review Stroke 6, 431-40.

[18] Dano, A. M. (2005). Road injuries and long-run effects on income and employment. Health Economics, 14(9): 955-970.

[19] Devicienti, F., Maida, A., P. Sestito (2007). Downward Wage Rigidity in Italy: Micro-Based Measures and Implications. The Economic Journal, 117 (November), F530?F552.

[20] Devicienti, F., Grinza, E., Vannoni, D. (2015) The Impact of Part-Time Work on Firm Total Factor Productivity: Evidence from Italy, Working papers 032, Department of Economics and Statistics, University of Torino. Turin.

[21] Dobkin C, Finkelstein A, Kluender R, Notowidigdo M J (2018). The economic consequences of hospital admissions. American Economic Review, volume 108, issue 2, p. 308 - 52

[22] European Commission (1999). Compendium - Good practice in employment of people with disabilities. Office for Official Pubblications of the European Communities: Luxemburg.

[23] European Commission (2009). Employment in Europe. Office for Official Pubblications of the European Communities: Luxemburg.

[24] Eurostat (2019), Employment and unemployment; LFS ad-hoc modules: 2002, Employment of disable persons; series: Employment by type of disability, sex, age and full-time/part-time employment.

[25] Flores M, Fernańdez M, Pena-Boquete Y. (2019). The impact of health on wages: Evidence from Europe before and during the Great Recession. Oxford Economic Papers, 1-28 (DOI: 10.1093/oep/gpz033) (available here)

[26] García-Gòmez P., Lopez Nicolaś, A. (2006). Health shocks, employment and income in the Spanish labour market. Health Economics, 15(9): 997-1009.

[27] García-Gòmez P., Jones, A.M., Rice, N. (2010). Health effects on labour market exits and entries. Labour Economics, 17(1): 62-76.

[28] García-Gòmez, P. (2011). Institutions, health shocks and labour market outcomes across Europe. Journal of Health Economics, 30(1): 200-213.

[29] Garciá-Gòmez, P., Van Kippersluis, H., O'Donnell, O., van Doorslaer, E. (2013). Long-term and spillover effects of health shocks on employment and income. Journal of Human Resources. 48 (4), 873-909.

[30] Grossman M. (1972). On the concept of health capital and the demand for health. Journal of Political Economy, 80(1): 223-255.

[31] Gupta ND, Kleinjans KJ, Larsen M. (2015). The effect of a severe health shock on work behavior: evidencefrom different health care regimes. Soc Sci Med 2015; 136:44?51.

[32] Haan, P., Myck, M. (2009). Dynamics of health and labour market risks. Journal of Health Economics, 28(6): 1116-1125.

[33] Hackett, M., Glozier, N., Jan, S., Lindley, R. (2012). Returning to Paid Employment after Stroke: The Psychosocial Outcomes in Stroke (POISE) Cohort Study. PloS ONE 7(7), e41795.

[34] Hainmueller, J. (2012). Entropy balancing for causal effects: a multivariate reweighting method to produce balanced samples in observational studies. Political Analysis, 20(1): 25-46.

[35] Hainmueller, J., Xu, Y. (2013). ebalance: A Stata package for entropy balancing. Journal of Statistical Software, 54, Issue 7: 1-18.

[36] Halla, M., Zweimuller, M. (2013). The effect of health on earnings: Quasi-experimental evidence from commuting accidents. Labour Economics, 24: 23-38.

[37] Heinesen, E., Kolodziejczyk, C. (2013). Effects of breast and colorectal cancer on labour market outcomes-average effects and educational gradients. Journal of Health Economics, 32(6): 1028-1042.

[38] Ho D., Imai K., King G., Stuart E. A., (2007). Matching as Nonparametric Preprocess- ing for Reducing Model Dependence in Parametric Causal Inference. Political Analysis, 15: 99-236.

[39] Holmlund B. (2014). What do labor market institutions do?.Labour Economics, 30 (2014), pp. 62-69

[40] Iacus, S. M., King, G., Porro, G. (2011). Multivariate Matching Methods That Are Monotonic Imbalance Bounding. Journal of the American Statistical Association, 106: 345-361.

[41] ISTAT (2017), Annuario Statistico Italiano, chapter 14, Rome.

[42] Jačkle R., Himmler O. (2010). Health and Wages: Panel Data Estimates Considering Selection and Endogeneity. Journal of Human Resources, University of Wisconsin Press, vol. 45(2).

[43] Jones A.M., Rice N., Zantomio F. (2019). Acute health shocks and labour market outcomes: evidence from the post crash era. Economics and Human Biology, forthcoming (online version available at https://doi.org/10.1016/j.ehb.2019.100811).

[44] Lindeboom, M., Llena-Nozal, A., van der Klaauw, B. (2016) Health shocks, disability and work, Labour Economics 43, 185-200.

[45] Lundborg,P., Nilsson, M., Vikstroṁ, J. (2015). Heterogeneity in the impact of health shocks on labour outcomes: evidence from Swedish workers. Oxford Economic Papers, 67(3): 715-739.

[46] Maczulskij, T., Bočkerman, P. (2019) Harsh times: do stressors lead to labor market losses? The Euroepan Journal of Health Economics, 20:357?373.

[47] Ministry of Health, 2018. Programma Nazionale Esiti - PNE 2018, available at https://pne.agenas.it/index.php

[48] Ministry of Health, 2010. Relazione sullo Stato Sanitario del Paese: 2009-2010. Chapter 2.1. Rome.

[49] Moran, J., Farley-Short, P., Hollenbeack, C.S. (2011). Long term employment effects of surviving cancer. Journal of Health Economics, 30(3): 505-514.

[50] European Commission (2009). Employment in Europe 2009. Directorate-General for Employment, Social Affairs and Equal Opportunities.

[51] OECD, (1994). The Employment Outlook, chapter 5.

[52] OECD, (2014). Older workers scoreboard. Accessed on 16/07/2015 from http://www.oecd.org.

[53] OECD, 2016, Older Workers Scoreboard, accessed on 05/09/2019

[54] OECD, 2017, Structural and Demographic Business Statistics: Structural business statistics ISIC Rev. 4. Available at: https://data.oecd.org/entrepreneur/enterprises-by-business-size.htm

[55] OECD, 2019, Labor Force Statistics. Available at: OECD.Stat accessed on 6/9/2019. Series: Incidence of FTPT employment - common definition; Incidence of involuntary part time workers

[56] O'Neill, S., Kreif, N., Greive, R., Sutton, M., Sekhon, J. (2016). Estimating causal effects: considering three alternatives to difference-in-differences estimation. Health Services and Outcomes Research Methodology, 16, 1-21

[57] Rosenbaum, P.R., Rubin, D.B. (1983). The central role of the propensity score in observational studies for causal effects, Biometrika, 70(1): 41-55.

[58] Smith, J. P. (1999). Healthy Bodies and Thick Wallets: The Dual Relation between Health and Economic Status. Journal of Economic Perspectives, 13(2): 145-166.

[59] Smith, J. (2005). Consequences and Predictors of New Health Events, in Wise, D. (ed) Analyses in the Economics of Ageing, University of Chicago Press.

[60] Spelten, E.R., Sprangers, M.A., Verbeek, J.H., 2002. Factors reported to influence the return to work of cancer survivors: a literature review. Psycho-oncology 11, 124-131.

[61] Trevisan E., Zantomio F., (2016). The impact of acute health shocks on the labour supply of older workers: Evidence from sixteen European countries. Labour Economics, 43, 171-185.

[62] Trygged, S., Ahacic, K., Kareholt, I., (2011). Income and Education as predictors of return to working life among younger stroke patients. BMC Public health 11: 742.

[63] Vestling, M., Ramel, E., Iwarsson, S., (2013). Thoughts and experiences from returning to work after stroke. Work 45, 201-211.

[64] Wilkins E, Wilson L, Wickramasinghe K, Bhatnagar P, Leal J, Luengo-Fernandez R, Burns R, Rayner M, Townsend N, (2017). European Cardiovascular Disease Statistics 2017. European Heart Network, Brussels.

[65] Wu, S. (2003). The Effects of Health Events on the Economic Status of Married Couples. Journal of Human Resources 38(1): 219-30.

[66] Zissimopoulos, J.M. Karoly L.A. (2007). Transitions to self-employment at older ages: The role of wealth, health, health insurance and other factors. Labour Economics 14 (2007) 269?295.

[67] Zucchelli, E. , Jones, A.M., Rice, N., Harris, A. (2010). The Effects of Health Shocks on labour Market Exits: Evidence from the HILDA Survey, Australian Journal of Labour Economics, 13(2): 191-218.

Appendices

Table A1: Descriptive Statistics

	Treated		Controls	
	Mean	*Sd*	Mean	*Sd*
Year	2004	0.811	2004	0.816
Age	50.73	7.402	39.77	9.591
Abirth_north	0.271	0.445	0.359	0.480
Abirth_center	0.142	0.349	0.133	0.339
Abirth_south&Isl.	0.508	0.500	0.354	0.479
Abirth_abroad	0.079	0.270	0.154	0.361
Country_underdev	0.073	0.260	0.140	0.346
Hosp_cvd_cum	0.037	0.190	0.001	0.034
Days_cvd_cum	0.409	2.870	0.012	0.451
Hosp_other_cum	0.311	0.463	0.190	0.392
Days_other_cum	2.814	7.280	6.211	1.303
Hosp_other_($\bar{t}$-1)	0.207	0.611	0.096	0.392
Days_other_($\bar{t}$-1)	0.993	4.132	0.440	3.349
Inv_benefit_cum	0.077	0.266	0.007	0.082
Sick_leave_cum	19.28	26.87	10.70	15.87
Work_active_cum	12.37	2.865	10.99	3.542
Nemployee_cum	14.23	3.843	13.20	4.295
Rate_employee_cum	97.01	11.01	97.90	8.996
Jobloss_cum	0.312	0.610	0.324	0.631
New_firm_cum	2.843	2.565	2.937	2.431
Nblue_collar_cum	12.78	4.052	10.84	4.739
Nwhite_collar_cum	0.281	1.430	0.261	1.277
Nmanager_cum	0.001	0.035	0.002	0.082
Rate_perm_cum	94.88	14.67	89.86	20.64
Rate_fullt_cum	96.39	13.59	96.55	12.80
Ever_CIG	0.384	0.486	0.335	0.472
Nunempl_cum	0.393	1.219	0.381	1.116
Unempl_($\bar{t}$-1)	0.039	0.193	0.059	0.236
Rate_selfempl_cum	3.699	13.08	2.596	10.95
Days_self_cum	165.5	613.8	130.6	562.9
Rate_atypical_cum	0.403	3.206	0.632	4.258
N_atypical_cum	0.050	0.425	0.062	0.441
Dist_last1_employee	1.044	0.360	1.056	0.386
Dist_last2_employee	2.141	0.796	2.153	0.784
Dist_last3_employee	3.261	1.093	3.267	1.104
Dist_last4_employee	4.391	1.376	4.413	1.408
Last_sick_leave	2.202	5.330	1.156	3.375
Last_weeks_paid	47.57	10.28	45.95	12.01
Last_fix_term	0.041	0.197	0.081	0.272
Last_jtenure	8.911	7.046	6.621	6.053
Last_awork_north	0.484	0.499	0.568	0.495
Last_awork_center	0.179	0.384	0.176	0.381
Last_awork_south&Isl.	0.336	0.473	0.256	0.426
Last_awork_abroad	0	0	0.002	0.015
Last_apprentice	0.001	0.025	0.017	0.127
Last_bluecollar	0.994	0.074	0.976	0.152
Last_whitecollar	0.005	0.070	0.007	0.086
Last_manager	0	0	$6.0e^{(-05)}$	0.008
Last_director	0	0	$3.1e^{(-05)}$	0.006

Source: WHIP&Health

(*continue*)

	Treated		Controls	
	Mean	*Sd*	Mean	*Sd*
Last_firm_015	0.297	0.457	0.368	0.482
Last_firm_16250	0.431	0.495	0.414	0.493
Last_firm_250	0.273	0.445	0.218	0.413
Last_sec_agriculture	0.001	0.025	0.0004	0.019
Last_sec_manufac	0.416	0.493	0.493	0.499
Last_sec_construc	0.169	0.375	0.172	0.377
Last_sec_extraction	0.008	0.089	0.005	0.072
Last_sec_energy	0.018	0.134	0.011	0.105
Last_sec_trade	0.069	0.253	0.101	0.301
Last_sec_foodservices	0.043	0.203	0.046	0210
Last_sec_transports	0.144	0.351	0.088	0.283
Last_sec_finance	0.123	0.329	0.076	0.266
Last_sec_realestate	0.006	0.074	0.003	0.055
Last_public	0.004	0.061	0.005	0.070
Last1_lab_income	22,310	9,468	20,835	11,403
Last2_lab_income	21,822	9,466	20,344	11,340
Last3_lab_income	21,491	9,636	19,851	12,070
Last4_lab_income	21,222	9,918	19,002	11,961
Last1_hwage	11.83	3.785	11.34	6.596
Last2_hwage	11.69	3.701	11.14	6.977
Last3_hwage	11.65	4.459	10.98	9.564
Last4_hwage	11.56	3.796	10.82	15.24
Last1_fulltime	0.950	0.219	0.962	0.191
Last2_fulltime	0.952	0.215	0.965	0.184
Last3_fulltime	0.956	0.204	0.965	0.183
Last4_fulltime	0.956	0.204	0.965	0.184
Last1_LMP	0.981	0.137	0.976	0.152
Last2_LMP	0.964	0.187	0.964	10.87
Last3_LMP	0.949	0.220	0.953	0.212
Last4_LMP	0.934	0.248	0.936	0.244

Source: WHIP&Health

Table A2: Post-CEM reached balance

	Pre-CEM				Post-CEM			
	Mean				Mean			
	Treated	Controls	%bias	p-value	Treated	Controls	%bias	p-value
Year	2004	2004	1.7	0.503	2004	2004	0.0	1.000
Age	50.73	39.77	127.9	0.000	50.68	50.68	0.0	1.000
Hosp_cvd_cum	0.037	0.001	26.6	0.000	0.024	0.024	0.0	1.000
Dist_last1_employee	1.044	1.056	-3.3	0.205	0.036	0.036	0.0	1.000
Last_fix_term	0.041	0.081	-16.9	0.000	0.036	0.036	0.0	1.000
Last_awork_north	0.484	0.568	-16.8	0.000	0.482	0.482	0.0	1.000
Last_awork_center	0.179	0.176	0.8	0.735	0.182	0.182	0.0	1.000
Last_awork_south&Isl.	0.336	0.256	17.8	0.000	0.336	0.336	0.0	1.000
Last_awork_abroad	0	0.002	-2.2	0.539	0	0	.	.
Last_firm_015	0.297	0.368	-15.2	0.000	0.298	0.298	0.0	1.000
Last_firm_16250	0.431	0.414	3.4	0.175	0.431	0.431	0.0	1.000
Last_firm_250	0.273	0.218	12.8	0.000	0.271	0.271	0.0	1.000

Source: WHIP&Health

Table A3: Post-EB moments balance

	Treated group			Control group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Year	2004	0.661	-0.057	2004	0.660	-0.057
Age	50.68	54.73	-0.688	50.68	56.29	-0.673
Abirth_north	0.273	0.199	1.018	0.273	0.199	1.018
Abirth_center	0.507	0.250	-0.028	0.507	0.250	-0.026
Country_underdev	0.072	0.0670	3.31	0.072	0.067	3.310
Hosp_other_($\bar{t}$-1)	0.204	0.370	4.536	0.204	0.520	16.08
Days_other_($\bar{t}$-1)	0.979	17.05	7.727	0.979	21.54	11.94
Hosp_cvd_cum	0.024	0.024	6.16	0.024	0.024	6.160
Days_cvd_cum	0.282	6.183	13.03	0.282	4.675	9.357
Hosp_other_cum	0.308	0.213	.8336	0.308	0.213	0.834
Days_other_cum	2.766	52.54	4.647	2.766	78.34	8.239
Inv_benefit_cum	0.068	0.064	3.423	0.068	0.063	3.423
Sick_leave_cum	19.10	711.9	3.095	19.09	859.1	3.650
Work_active_cum	12.41	8.049	-1.496	12.41	7.983	-1.469
Nemployee_cum	14.27	14.71	0.008	14.27	14.86	0.710
Rate_employee_cum	96.98	123	-4.038	96.98	125.5	-4.102
Jobloss_cum	0.315	0.371	2.184	0.315	.4247	3.886
New_firm_cum	2.846	6.645	2.731	2.847	6.495	2.463
Nblue_collar_cum	12.82	16.26	-0.24	12.82	15.53	-0.224
Nwhite_collar_cum	0.271	1.995	7.908	0.271	1.921	9.001
Nmanager_cum	0.001	0.001	28.2	0.001	0.003	67.35
Rate_perm_cum	95.11	202.5	-3.851	95.11	214.4	-3.903
Rate_fullt_cum	96.64	170.9	-5.045	96.64	172.4	-4.967
Ever_CIG	0.385	0.237	0.474	0.385	0.237	0.474
Nunempl_cum	0.384	1.398	4.285	0.384	1.394	4.171
Unempl_($\bar{t}$-1)	0.039	0.037	4.773	0.039	0.037	4.773
Rate_selfempl_cum	3.748	173.4	3.876	3.748	180.3	4.039
Days_self_cum	168.4	3837	4.341	168.4	3974	4.485
Rate_atypical_cum	0.374	9.055	10.79	0.374	10.25	11.97
N_atypical_cum	0.046	0.153	12.39	0.046	0.200	19.63
Dist_last1_employee	1.036	0.106	11.18	1.036	0.103	11.06
Dist_last2_employee	2.130	0.600	8.096	2.130	0.560	7.724
Dist_last3_employee	3.249	1.161	5.538	3.249	1.189	5.605
Dist_last4_employee	4.375	1.843	4.574	4.375	1.850	4.475
Last_sick_leave	2.167	27.73	4.404	2.167	31.37	6.268
Last_jtenure	8.952	49.57	0.331	8.952	49.18	0.338
Last_weeks_paid	47.65	102.9	-2.644	47.65	105	-2.625
Last_fix_term	0.036	0.034	5.004	0.036	0.034	5.002
Last_awork_north	0.182	0.149	1.651	0.182	0.149	1.651
Last_awork_center	0.336	0.223	0.695	0.3358	0.223	0.695
Last_apprentice	0	0	.	0.00004	0.00003	165.9
Last_bluecollar	0.996	0.004	-15	0.996	0.004	-14.93
Last_whitecollar	0.004	0.004	15	0.004	0.004	15
Last_manager	0	0	.	$1.12e^{-06}$	$1.12e^{-06}$	944.7
Last_firm_015	0.298	0.209	0.882	0.298	0.209	0.882
Last_firm_16250	0.431	0.245	0.278	0.431	0.245	0.278

Source: WHIP&Health

(*continue*)

	Treated group			Control group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Last_sec_agriculture	0.001	0.002	39.91	0.001	0.001	39.91
Last_sec_extraction	0.008	0.008	10.94	0.008	0.008	10.94
Last_sec_manufac	0.420	0.244	0.325	0.420	0.244	0.325
Last_sec_energy	0.019	0.018	7.087	0.019	0.018	7.087
Last_sec_construc	0.170	0.141	1.759	0.170	0.141	1.759
Last_sec_trade	0.068	0.064	3.423	0.068	0.064	3.423
Last_sec_foodservices	0.043	0.041	4.492	0.043	0.041	4.492
Last_sec_transports	0.144	0.123	2.034	0.1435	0.123	2.034
Last_sec_finance	0.119	0.105	2.353	0.119	0.104	2.353
Last_sec_realestate	0.006	0.006	13.20	0.006	0.006	13.20
Last1_lab_income	22429	$8.86e^{+07}$	0.529	22429	$3.02e^{+08}$	118.6
Last2_lab_income	21922	$8.91e^{+07}$	0.330	21922	$1.06e^{+08}$	34.40
Last3_lab_income	21620	$9.19e^{+07}$	0.220	21619	$1.11e^{+08}$	13.91
Last4_lab_income	21337	$9.72e^{+07}$	0.153	21337	$9.99e^{+07}$	0.491
Last1_fulltime	0.956	0.043	-4.419	0.956	0.043	-4.419
Last2_fulltime	0.956	0.043	-4.419	0.956	0.043	-4.419
Last3_fulltime	0.961	0.037	-4.773	0.960	0.037	-4.773
Last4_fulltime	0.960	0.039	-4.688	0.960	0.038	-4.688
Last1_LMP	0.984	0.015	-7.801	0.984	0.015	-7.799
Last2_LMP	0.966	0.033	-5.157	0.966	0.033	-5.157
Last3_LMP	.0950	0.048	-4.123	0.950	0.048	-4.123
Last4_LMP	0.937	0.059	-3.609	0.937	0.059	-3.609
Last1_hwage	11.85	14.30	1.211	11.85	84.27	111.1
Last2_hwage	11.72	13.69	1.033	11.72	25.52	73.04
Last3_hwage	11.67	20.01	7.690	11.67	223.6	215.2
Last4_hwage	11.61	14.24	1.035	11.61	15.11	2.313

Source: WHIP&Health

Table A4: Unconditional employment-related outcomes: ATTs

	CVD shock experienced in 2003/2004		*CVD shock experienced in 2003*	
	Probability of employment	**Annual income from employment**	**Probability of employment**	**Annual income from employment**
Time	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
t	-	-951.2***	-	-1290.6***
Rob. SE.	-	(241.5)	-	(324.5)
N. treated	-	1042	-	503
t+1	-0.039***	-2661.5***	-0.040**	-2914.7***
Rob. SE.	(0.011)	(339.5)	(0.015)	(460.4)
N. treated	1043	1043	503	503
t+2	-0.088***	-2549.4***	-0.078***	-2808.1***
Rob. SE.	(0.013)	(367.2)	(0.019)	(503.5)
N. treated	1043	1043	503	503
t+3	-0.097***	-2391.8***	-0.111***	-2307.0***
Rob. SE.	(0.014)	(380.2)	(0.020)	(528.8)
N. treated	1043	1043	503	503
t+4	-0.082***	-2259.5***	-0.093***	-2555.6***
Rob. SE.	(0.014)	(390.1)	(0.020)	(539.2)
N. treated	1043	1043	503	503
t+5	-0.080***	-2271.3***	-0.067***	-2490.8***
Rob. SE.	(0.014)	(380.7)	(0.020)	(525.9)
N. treated	1043	1043	503	503
t+6	-0.070***	-1816.1***	-0.065***	-2105.8***
Rob. SE.	(0.014)	(368.4)	(0.020)	(497.3)
N. treated	1043	1043	503	503
t+7	-0.067***	-1669.1***	-0.062***	-2016.9***
Rob. SE.	(0.014)	(363.5)	(0.019)	(485.2)
N. treated	1043	1043	503	503
t+8	-0.057***	-1608.8***	-0.061***	-2086.9***
Rob. SE.	(0.013)	(344.6)	(0.019)	(456.5)
N. treated	1043	1043	503	503
t+9	-	-	-0.086***	-2326.1***
Rob. SE.	-	-	(0.017)	(412.8)
N. treated	-	-	503	503

Source: WHIP&Health

Table A5: Employment-related unconditional outcomes by fixed-term jobs: ATT and Relative Effect

	Fixed-term job **Probability of labour market activity**		*Permanent job* **Probability of labour market activity**	
Time	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
t	-	-	-	-
Rob. SE.	-	-	-	-
N. treated	-	-	-	-
t+1	-0.130***	-14.27	-0.033***	-3.65
Rob. SE.	(0.045)		(0.009)	
N. treated	54		1539	
t+2	-0.138**	-16.34	-0.085***	-10.24
Rob. SE.	(0.055)		(0.011)	
N. treated	56		1539	
t+3	-0.169**	-21.17	-0.093***	-12.18
Rob. SE.	(0.061)		(0.011)	
N. treated	56		1539	
t+4	-0.068	-10.28	-0.078***	-11.23
Rob. SE.	(0.057)		(0.012)	
N. treated	57		1539	
t+5	-0.058	-9.45	-0.079***	-12.56
Rob. SE.	(0.056)		(0.012)	
N. treated	57		1539	
t+6	-0.045	-7.77	-0.080***	-13.76
Rob. SE.	(0.054)		(0.012)	
N. treated	57		1539	
t+7	-0.124**	-23.45	-0.067***	-12.78
Rob. SE.	(0.057)		(0.011)	
N. treated	57		1539	

Source: WHIP&Health

Table A6: Employment-related unconditional outcomes by full-time jobs: ATT and Relative Effect

Time	*Full-time job* **Probability of labour market activity** $\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	*Part-time job* **Probability of labour market activity** $\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
t	-	-	-	-
Rob. SE.	-	-	-	-
N. treated	-	-	-	-
t+1	-0.037***	-4.13	0.025	2.81
Rob. SE.	(0.009)		(0.040)	
N. treated	1525		70	
t+2	-0.088***	-10.60	-0.052	-6.67
Rob. SE.	(0.011)		(0.054)	
N. treated	1525		71	
t+3	-0.095***	-12.50	-0.073	-10.16
Rob. SE.	(0.011)		(0.058)	
N. treated	1525		71	
t+4	-0.079***	-11.39	-0.023	3.42
Rob. SE.	(0.012)		(0.057)	
N. treated	1525		70	
t+5	-0.078***	-12.30	-0.090	-14.94
Rob. SE.	(0.012)		(0.058)	
N. treated	1525		70	
t+6	-0.077***	-13.34	-0.093	-16.86
Rob. SE.	(0.011)		(0.057)	
N. treated	1525		70	
t+7	-0.069***	-13.03	-0.053	-10.63
Rob. SE.	(0.011)		(0.057)	
N. treated	1525		70	

Source: WHIP&Health