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LABOUR OUTCOMES ADJUSTMENTS TO HEALTH SHOCKS OVER THE LONG RUN: EVIDENCE FROM ITALIAN ADMINISTRATIVE RECORDS

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Labour Outcomes Adjustments to Health Shocks over the Long Run: Evidence from Italian Administrative Records

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Abstract: We investigate how the labour outcomes response to health shocks evolves in the long run. Using Italian administrative data covering employment, social security, and hospitalisation histories, we remove bias from observables and unobservables applying matching and parametric regression to multiple comparison groups. Results show that reductions in employment and income persist in the long run. The ability to continue to work is greater if treated in higher quality hospitals and for those employed in large firms. Whereas a generous social insurance system might permanently compensate for part of the earnings loss, our findings question the appropriateness of existing labor-inclusion policies.

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

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Introduction

Fostering older and unhealthy workers' inclusion in the labour market is a daunting task that appears on the policy agendas of many countries. Policymakers face complex choices in the choice between providing incentives to remain active and the protection that motivates social insurance institutions. Context-specific knowledge on behavioural responses to health shocks is central to shaping the policy agenda wisely. Empirical evidence has so far contributed to a relative consensus on a detrimental effect (Currie and Madrian, 1999) of health shocks on labour and other socioeconomic outcomes: participation in the labour market (Au et al., 2005; Bradley et al., 2013; García-Gómez et al., 2010; Jones et al., 2020), hours worked (Cai et al., 2014; Moran et al., 2011), income from labour (Flores et al., 2019; García-Gómez and López Nicolás, 2006; Halla and Zweimüller, 2013; Dano, 2005), and wealth because of increased health expenditure (Dobkin et al., 2018; Wu, 2003).

However, a recurrent limitation of this literature and its potential for informing policy design is that results are confined to a short time horizon. Except for a few cases that provide evidence for up to six years (García-Gómez et al., 2013; Dano, 2005; Moran et al., 2011), most studies cover one to three years after a health shock occurs. The reasons involve a combination of data availability and the requirements of identification strategies: Generally, the latter rely on pre-shock labour and health histories, resulting in a reduced observational window for analysing post-shock dynamics. As a result, the picture remains partial. A thorough assessment of the consequences of health shocks should account for the cumulative effects that fully transpire only over time. Exits from the labour market that are observed in the short term and are intended to be temporary, assuming a recovery to good health, could become permanent in the longer run, particularly in rigid labour markets that offer limited opportunities for re-entry to older outsiders. What's more, return to employment or recovery in earnings could emerge, not in the short term, but only in the medium to long run, through health improvements or the development of new forms of disability-specific human capital.[1]

No less important than the time frame is the particular institutional setting (Arpaia and Mourre, 2012; Holmlund, 2014) from which evidence is drawn. Most studies focus on Anglo-Saxon countries (e.g. Au et al., 2005; Coile, 2004; Dobkin et al., 2018; García-Gómez et al., 2010; Jones et al., 2019; Moran et al., 2011; Zucchelli et al., 2010), Nordic countries, (e.g. Datta Gupta et al., 2011; Dano, 2005; Fadlon and Nielsen, 2020; Heinesen et al., 2013; Lundborg et al., 2015; Maczulskij and Böckerman, 2019), and the Netherlands (García-Gómez et al., 2013), a pattern that reflects these countries' availability of appropriate data sources, which have sometimes allowed researchers to explore subgroups' responses (see, e.g., Dano, 2005; Heinesen et al., 2013; Lundborg et al., 2015). However, compared to other countries (EC, 1999; EC, 2009; OECD, 2014; OECD, 2016), these countries tend to feature higher levels of job mobility[2] and a more limited role for job protections. This partial view casts doubts on the robustness of these studies' results and the appropriateness of extending potential policy recommendations to institutional environments, like those of Southern European countries, which generally[3] feature highly regulated labour markets and comparatively low labour flow indicators (EC, 2009; OECD, 2016).

A third limitation of the extant literature is that heterogeneities regarding effects on labour market outcomes are explored mostly in terms of individual characteristics, such as age, gender, education, shock type, and severity, informative on targeted intervention needs while

[1] For example, in the US Charles (2003) observes that the immediate reduction in earnings has been followed by a recovery since the first two post-onset years.
[2] The Netherlands is a notable exception, which features comparatively low hiring rates: In 2006 the hiring rate for older workers (aged 55-64), measured as the percentage of employees with job tenure of less than one year, was 1.7 (against an OECD average of 9.2).
[3] One exception is Spain, which has high hiring rates. In 2006 the hiring rate for older workers was 7.7, while the same indicator was 4.0 for Italy, and the OECD average was 9.2. For evidence on the consequences of health shocks in Spain, see García-Gómez and Lopez Nicolás (2006).

effects based on the labour market and hospitals' institutional features are more useful in terms of reform interventions aimed at fostering recovery and are broadly neglected.

The present work addresses the limitations of an otherwise well-developed stream of literature by measuring the effect of health shocks for as much as nine years later and extending evidence on what drives the size of an effect magnitude to the labour environment and the quality of healthcare in Italy, which has a highly regulated labour market and strong job-protection policies. We study workers aged 18-64 years who were affected by acute forms of cardiovascular disease (CVD), resulting in hospitalisation. CVDs are highly prevalent[4], although survival rates have improved remarkably over the past several decades (Wilkins et al., 2017). Acute CVD often leads to physical and mental impairments, limiting daily activities and the ability to work.

In addition to its prevalence, the primary reason for focussing on acute CVD relates to the issue of health endogeneity that plagues empirical research on the effects of deteriorating health on labour market outcomes (Cai, 2010; Currie and Mandrian, 1999; Haan and Myck, 2009). Tackling endogeneity requires exploiting exogenous sources of variation in health: For example, some authors focus on commuting and car accidents (Dano, 2005; Halla et al., 2013), unplanned hospitalisations for a variety of health conditions (García-Gómez et al., 2013; Lindeboom et al., 2016), or the onset of certain kinds of major health shocks (Bradley et al., 2013; Coile, 2004; Datta Gupta et al., 2011; Jones et al., 2020; Smith, 1999, 2005; Trevisan et al., 2016). This last category might offer a source of unexpected variation in health because, although people may anticipate their risk of illness, the illness when it actually occurs is often

[4] Over the past 25 years, the incidence of CVD cases has increased in most European countries, including Italy. In 2015, the incidence of myocardial infarction was 2,968,582 among men and 2,784,341 among women; while new cases of stroke were 675,872 among men and 879,493 among women. Data on the crude prevalence for the same year depict an impressive situation, as more than 85 million people across Europe were living with CVD. CVD is a source of major human and economic cost (direct health costs, productivity loss and informal care costs) in developed countries. The myocardial infarction cost is estimated at about €59 billion a year, and the corresponding figure for stroke is €45 billion per year.

unexpected. Therefore, previous studies consider acute CVD shocks as well as cancer and lung diseases.

Combining the advantages of these approaches, we consider only unplanned hospitalisations for myocardial infarction (ischemic heart disease) or stroke (cerebrovascular disease). The onset of these two acute CVD conditions is clearly attributable to a specific, yet unpredictable, point in time. The risk is well known to depend on established factors (Braunwald et al., 2015), which aids in the selection of an appropriate comparison group for identification purposes. Therefore, to strengthen the case for regarding the timing of a shock as unanticipated, conditional on a measurable distribution of the probability of a shock, we disregard both unplanned hospitalisations that are related to other major conditions the onset of which is not related to a specific point in time, and unplanned hospitalisations following injuries or accidents whose conditional risk distribution is not as easily traceable to observable risk factors.

Studying the Italian institutional context is possible thanks to the availability of a new administrative dataset, WHIP&Health, which covers the work and social security histories of a 7 percent random sample drawn from the Italian Social Security (INPS, *Istituto Nazionale della Previdenza Sociale*) archives, which are linked to individuals' hospital discharge records from all private and public hospitals. The availability of administrative data on hospitalisations overcomes several measurement error challenges that are typically encountered with survey data, spanning from recall to justification biases (Baker et al., 2004; Benitez-Silva et al., 2004; Jackle and Himmler, 2010). A wide time window allows a long record of history information, up to fifteen years before the health shock occurrence, to be exploited. Conditioning on these long histories of health, labour and social insurance variables, we leverage the unanticipated timing of acute CVDs shocks and assume that the conditional probability that a worker will or will not experience a CVD health shock at a particular point in time, conditional on his or her underlying health risk distribution, is as good as random. Moreover, by conditioning on lagged outcomes, we remove bias that stems from time-invariant unobservables.

The identification strategy is implemented following two approaches: The main approach used to study long-term responses combines coarsened exact matching and entropy balancing procedures on individuals who are affected or not affected by a CVD shock at a particular point in time, before parametric estimation of the average treatment effect on the treated (ATT). In the alternative approach, which can be applied only to short- and medium-run dynamics, we exploit individuals who experience the same CVD shocks five years later as a control group that is plausibly less exposed to any unobserved heterogeneity concern remaining under the first approach.

Outcomes include employment, annual income from labour, receipt of disability insurance, and—for those who maintain employment—hourly wage and the probability of working full-time rather than part-time. We explore mechanisms and situations that result in effects of varying magnitude through heterogeneity analyses: besides age and the type of shock, we provide novel evidence on the role played by firm size, which is indicative of the level of employment protection and within-firm accommodation opportunities, and by the quality of healthcare provision, which affects the speed of healing and return to work.

The two identification approaches deliver strikingly similar results that are robust to the inclusion of weighting that accounts for selective mortality. The new evidence generated on the dynamic pattern of response over the nine years past the shock documents a reduction in employment that peaks three years past the shock, with only minor recovery thereafter. After nine years, the drop in employment reaches a relative size value that is five times larger than the one registered in the first year. While not compensated for by transitions to other forms of work, loss of employment leads to a substantial and persistent loss in annual earnings, amounting to 11-15 percent of the counterfactual value in each year past the shock. A major route of exit from employment is disability insurance, the probability of receipt of which increases over the long term. DI coverage ensures that acute CVD shocks do not increase the probability of a combination of being out of work and not in receipt of public benefits. For those who maintain employment, no significant adjustment in working hours emerges. Wage dynamics reveal a small negative effect of health shocks from a slowdown in wage growth with respect to the counterfactual. Heterogeneity analyses reveal that shocked workers' ability to continue working is permanently fostered by the quality of the first treatment hospital and is higher for employees of large firms, consistent with the higher employment protection legally granted to them and with their wider opportunities for finding less physically demanding tasks.

Overall, the new long-run evidence suggests that a highly regulated institutional setting provides limited scope for workers to flexibly adjust their work times and for employers to adjust the wages of less productive workers. This limitation may force some workers, who might have preferred to remain active through reduced work time and/or wages to withdraw from the labour force and enter the DI rolls as the only viable option. At the same time, firms might find ways to dismiss less healthy workers, relying on the partial income protection granted to them though DI programmes rather than investing in accommodations. In a sticky labour market like the Italian one, such an exit route is likely to become an absorbing state in the long run.

The paper is organised as follows. Section 2 discusses Italy's labour market and DI insurance programmes, while section 3 describes data, sample selection and the main identification approach. In Section 4 we illustrate the identification approach applied to short- and medium-run dynamics as well as the method to account for selective mortality. Section 5 presents our main findings and those from the analysis of heterogeneity. Section 6 discusses results, and the following Section concludes.

2 Institutional background

2.1 Labour Market

Comparative labour market indicators over the period covered by our study (1990-2012) suggest that Italy labour market is among the most highly regulated. The OECD *Strictness of Employment Protection*[5] indicator (ranging from 0 to 5) scores Italy at 2.76 (in the period 1990-end 2011, decreasing to 2.68 in 2012), a value close to those of other Southern European countries (e.g. Greece, 2.8) and much higher than those for Anglo-Saxon countries (e.g. UK, 1.1) or 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 not allowed[6] during most of the time period we study. Legal safeguards[7] were reduced when the 2012 Monti-Fornero reform introduced the possibility of dismissal for firm-related economic reasons, significantly lowering the firing restrictions that previously applied to medium and large companies. Employees in small firms (i.e. up to 15 employees, which are widespread in the Italian productive panorama in comparison with other OECD countries)[8], or who are under fixed term-contracts (which remain few in comparative terms, particularly for older workers, who are more exposed to health shocks)[9] have historically and throughout the period we consider relied on significantly less employment protection.

[5] Referring to individual dismissals in regular contracts.

[6] The sanction the employer was subject to in case of unlawful dismissal was reinstatement of the worker.

[7] 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 by the fear of a massive number of lawsuits 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 or her job back and has only the right to an indemnity ranging from 12 to 24 months of salary, the sum being decided by a court. Thus, the Fornero-Monti reform significantly lessened the restrictions to firing in Italy.

[8] Italy is the second leading OECD country in the number of micro-businesses (319k firms with 0 to 9 persons employed), preceded only by Turkey, and is third in the number of small 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 represented an additional 4.1% (ISTAT, 2017).

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

Italy's high level of regulation is confirmed by the OECD *Trade unions and Collective Bargaining* indicators. The collective bargaining coverage rate was 80 percent in the 1998-2016 period, similar to Spain, Portugal and Greece before the crisis, against an OECD average of 33 percent. Although Italy has no legal minimum wage, it is de facto set through collective bargaining agreements sector-by-sector. The resulting compensation structure is particularly rigid and displays a lifecycle-related profile of hourly wages that differs markedly from those of other countries (Contini, 2009). For many years, Italy has been the only European country in which remuneration did not decline at older ages[10] because, as long as open-ended contracts prevail, particularly in large firms, wages are linked to seniority until retirement.[11] Devicienti et al. (2007) also provide evidence of significant downward wage rigidity, with real rigidity prevalent over nominal rigidity, which could result in frictions that increase labour mobility and workers' reallocations. However, Italy is among the bottom ranks of countries in terms of hiring, separations and turnover (European Commission, 2009).[12] Disaggregated statistics on labour mobility (Contini, 2019[13]) document a hiring rate of about 50 percent in small firms, declining to 25 percent in firms with more than 200 employees, where stricter employment-protection legislation applies.

The large majority of part-time work is involuntary: focussing on men, in 2018, the share of voluntary part-timers as a percentage of total employment was only 1.5 percent, increasing only slightly for older men aged 55 to 64 (3.1 percent), which is in stark contrast to the corresponding OECD figures of 7.5 percent for men of all ages and 7.1 percent for older

[10] In Nordic countries and the UK, wages peak at around 45 years old. In Italy wages continue to increase until the worker is 60 years old.

[11] After 1991, Italy experienced a trend of declining union power and an 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%.

[12] During the 1980s and 1990s, the Italian labour market featured hiring rates and labour turnover indicators that were midway between those of central European and Anglo-Saxon countries (OECD 1994, Contini, 2019).

[13] Contini (2019) computations are based on administrative WHIP data for the period 1991-2012. The frequency of WHIP is monthly, so indicators of labour mobility cannot be compared with the European Commission indicators based on EU-LFS, which is quarterly. Open-ended contracts appear to be characterized by separation rates that are regularly greater than association rates; for these contracts, the value of labour turnover has been constant over time at around 25%, suggesting a surprisingly low average length of open-ended contracts of four years.

men (OECD, 2019). Further evidence from Eurostat (2019) reveals that the prevalence of part-time contracts among male workers aged 45 or older who suffer health-related limitations is only 12 percent, a figure that places Italy in the penultimate position among EU28 countries.

Overall, Italy features a highly regulated market in which firms are sharply limited in their ability to adjust working hours, require overtime work, make workers redundant, or engage in firm-level negotiations.

2.2 Disability Insurance

Italy's workers are entitled to paid sickness leave for a maximum of 180 days per calendar year. Combining the public benefit rate with other compensations that are available through collective bargaining agreements results in a full replacement rate[14]. After 180 days, if the employee does not return to work, the employer may rescind his or her contract.

Wider protection against health-related income risk is offered through two types of social insurance targeted to disabled workers. The first is a temporary disability benefit (*Assegno ordinario di invalidità*) for certified mental or physical impairment that reduced the capacity to work by at least two-thirds. The benefit is payable to employees who have contributed to the programme for at least five years, and the amount is relatively generous, as it is computed using the same formula that applies to the old-age pension[15]. Therefore, a worker who claims the benefit at age 50, after thirty years of contributions, receives a gross replacement rate of about 60 percent[16]. The entitlement lasts three years, and can be renewed twice after medical screening before becoming permanent, after which it is absorbed into the old-age

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

[15] In the period covered by our study, the prevailing old-age pension schemes were a more generous defined benefit scheme that applied to workers with more than 18 years of contributions paid by the end of 1995, and a less generous mixed (defined benefit/notional defined) contribution scheme paid to other (broadly, younger) workers.

[16] A replacement rate of 60 percent refers to a worker who is subject to the former defined benefit scheme; it is somewhat lower in case of the later mixed scheme.

pension when the claimant reaches the minimum age requirement. This disability benefit is compatible with working, as the earnings-related reduction binds only at high income levels.[17]

The second disability-related benefit is a permanent disability pension (*Pensione di inabilità*), which is paid to claimants who, after medical screening, present permanent and total inability to performing any kind of work[18]. It is incompatible with any type of paid work. This programme is highly generous and highly subsidized, computed using the old-age pension formula but with the addition of a sizable seniority premium related to the number of years before the claimant reaches age 60, so it is essentially a disability benefit that is equal to an old-age pension but that is received earlier in life. The resulting gross replacement rate could even exceed 100 percent for a relatively young beneficiary with an increasing income profile.[19]

3 Empirical Approach

3.1 Identification.

Ideally, the causal effect of health deterioration would be measured as the difference in individual 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 $Y_{i,t}^{1}$; in the other, it does not ($T_{i,\bar{t}} = 0$), yielding outcome $Y_{i,t}^{0}$. In that case, we could estimate the average treatment effects on the treated (i.e. on an individual who is affected by the CVD shock) $ATT_{\bar{t}+v}$ at time $\bar{t}+v$, that is, v years after the CVD shock, as:

$$E\left[Y_{i,\bar{t}+v}^{1} - Y_{i,\bar{t}+v}^{0} \mid T_{i,\bar{t}} = 1\right] = E\left[Y_{i,\bar{t}+v}^{1} \mid T_{i,\bar{t}} = 1\right] - E\left[Y_{i,\bar{t}+v}^{0} \mid T_{i,\bar{t}} = 1\right]$$

[17] The benefit is reduced by 25% (50%) when labour income is greater than four (five) times the minimum pension (i.e. euro 26.676,52 or euro 33.345,65 in 2019).
[18] Additional requirements to claim these benefits are five years of enrolment in Social Security and at least three years of contributions in the previous five.
[19] See Belloni and Maccheroni (2013) for more details.

In practice, though, an individual will only experience–and be observed–in one state, so the two potential health states ($T_{i,\bar{t}} = 1$, $T_{i,\bar{t}} = 0$) and their corresponding labour outcomes ($Y_{i,t}^{0}$, $Y_{i,t}^{1}$) are never simultaneously observed. The potential outcome approach addresses the evaluation problem by 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:

$$\left(Y_{i,t}^{0}, Y_{i,t}^{1}\right) \perp T_{i,\bar{t}} \mid \left(W_i, X_{i,\bar{t}-s}\right) \qquad s = 1 \ldots\ldots S,$$

where W_i is the individual time-invariant characteristics and $X_{i,\bar{t}-s}$is the time-varying ones, including labour, social insurance and health histories (indicative of individuals' underlying CVD risk), observed s years before the shock and up to past time S. Under unconfoundedness, conditioning on the observables W_i and $X_{i,\bar{t}-s}$ makes both potential outcomes independent with respect to the treatment status and makes 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 who experience the $T_{i,\bar{t}} = 0$ state and those who experience the $T_{i,\bar{t}} = 1$ state. Therefore, while untestable, its credibility relies on the scope of the available data, a point to which we come back 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 who experience the health shock and those who do not, so the conditional treatment probability for both groups is:

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

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

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

$$\equiv E\left[Y_{i,\bar{t}+v}^{1} \middle| W_i = w,\ X_{i,\bar{t}-s} = x\right] - E\left[Y_{i,\bar{t}+v}^{0} \middle| W_i = w, X_{i,\bar{t}-s} = x\right].$$

3.2 Data

WHIP&Health is an administrative dataset that combines the work and social insurance histories and the health histories of a 7 percent random sample of workers covered by the INPS, that is, all private sector workers, excluding agriculture and some categories of professionals, such as architects and lawyers, who are not covered by INPS.

The first component, the Work Histories Italian Panel (WHIP), which covers from 1990 to 2012, is a rich employer-employee database of detailed information about each period of employment (e.g. starting and ending dates, qualification, sector of activity, firm identifier, firm dimension, region of employment, labour income, type of contract). Other information includes other types of work periods (i.e. self-employment or atypical work) and non-work periods like unemployment. Information on receipt of a variety of social security programmes—including temporary and permanent disability programmes, unemployment, and old-age pensions—is also available, although not the amount received. Demographic information covers the years of birth and death, place of birth, and gender.

Workers are followed as long as they pay social security contributions to INPS in relation to labour activity or receive social security benefits. They leave the archive when they stop contributing because they leave the labour force, move to the public sector or agricultural sector, or die. While exits toward the public or agricultural sectors are rare, especially among older workers, observing mortality allows us to handle potential selective mortality bias, a point to which we return in Section 4.2.

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, that collects information on all types of hospitalisations between 2001 and 2012 for all individuals included in WHIP. Variables include the main and the secondary diagnoses according to the ICD codes (ICD-IX); the year and month of hospitalisation; the type of dismissal, which allows deaths that occurred while in the hospital to be identified; and the hospital code, which allows the availability of an intensive care ward and a coronary unit ward in that hospital, two proxies for the quality of care receivable by acute CVD patients, to be retrieved. Thus, we are able to identify unplanned hospitalisations related to an acute CVD shock (acute ischemic, codes: ICD-IX 410-414; acute cerebrovascular codes: ICD-IX 430-434 and 436-437) that does not result in death in the same year.

3.3 Research Design and Sample Selection

For the assumption of unconfoundedness to be credible, as much previous labour and health history information must be observed as possible, so this identification strategy requires a sizeable time window for observing pre-shock characteristics. However, the novel research question is centred on evaluating the effect of a health shock in the longer term. To balance the two, we place the time window of CVD shocks in the years 2003-2005 so we can observe up to s=15 years of previous labour and social insurance history (i.e. for individuals who experienced the CVD shock in 2005, with WHIP variables dating back to 1990), along with up to $v = 9$ years of labour outcomes past the health shock year (i.e. for individuals who experience the CVD shock in 2003, with WHIP variables observable up to 2012). Figure 1 clarifies the time window covered by the labour and social insurance (WHIP) and health (SDO) components of WHIP&Health, and how we exploit them to implement the research design.

FIGURE 1 ABOUT HERE

The sample for analysis consists of men who, in any year between 2003 and 2005, were employed as blue-collar workers and were between 18 and 64 years old. Female workers are excluded, as the available information on their labour market history is significantly less than that for male workers because of their more discontinuous employment patterns and lack of corresponding information in WHIP (which captures only periods in which the individual was employed or received social security). The exclusion of white-collar workers is motivated by the lack of information on their sickness leave, which is not captured in WHIP, although it is for blue-collar workers.[20] Episodes of sickness leave are a crucial confounder that allow us to capture health-related information for up to fifteen years, given that the SDO time frame is limited to up to four years prior to the health shock. The upper age limit corresponds to the year prior to the statutory retirement age in the period analysed. We exogenously set the upper age bound as commonly done in the related literature to avoid potentially endogenous sample selectivity induced by individual retirement decisions.[21]

Because of unobserved heterogeneity concerns, we also restrict the sample to those who did not experience an acute CVD shock in the two years before the treatment year (i.e. $\bar{t}-1;\ \bar{t}-2$) and to individuals who could claim at least four previous years of employment after 1990. We exclude cases with missing or inconsistent information on relevant variables.

The resulting sample consists of 325,083 individuals: among them, the 1,590 who experienced an acute CVD shock between 2003 and 2005 (493 in 2003, 542 in 2004, and 555 in 2005) represent the 'treated' subsample. While they might have experienced recurrent CVD events within the treatment window, we consider only the first shock observed within the 2003-2005 window as the reference shock. In line with the national and international statistics,[22] most cases involve myocardial infarctions (79,18 percent), and only about one in five (20,82 percent) are cerebrovascular events.

In our context, assignment to treatment happens dynamically within the time interval spanning from 2003 to 2005, so each of these years is taken in turn as year $\bar{t}$ for treatment assignment purposes. For each $\bar{t}$, individuals who experienced the acute CVD shock then are assigned to the treatment group, and individuals who had not yet experienced an acute CVD shock are assigned to the pool of potential controls. The underlying sample restriction to

[20] In the private sector, sickness leave is paid by INPS only to blue-collar and white-collar workers in certain sectors. For other workers, sickness leave is paid by the employer based on collective agreements.
[21] In our data, age 65 is a mass retirement point, although many individuals leave work earlier through early retirement schemes. In the following analysis, the latter cases are included and considered "not in employment" as long as they are under age 65.
[22] 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.

individuals who did not experience a CVD shock in the previous two years (i.e. $\bar{t}-1;\ \ \bar{t}-2$) ensures that, once an individual is shown as treated in $\bar{t},$ he cannot act as a potential control in later years. In addition, that is the only treatment year for that individual. On the other hand, an individual who acts as a potential control in a particular year could continue to do so or enter the pool of treated individuals in a later year. The subsample of those who act as potential controls amounts to 323,493 individuals.

Tables 1a and 1b describe the full set of variables that we use. In addition to basic demographics and health history variables, they include a large set of retrospective labour and social security history variables that reconstructs the workers' past for up to fifteen years. We derive multiple summary indicators of labour market trajectories, as well as time-and job-specific characteristics for previous employments to reduce the influence of time-varying unobservables to the extent they are correlated with observed confounders. We also include time-specific lagged outcomes, which allow the removal of any bias from time-invariant unobservables (O'Neill et al., 2016). Other unobserved heterogeneity concerns might arise from, for example, lack of available information on genetic or behavioural risk factors (e.g. smoking, eating habits, physical activity) that are correlated with labour market outcomes, a point to which we return in section 4.1. However, our results would not be invalidated if, besides genetic invariance over time, these behaviours were stable over time, in which case their effect would be purged via the inclusion of lagged outcomes. Full descriptive statistics for our working sample are reported in Appendix Table A1.

3.4 Implementation of main identification strategy for long term dynamics

Before any adjustment in composition, the distribution of characteristics varies between treated and control individuals (as shown in Tables 2a and 2b), revealing selection in experiencing CVD shocks. Individuals who experience an acute CVD shock are, on average, older, have poorer previous health outcomes (e.g. more frequent and longer previous hospitalisations, higher receipt of invalidity benefits, illness), and have significant differences in labour market outcomes, possibly related to their different age distribution, than control individuals do.

Following Ho et al. (2007), we compute ATTs by combining pre-processing procedures to balance the distribution of observed confounders between treated and control individuals through matching techniques, with later parametric estimation conducted on matched samples. The first component, matching, removes systematic links between treatment assignment and confounders that would cause bias, and reduces the risk of model dependence in the following parametric estimates. The second component, the post-matching parametric estimation, contributes to removing bias from imbalances remaining after matching, an occurrence that is not uncommon when non-exact matching procedures are used. In this respect, causal inference that combines matching and regression is superior to ATT estimations based on a simpler difference in mean outcomes in matched samples. This double-step procedure allows ATTs that are robust to model misspecification to be obtained[23].

Following Jones et al. (2020), we implement the balancing adjustment in two steps: coarsened exact matching (CEM) (Iacus et al., 2011) along a set of basic confounders, and entropy balancing matching (EB) (Hainmueller, 2012) 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 of this procedure over other matching procedures is that CEM reduces the imbalance in selected variables and implements common support on these without affecting the balancing in other variables (which other procedures, such as propensity score matching, might entail, trading off the balance obtainable for various variables). CEM also accounts for variables' interactions and nonlinearities. In practice, the CEM algorithm stratifies the sample by subsets of coarsened variables values (or exact variable

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

values in the case of dichotomous variables or if no coarsening is applied). Strata that lack at least one treated and one control unit are dropped; retained individuals are attributed a weight that accounts for the different number of treated and control individuals in each matched stratum.

A greater number of variables involved in CEM or a finer coarsening applied to non-dichotomous variables results in a higher proportion of cases discarded from further analysis because no exact match is found. Because of this drawback, we apply CEM to a limited set of basic confounders: We use uncoarsened variable values, which results in an exact match on age, year, years from the most recent time the individual was observed as an employee[24], whether the individual had experienced acute CVD shock[25], whether the individual worked under a part-time or a full-time contract, and whether the individual was under a fixed-term or open-ended contract as of $\bar{t}-1$. Two other variables included in CEM are coarsened instead: 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 a shock to avoid the chance of introducing the post-treatment bias that would arise if the variables were themselves affected by the shock, a possibility that we cannot rule out for year $\bar{t}$. However, in 88 percent of treated cases and 82 percent of control cases, the employer does not change between $\bar{t}-1$ and $\bar{t}$.

Out of the 17,114 strata obtained, only 937 were retained, which is a loss of only 31 treated individuals and about 47,5 percent of control individuals. Therefore, the ratio of the number of control individuals to the number of treated individuals is reduced from 203 controls for every treated pre-CEM to 109 controls for every treated post-CEM.

[24] The individual was observed as an employee in the previous year in 97.06% of cases. For the others, including this variable allows individuals with lagged outcomes referable to the same past calendar year to be compared.

[25] Health shocks would be captured in the available SDO data, that is, since 2001.

To remove imbalances that remain in the larger set of potential confounders, we apply EB matching on the CEM-retained samples of treated and control individuals. The EB procedure reweights observations so 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 a first moment condition on the extended set of variables and obtaining a significant overlap, as shown in Table 2 (and Table A.3 in Appendix for other moments). In the pre-processed samples, the *bias,* measured as the standardised percentage difference in means between treated and matched controls, is reduced to zero for all variables with a few exceptions, where it does not exceed -0.2.

Lack of bias in observables does not address the chance of remaining bias stemming from unobservables, particularly those that are time-varying (as the time-invariant is addressed by including lagged outcomes), which would invalidate our identification strategy. However, while we cannot entirely rule out this source of bias, it is reassuring to observe in Figures 2a and 2b the post-matching sample means obtained for each outcome $Y_{i,t}^{1}$ and $Y_{i,t}^{0}$ in the years before the shock. Time-varying unobservables that play a role as confounders would presumably emerge in detectable differences in pre-shock outcomes between treated and matched controls. That no such difference is detectable in the four years before $\bar{t}$ (i.e. year 0 Figures 2a and 2b) suggests that the matching procedure has balanced the distribution of pre-shock outcomes with their observed and unobserved determinants.

On the other hand, average outcomes for the two groups diverge at $\bar{t}+1$ in terms of employment and the probability of being employed full-time; they even diverge at $\bar{t}$ for annual employment income, hourly wages and receipt of disability insurance, signalling an immediate adjustment in the first months after the shock. Figures 2a and 2b may apparently suggest a drop in outcomes (annual income from employment and hourly wages) for the treated group since before the shock occurs. However, the visible drop actually results from the treated outcome means in $\bar{t}$, which average the months before and the months after the shock, being lower than in $\bar{t} - 1$.

FIGURE 2a ABOUT HERE

FIGURE 2b ABOUT HERE

In addition, the apparently increasing trend for employment before year $\bar{t}$ is caused by the sample selection criterion of being employed in year $\bar{t}$, regardless of previous or following employment status. This criterion also explains the decreasing trend in later employment for control individuals and why the employment rate is 100 percent for both treated and matched controls in year $\bar{t}$.

Finally, we estimate parametric models for each outcome (OLS or probit, according to the continuous or binary nature of each outcome), regressed on a selection of demographic, health and labour history variables. Estimation is conducted separately on the subsamples of treated individuals and matched control individuals. Then we obtain ATTs by predicting the counterfactual outcome for each treated unit and integrating the difference between the observed outcome and the predicted counterfactual outcome over the sample distribution of treated individuals' covariates.

4. Robustness

4.1 . Alternative identification strategy for short- and medium-run dynamics: exploiting individuals who are shocked later

One potential limitation of the identification strategy detailed above stems from concerns about the role of any time-varying confounder that is unobserved, particularly one that is uncorrelated with the observed characteristics that are included in the matching adjustment. In our setting, the availability of health risk indicators that are relevant to the treatment assignment appears limited when it is contrasted with the wide array of labour market information. As a result, one might still expect some systematic differences to persist between treated and controls after matching, such as in relation to health risk knowledge, health-related behaviours like smoking and, more generally, expectations about the distribution of future outcome dynamics, including the occurrence of a CVD shock, all of which may be correlated with labour market behaviour.

An approach that the programme evaluation literature proposes and uses convincingly in diverse contexts—see, for example, Fadlon and Nielsen (2020) for an application in the same thematic area—to address such concerns is that of using as a comparison group the set of units that undergo treatment at a later time. In our setting, this approach corresponds to individuals who go on to experience an acute CVD shock a few years later than the treated individuals did and so might be expected to be similar in terms of unobservables and in light of the unpredictable timing of CVD shocks. Although regarded as possibly superior in terms of bias reduction, this identification strategy comes at the cost of shortening the time horizon over which the effect can be credibly measured, that is the time between the year in which treated individuals experience the shock and the later year in which the controls do. The longer the time, the longer the time over which ATTs can be estimated, but also the wider the scope for dissimilarity in unobservables between treated and matched control units.

In the light of such a trade-off and our data's time coverage, as described in Figure 1, we use as potential controls individuals who experienced the same shock five years later, so we obtain estimates for ATTs only up to four years later. For this reason, the approach is presented as an alternative analyses for the short- and medium run, useful in gauging the robustness of the main identification approach.

In practice, the number of treated individuals who are available for matching under this approach is largely unaffected, but the number of potential controls available drops dramatically from about 200 to about 5.5 on average for each treated individual. However, assignment to the potential controls group here relies on later experience of an acute CVD shock, which may reduce the need to adjust for confounders, particularly as far as health characteristics are concerned.

As a result, the matching algorithm is simplified and adapted such that CEM involves only year, age and whether the individual had experienced an acute CVD shock. Exact matching on these variables, uncoarsened, leads to a minor loss of only 2.2 percent of treated individuals and 1 percent of potential controls, suggesting that the treatment assignment criteria contribute to balancing confounders even before matching. After CEM, EB involves all remaining variables (as listed in Table 1) with the addition of interaction terms between the variables maintained in CEM and other basic confounders previously included in CEM but excluded in this round: years from the most recent time the individual was observed as an employee, whether the individual worked under a part-time or a full-time contract and whether the individual worked under a fixed-term or open-ended contract as of $\bar{t}-1$. In this way, it is possible extend balancing to variables' interactions and co-moments, beyond the univariate distributions of separate confounders.

Figures 3a and 3b report the post-matching average outcomes for treated and controls over time, as in Figures 2a and 2b for the main identification approach. Again, time is measured in terms of years since the (treated individuals) shock occurrence $\bar{t}$. Figures 3a and 3b show the years of shock occurrence for the treated (earlier in time) and controls (five years later). Again, average outcomes are substantially aligned in the pre-shock years up to year $\bar{t}-1$. Divergence in average outcomes is detectible beginning in year t in annual earnings, wages, and receipt of disability insurance, while is minor for full-time employment at that point. The same considerations drawn for Figures 2a and 2b apply here. It is worth observing similarities in the slope of connecting lines around the two vertical bars, that is around the year of CVD shock for treated and controls respectively.

Post-matching parametric estimation will further purge the sample means of any remaining lack of balance that is attributable to non-exact matching of the confounders that were adjusted only through EB. For this reason, discussion of post-shock outcomes trends and differences between treated and controls is postponed to Section 5, where the ATT estimates are reported and plotted

FIGURE 3a ABOUT HERE

FIGURE 3b ABOUT HERE

4.2 Selective mortality

CVD is among the leading causes of death in developed countries, including Italy[26]. Between 30 percent and 40 percent of fatal events in the age range 35-64 occur right after the symptoms start and before the individual reaches the hospital (Ministry of Health, 2010). Our analysis uses only individuals who survive to leave the hospital they first entered when they experience the acute CVD. Observing the year of death allows to exclude from the estimation of $ATT_{\bar{t}+v}$ (i.e. v years after the acute CVD shock) individuals who died by $\bar{t}+v$.

However, this approach is not sufficient to address the chance of bias from selective mortality—that is, non-random exit from the estimation sample that is attributable to the higher risk of death after $\bar{t}$ for treated individuals as a consequence of the acute CVD shock they experience. Such endogenous selection would result in underestimation of $ATT_{\bar{t}+v}$. This issue becomes more relevant in long-term analyses, when the balancing of confounders between treated and matched control individuals could worsen progressively over time, as certain types of treated individuals non-randomly leave the estimation sample.

FIGURE 4 ABOUT HERE

To detect the presence of selective mortality patterns, we estimate $ATT_{\bar{t}+v}$ for the death outcome using the main methodology outlined in section 3 to determine whether the acute CVD

[26] For men in particular, CVD diseases are the most common cause of death for those under age 65 in Europe (31% of deaths), compared to about 22% of deaths that are related to cancer.

shocks we study increase the probability of later death. Evidence shown in Figure 4 signals a differential probability of death, conditional on the individual's surviving until he leaves the hospital, that is significant only in $\bar{t}+1$. However, if the individual survives until then, we do not detect a significantly different mortality risk. This result is not necessarily at odds with epidemiologic findings for the general population (e.g., Taylor et al., 2019; Rosato et al., 2015), considering that our results refer to blue-collar workers who did not have a CVD shock in the prior two years and are obtained by exploiting an appropriately selected control group that faces a comparable risk of experiencing the same shock.[27]

Based on these considerations, it seems unlikely that the mortality-based selectivity issue will bias our findings, but, in recognition of the potential threat, we exploit the mortality information to derive mortality weights and assess the sensitivity of our results to their inclusion. Assuming that mortality is selective on observables, mortality weights are obtained by estimating a binary model for probability of death, regressed on the same confounders that we controlled for in the main analysis. Weights are given by the inverse of the estimated probability of survival and are integrated into our main ATT estimation procedure, with results discussed in the next section.

5. Results

In this section, we present results for each outcome in terms of estimated ATTs ($\hat{\tau}_{\bar{t}+v}$) and corresponding relative size effect (RSE), computed as

$$RSE = \frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}} * 100.$$

that is, as the ratio of each ATT $\hat{\tau}_{\bar{t}+v}$ to the mean of the contemporaneous counterfactual outcome $Y^0_{i,\bar{t}+v}$ in the matched controls sample. Results from both the main and the alternative identification approaches are also compared for each outcome.

[27] Estimating mortality effects on the full sample of potential controls reveals sizable and significant ATTs over time. See Figure A.3 in the Appendix.

5.1. Employment, Employment Income, and Receipt of DI

Table 3 reports ATT and RSE estimates for the probability of employment (i.e. working as an employee) and annual income from employment; ATTs and corresponding 95 percent confidence intervals are also depicted in Figures 5a and 5b.

CVD shocks reduce blue-collar workers' likelihood of employment, a result that is in line with studies on other countries. In the main approach, loss of employment occurs beginning in the year after the shock, peaks three years after the shock, reaching an ATT of -8.1 percentage points, and displays only a minor recovery thereafter. Seven years later, having experienced a CVD shock amounts to a 6.5 percentage points lower probability of employment, thus reaching in the longer term a value that is almost three times that of the short-term effect (i.e. $\bar{t}+1$). In terms of RES, the size of the reduction in the probability of employment is largely constant from $\bar{t}+3$ onwards, ranging from 9 percent to 11 percent. Medium-run results obtained using the alternative approach are very similar. Almost unchanged are the results obtained using selective mortality weights (see Appendix Figure A1).

In line with the most of the extant literature, loss of employment entails in immediate (i.e. beginning in the shock year) and substantial loss of income from employment. Our longer-term analysis also reveals how persistent this loss is, amounting to more than 11 percent of the earnings those blue-collar workers would have obtained in the absence of the shock in any of the seven years after the shock, up to a RES of about 13 percent in $\bar{t}+7$.

FIGURE 5a ABOUT HERE

FIGURE 5b ABOUT HERE

TABLE 3 ABOUT HERE

The ATT peak in earnings loss appears in the short term, perhaps in relation to taking sickness leave that is only partially covered by the employer (the remaining replacement being granted trough public transfers). Again, the alternative approach provides similar results, which are also confirmed when accounting for selective mortality through appropriate weighting (see Appendix Figure A2).

Table 4 shows a wider concept of labour market activity, which includes employment, self-employment, and atypical work. This approach allows for possible transitions out of (wage) employment. The results are not statistically different from those obtained on employment. Only in the first year past the shock is the size of the negative ATT for wider labour market activity larger than it is for employment, suggesting a shock-induced reduction in the probability of switching from employment to other forms of labour in the short term. This result might appear to be at odds with the argument of individuals' being "pushed" into self-employment by a lack of opportunities as employees (e.g., Blanchflower and Oswald, 1998). In the self-employment literature, some studies identify health-related limitations as a main driver of moves to self-employment and report a higher percentage of disabled persons among the self-employed, who are better than other workers at accommodating their conditions (e.g., Zissimopoulos and Karoly, 2005). However, in the Italian institutional context, our finding might be explained by the short-run health-related protection granted during employment (i.e. sickness leave paid for six months with the contract maintained and the option to resume working later). Such protection may lower the incentive to switch to other forms of work that, although they may provide more flexibility, grant lower income protection.

Table 4 and Figure 6 show how Disability Insurance offers a major route of exit from employment. Suffering an acute CVD shock leads to a sizeable increase in the probability of being granted a disability benefit. The ATT amounts to almost 16 percentage points in the year of the shock and reaches the value of about 0.24 in $\bar{t}+2$ before remaining constant in the following years. The RSE are always higher than 200 percent.

TABLE 4 ABOUT HERE

FIGURE 6 ABOUT HERE

FIGURE 7 ABOUT HERE

Social insurance routes of exit from the labour market in Italy other than DI can substitute for DI. Early retirement programmes like the so-called seniority pension are widely exploited by employees who are ineligible for DI (like the individuals in our control group). DI is by far more generous than early retirement schemes for those who have a choice. For a more complete picture on social insurance, we construct a binary indicator to identify individuals who are out of work and do not receive any social insurance benefit. The ATT for this outcome, whose dynamic response is represented in Figure 7, is never statistically different from zero during the observational period except for $\bar{t}+3$, when the temporary DI benefits granted in the year of the shock occurrence come to their first renewal phase.

5.2 Labour outcomes, conditional on remaining in employment

Tables 5 and 6 and Figures 8a–d, report the estimated ATTs and RSEs for outcomes observed conditional on remaining in employment. Table 5 considers annual income from employment and the probability of being employed full-time (versus part-time), while Table 6 shows hourly wages[28] and the probability of working with the same employer as in $\bar{t}$ (year of shock). As evident in Figure 8a, even workers that continue employment after an acute CVD shock suffer significant losses in earnings, again with a peak in $\bar{t}+1$, perhaps because of taking sickness leave. In relative terms, the loss amounts to about 10 percent in the first year; later, while reduced in size (up to a 4% loss in $\bar{t}+7$), it remains significant throughout the longer run. Clearly, exit from employment explains the quantitative difference between the relative effect

[28] We compute hourly wages by combining information on labour income, paid weeks and the type of work (part-time or full-time). The WHIP data does not have the number of hours worked, but we do have the distribution of hours worked for male blue-collar workers from the EU QLFS data. We find that this distribution is highly concentrated around two mass points: 20 hours for part-timers and 40 hours for full-timers (with no dispersion in the latter case, which is consistent with legal provisions). In computing the hourly wage, we attribute 20 hours of work to part-time contracts and 40 hours to full-time contracts. More than 94% of prevalent annual contracts in our data are full-time.

measured on unconditional (Table 3) and conditional (Table 5) annual labour income. The alternative approach confirms these results.

TABLE 5 ABOUT HERE

TABLE 6 ABOUT HERE

FIGURE 8a ABOUT HERE

FIGURE 8b ABOUT HERE

Table 5 and Table 6 shed light on the channels that may explain why workers suffer a reduction in annual income, despite remaining employed. Table 5 addresses the possibility of an adjustment in hours worked by looking at the probability of working full time. The probability of working full time is substantially unaltered—see also Figure 8b—with respect to what would have happened in the absence of the CVD shock. In only a few years (from $\bar{t} + 2$ to $\bar{t} + 5$, according to the main approach) the ATT of full-time (versus part- time) employment is significant and negative, yet small. The RSE in those years does not exceed 3 percent and is only slightly larger (and extending to t+1) under the alternative approach. Lack of hours adjustment is not surprising because voluntary part-time work is uncommon in Italy, particularly among the men blue-collar workers studied here.

We also investigate hourly wage adjustments—see Figure 8c and Table 6—and find negative and significant ATTs. In relative terms, the magnitude is low, ranging from 2 percent to 5 percent in the first year after the shock, and tends to lose significance over time. The later wage dynamics for individuals in the treatment and control groups reveal, consistent with a downward wage rigidity scenario, that the negative effect is mostly traceable to the lower nominal growth experienced by individuals who have a CVD shock with respect to matched controls.

Another mechanism through which labour income losses might occur is transition to another employer, motivated by the search for tasks that accommodate disability, even with reduced pay. In our case—see Figure 8d and Table 6—the probability of working with the same employer as at the time of the shock approaches significance with a small positive point estimate only in $\bar{t}+1$ under the alternative strategy. The timing of this increase matches that observed for the reduction in transitions to self-employment or atypical work, and corresponds to the time when sickness protection is being granted under employment. In no other year do transitions to other employer appear as an adjustment channel that is actually pursued by Italian blue-collar workers.

FIGURE 8c ABOUT HERE

FIGURE 8d ABOUT HERE

5.3 Employment, employment income and receipt of DI in the long(er) run

Table 7 reports results for the probability of employment, annual labour income and receipt of DI benefits in the (even) longer run, up to $\bar{t}+8$ and $\bar{t}+9$, which can be estimated only for workers who experience CVD shocks in 2003-2004 (for $\bar{t}+8$) and 2003 (for $\bar{t}+9$). We report RSE to enhance comparability across results obtained from these restricted subsamples (although corresponding ATTs are shown in Appendix Table A4).

Exploiting the two subsamples for which long-run outcomes can be observed, Table 7 illustrates results extended up to $\bar{t}+8$ and $\bar{t}+9$[29]. Overall, the results highlight the persistence of the long-term effect for all outcomes.

The effects in $\bar{t}+9$ deviate from those in previous years/periods: The relative reduction in employment probability jumps to 18 percent (from a reduction of 9.5 percent in 2011). Similarly, annual earnings drop suddenly in terms of relative effect size from a 14.5 percent reduction to a 22 percent reduction. While we cannot rule out the chance of effect dynamics specific to the ninth year after the shock, the 2012 evidence fits the important legislative change

[29] A one-to-one relationship between time elapsed since the shock and the calendar year can be established: $\bar{t}+9$ corresponds to the calendar year 2012.

of the Monti-Fornero reform of labour law (and partly the September 2011 Berlusconi reform), which significantly reduced firing restrictions in medium-sized and large firms.

TABLE 7 ABOUT HERE

5.4. Heterogeneous effects

5.4.1 Quality of healthcare received at first treatment hospital

To our knowledge, the only work that considers the quality of treatment received as a mechanism that affects the size of labour adjustment is Lundborg et al. (2015). Seeking to explain differences in the effect of health shocks among differently educated groups—the higher educated deemed more likely to access better quality hospitals—the authors proxy quality with whether the hospitalisation occurred in a university hospital. In contrast, we proxy quality with whether the hospital in which the individual was first hospitalised offered both an intensive care ward and a coronary unit[30], as opposed to only one or none (lower quality). This indicator seems to be more directly pertinent to the type of shocks we cover based on wide epidemiological evidence[31]. We were able to retrieve this information about the hospital wards for 74 percent of treated individuals.

High-quality hospitals are spread throughout the country[32], so it seems unlikely that heterogeneous effects reflect geography (e.g. higher quality concentrated in the North of the country, also featuring higher labour market opportunities). Patients do not choose the hospital where they are initially treated, as the choice is made by health professionals based on distance

[30] Historical data on public and private hospitals wards were taken from the Ministry of Health (2020).
[31] In the epidemiological literature, several studies focus on the impact of certain hospital structures on clinical outcomes. Cashin et al.(2020) highlight the current limitations of performance indicators in OECD countries and report that "in practice measurement typically relies on measures of the structure of care (for example, the presence of certain elements of service infrastructure such as a dedicated stroke unit)" (p. 8, Health provider P4P and strategic health purchasing). For instance, Lee, Clark, Namburi, et al. (2020) find that the implementation of a dedicated cardiac surgical intensive care service leads to significant improvements in several clinical outcomes, with the greatest benefit seen in patients who are undergoing coronary artery bypass. In the respiratory field, Agabiti et al. (2010) point out that, among the structurally related factors of variability across hospitals, the presence of a specialist respiratory ward is particularly important in improving clinical outcomes in chronic obstructive pulmonary disease. Na et al. (2016) go deeper and, after emphasising that the introduction of dedicated coronary unit in the early '60 in American hospitals reduced in-hospital mortality by a half among patients with acute myocardial infarction, conclude that the presence of a dedicated cardiac intensivist is associated with a reduction in cardiac intensive care unit mortality rates in patients with CVD who require critical care.
[32] High-quality hospitals are 83% of all hospitals in the North, 74% in the centre, and 64% in the South.

from the location of the health shock and an initial assessment of case severity, with more severe cases likely to be directed to high-quality hospitals, such as those that are equipped with both intensive care and coronary units[33].

FIGURE 9a ABOUT HERE

FIGURE 9b ABOUT HERE

Figure 9a reports results for employment and receipt of DI based on quality of treatment; the reduction in employment is much lower if the individual was hospitalised in a high-quality hospital. Moreover, partial recovery over time for these individuals can be detected, which does not happen for those treated in lower quality hospitals. As a result, the hospital quality's effect on employment tends to increase over time (e.g. in $\bar{t}+1$, RSE is -8 percent in high-quality hospitals and -12 percent in low-quality hospitals; in $\bar{t}+7$, RSEs are -8 percent and -20 percent respectively). A qualitatively similar and corresponding (greater effects for those treated in low-quality hospitals) dynamic is found for receipt of DI. The findings for annual income from employment (Figure 9b), mirror those on employment in terms of both level and shape. Seven years after the shock, the income loss amounts to 10 percent of the mean counterfactual if the individual was treated in a high-quality hospital, and to 23 percent otherwise.

These findings are likely to represent a lower bound of the true differential effect of hospital quality on labour market outcomes; because of the patient allocation rules, high-quality hospitals may end up treating more severe cases, leading to a downward bias in the estimated differential effects. Finally, we acknowledge that the role of high-quality treatment deserves further investigation in terms of channels because, while patients do not usually choose the hospital of first treatment, the allocation to hospitals might reflect endogenous residential decisions.

5.4.2 Firm size

[33] Patients who arrive autonomously to the (closest) hospital emergency unit are immediately screened and, if appropriate, redirected to a high-quality hospital without prior hospitalisation at the emergency unit hospital.

To our knowledge, no previous work investigates whether the size of adjustment varies by firm size (measured as of $\bar{t}-1$, i.e. just before the shock). In our context, firm size captures the extent of employment protection granted[34], but firms of larger size also feature a wider scope of organizational practices that encourage disabled workers' inclusion, such as workplace training, accommodation of disability, and reallocation to new tasks or branches in the firm (e.g. Bassanini et al., 2007).

Figure 10a displays ATTs, distinguishing firms with up to 15 employees, from 16 to 250 employees, and more than 250 employees[35], and shows evidence of a negative gradient in employment reduction by firm size. In small firms (which are not subject to the Worker's Statute, which raises firing costs[36]), the RSE increases over time from 9.1 percent in $\bar{t}+1$ up to 18.6 percent in $\bar{t}+7$, figures that are halved in the case of medium-sized firms and that permanently lose significance for large firms. A corresponding gradient occurs in receipt of DI, with RSEs amounting to 420 percent in $\bar{t}+2$ in small firms and to 270-300 percent in medium-sized and large firms. A qualitatively similar gradient emerges in annual income (Figure 10b), where no statistically significant income loss is detected in large firms, although its inverted U-shaped ATT profile suggests that some significant effect may emerge in the longer run. These results are more reliable in the short run since workers may change firms (and firm size) after a shock.

FIGURE 10a ABOUT HERE

FIGURE 10b ABOUT HERE

[34] Hiring rates based on Contini (2009) have been estimated at 50% in smaller firms, declining to 25% in firms with more than 200 employees).

[35] The sample distribution of firm size that emerges from Table 2 differs from that reported in footnote 8, which provides evidence of a high percentage of micro and small firms. This occurs because *WHIP&Health* offers a sample representative of workers, rather than firms, thus over-representing larger firms.

[36] See section 2, footnote 12.

5.4.3 Individuals' characteristics: age and type of the shock

Older individuals might be less attached to the labour market because of available routes of permanent exit from the labour market, such as early retirement or disability pensions. Human capital destruction following a shock is also likely to be higher for older workers (García-Gómez et al., 2013), who may also experience more severe shocks. In a model of health capital formation, investments in the health-specific human capital that supports returning to work may be more attractive to younger individuals, given expected earnings-related returns over a longer time horizon (Charles, 2003). A larger reduction in employment for older worker has emerged in a few previous studies (e.g. Jones et al., 2020) and is confirmed in ours, with the RSE for workers aged above the median of 52 years old two to three times larger than that for younger workers. Corresponding ATTs are reported in Appendix, Figures A.4a and A.4b.

Finally, we consider the specific type of CVD shock experienced, distinguishing ischemic heart diseases from cerebrovascular diseases, the latter of which is often a more severe condition that leads to greater impairment[37]. As in Trevisan et al. (2016), we find that cerebrovascular leads to a larger reduction in employment and labour income than ischemic heart diseases do. Our long-run evidence, reported in Appendix Figures A.5a and A.5b, confirms that the difference is persistent over time. Heterogeneity by shock type in our sample can barely be traced to differences in shock-specific age at onset, as the median age of onset for the two conditions are similar—52 and 51—suggesting that age and the type of shock are broadly independent dimensions of heterogeneity.

6. Discussion

Our findings offer a novel representation of the long-term consequences of health shocks on labour market outcomes in a rigid and highly regulated labour market: These frictions find little

[37] Shock severity has an *a priori* undefined effect on preference for leisure or work. A more severe shock may increase the value of leisure as a consequence of an expected lowered life expectancy or reduce its value by limiting the possibility of performing or enjoying leisure activities.

room for adjustment in the hours or wage margins for Italian blue-collar workers. The bulk of response emerges along the extensive margin in terms of employment exits in a setting where low hiring rates hamper later return to work: On our sample, among those who leave employment within the first year after the shock, only 27 percent resume employment within the following six years. Relatedly, transitions to less demanding jobs do not generally offer a viable route of adjustment in the medium to long term, suggesting that employment exit might become an absorbing state. Indeed, the long-term analysis clarifies that loss of employments persists for at least nine years after the health shock and presumably thereafter, entailing a substantial earnings loss. A relatively generous social insurance system compensates permanently yet partially (i.e. with a gross replacement rate of about 60 percent for a representative worker satisfying relatively mild contribution requirements) for such earnings losses. We do observe sizeable rates of taking up DI and no evidence suggesting a significant increase in the likelihood of being out of work and not receiving social insurance support.

Our findings can be compared with García-Gómez et al. (2013) and Fadlon and Nielsen (2020), studies that are also based on administrative data, cover other European countries that feature more flexible labour markets (the Netherlands and Denmark, respectively), and analyse the full range of workers' ages[38]. In fact, our results are similar to those of García-Gómez et al. (2013): For men's employment, they report a small RSE in $\bar{t}+1$, increasing to 7.2 percent in the following year and showing no recovery afterward. Our effect in $\bar{t}+2$ is slightly higher (8.8 percent), but this is consistent with the different type of shock García-Gómez et al. consider[39]. The impact on receipt of DI is also comparable, with their RSE in the range of 300–350 percent, which is consistent with greater access to DI in the Netherlands with respect to

[38] Less comparable with our paper in terms of set-up is the contribution by Dobkin et al. (2018) for the US, documenting a strong negative impact on income and employment in the short run in a context in which, with respect to European countries, only a minor part of the realized loss for workers aged 50-59 is socially insured.

[39] García-Gómez et al. (2013) consider a wider category of acute hospital admission; in addition to diseases of the circulatory system, they include external causes of injury, digestive system hospitalisations, and others. They perform a sensitivity analysis by specific type of health shock and report that the negative impact of heart attacks and strokes is the strongest among the causes of hospitalisation they analysed.

Italy.[40] As to annual earnings, they find a much lower RSE (e.g. a drop of 4.5 percent in $\bar{t}+2$ against our 11 percent), but the comparison is flawed by the underlying income measures, as they consider annual personal income (including income from additional sources, which are unlikely to be affected by the health shock)[41], rather than labour income only. Fadlon and Nielsen (2020) find a stronger negative RSE for employment in the short run, ranging from -12 percent in $\bar{t}+1$ and increasing to -17 percent in $\bar{t}+3$, an increase that is similar to our findings. Fadlon and Nielsen also document a stronger decline in (unconditional) annual earnings in the first year after the shock (-15 percent versus our -12 percent), increasing to -19 percent (versus our -11 percent) two years later, paralleling the results for employment.

Overall, considering the underlying differences in method, measurement, definition of health shock, and estimation samples, our findings are broadly in line with these studies, despite the differing institutional environments (particularly in terms of labour) from which evidence is drawn.

Despite this similarity, the underlying options available to workers, and the channels that lead to similar impacts are likely to differ and to have different consequences for individuals' welfare. More flexible labour markets allow individuals to choose whether to apply for a DI benefit and leave previous employment based on preferences for leisure and risk, or to exploit other ways to adjust, such as switching to part-time work, accepting a lower pay, or moving to less-demanding occupations. Even if an individual exits the labour market in the short term, they have a plausible prospect of re-entry in the future.

In contrast, in a rigid labour market like the Italian one, such adjustments are rarely available. In practice, remaining at work might be problematic for individuals who experience

[40] According to Trevisan and Zantomio (2016), the disability recipiency rate in 2005 was 8.7% in the Netherlands and 5.5% in Italy.
[41] Christelis et al. (2009) use SHARE data and report that, among the elderly, the share of capital income as a percentage of total annual income in 2004 was the highest in the Netherlands among the European countries that were analysed.

a severe health shock, particularly if they cannot reduce their work hours. Currently, firms avoid offering part-time options because they entail lower productivity (e.g. in relation to the fixed cost of hiring a new worker) and ultimately higher costs when there is no chance of compensating less-productive individuals by adjusting their wages (Devicienti et al., 2015). A viable policy recommendation is to provide public incentives for firms to agree on voluntary part-time work as a way to reconcile work and health-related limitations (Devicienti et al., 2015). Acting on the wage mobility side appears to be a less viable option, at least in the short term, given the extensive role currently played by collective bargaining. Application for a disability pension often remains the only available alternative to continuing the pre-shock employment. Indeed, the existence of a relatively generous and accessible DI programme counteracts labour market rigidities. However, despite such income protection, leaving employment permanently entails additional losses. 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 relate work to wellbeing through self-esteem, motivation, a sense of purpose, and social interactions (e.g. Hackett et al., 2012; Spelten et al., 2002; Vestling et al., 2013). Therefore, the overall welfare loss following a severe health shock is likely to be much higher in institutional contexts like the Italian one, that broadly offer only exit from the labour market as a route of adjustment.

Conclusions

The extension of work life induced by social security sustainability increases the chance for older workers' health to deteriorate, along with the related economic risk. The present study shows how the work-related response to acute cardiovascular shocks experienced by workers evolves in the long run, extending the time horizon covered in previous studies to up to nine years after the shock. The analysis is conducted in Italy, a country featuring a rigid and highly regulated labour market with respect to countries that previous studies usually cover, which helps to clarify the role of particular policy instruments and institutional features in mitigating or exacerbating the effects of health shocks on employment and other labour market outcomes. Based on administrative data that offers a long record of employment and social security and hospitalisation histories, we exploit multiple identification strategies to remove bias from observable and unobservable confounders by applying matching and parametric regression techniques on comparison groups that include both observationally identical individuals who are not affected by health shocks and individual who experience them a few years later.

We acknowledge that the evidence we offer is subject to limitations. To begin with, our evidence concerns only a segment of the labour force, blue-collar workers, as they are more exposed than others are to the risk of work-related limitations since they are generally employed in more physically demanding tasks. Another limitation of the study is that it concerns only individuals who experience acute CVD conditions, although other types of health deteriorations might affect workers as well. Moreover, while using administrative data presents major advantages, it also has drawbacks, as the limited coverage of relevant topics hampered the scope for further heterogeneity analyses and limited the range of observed confounders we could exploit for identification.

Bearing these limitations in mind, our results, which are robust across identification strategies and to the inclusion of selective mortality weights, show that the sizeable reductions in employment and labour income observed in the short run, as well as the significant increase in receipt of DI, persist in the long run, while hours and wage adjustments appear limited. New heterogeneity analyses based on hospital quality and firm size shed light on the institutional mechanisms that foster recovery, which is helpful in pinpointing the need for policy interventions, while previously investigated gradients in response by individual characteristics like age and type of shock are confirmed. Overall, compared to existing studies on other European countries that featuring more flexible labour markets, the work- and income-related adjustment observed in Italy is not dissimilar in terms of employment reduction and receipt of DI. However, in Italy these similar results seem more likely to arise as a forced route of adjustment, rather than being selected as the preferred option, resulting in welfare implications. Even if a relatively generous social insurance system permanently (yet partially) contributes to income maintenance, our findings question the appropriateness of existing labour inclusion policies for unhealthy workers, besides their longer-run income opportunities.

References

Agabiti, N., Belleudi, V., Davoli, M., Forastiere, F., Faustini, A., Pistelli, R., Fusco, D., and Perucci, C. A. (2010). "Profiling Hospital Performance to Monitor the Quality of Care: The Case of COPD." *European Respiratory Journal*, 35: 1031–1038.

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.

Au, D. W. H., Crossley, T. F., and 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.

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

Bassanini, A., Booth, A., Brunello, G., De Paola, M., and Leuven, E. (2007). "Workplace Training in Europe." In: Brunello, G., Garibaldi, P., and Wasmer, E. (eds.). *Education and Training in Europe*. Oxford: Oxford University Press, pp. 8–13.

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.

Benitez-Silva, H., Buchinsky, M., Chan, H., Cheidvasser, S., Rust, J. (2004). "How Large is the Bias in Self Reported Disability?" *Journal of Applied Econometrics* 19(4): 649-670.

Berton F., Richiardi, M., and Sacchi S. (2012). *The Political Economy of Work Security and Flexibility: Italy in Comparative Perspective*. Bristol: The Policy Press.

Blanchflower, D. G., and Oswald, A. J. (1998). "What Makes an Entrepreneur?" *Journal of Labor Economics* 16(1), 26–60.

Bradley, C. J., Neumark, D., and Barkowski, S. (2013). "Does Employer Provided Health Insurance Constrain Labour Supply Adjustments to Health Shocks? New Evidence on Women Diagnosed with Breast Cancer." *Journal of Health Economics* 32(5): 833-849.

Braunwald, E., Mann, D. L., Zipes, D. P., Libby, P., and Bonow, R. O. (2015). *Braunwald's Heart Disease: A Textbook of Cardiovascular Medicine*. Philadelphia, PA: Elsevier/Saunders.

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.

Cai, L., Mavromaras, K., and Oguzoglu, U. (2014). “The Effects of Health and Health Shocks on Hours Worked.” *Health Economics* 23(5): 516-528.

Cashin, C., Chi, Y., Smith, P., Borowitz, M, and Thomson, S. (2020). “Health provider P4P and strategic health purchasing.” In: *Paying for Performance in Health Care: Implications for health system performance and accountability.* Cashin, C., Chi, Y., Smith, P., Borowitz, M, and Thomson, S. (eds.) European Observatory on Health Systems and Policies Series: McGraw Hill, pp. 3-21.

Charles, K. (2003). “The Longitudinal Structure of Earnings Losses among Work-Limited Disabled Workers.” *Journal of Human Resources* 38(3): 618-646.

Christelis, D., Jappelli, T., Paccagnella, O., and Weber, G. (2009). “Income, Wealth and Financial Fragility in Europe.” *Journal of European Social Policy* 19(4): 359-376.

Coile, C. (2004). “Health Shocks and Couples’ Labour Supply Decisions.” NBER Working Paper No. 10810.

Contini, B. (2019). *Dai “lavori usa e getta” al Jobs Act*. Rome: Aracne Editrice.

Currie, J., and Madrian, B. C. (1999). “Health, Health Insurance and the Labor Market.” In: Ashenfelter, O., and Card, D. (eds.) *Handbook of Labor Economics* (vol. 3C). New York: Elsevier Science, pp. 3309-3416.

Daniel, K., Wolfe, C. D., Busch, M. A., and McKevitt, C., (2009). “What are the Social Consequences of Stroke for Working-Aged Adults? A systematic review.” Stroke 6: 431-40.

Dano, A. M. (2005). “Road Injuries and Long-Run Effects on Income and Employment.” *Health Economics* 14(9): 955-970.

Devicienti, F., Maida, A., and P. Sestito (2007). “Downward Wage Rigidity in Italy: Micro-Based Measures and Implications.” *The Economic Journal* 117 (November): F530–F552.

Devicienti, F., Grinza, E., and 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.

Dobkin, C., Finkelstein, A., Kluender, R., and Notowidigdo, M. J. (2018). “The economic consequences of hospital admissions.” *American Economic Review* 108(2): 308–352.

European Commission. (1999). *Compendium: Good practice in employment of people with disabilities*. Office for Official Publications of the European Communities: Luxemburg.

European Commission. (2009). *Employment in Europe*. Office for Official Publications of the European Communities: Luxemburg.

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

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.

Fadlon, I., and Nielsen, T. H. (2020). "Family Labor Supply Responses to Severe Health Shocks: Evidence from Danish Administrative Records." *American Economic Journal: Applied Economics* (forthcoming).

Flores M., Fernández, M., and 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).

García-Gómez, P. (2011). "Institutions, Health shocks and Labour Market Outcomes across Europe." *Journal of Health Economics* 30(1): 200-213.

García-Gómez P., Jones, A. M., and Rice, N. (2010). "Health Effects on Labour Market Exits and Entries." *Labour Economics*, 17(1): 62-76.

García-Gómez P., and Lopez Nicolás, A. (2006). "Health Shocks, Employment and Income in the Spanish Labour Market." *Health Economics* 15(9): 997-1009.

García-Gómez, 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.

Grossman, M. (1972). "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy* 80(1): 223-255.

Gupta, N. D., Kleinjans, K. J., and Larsen, M. (2015). "The Effect of a Severe Health Shock on Work Behavior: Evidence from Different Health Care Regimes." *Social Science Medicine* 136: 44–51.

Haan, P., and Myck, M. (2009). "Dynamics of Health and Labour Market Risks." *Journal of Health Economics*, 28(6): 1116-1125.

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

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.

Hainmueller, J., and Xu, Y. (2013). “ebalance: A Stata Package for Entropy Balancing.” *Journal of Statistical Software* 54(7): 1-18.

Halla, M., and Zweimüller, M. (2013). “The Effect of Health on Earnings: Quasi-Experimental Evidence from Commuting Accidents.” *Labour Economics* 24: 23-38.

Heinesen, E., and 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.

Ho, D., Imai, K., King, G., and Stuart, E. A. (2007). “Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference.” *Political Analysis* 15: 99-236.

Holmlund B. (2014). “What do labor market institutions do?” *Labour Economics* 30(2014): 62-69.

Iacus, S. M., King, G., and Porro, G. (2011). “Multivariate Matching Methods that are Monotonic Imbalance Bounding.” *Journal of the American Statistical Association* 106: 345-361.

ISTAT. (2017). *Annuario Statistico Italiano*, Rome: ISTAT.

Jäckle, R., and Himmler, O. (2010). “Health and Wages: Panel Data Estimates Considering Selection and Endogeneity.” *Journal of Human Resources* 45(2): 364-406

Jones, A. M., Rice, N., and Zantomio, F. (2020). “Acute Health Shocks and Labour Market Outcomes: Evidence from the Post Crash Era.” *Economics and Human Biology*, 36: 1-17.

Lee, L. S., Clark, A. J., Namburi, N., et al. (2020). “The Presence of a Dedicated Cardiac Surgical Intensive Care Service Impacts Clinical Outcomes in Adult Cardiac Surgery Patients.” *Journal of Cardiac Surgery* 35: 787–793.

Lindeboom, M., Llena-Nozal, A., and van der Klaauw, B. (2016). “Health Shocks, Disability and Work.” *Labour Economics* 43: 185-200.

Lundborg, P., Nilsson, M., and Vikström, J. (2015). “Heterogeneity in the Impact of Health Shocks on Labour Outcomes: Evidence from Swedish Workers.” *Oxford Economic Papers* 67(3): 715-739.

Maczulskij, T., and Böckerman, P. (2019). “Harsh Times: Do Stressors Lead to Labor Market Losses?” *The European Journal of Health Economics* 20: 357–373.

Ministry of Health (2020). “Posti Letto per Stabilimento Ospedaliero e Disciplina.” Available at: http://www.dati.salute.gov.it/dati/dettaglioDataset.jsp?menu=dati&idPag=96

Ministry of Health (2018). Programma Nazionale Esiti - PNE 2018. Available at https://pne.agenas.it/index.php

Ministry of Health. (2010). Relazione sullo Stato Sanitario del Paese: 2009-2010. Chapter 2.1. Rome.

Moran, J., Farley-Short, P., and Hollenbeack, C. S. (2011). “Long Term Employment Effects of Surviving Cancer.” *Journal of Health Economics* 30(3): 505-514.

Na, S.J., Chung, C.R., Jeon, K., Park, C.M., Suh, G.Y., Ahn, J.H., Carriere, K.C., Song, Y.B., Choi, J.O., Hahn, J.Y., Choi, J.H., Choi, S.H., On, Y.K., Gwon, H.C., Jeon, E.S., Kim, D.K., Yang, J.H. (2016). Association Between Presence of a Cardiac Intensivist and Mortality in an Adult Cardiac Care Unit. *Journal of The American College of Cardiology*, 68(24): 2637-2648.

OECD. (1994). The Employment Outlook, chapter 5.

OECD. (2014). Older workers scoreboard. Available at: http://www.oecd.org

OECD. (2016). Older Workers Scoreboard, Available at: http://www.oecd.org

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

OECD. (2019). Labor Force Statistics. Series: Incidence of FTPT employment - common definition; Incidence of involuntary part time workers. Available at: OECD. Stat

O'Neill, S., Kreif, N., Greive, R., Sutton, M., and Sekhon, J. (2016). “Estimating Causal Effects: Considering Three Alternatives to Difference-in-Differences Estimation.” *Health Services and Outcomes Research Methodology* 16: 1-21

Rosenbaum, P. R., and Rubin, D. B. (1983). “The Central Role of the Propensity Score in Observational Studies for Causal Effects.” *Biometrika* 70(1): 41-55.

Smith, J. (2005). “Consequences and Predictors of New Health Events.” In: Wise, D. (ed.) *Analyses in the Economics of Ageing*. Chicago: University of Chicago Press.

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.

Spelten, E. R., Sprangers, M. A., and Verbeek, J. H. (2002). “Factors Reported to Influence the Return to Work of Cancer Survivors: a Literature Review.” *Psycho-oncology* 11: 124-131.

Taylor, C. J., Ordóñez-Mena, J. M., Roalfe, A, K., Lay-Flurrie, S., Jones, N. R., Marshall, T., and Hobbs, F. D. R. (2019). “Trends in Survival after a Diagnosis of Heart Failure in the United Kingdom 2000-2017: Population Based Cohort Study.” *British Medical Journal*, 364: l223

Trevisan, E., and 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.

Trygged, S., Ahacic, K., and Kareholt, I. (2011). “Income and Education as Predictors of Return to Working Life among Younger Stroke Patients.” *BMC Public Health* 11: 742.

Vestling, M., Ramel, E., and Iwarsson, S. (2013). “Thoughts and Experiences from Returning to Work after Stroke.” Work 45: 201-211.

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

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

Zissimopoulos, J. M., and 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.

Zucchelli, E., Jones, A. M., Rice, N., and 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.

Table 1a: Description of variables: demographics, health and work history

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 (centre)
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 was ever hospitalised for CVD until ($\bar{t}-1$)
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 was ever hospitalised 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 on sick leave until ($\bar{t}-1$)
	Work History
Work_active_cum	Number of years the person was an employee, self-employed, or an atypical worker until ($\bar{t}-1$)
Nemployee_cum	Number of contracts as an employee until ($\bar{t}-1$)
Rate_employee_cum	Percentage of years as an employee over the total time as a worker until ($\bar{t}-1$)
Jobloss_cum	Number of involuntary job losses experienced until ($\bar{t}-1$)
New_firm_cum	Number of employer changes until ($\bar{t}-1$)
Nblue_collar_cum	Number of contracts as a blue-collar worker until ($\bar{t}-1$)
Nwhite_collar_cum	Number of contracts as a white-collar worker until ($\bar{t}-1$)
Rate_perm_cum	Permanent contracts as a percent of total contracts 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 was ever 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	Years self-employed as a percent of the total years as a worker until ($\bar{t}-1$)
Days_self_cum	Total number of days self-employed until ($\bar{t}-1$)
Rate_atypical_cum	Years as an *atypical worker* as a percent of the total years as a worker until ($\bar{t}-1$)
N_atypical_cum	Total number of contracts as an atypical worker until ($\bar{t}-1$)

Source: WHIP&Health

Table 1b: Description of variable: pre-shock employment and lagged outcomes

Variable name	Description
Characteristics of the last (pre-shock) job as an employee	
Dist_last1_employee	Time between the treatment year and the last job as an employee as of ($\bar{t}$ −1)
Dist_last2_employee	Time between the treatment year and the second previous job as an employee as of ($\bar{t}$ −1)
Dist_last3_employee	Time between the treatment year and the third previous job as an employee as of ($\bar{t}$ −1)
Dist_last4_employee	Time between the treatment year and the fourth previous job as an employee as of ($\bar{t}$ −1)
Last_sick_leave	Number of weeks on sick leave in the last job as an employee as of ($\bar{t}$ −1)
Last_weeks_paid	Number of paid weeks in the last job as an employee as of ($\bar{t}$ −1)
Last_fix_term	Equal to 1 if the person was working under a permanent contract during the last job as an employee as of ($\bar{t}$ −1)
Last_jtenure	Number of years under the same employer before the last job as an employee as of ($\bar{t}$ −1)
Last_awork_north	Area of work (north) of the last job as an employee as of ($\bar{t}$ −1)
Last_awork_center	Area of work (centre) of the last job as an employee as of ($\bar{t}$ −1)
Last_awork_south&Isl.	Area of work (south or islands) of the last job as an employee as of ($\bar{t}$ −1)
Last_awork_abroad	Area of work (abroad) of the last job as an employee as of ($\bar{t}$ −1)
Last_apprentice	Job qualification (apprentice) of the last job as an employee as of ($\bar{t}$ −1)
Last_bluecollar	Job qualification (blue-collar) of the last job as an employee as of ($\bar{t}$ −1)
Last_whitecollar	Job qualification (white-collar) of the last job as an employee as of ($\bar{t}$ −1)
Last_manager	Job qualification (manager) of the last job as an employee as of ($\bar{t}$ −1)
Last_director	Job qualification (director) of the last job as an employee as of ($\bar{t}$ −1)
Last_firm_015	Firm size (0 to 15 employees) as of ($\bar{t}$ −1)
Last_firm16250	Firm size (16 to 250 employees) as of ($\bar{t}$ −1)
Last_firm_250	Firm size (more than 250 employees) as of ($\bar{t}$ −1)
Last_sec_agriculture	Sector of activity (agriculture) of the last job as an employee as of ($\bar{t}$ −1)
Last_sec_manufac	Sector of activity (manufacturing) of the last job as an employee as of ($\bar{t}$ −1)
Last_sec_construc	Sector of activity (construction) of the last job as an employee as of ($\bar{t}$ −1)
Last_sec_extraction	Sector of activity (mineral extraction) of the last job as an employee as of ($\bar{t}$ −1)
Last_sec_energy	Sector of activity (energy) of the last job as an employee as of ($\bar{t}$ −1)
Last_sec_trade	Sector of activity (trade) of the last job as an employee as of ($\bar{t}$ −1)
Last_sec_foodservices	Sector of activity (food and hotel services) of the last job as an employee as of ($\bar{t}$ −1)
Last_sec_transports	Sector of activity (transports) of the last job as an employee as of ($\bar{t}$ −1)
Last_sec_finance	Sector of activity (finance services) of the last job as an employee as of ($\bar{t}$ −1)
Last_sec_realestate	Sector of activity (real estate services) of the last job as an employee as of ($\bar{t}$ −1)
Last_public	Sector of activity (public services) of the last job as an employee as of ($\bar{t}$ −1)
Lagged outcomes	
Last1_lab_income	Annual earnings from the last job as an employee as of ($\bar{t}$ −1)
Last2_lab_income	Annual earnings from the second previous job as an employee as of ($\bar{t}$ −2)
Last3_lab_income	Annual earnings from the third previous job as an employee as of ($\bar{t}$ −3)
Last4_lab_income	Annual earnings from the fourth previous job as an employee as of ($\bar{t}$ −4)
Last1_hwage	Hourly wage of the last job as an employee as of ($\bar{t}$ −1)
Last2_hwage	Hourly wage of the second previous job as an employee as of ($\bar{t}$ −2)
Last3_hwage	Hourly wage of the third previous job as an employee as of ($\bar{t}$ −3)
Last4_hwage	Hourly wage of the fourth previous job as an employee as of ($\bar{t}$ −4)
Last1_fulltime	Equal to 1 if the person was full-time employed in the last job as an employee as of ($\bar{t}$ −1)
Last2_fulltime	Equal to 1 if the person was full-time employed in the second previous job as of ($\bar{t}$ −2)
Last3_fulltime	Equal to 1 if the person was full-time employed in the third previous job as of ($\bar{t}$ −3)
Last4_fulltime	Equal to 1 if the person was full-time employed in the fourth previous job as of ($\bar{t}$ −4)
Last1_wemployee	Equal to 1 if the person was an employee in $\bar{t}$-1
Last2_ wemployee	Equal to 1 if the person was an employee in $\bar{t}$-2
Last3_ wemployee	Equal to 1 if the person was an employee in $\bar{t}$-3
Last4_ wemployee	Equal to 1 if the person was an employee in $\bar{t}$-4

Source: WHIP&Health

Table 2a: Pre- and post-matching balance: demographics, labour and health history

	Pre-matching				Post-matching			
	Mean				Mean			
	Treated	Controls	%bias	p-value	Treated	Controls	%bias	p-value
	(1590)	*(766,299 obs.)*			*(1559)*	*(292,733 obs.)*		
Year	2004	2004	1,8	0,46	2004	2004	0,0	0,999
Age	50,52	39,70	127,6	0,00	50,47	50,47	0,0	0,998
Abirth_north	0,27	0,36	-18,7	0,00	0,275	0,275	0,0	1,000
Abirth_center	0,14	0,13	2,5	0,30	0,142	0,142	0,0	1,000
Abirth_south&Isl.	0,50	0,35	30,8	0,00	0,504	0,504	0,0	1,000
Abirth_abroad	0,08	0,15	-22,7	0,00	0,080	0,080	0,0	1,000
Country_underdev	0,07	0,14	-20,9	0,00	0,074	0,074	0,0	1,000
Hosp_cvd_cum	0,038	0,001	27	0,000	0,025	0,025	0,0	1,000
Days_cvd_cum	0,419	0,012	19,6	0,000	0,289	0,289	0,0	1,000
Hosp_other_cum	0,309	0,190	27,8	0,000	0,305	0,305	0,0	1,000
Days_other_cum	27,40	1,29	21,7	0,000	26,89	26,89	0,0	1,000
Hosp_other_($\bar{t}$-1)	0,197	0,095	20,8	0,000	0,193	0,193	0,0	1,000
Days_other_($\bar{t}$-1)	0,926	0,432	13,7	0,000	0,909	0,909	0,0	1,000
Inv_benefit_cum	0,074	0,007	34,9	0,000	0,066	0,066	0,0	1,000
Sick_leave_cum	19,24	1,068	38,8	0,000	19,06	19,06	0,0	1,000
Work_active_cum	12,39	10,99	43,7	0,000	12,43	12,43	0,0	0,998
Nemployee_cum	14,26	13,20	26,0	0,000	14,30	14,30	0,0	0,999
Rate_employee_cum	97,01	97,91	-9,0	0,000	96,98	96,98	0,0	1,000
Jobloss_cum	0,313	0,323	-1,8	0,493	0,314	0,314	0,0	1,000
New_firm_cum	2,850	2,936	-3,4	0,158	2,853	2,853	0,0	1,000
Nblue_collar_cum	12,80	10,84	44,5	0,000	12,85	12,85	0,0	0,998
Nwhite_collar_cum	0,282	0,261	1,6	0,506	0,272	0,272	0,0	1,000
Rate_perm_cum	95,01	89,85	29,1	0,000	95,22	95,22	0,0	0,998
Rate_fullt_cum	96,36	96,54	-1,4	0,564	96,59	96,59	0,0	1,000
Ever_CIG	0,385	0,335	10,5	0,000	0,386	0,386	0,0	1,000
Nunempl_cum	0,391	0,380	1,0	0,678	0,382	0,382	0,0	1,000
Unempl_($\bar{t}$-1)	0,038	0,059	-10,0	0,000	0,038	0,038	0,0	0,999
Rate_selfempl_cum	3,711	2,591	9,3	0,000	3,757	3,757	0,0	1,000
Days_self_cum	165,7	130,5	6,0	0,013	168,4	168,4	0,0	1,000
Rate_atypical_cum	0,412	0,633	-5,8	0,039	0,383	0,383	0,0	1,000
N_atypical_cum	0,052	0,062	-2,3	0,367	0,047	0,047	0,0	1,000

Table 2b: Pre- and post-matching balance: pre-shock employment

	Pre-matching				Post-matching			
	Mean				Mean			
	Treated *(1590)*	Controls *(766,299 obs.)*	%bias	p-value	Treated *(1559)*	Controls *(292,733 obs.)*	%bias	p-value
Dist_last1_employee	1,04	1,06	-3,9	0,146	1,037	1,037	0,0	1,000
Dist_last2_employee	2,13	2,15	-3,3	0,204	2,118	2,118	0,0	1,000
Dist_last3_employee	3,25	3,27	-1,7	0,505	3,238	3,238	0,0	1,000
Dist_last4_employee	4,38	4,41	-2,3	0,363	4,366	4,366	0,0	1,000
Last_sick_leave	2,17	1,15	23	0,000	2,133	2,133	0,0	1,000
Last_weeks_paid	47,61	46	14,8	0,000	47,68	47,68	0,0	0,999
Last_fix_term	0,038	0,081	-18	0,000	0,034	0,034	0,0	0,997
Last_jtenure	8,922	6,619	35,1	0,000	8,958	8,958	0,0	0,999
Last_awork_north	0,486	0,569	-16,6	0,000	0,484	0,484	0,0	1,000
Last_awork_center	0,180	0,176	1	0,685	0,182	0,182	0,0	1,000
Last_awork_south&Isl	0,334	0,255	17,3	0,000	0,334	0,334	0,0	1,000
Last_awork_abroad	0,000	0,000	-2,2	0,543	0,000	0,000	.	.
Last_apprentice	0,001	0,017	-17,3	0,000	0,000	0,000	-0,2	0,811
Last_bluecollar	0,994	0,976	15,2	0,000	0,996	0,995	0,1	0,987
Last_whitecollar	0,005	0,007	-3	0,275	0,004	0,004	0,0	1,000
Last_manager	0,000	0,000	-1,1	-0,31	0,000	0,000	0,0	0,961
Last_director	0,000	0,000	-0,8	-0,22	0,000	0,000	0,0	0,966
Last_firm_015	0,296	0,368	-15,4	0,000	0,298	0,298	0,0	0,999
Last_firm16250	0,431	0,414	3,4	0,168	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	0,999
Last_sec_agriculture	0,001	0,000	1,1	0,611	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	0,171	-0,6	0,809	0,170	0,170	0,0	1,000
Last_sec_extraction	0,008	0,005	3,6	0,108	0,008	0,008	0,0	1,000
Last_sec_energy	0,019	0,011	6,3	0,004	0,019	0,019	0,0	1,000
Last_sec_trade	0,070	0,101	-11,1	0,000	0,069	0,069	0,0	1,000
Last_sec_foodservices	0,043	0,046	-1,6	0,519	0,043	0,043	0,0	1,000
Last_sec_transports	0,143	0,087	17,6	0,000	0,144	0,144	0,0	1,000
Last_sec_finance	0,121	0,076	15,1	0,000	0,117	0,117	0,0	1,000
Last_sec_realestate	0,006	0,003	4	0,056	0,006	0,006	0,0	1,000
Last_public	0,004	0,005	-1,6	0,556	0,003	0,003	0,0	1,000

Source: WHIP&Health

Table 3. Employment-related unconditional outcomes: ATT and RSE

	Probability of employment				**Annual income from employment**			
	Main Approach[a]		**Alternative Approach**[b]		**Main Approach**[a]		**Alternative Approach**[b]	
Time	$\hat{\boldsymbol{\tau}}_{\bar{t}+v}$	$\frac{\hat{\boldsymbol{\tau}}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\boldsymbol{\tau}}_{\bar{t}+v}$	$\frac{\hat{\boldsymbol{\tau}}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\boldsymbol{\tau}}_{\bar{t}+v}$	$\frac{\hat{\boldsymbol{\tau}}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\boldsymbol{\tau}}_{\bar{t}+v}$	$\frac{\hat{\boldsymbol{\tau}}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
$\bar{t}$	-	-	-	-	-643.9**	*-3.17*	-581.4**	-2.67
Rob. SE.	-	-	-	-	(213.7)		(188.3)	
N .treated	-	-	-	-	1557		1,558	
$\bar{t}$ +1	-0.023**	*-2.57*	-0.023**	-3,4	-2248.9***	*-11.14*	-2282.9***	-11.34
Rob. SE.	(0.011)		(0.011)		(336.1)		(322.0)	
N. treated	1,543		1,543		1,527		1,527	
$\bar{t}$+2	-0.073***	*-8.83*	-0.073***	-8.77	-2232.5***	*-11.74*	-2360.5***	-12.42
Rob. SE.	(0.014)		(0.014)		(388.0)		(381.3)	
N. treated	1,507		1,506		1,491		1,490	
$\bar{t}$+3	-0.081***	*-10.46*	-0.086***	-11.02	-2039.5***	*-11.35*	-2160.9***	-12.04
Rob. SE.	(0.015)		(0.015)		(425.1)		(422.9)	
N. treated	1,463		1,460		1,445		1,441	
$\bar{t}$+4	-0.066***	*-9.12*	-0.078***	-10.72	-1997.5***	*-11.99*	-2138.3***	-12.84
Rob. SE.	(0.016)		(0.016)		(452.1)		(447.1)	
N. treated	1,426		1,424		1,408		1,406	
$\bar{t}$+5	-0.074***	*-10,99*	-	-	-2138.2***	*-13.92*	-	-
Rob. SE.	(0.017)		-	-	(473.9)		-	-
N. treated	1,368		-	-	1,353		-	-
$\bar{t}$+6	-0.064***	*-10.17*	-	-	-1685.2**	*-11.78*	-	-
Rob. SE.	(0.017)		-	-	(485.6)		-	-
N. treated	1,309		-	-	1,298		-	-
$\bar{t}$+7	-0.065***	*-10.88*	-	-	-1769.6***	*-13.24*	-	-
Rob. SE.	(0.018)		-	-	(488.5)		-	-
N. treated	1,237		-	-	1,225		-	-

Source: WHIP&Health

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

* p<0.1, ** p<0.05, *** p<0.01

[a] See section 3.4.

[b] See section 4.1.

Table 4. Any Labour market activity and DI receipt: ATT and RSE

	Probability of labour market activity				**Probability of receiving DI**			
	Main Approach[a]		**Alternative Approach**[b]		**Main Approach**[a]		**Alternative Approach**[b]	
Time	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
$\bar{t}$ +1	-0.028**	-3.13	-0.023**	-2.56	0.158***	232.6	0.151***	211.1
Rob. SE.	(0.011)		(0.011)		(0.010)		(0.010)	
N. treated	1,543		1,543		1,559		1,560	
$\bar{t}$+2	-0.074***	-8.75	-0.0723***	-8.60	0.231***	309.6	0.220***	262.4
Rob. SE.	(0.014)		(0.014)		(0.012)		(0.012)	
N. treated	1,507		1,506		1,543		1,560	
$\bar{t}$+3	-0.081***	-10.18	-0.086***	-10.70	0.244***	3030.2	0.226***	243.8
Rob. SE.	(0.015)		(0.015)		(0.012)		(0.012)	
N. treated	1,463		1,460		1,507		1,560	
$\bar{t}$+4	-0.067***	-9.02	-0.079***	-10.40	0.249***	283.1	0.224***	218.9
Rob. SE.	(0.016)		(0.016)		(0.013)		(0.013)	
N. treated	1,426		1,424		1,463		1,560	
$\bar{t}$+5	-0.073***	-10.46	-	-	0.241***	257.8	0.207***	181.3
Rob. SE.	(0.016)		-	-	(0.013)		(0.013)	
N. treated	1,368		-	-	1,426		1,560	
$\bar{t}$+6	-0.066***	-10.05	-	-	0.246***	249.4	-	-
Rob. SE.	(0.017)		-	-	(0.013)		-	-
N. treated	1,309		-	-	1,368		-	-
$\bar{t}$+7	-0.066***	-10.44	-	-	0.234***	224.8	-	-
Rob. SE.	(0.017)		-	-	(0.014)		-	-
N. treated	1,237		-	-	1,309		-	-

Source: WHIP&Health

Notes: Marginal effects are reported for the *Probability of labour market activity* (ATTs); by sample selection all individuals were employed in $\bar{t}$, so the probability of labour market activity in that year is 1 by construction. * p<0.1, ** p<0.05, *** p<0.01

[a] See section 3.4.

[b] See section 4.1.

Table 5. Annual labour income and full-time work, conditional on employment: ATT and RSE

	Annual income from employment				Probability of being employed full-time			
	Main Approach[a]		Alternative Approach[b]		Main Approach[a]		Alternative Approach[b]	
Time	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
$\bar{t}$	-643.7**	-2.94	-581.4**	-2.67	0.001	*0.10*	0.001	0.07
Rob. SE.	(213.6)		(188.3)		(0.004)		(0.004)	
N .treated	1,557		1,558		1,557		1,558	
$\bar{t}$ +1	-2223.5***	*-9.83*	-2316.1***	-10.26	-0.008	*-0.86*	-0.013**	-1.38
Rob. SE.	(298.2)		(256.2)		(0.006)		0.006	
N. treated	1,327		1,324		1,327		1,324	
$\bar{t}$+2	-1125.7***	*-4.92*	-1282.3***	-5.59	-0.014*	*-1.47*	-0.023***	-2.40
Rob. SE.	(320.4)		(280.9)		(0.007)		(0.007)	
N. treated	1,127		1,122		1,127		1,122	
$\bar{t}$+3	-660.4*	*-2.85*	-723.3**	-3.13	-0.015*	*-1.55*	-0.020**	-2.17
Rob. SE.	(343.8)		(308.9)		(0.009)		(0.009)	
N. treated	1,000		991		1,000		991	
$\bar{t}$+4	-937.2**	*-4.05*	-862.1**	-3.77	-0.026**	*-2.74*	-0.038***	-4.01
Rob. SE.	(395.7)		(348.1)		(0.010)		(0.010)	
N. treated	917		911		917		911	
$\bar{t}$+5	-1100.2**	*-4.79*	-	-	-0.024**	*-2.63*	-	-
Rob. SE.	(423.1)		-	-	(0.012)		-	-
N. treated	801		-	-	801		-	-
$\bar{t}$+6	-654.1	*-2.87*	-	-	-0.021	*-2.30*	-	-
Rob. SE.	(462.6)		-	-	(0.013)		-	-
N. treated	728		-	-	728		-	-
$\bar{t}$+7	-906.9*	*-4.02*	-	-	-0.018	*-1.92*	-	-
Rob. SE.	(482.0)		-	-	(0.014)		-	-
N. treated	643		-	-	643		-	-

Source: WHIP&Health

Notes: * p<0.1, ** p<0.05, *** p<0.01

[a] See section 3.4.

[b] See section 4.1.

Table 6. Hourly Wage and Same Employer, conditional on employment: ATT and RSE

	Hourly wage				Probability of working with the same employer as in T			
	Main Approach[a]		Alternative Approach[b]		Main Approach[a]		Alternative Approach[b]	
Time	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$	$\hat{\tau}_{\bar{t}+v}$	$\frac{\hat{\tau}_{\bar{t}+v}}{Y^0_{i,\bar{t}+v}}$
t̄	-0.306**	-2.56	-0.275***	-2.31	-	-	-	-
Rob. SE.	(0.101)		(0.081)		-	-	-	-
N .treated	1,557		1,558		-	-	-	-
t̄ +1	-0.620***	-5.08	-0.606***	-4.99	0.019	2.15	0.022*	2.50
Rob. SE.	(0.138)		(0.105)		(0.012)		(0.012)	
N. treated	1,327		1,324		1,337		1,334	
t̄+2	-0.335**	-2.72	-0.293**	-2.39	0.004	0.46	-0.005	-0.64
Rob. SE.	(0.120)		(0.106)		(0.016)		(0.015)	
N. treated	1,127		1,122		1,135		1,130	
t̄+3	-0.259*	-2.07	-0.291**	-2.32	-0.011	-1.60	-0.026	-3.61
Rob. SE.	(0.136)		(0.126)		(0.019)		(0.018)	
N. treated	1,000		991		1,011		1,003	
t̄+4	-0.287*	-2.29	-0.153	-1.23	-0.022	-3.35	-0.030	-4.60
Rob. SE.	(0.147)		(0.127)		(0.020)		(0.020)	
N. treated	917		911		930		924	
t̄+5	-0.323*	-2.57	-	-	0.002	0.39	-	-
Rob. SE.	(0.170)		-	-	(0.022)		-	-
N. treated	801		-	-	812		-	-
t̄+6	-0.352*	-2.80	-	-	-0.009	-1.60	-	-
Rob. SE.	(0.202)		-	-	(0.024)		-	-
N. treated	728		-	-	734		-	-
t̄+7	-0.354	-2.83	-	-	-0.001	-0.16	-	-
Rob. SE.	(0.251)		-	-	(0.025)		-	-
N. treated	643		-	-	649		-	-

Source: WHIP&Health

Notes: * p<0.1, ** p<0.05, *** p<0.01

[a] See section 3.4.

[b] See section 4.1.

Table 7. Long(er) term unconditional employment-related outcomes: RSE

	CVD shock experienced in 2003/2004			CVD shock experienced in 2003		
Time	**Probability of employment**	**Annual income from employment**	**Probability of receiving a DI benefit**	**Probability of employment**	**Annual income from employment**	**Probability of receiving a DI benefit**
$\bar{t}$	-	-3.14	264.0	-	-3.41	279.7
N. treated	-	1015	1016	-	490	490
$\bar{t}$+1	-3.37	-11.05	345.2	-3.45	-11.93	348.5
N. treated	1003	996	1003	483	482	483
$\bar{t}$+2	-8.60	-11.19	349.5	-6.78	-11.49	340.6
N. treated	981	974	981	472	470	472
$\bar{t}$+3	-10.73	-10.73	333.6	-11.51	-9.49	321.6
N. treated	953	942	953	456	455	456
$\bar{t}$+4	-11.01	-11.28	312.2	-10.02	-11.55	302.6
N. treated	926	915	926	444	439	444
$\bar{t}$+5	-11.22	-13.77	322.2	-8.88	-15.31	321.4
N. treated	895	887	895	430	426	430
$\bar{t}$+6	-9.02	-10.80	304.3	-8.28	-13.66	305.1
N. treated	858	849	858	409	406	409
$\bar{t}$+7	-10.72	-11.69	305.8	-8.92	-12.63	312.7
N. treated	811	804	811	381	379	381
$\bar{t}$+8	-9.99	-12.31	307.1	-9.55	-14.57	315.7
N. treated	760	751	760	350	345	350
$\bar{t}$+9	-	-	-	-18.39	-22.23	326.0
N. treated	-	-	-	326	324	326

Source: WHIP&Health

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

Figure 1: Dataset time coverage and related identification strategy

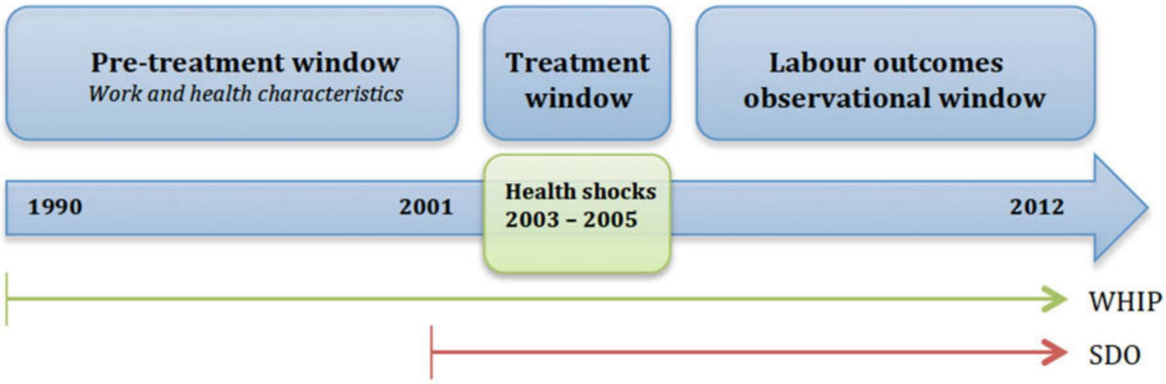
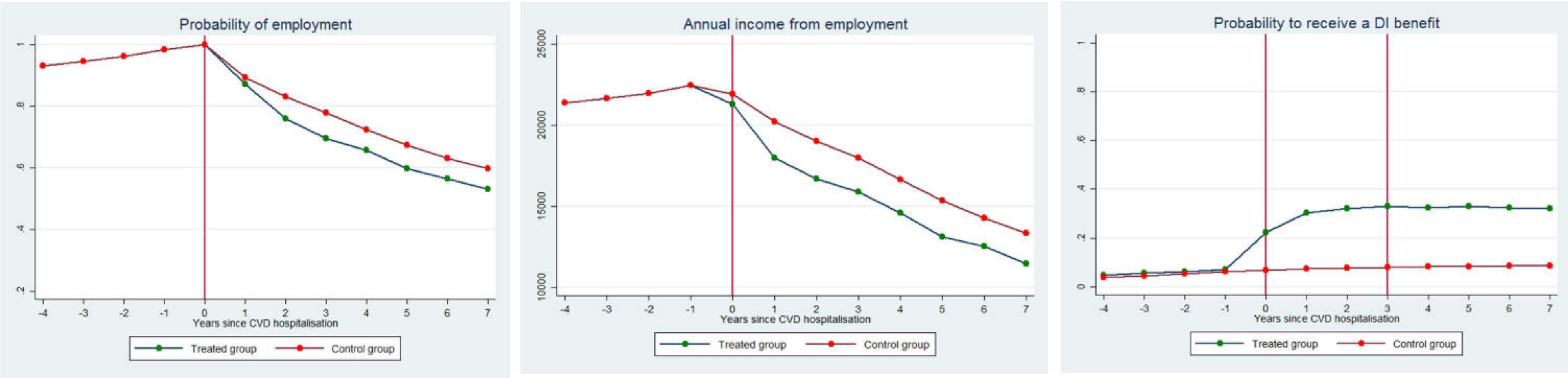
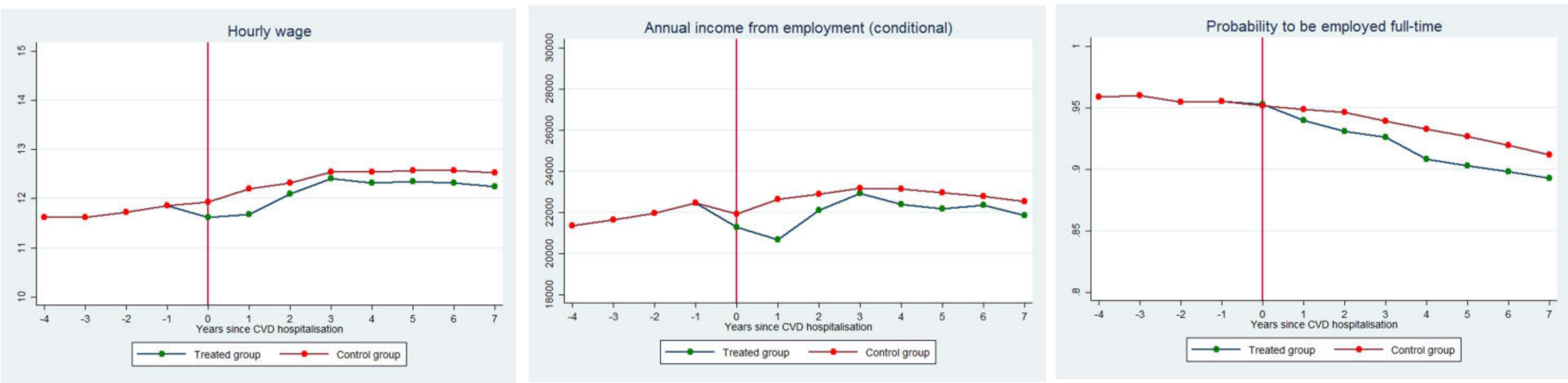


Figure 2a: Sample means for labour outcomes after matching adjustment: main approach



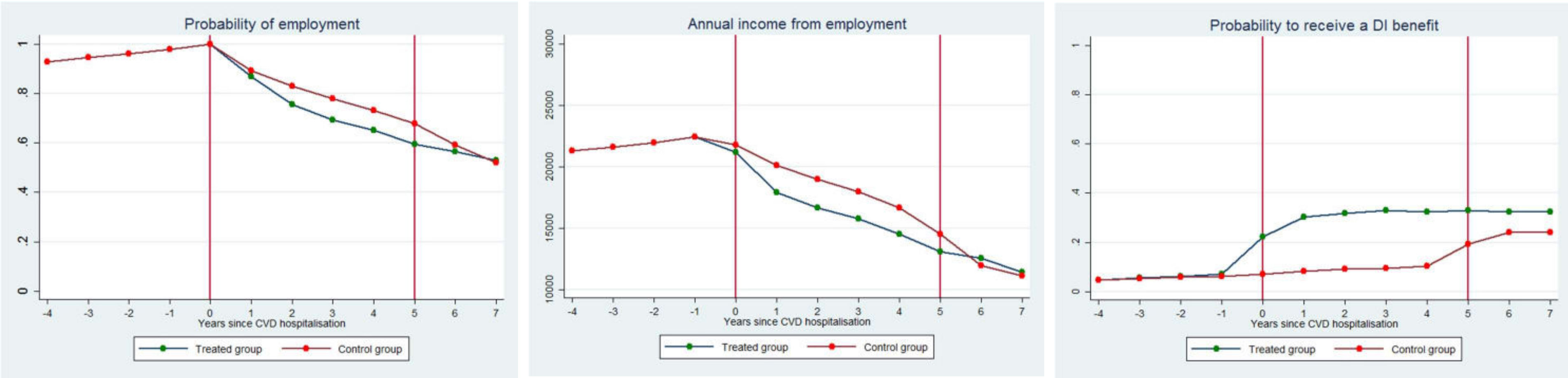
Source: WHIP&Health. Notes: Control group sample means are computed on successfully matched controls only. Continuous lines connect time-specific sample means.

Figure 2b: Sample means for labour outcomes conditional on employment, after matching adjustment: main approach



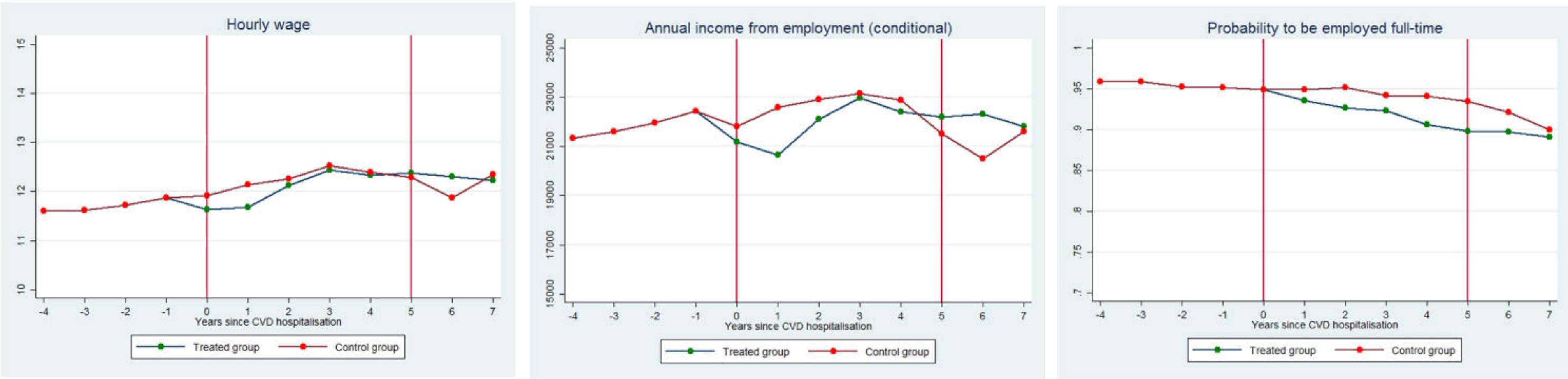
Source: WHIP&Health. Notes: Control group sample means are computed on successfully matched controls only. Continuous lines connect time-specific sample means.

Figure 3a: Sample means for labour outcomes after matching adjustment: alternative approach



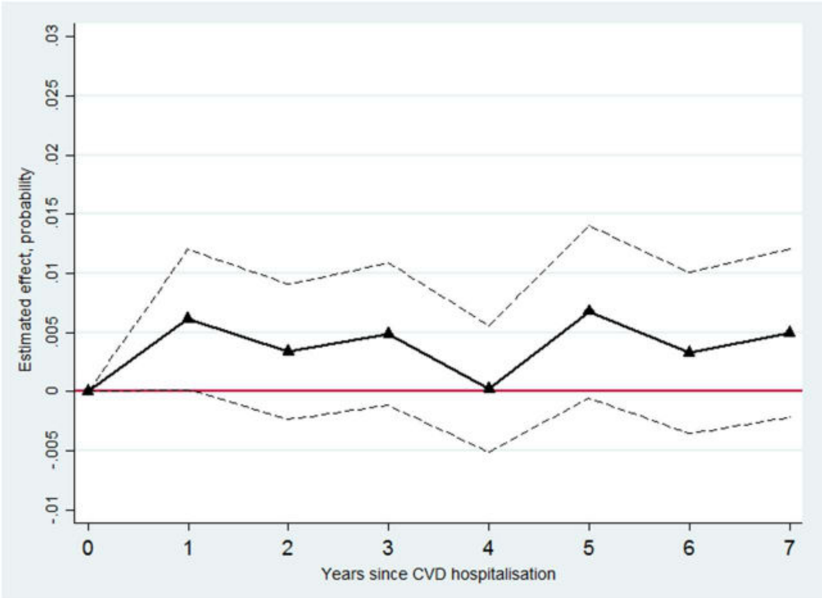
Source: WHIP&Health. Notes: Control group sample means are computed on successfully matched controls only. Continuous lines connect time-specific sample means.

Figure 3b: Sample means for labour outcomes conditional on employment, after matching adjustment: alternative approach



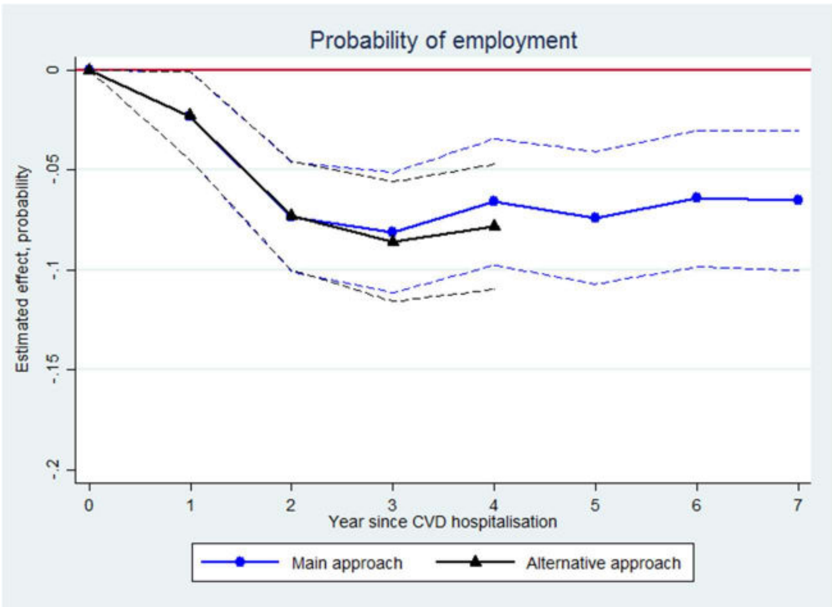
Source: WHIP&Health. Notes: Control group sample means are computed on successfully matched controls only. Continuous lines connect time-specific sample means

Figure 4: ATTs by year since CVD hospitalisation: Mortality



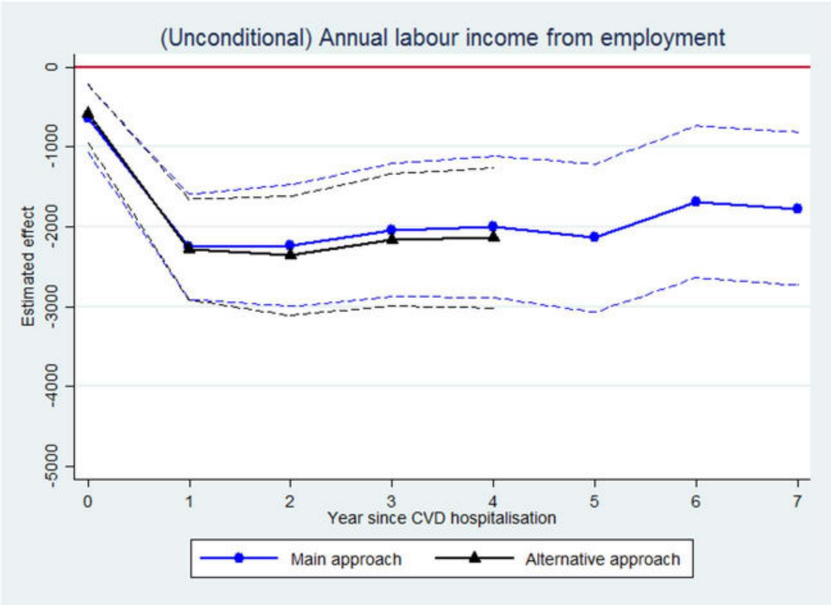
Source: WHIP&Health. Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported; by sample selection all individuals were alive in the year of the shock, so the ATT is 0 in that year.

Figure 5a: ATT by year since CVD hospitalisation: employment



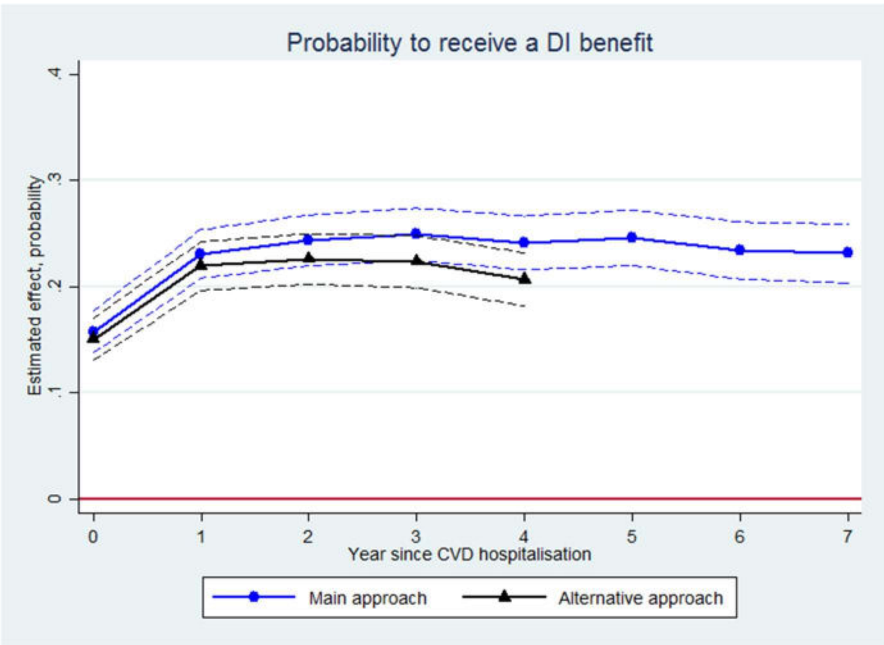
Source: WHIP&Health
Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported; by sample selection all individuals were employed in the year of the shock, so the ATT is 0 in that year.

Figure 5b: ATT by year since CVD hospitalisation:
annual income from employment



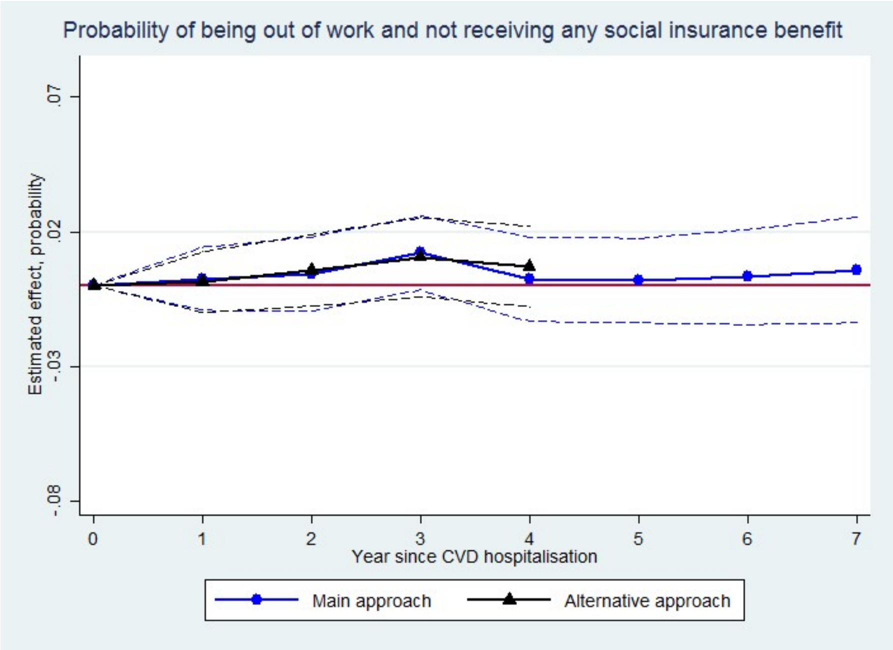
Source: WHIP&Health
Notes: ATTs: point estimates (connected line) and 95% confidence intervals (dashed lines).

Figure 6: ATTs by year since CVD hospitalisation:
probability of receiving a Disability Insurance benefit



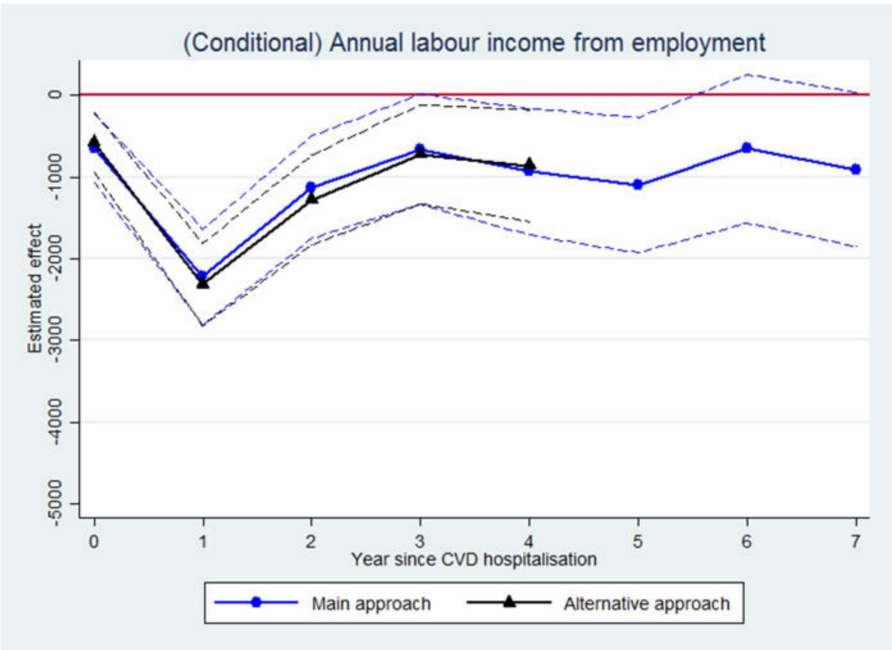
Source: WHIP&Health
Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

Figure 7: ATTs by year since CVD hospitalisation:
probability of being out of work and not receiving any Social Insurance benefit



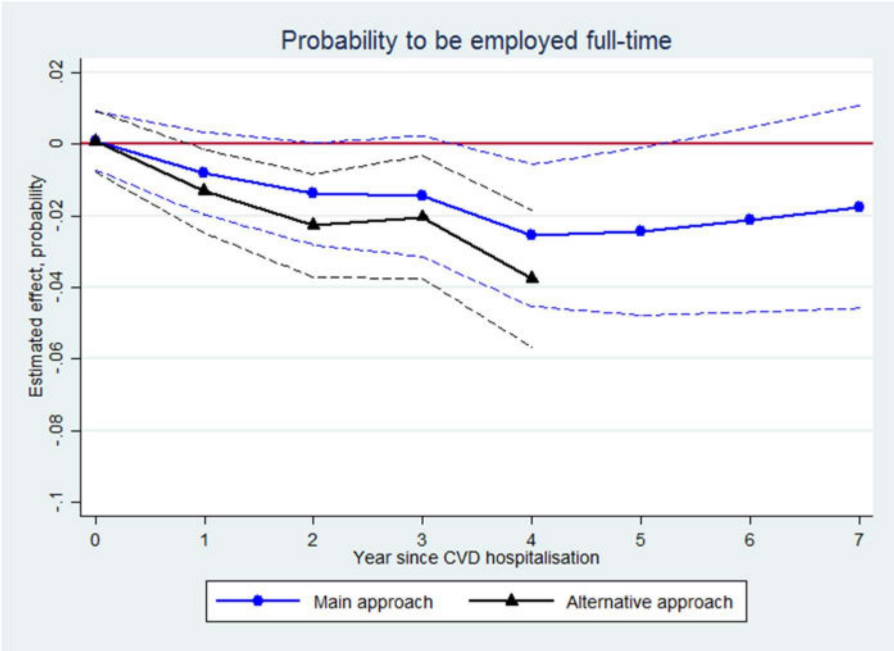
Source: WHIP&Health
Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

Figure 8a: ATTs by year since CVD hospitalisation: (conditional) annual income from employment



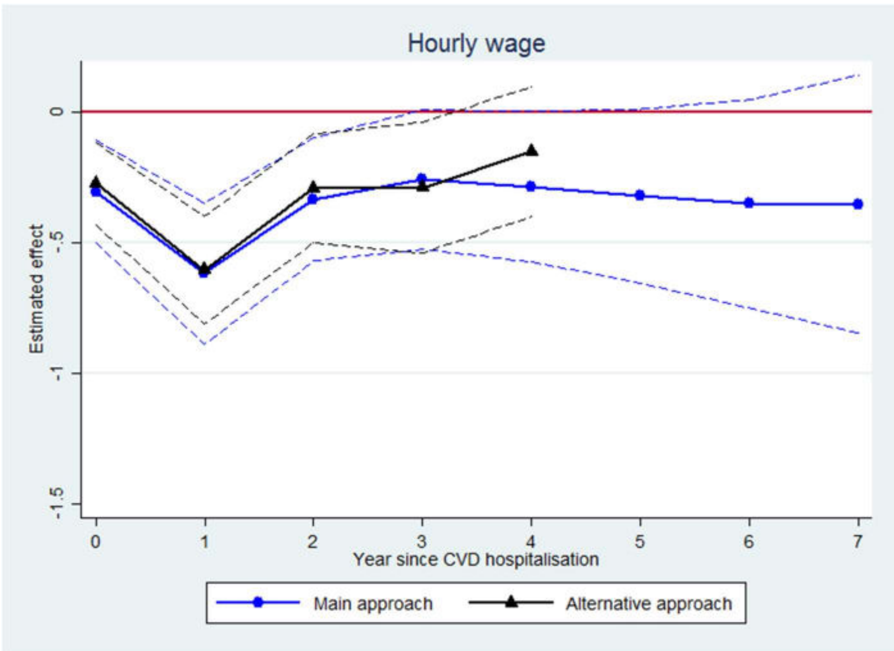
Source: WHIP&Health
Notes: ATTs: point estimates (connected line) and 95% confidence intervals (dashed lines).

Figure 8b: ATTs by year since CVD hospitalisation: probability of working full-time (versus part-time)



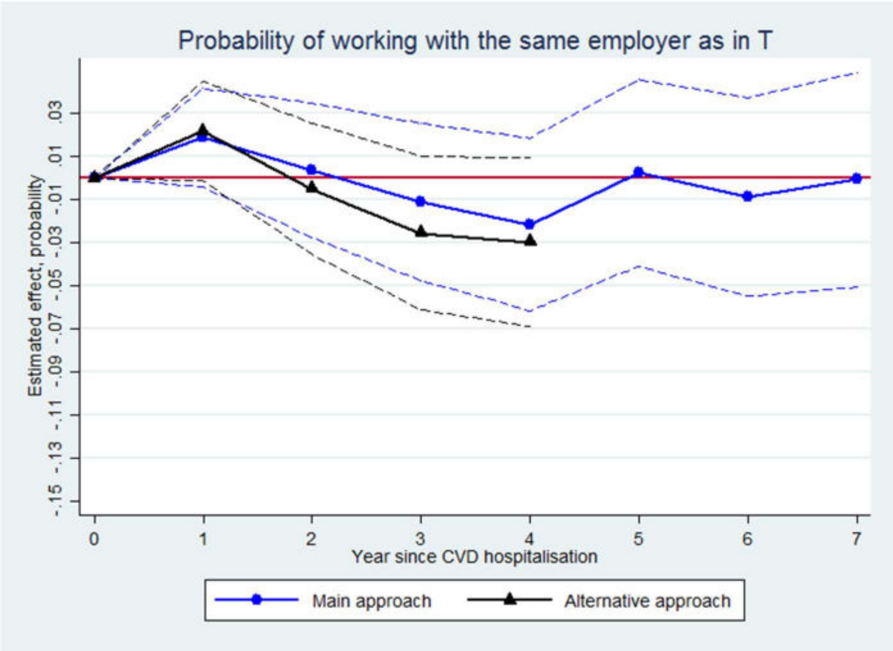
Source: WHIP&Health
Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

Figure 8c: ATTs by year since CVD hospitalisation: hourly wage



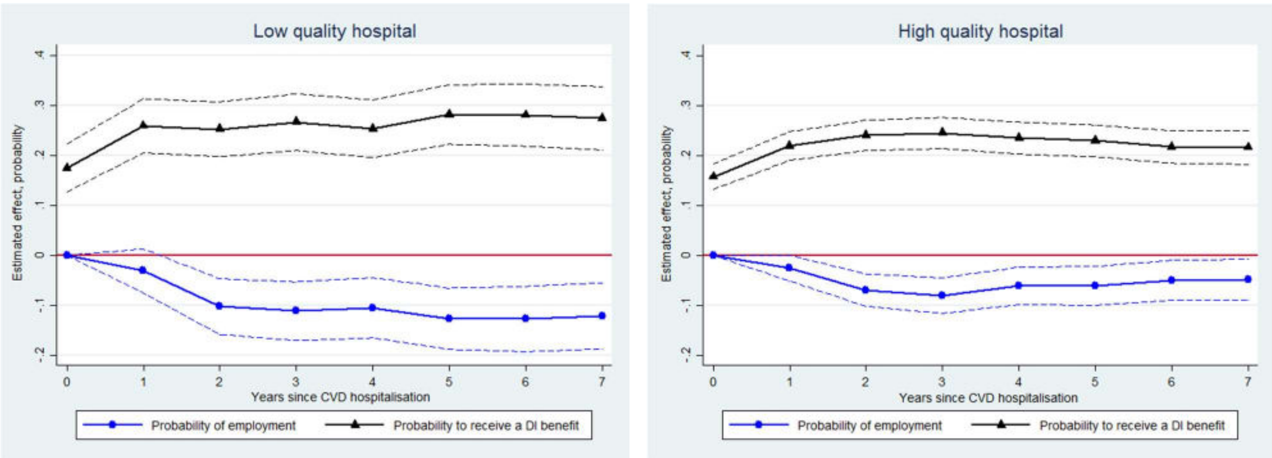
Source: WHIP&Health
Notes: ATTs: point estimates (connected line) and 95% confidence intervals (dashed lines).

Figure 8d: ATTs by year since CVD hospitalisation:
(conditional) probability of working with the same employer as in $\bar{t}$



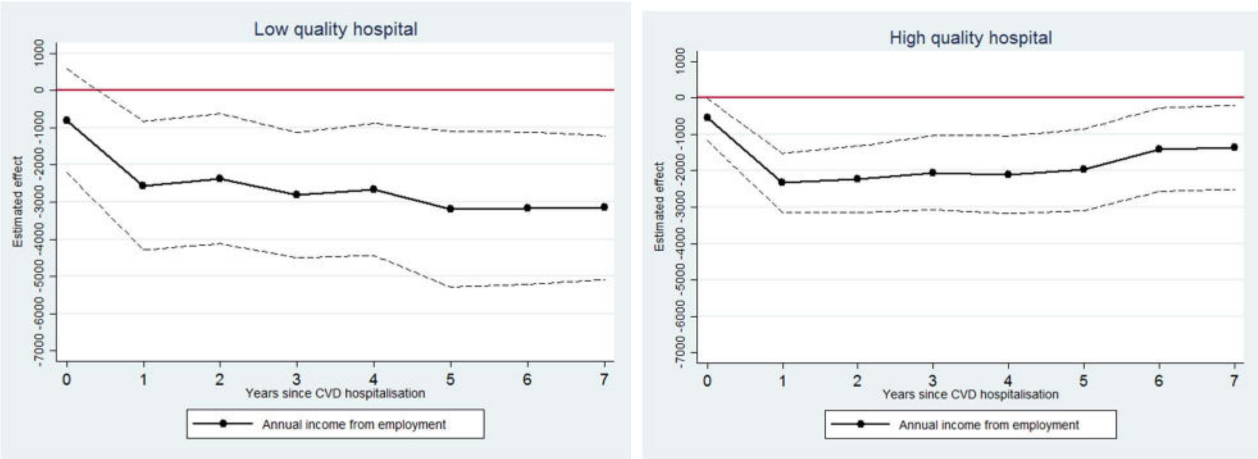
Source: WHIP&Health
Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

Figure 9a: ATT by year since CVD hospitalisation: probability of employment and probability of receiving a DI benefit



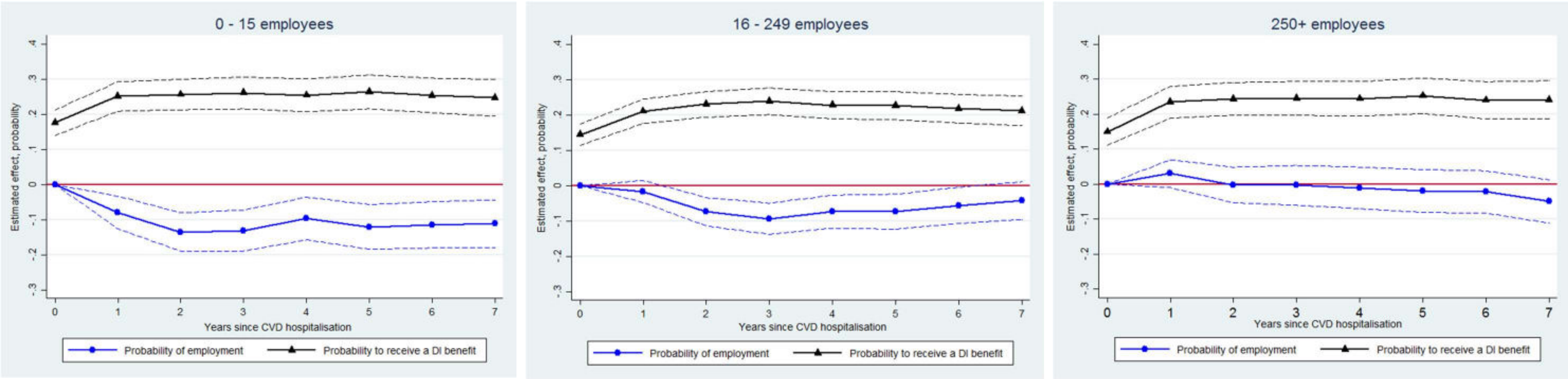
Source: WHIP&Health
Notes: ATTs: point estimates (connected line) and 95% confidence intervals (dashed lines).

Figure 9b: ATT by year since CVD hospitalisation: annual income from employment



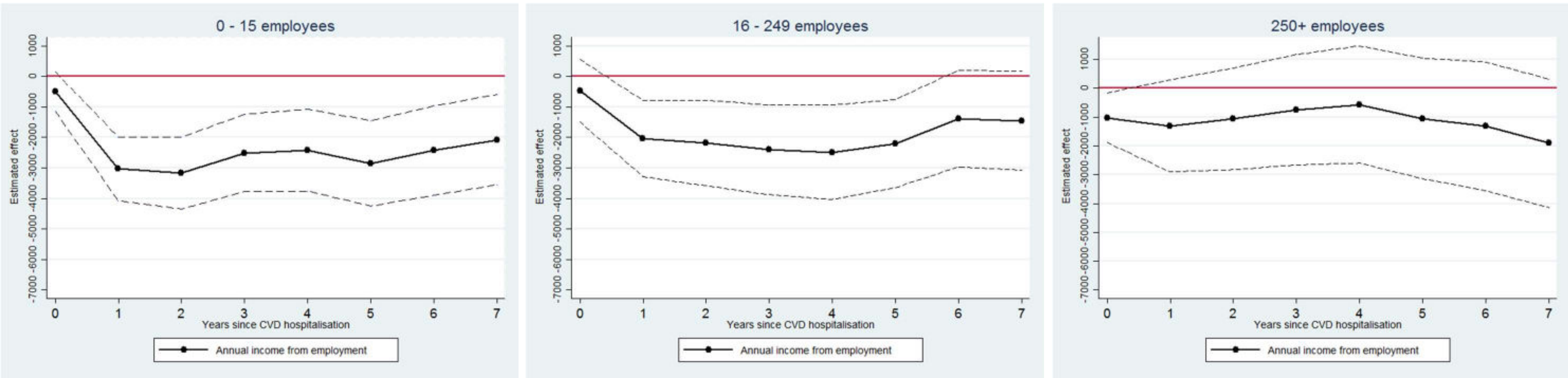
Source: WHIP&Health
Notes: ATTs: point estimates (connected line) and 95% confidence intervals (dashed lines).

Figure 10a: ATT by year since CVD hospitalisation: probability of employment and probability of receiving a DI benefit



Source: WHIP&Health . Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

Figure 10b: ATT by year since CVD hospitalisation: annual income from employment



Source: WHIP&Health. Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported

Appendix

Table A1: Descriptive Statistics

	Treated		Controls	
Variable	*Mean*	*Sd*	*Mean*	*Sd*
Year	2004	0.811	2004	0.8116
Age	50.52	7.277	39.70	9.521
Abirth_north	0.273	0.445	0.359	0.480
Abirth_center	0.142	0.349	0.133	0.339
Abirth_south&Isl.	0.504	0.500	0.354	0.478
Abirth_abroad	0.081	0.273	0.154	0.361
Country_underdev	0.075	0.263	0.139	0.346
Hosp_cvd_cum	0.038	0.192	0.001	0.034
Days_cvd_cum	0.419	2.905	0.012	0.449
Hosp_other_cum	0.309	0.462	0.190	0.392
Days_other_cum	2.740	7.177	1.290	6.160
Hosp_other_($\bar{t}-1$)	0.197	0.575	0.095	0.386
Days_other_($\bar{t}-1$)	0.927	3.893	0.432	3.297
Inv_benefit_cum	0.074	0.262	0.007	0.081
Sick_leave_cum	19.24	26.93	10.68	15.83
Work_active_cum	12.39	2.849	10.99	3.544
Nemployee_cum	14.26	3.835	13.20	4.295
Rate_employee_cum	97.91	10.99	97.91	8.982
Jobloss_cum	0.313	0.608	0.323	0.631
New_firm_cum	2.850	2.581	2.936	2.429
Nblue_collar_cum	12.80	4.046	10.84	4.740
Nwhite_collar_cum	0.282	1.439	0.261	1.277
Nmanager_cum	0.001	0.035	0.002	0.082
Rate_perm_cum	95.01	14.23	89.85	20.64
Rate_fullt_cum	96.34	13.69	96.54	12.78
Ever_CIG	0.385	0.487	0.335	0.472
Nunempl_cum	0.391	1.220	0.380	1.115
Unempl_($\bar{t}-1$)	0.038	0.191	0.059	0.236
Rate_selfempl_cum	3.710	13.09	2.591	10.94
Days_self_cum	165.7	613.2	130.4	562.7
Rate_atypical_cum	0.412	3.245	0.633	4.261
N_atypical_cum	0.052	0.430	0.062	0.441
Dist_last1_employee	1.042	0.342	1.056	0.385
Dist_last2_employee	2.127	0.722	2.152	0.782
Dist_last3_employee	3.248	1.048	3.266	1.101
Dist_last4_employee	4.380	1.355	4.380	1.345
Last_sick_leave	2.172	5.308	1.151	3.361
Last_weeks_paid	47.61	10.23	45.96	12.00
Last_fix_term	0.038	0.192	0.081	0.272
Last_jtenure	8.922	7.034	6.619	6.051
Last_awork_north	0.486	0.500	0.569	0.495
Last_awork_center	0.180	0.384	0.176	0.381
Last_awork_south&Isl.	0.334	0.472	0.255	0.436
Last_awork_abroad	0.000	0.000	0.000	0.015

Last_apprentice	0.001	0.025	0.017	0.128
Last_bluecollar	0.994	0.075	0.976	0.153
Last_whitecollar	0.005	0.071	0.007	0.007
Last_manager	0.000	0.000	0.000	0.086
Last_director	0.000	0.000	0.000	0.008
Last_firm_015	0.296	0.456	0.368	0.482
Last_firm16250	0.431	0.495	0.414	0.493
Last_firm_250	0.273	0.446	0.218	0.413
Last_sec_agriculture	0.001	0.025	0.000	0.019
Last_sec_manufac	0.416	0.493	0.493	0.500
Last_sec_construc	0.169	0.375	0.171	0.377
Last_sec_extraction	0.008	0.090	0.005	0.072
Last_sec_energy	0.019	0.136	0.011	0.105
Last_sec_trade	0.070	0.255	0.101	0.301
Last_sec_foodservices	0.043	0.202	0.046	0.210
Last_sec_transports	0.143	0.351	0.087	0.282
Last_sec_finance	0.121	0.327	0.076	0.266
Last_sec_realestate	0.006	0.075	0.003	0.055
Last_public	0.004	0.061	0.005	0.069
Last1_lab_income	22.344	9441	20843	11408
Last2_lab_income	21859	9459	20350	11345
Last3_lab_income	21516	9652	19855	12077
Last4_lab_income	21253	9937	19005	11948
Last1_hwage	11.34	6.603	11.85	3.779
Last2_hwage	11.70	3.712	11.14	6.986
Last3_hwage	11.60	3.701	10.98	9.580
Last4_hwage	11.59	3.819	10.82	15.27
Last1_fulltime	0.950	0.219	0.962	0.191
Last2_fulltime	0.951	0.216	0.965	0.184
Last3_fulltime	0.956	0.205	0.966	0.182
Last4_fulltime	0.956	0.205	0.965	0.184
Last1_LMP	0.979	0.143	0.971	0.168
Last2_LMP	0.959	0.198	0.955	0.207
Last3_LMP	0.944	0.230	0.943	0.232
Last4_LMP	0.928	0.258	0.925	0.263

Source: WHIP&Health

Table A2: Post-CEM balance

	Pre-CEM				*Post-CEM*			
	Mean				Mean			
	Treated	Controls	%bias	p-value	Treated	Controls	%bias	p-value
Year	2004	2004	1.8	0.460	2004	2004	0.00	1.000
Age	50.52	39.70	127.6	0.000	50.47	50.47	0.00	1.000
Hosp_cvd_cum	0.038	0.001	27	0.000	0.03	0.03	0.00	1.000
Dist_last1_employee	1.040	1.060	-3.9	0.146	1.04	1.04	0.00	1.000
Last_fix_term	0.038	0.081	-18	0.000	0.03	0.03	0.00	1.000
Last1_fulltime	0.950	0.962	-6.1	0.009	0.96	0.96	0.00	1.000
Last_awork_north	0.486	0.569	-16.6	0.000	0.48	0.48	0.00	1.000
Last_awork_center	0.180	0.176	1	0.685	0.18	0.18	0.00	1.000
Last_awork_south&Isl.	0.334	0.255	17.3	0.000	0.33	0.33	0.00	1.000
Last_awork_abroad	0.000	0.000	-2.2	0.543	0.00	0.00	.	.
Last_firm_015	0.296	0.368	-15.4	0.000	0.30	0.30	0.00	1.000
Last_firm16250	0.431	0.414	3.4	0.168	0.43	0.43	0.00	1.000
Last_firm_250	0.273	0.218	12.8	0.000	0.27	0.27	0.00	1.000

Source: WHIP&Health

Table A3: Post-EB moments balance

	Treated group			**Control group**		
	Mean	*Variance*	*Skewness*	*Mean*	*Variance*	*Skewness*
Year	2004	0.662	-0.062	2004	0.661	-0.062
Age	50.47	52.89	-0.749	50.47	54.43	-0.730
Abirth_north	0.275	0.199	1.01	0.275	0.199	1.010
Abirth_center	0.142	0.122	2.047	0.142	0.122	2.047
Abirth_sud	0.504	0.250	-0.014	0.504	0.250	-0.014
Country_underdev	0.074	0.068	3.261	0.074	0.068	3.261
Hosp_other_($\bar{t}-1$)	0.025	0.024	6.083	0.025	0.024	6.083
Days_other_($\bar{t}-1$)	0.289	6.327	12.88	0.289	4.756	9.242
Hosp_cvd_cum	0.305	0.212	0.845	0.305	0.212	0.846
Days_cvd_cum	2.689	50.94	4.811	2.689	74.65	8.513
Hosp_other_cum	0193	0.327	4.502	0.193	0.438	15.89
Days_other_cum	0.909	15.08	8.289	0.909	18.37	11.68
Inv_benefit_cum	0.066	0.062	3.494	0.066	0.062	3.494
Sick_leave_cum	19.06	714.8	3.116	19.06	858.1	3.680
Work_active_cum	12.43	7.947	-1.492	12.43	7.930	-1.48
Nemployee_cum	14.30	14.63	0.028	14.30	14.89	0.997
Rate_employee_cum	96.98	122.4	-4.03	96.98	125.3	-4.108
Jobloss_cum	0.314	0.368	2.177	0.314	0.423	3.846
New_firm_cum	2.853	6.722	2.734	2.853	6.495	2.442
Nblue_collar_cum	12.85	16.19	-0.234	12.85	15.55	-0.207
Nwhite_collar_cum	0.272	2.015	7.928	0.272	1.979	9.771
Nmanager_cum	0.001	0.001	27.87	0.001	0.003	66.80
Rate_perm_cum	95.22	190.2	-3.809	95.22	202.1	-3.869
Rate_fullt_cum	96.59	174.2	-5.004	96.59	175.5	-4.933
Ever_CIG	0.386	0.237	0.468	0.386	0.237	0.468
Nunempl_cum	0.382	1.395	4.328	0.382	1.384	4.206
Unempl_($\bar{t}-1$)	0.038	0.036	4.844	0.038	0.036	4.843
Rate_selfempl_cum	3.757	173.4	3.864	3.757	181.6	4.057
Days_self_cum	168.4	382729	4.333	168.4	399778	4.502
Rate_atypical_cum	0.383	9.267	10.66	0.383	10.50	11.84
N_atypical_cum	0.047	0.157	12.24	0.047	0.203	19.08
Dist_last1_employee	1.037	0.108	11.05	1.037	0.107	10.94
Dist_last2_employee	2.118	0.498	8.285	2.118	0.461	7.831
Dist_last3_employee	3.238	1.074	5.583	3.238	1.089	5.679
Dist_last4_employee	4.366	1.766	4.609	4.366	1.757	4.511
Last_sick_leave	2.133	27.45	4.503	2.133	30.77	6.375
Last_jtenure	8.958	49.36	0.328	8.958	49.15	0.338
Last_weeks_paid	47.67	102.3	-2.657	47.67	104.4	-2.641
Last_fix_term	0.034	0.033	5.143	0.034	0.033	5.141
Last_awork_north	0.484	0.250	0.063	0.484	0.250	0.063
Last_awork_center	0.182	0.1491	1.647	0.182	0.149	1.647
Last_apprentice	0	0	.	0.000	0.000	164.7
Last_bluecollar	0.996	0.004	-14.82	0.996	0.005	-14.76
Last_whitecollar	0.004	0.004	14.82	0.004	0.004	14.82
Last_manager	0	0	.	1.54e-06	1.54e-06	805.5
Last_firm_015	0.298	0.209	0.885	0.298	0.209	0.886
Last_firm16250	0.431	0.245	0.279	0.431	0.245	0.279
Last_sec_agriculture	0.0004	0.0001	39.45	0.0004	0.001	39.45
Last_sec_extraction	0.008	0.008	10.81	0.008	0.008	10.81

Last_sec_manufac	0.420	0.244	0.324	0.420	0.244	0.324
Last_sec_energy	0.019	0.019	6.999	0.019	0.019	6.999
Last_sec_construc	0.170	0.141	1.757	0.170	0.141	1.757
Last_sec_trade	0.069	0.065	3.393	0.070	0.064	3.393
Last_sec_foodservices	0.043	0.041	4.507	0.043	0.041	4.507
Last_sec_transports	0.144	0.123	2.032	0.144	0.123	2.032
Last_sec_finance	0.117	0.103	2.387	0.117	0.103	2.387
Last_sec_realestate	0.006	0.006	13.05	0.006	0.006	13.05
Last1_lab_income	22446	8.83e+07	0.517	22446	2.49e+08	118.4
Last2_lab_income	21955	8.90e+07	0.333	21955	9.65e+07	14.59
Last3_lab_income	21639	9.22e+07	0.220	21639	9.44e+07	1.190
Last4_lab_income	21358	9.76e+07	0.165	21358	9.99e+07	0.443
Last1_fulltime	0.955	0.043	-4.395	0.955	0.043	-4.395
Last2_fulltime	0.955	0.044	-4.360	0.955	0.043	-4.360
Last3_fulltime	0.960	0.038	-4.710	0.960	0.038	-4.710
Last4_fulltime	0.959	0.039	-4.626	0.959	0.039	-4.626
Last1_wemployee	0.983	0.017	-7.40	0.983	0.017	-7.398
Last2_wemployee	0.962	0.036	-4.844	0.962	0.036	-4.844
Last3_wemployee	0.944	0.053	-3.870	0.944	0.053	-3.870
Last4_wemployee	0.930	0.065	-3.373	0.930	0.065	-3.373
Last1_hwage	11.86	14.25	1.188	11.86	78.13	106.6
Last2_hwage	11.72	13.75	1.030	11.72	21.25	50.33
Last3_hwage	11.62	13.68	0.950	11.62	21.31	156.9
Last4_hwage	11.61	14.40	1.039	11.61	15.09	2.220

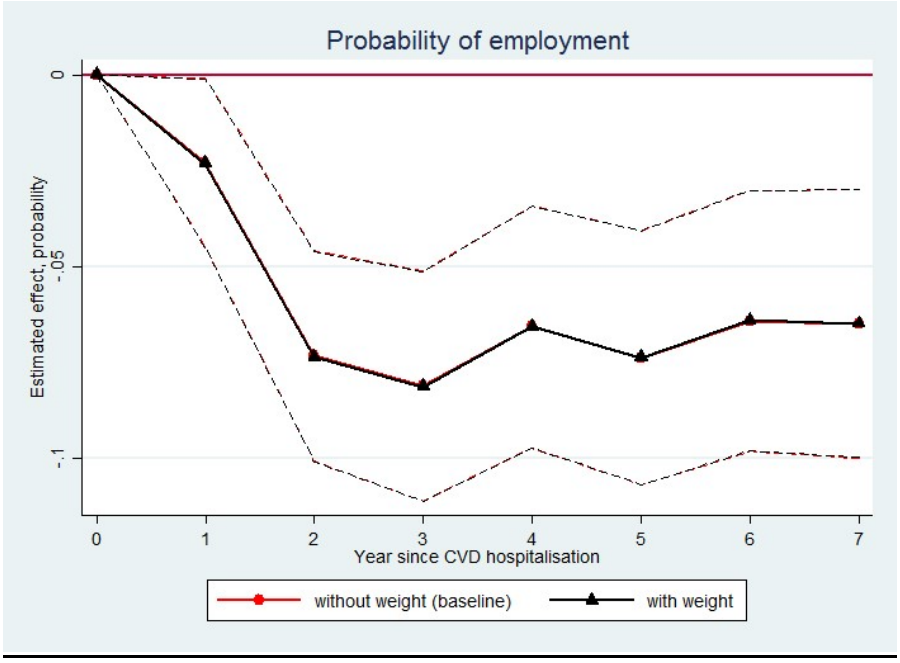
Source: WHIP&Health

Table A4: Outcomes in the Longer Run: ATTs

Time	*CVD shock experienced in 2003/2004*			*CVD shock experienced in 2003*		
	Probability of employment	**Annual income from employment**	**Probability of receiving a DI benefit**	**Probability of employment**	**Annual income from employment**	**Probability of receiving a DI benefit**
$\bar{t}$	-	-897.4**	0.165***	-	-743.7*	0.173***
Rob. SE.	-	(420.5)	(0.012)	-	(385.8)	(0.018)
N. treated	-	1015	1016	-	490	490
$\bar{t}$+1	-0.030**	-2220.4***	0.234***	-0.030	-2363.5***	0.240***
Rob. SE.	(0.014)	(436.6)	(0.014)	(0.021)	(590.4)	(0.021)
N. treated	1003	996	1003	483	482	483
$\bar{t}$+2	-0.071***	-2103.2***	0.249***	-0.054**	-2081.5***	0.251***
Rob. SE.	(0.018)	(485.4)	(0.015)	(0.026)	(703.8)	(0.022)
N. treated	981	974	981	472	470	472
$\bar{t}$+3	-0.083***	-1928.5***	0.251***	-0.087***	-1636.5**	0.252***
Rob. SE.	(0.019)	(528.1)	(0.016)	(0.028)	(759.7)	(0.023)
N. treated	953	942	953	456	455	456
$\bar{t}$+4	-0.071***	-1912.4***	0.239***	-0.071**	-1905.3**	0.242***
Rob. SE.	(0.019)	(563.3)	(0.016)	(0.029)	(806.6)	(0.023)
N. treated	926	915	926	444	439	444
$\bar{t}$+5	-0.076***	-2131.8***	0.249***	-0.058	-2334.5**	0.256***
Rob. SE.	(0.021)	(584.2)	(0.016)	(0.030)	(837.5)	(0.024)
N. treated	895	887	895	430	426	430
$\bar{t}$+6	-0.057**	-1551.9	0.240***	-0.051*	-1895.1**	0.249***
Rob. SE.	(0.021)	(595.9)	(0.017)	(0.031)	(847.0)	(0.025)
N. treated	858	849	858	409	406	409
$\bar{t}$+7	-0.065***	-1592.9**	0.239***	-0.053*	-1681.7*	0.254***
Rob. SE.	(0.022)	(609.6)	(0.017)	(0.032)	(880.5)	(0.026)
N. treated	811	804	811	381	379	381
$\bar{t}$+8	-0.057**	-1559.7**	0.240***	-0.054	-1851.3**	0.251***
Rob. SE.	(0.022)	(615.3)	(0.018)	(0.033)	(906.8)	(0.027)
N. treated	760	751	760	350	345	350
$\bar{t}$+9	-	-	-	-0.098***	-2563.2**	0.256***
Rob. SE.	-	-	-	(0.034)	(902.8)	(0.028)
N. treated	-	-	-	326	324	326

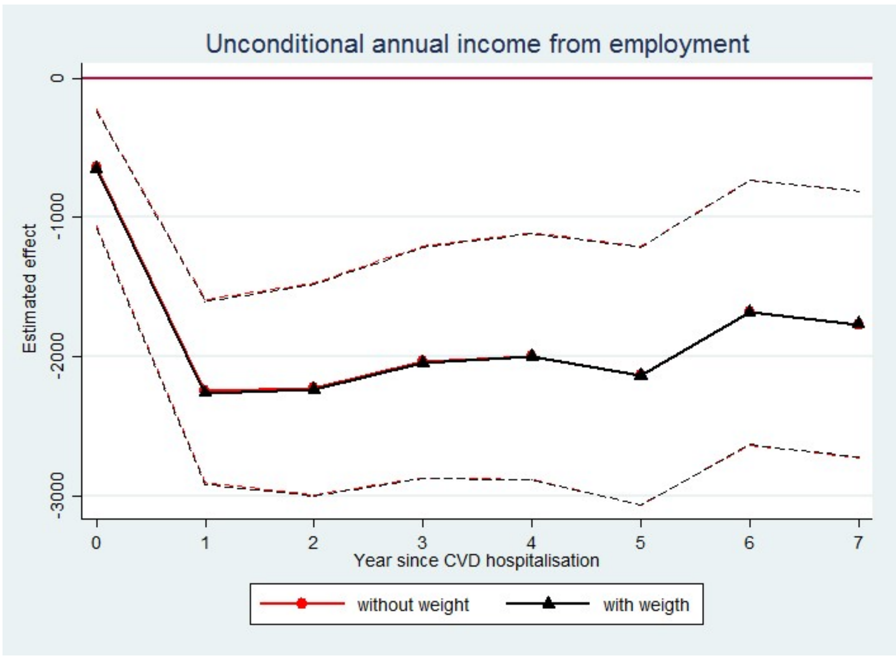
Source: WHIP&Health
Notes: * p<0.1, ** p<0.05, *** p<0.01

Figure A.1: ATT on employment, with and without mortality weights



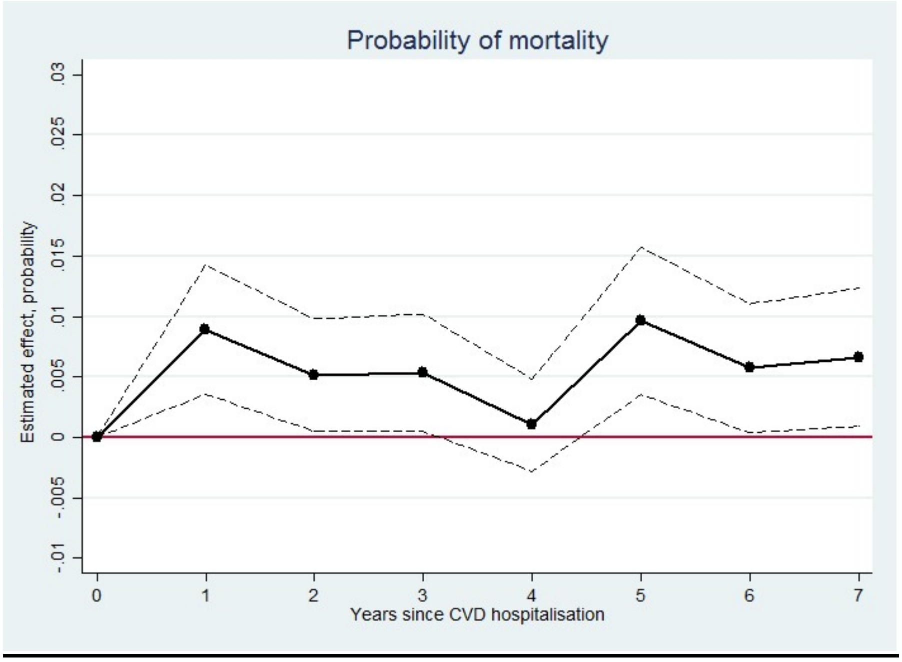
Source: WHIP&Health
Notes: ATTs: point estimates (connected line) and 95% confidence intervals (dashed lines).

Figure A.2: ATT on annual labour income, with and without mortality weights



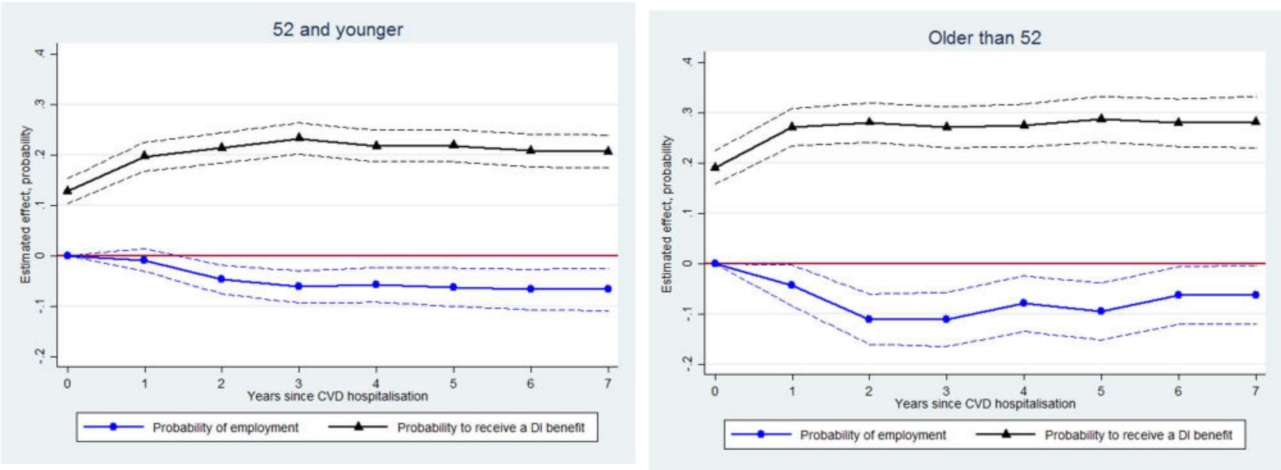
Source: WHIP&Health
Notes: ATTs: point estimates (connected line) and 95% confidence intervals (dashed lines).

Figure A.3: ATT on mortality – treated vs. all potential controls



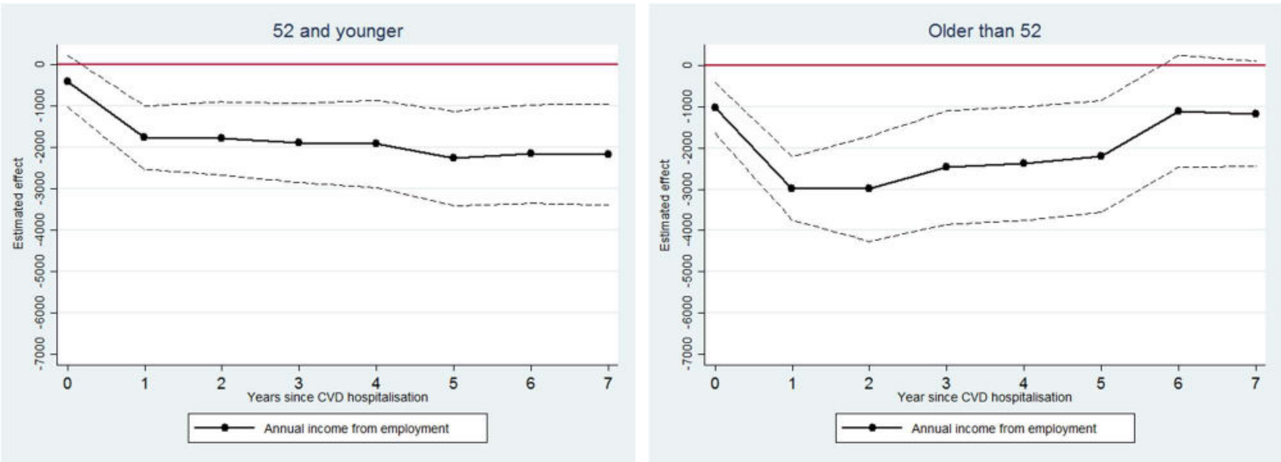
Source: WHIP&Health. Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported; by sample selection all individuals were alive in the year of the shock, so the ATT is 0 in that year. The regressions include only age as covariate.

Figure A.4a: ATT by year since CVD hospitalisation: probability of employment and probability of receiving a DI benefit



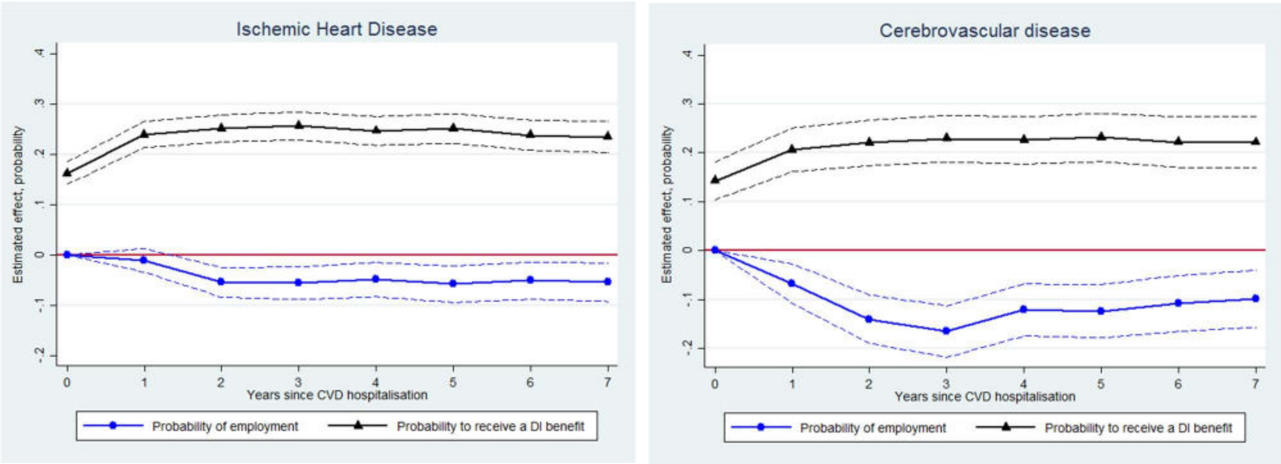
Source: WHIP&Health
Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

Figure A.4b: ATT by year since CVD hospitalisation: annual income from employment



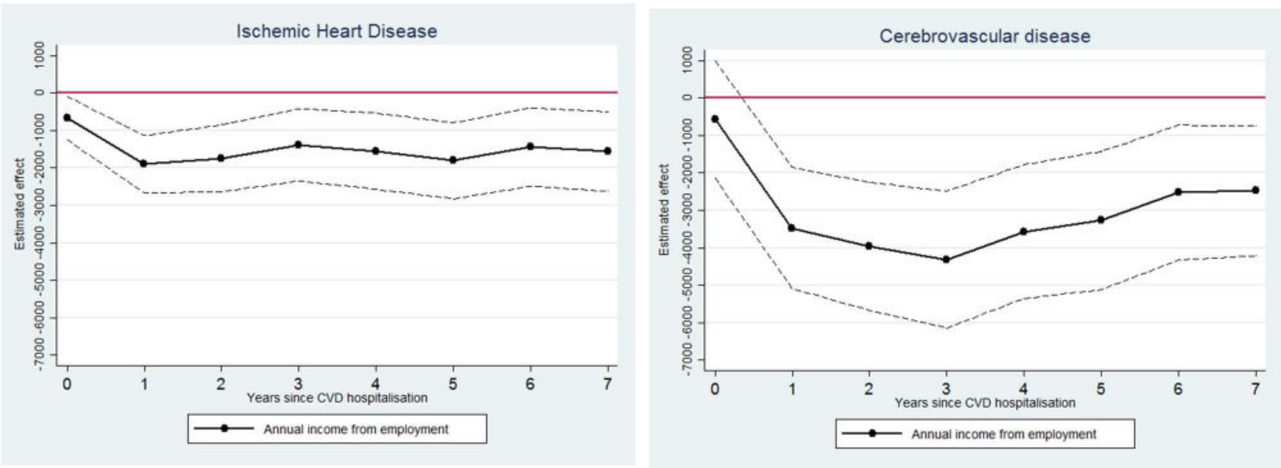
Source: WHIP&Health
Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

Figure A.5a: ATT by year since CVD hospitalisation: probability of employment and probability of receiving a DI benefit



Source: WHIP&Health
Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

Figure A.5b: ATT by year since CVD hospitalisation: annual income from employment



Source: WHIP&Health
Notes: ATTs: point estimates (connected lines) and 95% confidence intervals (dashed lines); marginal effects are reported.

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