**Scar on my heart: effects of unemployment experiences on coronary heart disease**



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# Scar on my Heart. Effects of Unemployment Experiences on Coronary Heart Disease.


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## Abstract

Purpose

The aim of the present work is to study the impact of unemployment on coronary heart diseases (CHD) in Italy on a sample of the male population employed as manual worker in the private sector.

Design/methodology/approach

The paper investigates the association between unemployment and CHD in Italy, exploiting a very long administrative database which allows designing a 12-years pre-treatment period, on which to balance workers individual characteristics; a 7-years treatment period to measure the occurrence of unemployment; and a 5-years follow up to measure the occurrence of CHD. The workers characteristics and the probability of receiving the treatment are balanced by means of Propensity Score Matching.

Findings

We find a significant increase of CHD probability for workers who experience more than three years of unemployment, and for those who exit unemployment starting a self-employment activity. Using different selections of the study population, a clear pattern emerges: the healthier and more labour market attached are workers during pre-treatment, the greater is the negative impact of unemployment on health.

Originality/value

The very large representative (n=69,937) and the deep longitudinal dimension of the data (1985-2008) allowed us to minimize the risks of health selection and unemployment misclassification. Moreover, the adopted definition of unemployment corrected some undercoverage and misclassification issues that affect studies based on a purely administrative definition.


Key words: Unemployment; Health; Coronary Heart Diseases; Propensity Score Matching; Self-employment

## INTRODUCTION

There is a solid evidence that unemployment experiences may have a long lasting “scarring” effect on the work careers of individuals in terms of lower wages and employment possibilities (Arulampalam, 2001; Jacobson et al. 2009). The public health literature has shown that there are several pathways leading also to harmful consequences on their health (Bartley 1994; Landsbergis et al. 2014; Wanberg 2012). A physiological pathway goes through the material and economic deprivation associated to the job loss, which may reduce ability to afford health care, healthy food and other necessities. Furthermore, biological processes linked to the experience of frequent or prolonged episodes of stress can lead to wear and tear on the body, increasing the organism’s inflammation levels and the risk for sickness (McEwen et al. 1993; Lundin et al. 2014). According to the psychological research, employment provides crucial immaterial resources such as time structure, definition of own identity and enlarged social networks, and unemployed individuals may experience severe consequences for mental health because of the lack of such intangible assets[1]. Finally, poor mental health, beyond being itself a risk factor for physical health (Hert et al. 2011), may also increase vulnerability to subsequent adverse life events and trigger destructive behavioural responses, like smoking, alcohol consumption and suicidal intention.

Although all these pathways have been widely investigated, to isolate their net impact on health is a challenging empirical issue, since there are also countervailing factors at work – the first of which is that individuals are no more exposed to occupational risk factors – and the direction of causality goes also from health status to labour market performance. In fact, the observation of unhealthy unemployed may be due to the selection of ill workers into unemployment and/or to the selection of healthy unemployed out of unemployment. This is because underlying medical conditions may make one a less productive worker and consequently increase the risk of being laid off and, afterward, of meeting difficulties in re-entering the labour market.

One of the health outcomes on which the international evidence is still controversial is Coronary Heart Disease (CHD), which is one of the leading cause of death among adults worldwide (WHO 2014). Here, besides the reverse causality issue, additional difficulties are linked to data availability. The first regards the long latency between the exposure to unemployment and the occurrence of CHD, which can operate within a few years to a decade (O’Flaherti 2011). Consequently, there is a need for sufficiently large and long longitudinal data. The second regards a sort of trade-off in the accuracy of the available measures of the treatment and the outcome. While in survey data a precise definition of unemployment is recorded, self-rated health status offers a weak measure of the outcome. In administrative data, on the opposite, very precise physicians’ assessments of health, but potentially poor measures of unemployment are available. Actually, only “registered unemployement” is observed, that is, periods in which individuals are registered with the Public Employment Services and/or are receiving unemployment benefits. Depending on country specific labour market regulations, however, these measures are prone to include inactive or even employed individuals, and their coverage of total unemployment may be very poor (Aleksynska e Schindler, 2011; Immervoll et al, 2006; Melis and Lüdeke, 2006). Unsurprisingly, a better understanding of the link between unemployment and cardiovascular diseases has been pointed out as a top-priority for future research agenda (Landsbergis et al. 2014; Wanberg 2012).

The aim of the present work is to study the impact of unemployment on coronary heart diseases (CHD) in Italy, a country where the studies on the issue are virtually absent, although CHD represents the leading

[1] Some of the most influential theoretical models are provided by Jahoda 1981, Fryer 1986, Warr 1987.

cause of hospitalization, after childbirth (Ministero della Salute, 2014). A large administrative database linking work histories and several health archives, among which hospital dismissal forms, provides us with a precise measure on the occurrence of CHD, and a very rich longitudinal description of careers. This allows to enhance the definition of unemployed – only based on the receipt of unemployment benefits –adding periods of non-employment not covered by benefits in which individuals are most likely unemployed (e.g. after the expiring of a benefit) and, excluding from it the periods in which individuals are most likely temporarily inactive (e.g. during a temporary layoff from a firm and a subsequent re-entry into the same firm).

To avoid selection biases, particularly relating to the health status and the exposure to occupational risks, we focus on a very homogenous sample of workers composed by male, mid-age, blue collars, who during a 12-years pre-treatment period showed a good general health and a high labour market attachment. We then consider a 7-years treatment period using different durations for the treatment definition (total unemployment lower than 1 year; between 1 and 3 years; over 3 years). We finally observe, over a 5-years follow up, the occurrence of hospital discharges for CHD. To reproduce a quasi-experimental setup, the characteristics of workers and the probability of receiving the treatment are balanced by means of propensity score matching, so that two groups of Treated and Controls are formed, and their average probability of being hospitalized can be compared.

The main result is that a statistically detectable, positive effect of unemployment on CHD is to be found for total unemployment over 3 years, with relative risks 90% higher with respect to workers with stable careers. We further investigated this association considering some plausible heterogeneity effects among the treated. A first pattern emerged for those who left unemployment starting a self-employment activity. In case of limited social protection and/or personal difficulties, many individuals simply cannot afford to be unemployed. In these circumstances, they must survive by any means, by taking up low quality, poorly remunerated jobs in the informal economy or by starting an autonomous activity as the best alternative available at the time. A clear excess on the risk of CHD is detected for these workers, also for short unemployment durations. A second pattern emerged applying increasingly stricter criteria to select the study population at the baseline. The more healthy and attached to the labour market the treated are, the higher the increase in the risk of CHD is, pointing to a possible "disappointment effect" (Osika et al, 2008; Montgomery et al, 2013).

The rest of the paper is organized as follows. In Session 1, we discuss the state of the art of literature on the relationship between unemployment and health and in particular with CHD. Session 2 describes the data used, the empirical strategy and the study design and discusses the definition of the treatment. Section 3 describes the statistical methods. Section 4 presents the results and the last section offers concluding comments and policy implication.

## Section 1: LITERATURE

In the voluminous literature on the health effects of job-loss, a negative causal effect of unemployment was found on some health outcomes, among which mental disorders (McKee-Ryan et al. 2005; Paul et al. 2009) and mortality (for a systematic review, see Roelfs et al., 2011) are the most well established. The importance of the behavioural pathways is also recognised. Involuntary job loss significantly increases the risk of hospitalization due to alcohol-related conditions, traffic accidents and suicidal intention in Sweden

(Eliason et al. 2009) and in Denmark (Browning et al., 2012). In Germany, involuntary job loss increases the body mass index and smoking initiation (Marcus 2014).

On other physical health outcomes, such as Coronary Heart Diseases (CHD) – which is the leading cause of death in Europe among adults – the international evidence is still controversial, and many null results have been recently published. Works dating back to the nineties reflect the difficulties that early research had in dealing with endogeneity issues. Weber and colleagues (1997) reviewed studies focusing on the association between unemployment and cardiovascular diseases (CVD), published in 1980-1995. They concluded that, although the associations found were strong, severe methodological shortcomings did not allow establishing whether the link was causal[2]. Many of the reviewed studies, in fact, generally grounded on cross-sectional design or observational follow-up studies of individuals with no or few controls for pre-baseline characteristics. Usually, in such studies, the exposure to unemployment and possible confounders were assessed only at baseline and the cohort was then followed for health outcome. This methodology, little can say about a true causal effect of unemployment on health, since persons likely to become unemployed, at baseline, may have pre-existing ill-health, that increase independently the risk of future health worsening.

More recently, researchers have put a greater attention to adopt study designs that allow the interpretation of the association between unemployment and health as causal. In a previous work (d'Errico et al. 2015), we followed a cohort of recipients of a particular welfare measure targeting long term unemployed and we identified a significant association between CHD risk and long unemployment, at the net of pre-existing health differentials. While the longitudinal nature of the data allowed us to tackle with the causality issue, the external validity of the result is limited to the specific subpopulation considered, i.e. unemployment benefits recipients.

An important branch of the economic literature has typically tried to overcome the reverse causality problem adopting study designs that reproduce an "as-if exogenous" change in labour market status, analysing the health effects of being exposed to a mass layoff or plant closure (Browning et al. 2006, 2012; Jacobson et al. 2009; Eliason et al. 2009; Schmitz 2011; Salm 2009)[3]. The basic assumption is that a layoff due to a firm severe downsizing should be unrelated to worker's characteristics. Although the "plant closure" remains the most widely accepted solution to the problem of endogeneity, the design suffers from some drawbacks. The first regards the internal validity of the results. Even in case of a mass layoff, firms likely choose the workers to fire, possibly on the bases of their characteristics, health included, and under the influence of workers' unions and national laws on collective dismissals. Second, workers could anticipate firms' closure by quitting the job, and "early exiters" may have different characteristics than the stayers[4]. In these cases, the pretention of exogeneity of plant closure or mass layoff should be taken cautiously. Moreover, it is worth remembering that losing one's job does not necessarily mean that the person becomes unemployed: many workers may find a new job straight away, or after a brief period, particularly when the firm restructuring is anticipated. Finally, psychological consequences of losing one's

[2] Jin et al. (1997) reached a similar conclusion, reviewing literature on the impact of job loss on different health outcomes. Although they found a strong evidence of positive association between unemployment and mortality rate, morbidity rate and use of health care services, they considered the conclusion that unemployment causes these outcomes unwarranted because of many methodological inadequacies.

[3] The plant closure design has been widely adopting also from authors working on the consequences of job loss for future earnings (Jacobsen et al. 1993; Stevens 1997; Sullivan and von Wachter 2009); job injuries (Leombruni et al. 2013); marriage stability (Eliason 2011) and children's school outcomes (Rege et al. 2014).

[4] This issue is controlled only by few of the quoted studies, e.g. Eliason et al. 2009, Leombruni et al. 2013.

job because of an individual layoff or a non-renewal of a temporary position may be very different to that experienced with a plant closure. In this latter case, it is the external validity of the results that can be questioned.

Another weakness of this thematic literature is that unemployment is generally treated as a unique career event, measured through a dichotomous variable, which not only prevents the assessment of any dose-response relationship, but also ignores the complexity of the experience of unemployment, which may result from the combination of multiple spells and durations. Garcy et al. (2012) and Dupre et al. (2012) are among the few scholars who specifically investigate the presence of a dose-response relationship. Garcy et al. (2012) studied the effect of different lengths of unemployment on overall and cause specific mortality, using data on the entire Swedish population. They concluded that for males, the adjusted mortality risk for stroke and CHD increase with the duration of unemployment in a quadratic way. Dupre et al. (2012) studied the impact of total number of spells of unemployment on the insurgence of acute myocardial infarction (AMI), using a large representative sample of North American elder workers. They found that AMI risks were significantly higher among the unemployed and the relative risk raised incrementally from one (1.22; 95% C.I. 1.04-1.42) to four or more job losses (1.63; 95% C.I. 1.29-2.07).

## Section 2: DATA AND STUDY POPULATION

The study is based on WHIP&Health, a longitudinal database on work and health histories in Italy built upon a 7% systematic sample of several administrative archives (Bena et al. 2012).

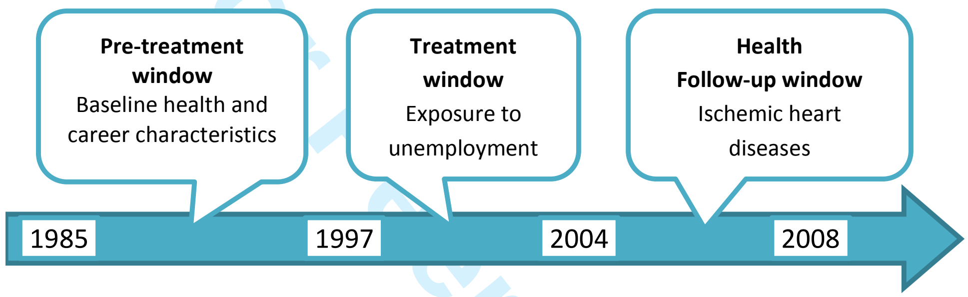
The section on work histories (WHIP, the *Work Histories Italian Panel*) is a linked employer-employee database built upon the archives of the National Social Security Administration (INPS). The reference population includes all individuals employed in private companies in the manufacturing, construction and service sectors; self-employed individuals as artisans and traders; workers with quasi-dependent employment. This group amounts to approximately 23 million of workers, representing more than 80% of the work force in Italy. Individuals excluded from the reference population are those working in the public- and the agriculture sector, high skill self-employed (e.g. lawyers or architects) and informal workers. The data collected cover individual careers from labour market entry up to 2005, with rich information particularly on dependent work episodes (among which days worked, wage, skill level, tenure, full- or part-time, type of contract, sector of activity, firm size, firm age) and a more limited one on other employment spells (duration of the employment period and earnings). Among non-work periods, the transition to retirement is observed, plus all periods in which the individual received any kind of social security benefit (e.g. unemployment benefits, partial unemployment benefits, maternity benefits, etc.).

The section on health includes data on work injuries and professional diseases from the National Work Injuries Insurance Administration (INAIL), available from 1994 to 2010; on cause specific hospital dismissal forms from the Italian Ministry of Health, available from 2001 to 2008; and on cause specific mortality from the Italian Institute of Statistics (ISTAT), available from 1999 to 2008. A further information on the health status of individuals may be inferred for dependent workers, for whom the number of weeks spent in sick leave are reported.

The archive on hospital dismissal is based on the systematic collection at the national level, by the Italian Ministry of Health, of the regional archives of hospital admissions and contains information on all patients admitted to public or private hospitals across the country, including the diagnosis at the moment of the discharge from the hospital, codified according ICD disease codes (ICD-IX)[5]. In the present work we investigate the risk associated to unemployment of myocardial infarction and other acute or chronic forms of Coronary Heart Diseases, defined by ICD-IX codes 410–414. This group of diseases represents the leading cause of death worldwide and in Italy (WHO, 2014), where it is also the first cause for hospitalization after childbirth (Ministero della salute, 2004-2008).

We exploited the panel dimension of the data to create three temporal windows, referring to a pre-treatment (1985-1996), treatment (1997-2003) and follow-up period (2004-2008) (see Figure 1). In this way we could impose the desired temporality to the sequence of events, i.e. one can observe if health in (t+1) is affected by a labour market event occurred during t, once the baseline characteristics in (t-1) are taken into account. Therefore, the pre-treatment window was used to identify the baseline characteristics of the study population, the treatment window to generate the treatment indicator variable, while the health outcome was observed during the follow-up window.

***Figure 1: The study design***




The choice of the cut-off years is due to several reasons, mainly dictated by data availability. The pre-treatment window starts in 1985, the first year with highly detailed employment and career information. The second window, where we measure the exposure to treatment, covers a broad period (seven years) to increase the sample size of treated, having to do with a rare health outcome that threats statistical power. Finally, the health follow up window was constrained by the years for which hospitalization data are available, i.e. years 2001-2008. We chose to start the follow up in 2004 to be able to exclude those with a first episode of CHD in 2001-2003, reducing this way the likelihood to observe a recurrent CHD episode in the follow-up.

The large sample size allowed us to restrict the analysis to a sample of homogenous workers with high labour market attachment and good health at the baseline. The group we selected was that of Italian males 30 to 55 years old at 2003, who during pre-treatment collected at least 4 years of tenure, was out of employment for no more than one fourth of weeks, and worked exclusively as blue-collar employees. We excluded from this group those who during pre-treatment were detected as being seasonal workers or being recalled from the same employer after a non-employment spell, since their labour market attachment is poorly measured with the data available (see below the section on the treatment identification). In order to limit from the outset the issue of reverse causality, we excluded also those individuals who ever received any social security benefit for invalidity or disability, or for whom a hospital



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[5] ICD-9-CM is the ninth version of the International Classification of Diseases, adopted in 1975 by the World Health Organization. This is the classification adopted by Italian Ministry of Health to codify diagnosis and procedures included in the Hospital Discharge Data (Scheda di Dimissione Ospedaliera , SDO). For more detail visit the page: http://www.salute.gov.it/portale/temi/p2_6.jsp?lingua=italiano&id=1277&area=ricoveriOspedalieri&menu=classificazione

dismissal for CHDs during treatment was observed. Finally, we excluded those who directly transited from non-employment to retirement, since, because of the very generous welfare provisions available in those years in Italy for individuals approaching retirement, their non-employment status may not be clearly considered a health risk, and both the psychological and economic distress experience are ambiguous in this case. This is what we called the "Base Selection" (see Table 1).

***Table 1: The Study Population***

| **Base Selection** | **Selection 1** | **Selection 2** | **Selection 3** |
|---|---|---|---|
| Male<br>30-55 years old in 2003<br>Blue Collar in pre-treatment<br>No recall and seasonal worker in pre-treatment<br>No work as self-employment in pre-treatment<br>At least 4 years of tenure in pre-treatment<br>Employment intensity > 75% in pre-treatment<br>No worker with invalidity or disability<br>No direct transitions mobility-pension<br>No CHD in 2001-2003 | Base Selection +<br>Employment intensity > 90% in pre-treatment | Selection 1 +<br>Average sick-weeks < 4 in pre-treatment | Selection 2 +<br>Average sick-weeks < 3 in pre-treatment +<br>Max yearly sick-weeks < 10 in pre-treatment |
| **N. Obs. 69.937** | **N. Obs. 63.568** | **N. Obs. 56.201** | **N. Obs. 45.857** |

Beyond the Base one, we identified three further selections gradually tightening the criteria for inclusion, with the intention to reduce the reverse causality by eliminating from the sample those workers with chronic health problems or who experienced severe health shocks in one specific year. The first, which we call "Selection 1", adds to all the criteria already used a more stringent constraint on labour market attachment, requiring an employment intensity – computed as the average ratio of worked weeks per year – greater than 90%. The "Selection 2" asks additionally for a better health at baseline, excluding those who were absent at least 4 weeks per year for illness[6]. The threshold is half the average duration of sick leave after a CHD episode that we measured for the years (2001-2008) on which hospitalizations for CHD and sick leave durations were available. The "Selection 3" makes even stricter the health requirement, excluding also those who were absent for more than 10 weeks in any single year. These selection criteria give a final sample of 69,937 individuals for the Base selection, down to 45,857 individuals for Selection 3.

## Identification of the treatment: unemployment definition

The issue of measuring unemployment in administrative data is not an easy one. In public registers one may identify what are commonly called "registered unemployed", who are either those registered to a Public Employment Office as job seekers, or those who are receiving an unemployment benefit. In both cases the definition of unemployment differs from the internationally accepted one, which considers as

[6] The threshold value of 4 weeks is intended for a worker who worked an entire year. The actual threshold value over which the selection is done is the ratio of sick weeks over worked weeks per year; i.e. workers whose average absence ratio was greater than 8% were excluded.

unemployed those who are not working and are both actively searching and available for employment. A clear cut example of the difference between the two definitions is that an individual whose only search action was that of registering to a Public Employment Office (and then is considered a "registered unemployed") is not classified as actively searching, and hence is not considered as unemployed according to the internationally received definition. S/he will be rather classified as inactive, *i.e.* among those who are not working but are not actively searching or available for employment.

Indeed, the official definition is questionable, and there is an ongoing debate (Jones et al. 1999 and 2006; Viviano 2003; Brandolini et al. 2006) about the classification as inactive of discouraged workers – i.e. those who are not actively searching since they did it for a long time without finding anything – and about the classification as employed of individuals who are under-employed, having access only to casual work opportunities. In both cases, the "inactive" or the "employed" status bears a similar stress to the individual as the one experienced by an unemployed.

The registered unemployment definition however has more severe limitations. The first one has to do with its coverage: not all unemployed are registered to a Public Employment Office, or are receiving an unemployment benefit. This brings an issue about its external validity as a measure of distress: typically, individuals who look for a job through a Public Employment Office have a weaker position in the labour market; while, on the opposite, the unemployment experience of those who are receiving a benefit is less tough with respect to those without a welfare coverage. The second limitation is about some empirically relevant missclassifications. Limiting ourselves the case of benefit recipients, which is the measure available in our data, two issues are to be quoted. The first is about temporarily inactive people who are eligible to an unemployment benefit. This is the case of seasonal workers in the break between seasons, and of temporarily laid off workers, who are waiting a re-entry into their job after a suspension for technical or economic reasons. In both cases the individual is registered as unemployed but there is just a suspension in the work activity, which bears a limited stress to the individual. A second missclassification is about benefit recipients who are actually working: in Italy, as in many other countries, there are several cases in which a work activity is compatible with unemployment benefits. In this case, we classify as "registered unemployed" people who are actually working.

Empirically, the relevance of under-coverage and misclassification crucially depends on country-specific welfare regulations, and namely on the criteria and eligibility rules adopted in a country to grant individuals a public support. As an example, Germany, Austria and Finland are countries where the administrative definition produce figures on unemployment which are higher that the official one (up to 27% higher in the case of Finland), while in Nederland they are almost half of it (Melis and Lüdeke, 2006). About the misclassification issue, Immervol *et al.* (2004), in a study on 21 OECD countries where a comparison was possible, found that in 2001 in half of the countries they considered the number of employed and inactive persons receiving an unemployment benefit outnumbered the unemployed. In the case of Italy, the disproportion is dramatically higher. In the case of people registered as Job Seekers, registered unemployed are about twice as much with respect to the official definition (Anastasia and Disarò, 2005; Guerrazzi 2012), while the estimates about how large is the unemployment benefits' coverage range from as low as 15% to 30% (Leombruni *et al.*, 2012).

In the case of definitions based on benefit recipiency, both the under-coverage and the misclassification will tend to hinder the identification of an effect, since unemployed with benefits are better off than those without it, and benefit recipients who are actually inactive or even engaged in some work activity are not exposed to the risk factors linked to the unemployment status.

In order to achieve a definition of unemployment closer to the statistical one, inclusive of all unemployed individuals and excluding as far as possible people who are not exposed to a stressful condition, the following strategy was adopted:

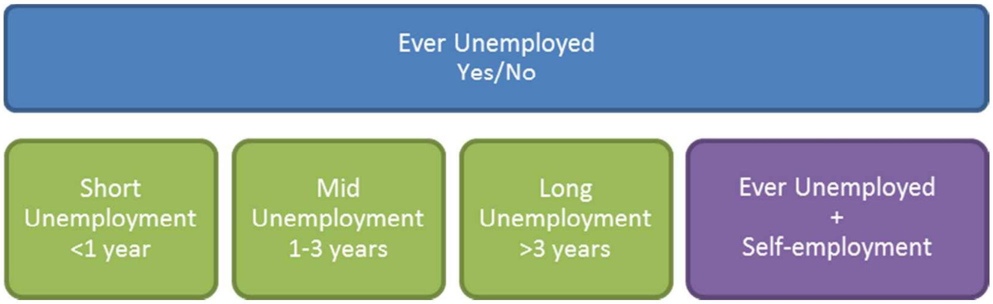
1) To overcome the under-coverage issue, a straightforward option would be to extend the definition to all periods of non-employment. This is the broadest way of defining unemployment, but poses a severe upward bias in the unemployment measure, since it includes all individuals who are inactive. Biewen et al. (2005), using German administrative data, proposed to consider only those periods of non-employment which are partially covered by unemployment benefits. In this way, the registration to a Public Employment Office serves the purpose of identifying those who actually entered into unemployment; but at benefit expiration individuals who do not find a new job will still be considered as unemployed. Since, however, an individual entering unemployment not always meet the criteria to receive a benefit, the definition is again strict. What we chose was to consider the partial coverage by benefits in a longitudinal way, classifying as unemployment all the non-employment periods of individuals who at least in one of them were benefit recipients.
2) To avoid as far as possible the inclusion of periods in which the individuals are inactive, we exploited the longitudinal dimension of the data excluding individuals with a seasonal pattern of employment/non-employment periods, and recalled individuals, *i.e.* those who after a separation from an employer re-entered within few months into the same firm.

These selections, together with the exclusion from the sample of women (who may decide to become inactive due to their family burdens) and of younger worker (who more frequently alternate periods in and out of the labour force), provided us with a study population with a strong attachment to the labour market, so that periods of registered unemployment or of not-employment as modified following points 1) and 2) are most plausibly indicating an unemployment status or a period of a great labour market difficulty – as in the case of under-employed people in the informal sector.

With this definition at hand, we identified several ways in which an individual may be "treated" by an unemployment experience, focusing on the different lengths and patterns that unemployment spells can take and making clear whether this entails heterogeneous effects on health.

Figure 2 depicts the different treatment definitions investigated. A first round of analysis focused on unemployment considered as a unique career event, operationalized by a dichotomous variable 0/1 indicating whether an individual was ever unemployed, whatever the length of the spell. Then, different lengths were analysed separately; we categorized spells based on their total duration, in short, medium and long unemployment. Finally, we focused on a specific category of unemployed, i.e. those who managed to escape it starting a new own business, i.e. reentering in the labour market as self-employed.

*Figure 2 Different type of treatment used in our analysis*




In Table 2, we present descriptive statistics of the Base selection, separately for treated and controls. Workers who, during the treatment window (1997-2003), did not experience any unemployment form the control group, whereas the treated are those who, during the treatment window, cumulated unemployment of different durations. These summaries have been constructed by looking at the characteristics observed during the 12 pre-treatment years (1985-1996), i.e. before the unemployment experiences.

There are some interesting differences in the health and employment profiles among treated and control on display in the baseline years. Control earned more than treated both at the beginning of their careers and on average. More remarkable are the differences in the weeks of cumulated unemployment, revealing a clear persistency of it, as the treated group experienced much more unemployment than controls already at the baseline. Controls indeed cumulated only 7 weeks of unemployment, against the 20, 24 and 31 weeks cumulated by the three categories of treated (short, middle and long unemployment, respectively). The controls tend also to show a better health profile, having a lower sickness absence rate than the treated[7]. This descriptive evidence is suggestive of the fact that we could not conclude that unemployment worsens health, from simply observing in the follow up a CHD differential among treated and control, because of important heterogeneity already present at baseline.

[7] In WHIP-HEALTH data, the information on sickness absence is registered on week's units only, thus if the employee was absent less than one full week, there is no track of such absence in the data. This is because, in case of a sickness absence lasting less than one week, the sick leave is entirely paid by the employer and not by the National Social Security Agency.

***Table 2: Description of the "Base Selection" sample by treatment status***

| | Never Unemployed | | Short Unemployment | | Middle Unemployment | | Long Unemployment | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **Std Dev** | **Mean** | **Std Dev** | **Mean** | **Std Dev** | **Mean** | **Std Dev** |
| Age | 40.13 | 5.52 | 39.06 | 5.51 | 39.95 | 5.66 | 40.44 | 5.56 |
| Entry weekly wage | 339.34 | 134.37 | 309.15 | 104.23 | 312.30 | 94.21 | 322.71 | 98.22 |
| Mean weekly wage | 395.89 | 89.59 | 358.29 | 82.58 | 362.13 | 86.04 | 369.97 | 94.88 |
| Weeks unemployed | 7.49 | 20.60 | 19.79 | 31.65 | 23.74 | 34.24 | 30.82 | 39.38 |
| Weeks subsidy | 0.22 | 3.14 | 0.90 | 7.06 | 0.96 | 7.16 | 2.07 | 11.89 |
| Weeks worked | 597.08 | 45.27 | 571.32 | 60.54 | 567.56 | 60.90 | 562.59 | 63.87 |
| Weeks sick absence | 7.56 | 10.73 | 8.66 | 12.28 | 8.80 | 13.25 | 8.16 | 15.28 |
| Professional diseases (0/1) | 0.00 | 0.06 | 0.00 | 0.05 | 0.00 | 0.04 | 0.00 | 0.04 |
| Severe injuries (0/1) | 0.04 | 0.19 | 0.04 | 0.21 | 0.04 | 0.20 | 0.04 | 0.20 |
| Firm size (0/1) | | | | | | | | |
| 0-9 | 0.20 | 0.40 | 0.34 | 0.48 | 0.30 | 0.46 | 0.26 | 0.44 |
| 10-19 | 0.11 | 0.32 | 0.13 | 0.34 | 0.11 | 0.31 | 0.09 | 0.29 |
| 20-199 | 0.34 | 0.47 | 0.35 | 0.48 | 0.35 | 0.48 | 0.29 | 0.45 |
| 200-999 | 0.16 | 0.37 | 0.11 | 0.32 | 0.11 | 0.32 | 0.15 | 0.35 |
| >=1000 | 0.18 | 0.39 | 0.06 | 0.24 | 0.12 | 0.33 | 0.22 | 0.41 |
| Sector of activity (0/1) | | | | | | | | |
| Primary sector | 0.01 | 0.10 | 0.02 | 0.12 | 0.02 | 0.13 | 0.01 | 0.11 |
| Manufacturing | 0.65 | 0.48 | 0.54 | 0.50 | 0.50 | 0.50 | 0.42 | 0.49 |
| Costruction | 0.09 | 0.28 | 0.19 | 0.39 | 0.19 | 0.39 | 0.15 | 0.35 |
| Commerce | 0.09 | 0.28 | 0.11 | 0.31 | 0.10 | 0.30 | 0.09 | 0.29 |
| Transport | 0.09 | 0.29 | 0.07 | 0.25 | 0.09 | 0.29 | 0.07 | 0.26 |
| Other service | 0.07 | 0.25 | 0.08 | 0.28 | 0.10 | 0.30 | 0.25 | 0.44 |
| **N. Obs.** | **55,914** | | **4,951** | | **4,027** | | **5,045** | |

*Note: for Short Unemployment we mean an unemployment duration under 1 year; 1-3 years for Middle Unemployment and over 3 years for Long Unemployment. All variables are related to pre-treatment period.*



## Section 3: METHODS

### The propensity score matching (PSM)

In observational data, the simple difference in CHD incidence between treated and non-treated – i.e. between people who incurred or not in unemployment – may reflect differences that would have been observed also in the absence of the treatment (the selection bias). In our context, the risk for a selection bias is likely, due to the presence of pre-treatment differences affecting at the same time the risk of unemployment and of CHD occurrence, and to the reverse causality channel in the unemployment-health relationship – one's bad health status may lead to a job loss, and then to the occurrence of CHD.

To correctly evaluate the causal effect of unemployment on the occurrence of CHD we opted for a propensity score matching estimator. The technique was originally proposed by Rosenbaum and Rubin (1983) to mimic randomized trials in observational data. The basic idea of matching estimators is to form groups of treated and controls who are similar with each other not because of ex-ante randomization, but as the ex-post result of matching each treated unit to untreated ones who are observationally similar to them. This strategy, however, meets a limit when high-dimensional vectors of characteristics are to be balanced – the so called "curse of dimensionality". What Rosenbaum and Rubin (1983) proposed was to estimate the probability of receiving the treatment given pre-treatment characteristics (the so-called propensity score), and match treated and controls who are as similar as possible in terms of it, converting in this way the multidimensional setup of matching into a one-dimensional setup. Matching based on the propensity score, then, allows to control for the selection bias reproducing a random-like assignment to the treatment, so that the difference in CHD incidence between treated and non-treated in the matched sample may be interpreted as the causal effect of unemployment.

Matching has some important advantages over regression-based methods. First, being a less-parametric method, one does not need to impose any specific assumption about the shape of the relation between all risk factors and CHD incidence. Matching explicitly tries to find for each treated individual a "statistical twin", so that one has not to control for differences in other characteristics besides the treatment, and the potential biases due to misspecification of the functional form are avoided. Second, when the outcome event is rare, whilst the exposure is much more common and the number of confounders is high, propensity score methods behaves particularly well, producing less biased, more robust and more precise estimates than logistic regression methods (Cepeda et al. 2003)[8]. Third, matching addresses the problem of similarity in a way that linear regression does not. Regression analysis is not concerned with how covariates distribute across the treated and controls, and identifies the parameter of interest by comparing observationally different persons. By using propensity score matching methods, one can find out how many units are in fact comparable and consider only comparable people (Heckman et al. 1999).

Among the various propensity score estimators proposed in the literature, we opted for kernel matching (Heckman et al., 1997, 1998). With kernel matching, each treated is matched with all controls falling within a given bandwidth, but the more a control is distant from the treated, the lower is the weight assigned to it, using a kernel function to compute weights (in our case the Epanechnikov function). Averaging the outcomes between several controls allows having more precise estimates with respect to nearest neighbour ones', while weighting allows to limit the potential bias one may incur into considering controls that are not close to the treated. We used bootstrapping with 100 cycles to compute standard errors. The estimator has been computed in SAS®, using the implementation introduced in Leombruni and Mosca (2015).

As a robustness check, we replicated all the analysis adopting a multivariate Poisson Regression Model with Huber-White sandwich estimator of variance, usually regarded as an appropriate approach for analysing rare (<5%) events when subjects are followed for a variable length of time (Zou 2004; Katz 2011)[9].

## Post-estimation diagnostics

The main hypothesis on which PSM estimators rely on is unconfoundedness, or conditional independence assumption. This assumption implies that conditioning on an observables set of X-variables, the expected potential health outcome for controls is the same for the two groups of unemployed and non-unemployed, respectively. This assumption cannot be formally tested; it is upon the researcher to argue that the selection into treatment depends (at most) on observable characteristics. Besides this, a good performance of the estimators requires both a sufficient overlap of the propensity score distributions among the treated and controls (i.e. common support), and a good performance of matching in achieving the balance in treated and controls' observable characteristics. While to assess the common support a visual analysis of the density distribution of the propensity score in both groups is considered sufficient, several formal testing procedures exist to evaluate the quality of the matching (Caliendo et al. 2008).

[8] Cepeda et al. (2003) show with Monte Carlo Simulation that propensity score behaves better than logistic regression when there are seven or fewer outcome events per confounder, as it happens in our data.

[9] The Poisson Regression Model is used in d'Errico et al. (2015) to estimate the probability of CHD in case of long term unemployment subsidy "*mobilità*".

The standardized differences (SD) is a suitable indicator to assess if the distribution of the relevant variables is well balanced in both the control and treatment group. This statistics measures the distance in marginal distributions of the X-variables in the unbalanced and in the matched sample, as suggested by Rosenbaum and Rubin (1985). For each covariate, the standardized difference is defined as the difference of sample means in the treated and matched control subsamples as a percentage of the square root of the average of sample variances in both groups. The desired situation is one in which post-matching standardized differences are smaller than pre-matching ones. Additionally, Austin (2009) shows that a standardized difference of 10% is equivalent to having a correlation coefficient of 0.05 (indicating negligible correlation) between the treatment variable and the covariate.

Another test for the quality of the match is obtained re-estimating the propensity score on the matched sample (Sianesi 2004), that is only on participants and matched non-participants, and compare the pseudo-$R^2$ achieved by the probability model before and after the matching. Since the pseudo-$R^2$ indicates how well the regressors explain the treatment probability, and after matching there should be no systematic differences in the distribution of covariates between groups, the pseudo-R2 should be fairly low. Furthermore, one can perform an F-test on the joint significance of all regressors. The test should not be rejected before, and should be rejected after matching.

## Section 4: RESULTS

We present now the estimates for the average treatment effect of being unemployed we obtained using kernel matching based on the propensity score and a Poisson regression model as a robustness check.

To achieve a balance of the individual, career and health characteristics over the 12 years of the pre-treatment window (1985-1996), the propensity score was estimated with a Logit model regressing the various treatment indicator variables on socio-demographics (age and age-square), occupational characteristics (modal sector of activity divided in 32 sectors dummies; firm size categorized in 5 groups; 5 macro regions; entry wage and average wage; total number of unemployment weeks; total number of unemployment subsidy) and health status (number of sick leave weeks; occupational injuries; professional diseases).

Table 3 and 5 present the results from the PSM estimation of the effect of being exposed to different treatments, relative to workers continuously employed. In both the tables, several statistics are reported: the relative risk (RR), the average treatment effect on the treated (ATT), the relative standard errors (ATT st.err.), the factual and counterfactual prevalence of CHD in the treated (Factual) and control sample (Counterfactual). The number of treated and control individuals (n° T, n° C) and of successful matches are also reported. The last two columns provide synthetic indicators telling whether post-estimation diagnostics have been passed.

*Table 3 PSM estimation results, Relative Risks of CHD for Unemployed VS Continuously Employed*

| | RR | ATT | ATT st.err. | Factual | Counter-factual | n° T | n° C | n° matches | STD diff. %success | Sianesi Test |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Ever unemployed** | | | | | |
| Base Selection | 1.096 | 0.001 | 0.003 | 0.017 | 0.015 | 3,131 | 55,914 | 3,131 | 100% | Pass |
| Selection 1 | 1.159 | 0.002 | 0.003 | 0.018 | 0.015 | 2,622 | 52,701 | 2,619 | 100% | Pass |
| Selection 2 | 1.183 | 0.003 | 0.003 | 0.018 | 0.015 | 2,560 | 52,000 | 2,556 | 100% | Pass |
| Selection 3 | 1.275 | 0.004 | 0.003 | 0.017 | 0.014 | 2,256 | 46,785 | 2,253 | 100% | Pass |
| | | | | | **Short unemployment (<1year)** | | | | | |
| Base Selection | 0.931 | -0.001 | 0.004 | 0.012 | 0.013 | 1,229 | 55,914 | 1,229 | 100% | Pass |
| Selection 1 | 0.993 | 0.000 | 0.004 | 0.013 | 0.013 | 1,088 | 52,701 | 1,088 | 100% | Pass |
| Selection 2 | 0.993 | 0.000 | 0.004 | 0.013 | 0.013 | 1,071 | 52,000 | 1,071 | 100% | Pass |
| Selection 3 | 0.940 | -0.001 | 0.004 | 0.012 | 0.012 | 946 | 46,785 | 946 | 100% | Pass |
| | | | | | **Middle unemployment (1-3 years)** | | | | | |
| Base Selection | 0.907 | -0.001 | 0.003 | 0.012 | 0.014 | 1,535 | 55,914 | 1,535 | 100% | Pass |
| Selection 1 | 1.030 | 0.000 | 0.003 | 0.012 | 0.012 | 1,370 | 52,701 | 1,369 | 100% | Pass |
| Selection 2 | 1.063 | 0.001 | 0.004 | 0.013 | 0.012 | 1,351 | 52,000 | 1,351 | 100% | Pass |
| Selection 3 | 0.864 | -0.002 | 0.004 | 0.012 | 0.014 | 1,192 | 46,785 | 1,192 | 100% | Pass |
| | | | | | **Long unemployment (>3 years)** | | | | | |
| Base Selection | **1.912*** | 0.013 | 0.007 | 0.026 | 0.014 | 761 | 55,914 | 760 | 96% | Pass |
| Selection 1 | **1.956**** | 0.015 | 0.008 | 0.031 | 0.016 | 572 | 52,701 | 572 | 98% | Pass |
| Selection 2 | **2.223**** | 0.018 | 0.009 | 0.032 | 0.015 | 555 | 52,000 | 555 | 100% | Pass |
| Selection 3 | **2.787***** | 0.023 | 0.009 | 0.036 | 0.013 | 478 | 46,785 | 478 | 100% | Pass |

Note: Analysis adjusted for: age and age-square; modal sector of activity (32 cat.); firm size (5 cat.); 5 macro regions (5 cat.); entry wage and average wage; total number of unemployment weeks; total number of unemployment subsidy; total number of sick leave weeks; occupational injuries; professional diseases. All controls variables are related to pre-treatment period. Legend: * p<0.10, **p <0.05, *** p<0.01

In table 3 we present the estimated effect of different duration of unemployment. No negative impact on the probability of being hospitalized for CHD was to be found about individuals who were ever unemployed during the treatment window. Also being unemployed for a short or medium period seems to have no excess in the risk of CHD, as it appears even protective. Although not significant, the risk of CHD for workers who get unemployed for less than one year, relative to continuously employed, were 6-7% lower in the Base and the 3rd selections. The striking results emerged with unemployment duration lasting more than 3 years. In fact, once the focus is on long-term unemployment, persons seem to suffer a lot for unemployment, with a risk of myocardial infarction or other kind of CHD considerably and significantly higher than in the continuously employed group.

Interestingly, the relative risks show a clear pattern along the selections we made, as the healthier and more labour market attached are the individuals, the greater is the negative impact of unemployment on CHD risk: gradually restricting the criteria of inclusion from the Base population to Selection 3, the RR goes from 1.92 (p<.10) to 2.79 (p<.01).

Robustness checks done with a Poisson regression model, controlling for the same variables used in the matching to balance the treated and control groups, confirmed the result that only unemployment longer than 3 years significantly increase the probability of CHD (Table 4). Although the estimated RRs are slightly smaller, also the pattern is confirmed, and the RR of myocardial infarction for a long unemployed is 1.63

(p<.05) in the Base Selection and increased progressively, up to a twofold RR in the Selection 3 (RR=2.23, p<.01).

The matching procedure produced a good quality of the balancing, and the common support assumption was always satisfied. At the end of the matching, the sub samples of treated and control do not present significant differences in all the observable covariates, also for crucial characteristics such as baseline health and cumulated unemployment, as demonstrated by very low standardized differences consistently below the 10% threshold (Appendix 1). In the next-to-last column in Table 3 we report the percentage of covariates whose standardized difference was successfully reduced below the threshold, never lower than 96%. Thus, we can conclude that the matching procedure passed the test proposed by Rosenbaum and Rubin (1985), since almost all the characteristics now are very well balanced between the two groups. We also reached the overlap of the common support, as only for one treated individual we could not find a "similar" control, as shown by the comparison of the number of treated and number of matches. Furthermore, also trough visual inspection (Appendix 3) is evident that the distribution of the two subsamples overlap.

***Table 4 Poisson estimation results, Relative Risks of CHD for Long Unemployment VS Continuously Employed***

| | RR | S.E. | P>\|z\| |
|---|---|---|---|
| Base Selection | 1.63** | 0.401 | 0.047 |
| Selection 1 | 1.91*** | 0.472 | 0.009 |
| Selection 2 | 2.01*** | 0.497 | 0.005 |
| Selection 3 | 2.23*** | 0.570 | 0.002 |

*Note: For Long Unemployment we mean an unemployment duration over 3 years. Analysis are adjusted for: age and age-square; modal sector of activity (32 cat.); firm size (5 cat.); 5 macro regions (5 cat.); entry wage and average wage; total number of unemployment weeks; total number of unemployment subsidy; total number of sick leave weeks; occupational injuries; professional diseases. All controls variables are related to pre-treatment period. The model includes also an offset variable, for the time occurred between the end of the treatment and the realization of the CHD event.* Legend: * p<0.10, **p <0.05, *** p<0.01

It should be noticed that an increasing relative risk going from Selection 1 to the 2 and the 3 is somewhat unexpected. The idea behind these selections was that of focusing on individuals with a better health during pre-treatment, to avoid the residual confounding linked to health differences at the baseline. Was the matching algorithm not effective in balancing the health status of treated and controls, we would have had treated individuals with worse health at the baseline and the higher incidence of CHD would have been, at least in part, the consequence of this selection. Consequently, the relative risks in Selections 2 and 3 should have rather gone down, inasmuch the choice of a healthier population at the baseline limits the selection bias. The finding that workers who get unemployed display a risk of hospitalization that increases along with the selections could be the results of a twofold process. First, there could be a residual measurement issue: keeping only a sample of highly labour market attached and in good health individuals guarantees that the observed non-employment periods are actually involuntary unemployment ones, thus reducing misclassification of the treatment and the related attenuation bias. Second, this is coherent with the measure we adopted to select healthier individuals in selections 2 and 3, i.e. the length of sick-leaves. It is well documented that sickness absence is only partially determined by health (Marmot et al., 1995; Andrea et al. 2003), whereas social and contextual factors and personal attitudes of workers appear to play an important role. People taking less frequently or shorter sick-leaves tend to work under better working condition (Kristensen, 1991; Ardito et al. 2012) and to be more committed to their job (Siegrist 2006; Hansen and Andersen 2008). Thus, we may presume that along with these selections, we are targeting workers who are more attached to their job. If their attachment is proportional to the Pecuniary and Non-Pecuniary Rewards associated with the job, we might expect that therefore also the loss associated with that job becomes bigger and more detrimental. This stylized fact has been already recognized as a pattern of reaction to adversity called “disappointment paradox”, i.e. when individuals with greater potential and expectations encounter adversity in adulthood, the experience is relatively more unexpected and harmful to different aspects of health (Osika et al. 2008). In a context similar to ours, Montgomery and colleagues (2013) found that unemployment was associated with higher mortality risks among individuals who were previously advantaged, with higher qualifications and better cognitive functions.

The result that long-term unemployment is more impairing than short-term unemployment is coherent with several other studies. In Finland, Böckerman et al. 2009 found that only unemployment longer than 6 months reduces self-assessed health; Gordo (2006) showed that for men, being unemployed for more than two years has a more significant and negative effect than shorter unemployment, while for women, only long-term unemployment has a significant and negative effect; Paul and Moser (2009), in their meta-analysis of 87 longitudinal studies, confirmed that the negative effects of unemployment on mental health is larger among long-term unemployed persons (>6 months) compared to short-term unemployed persons (<6 months).

The apparently protective effect of short period of unemployment is quite unexplored in the micro econometrics literature, while the pro-cyclical pattern of unemployment is typically pointed out by scholars working with macro data. This finding is coherent with Lundin (2014) who revealed that short unemployment (<90 days) had a protective effect (not significant) while long unemployed had an elevated hazard rate of CHD. Ruhm (1996) was the first to establish that mortality in USA lowered when national unemployment rate was high and vice versa, then confirmed also for other non-US countries (Neumayer 2004; Tapia et al. 2008). These finding can be reconciled with the micro-economics literature on job loss by the fact that some of the mechanisms mediating the health effects of unemployment are quite contemporaneous (e.g., the decreased levels of occupational risk exposure; fewer traffic accidents, etc.), while other take time to realize (e.g., the detrimental effect of cumulating psychological and financial distress, the effect of unhealthy behaviour like increased smoking, etc.).

Another signs of the presence of heterogeneous effect of unemployment on health was finally derived from the analysis of the career paths. Among the unemployed, those who suffered more were those who re-entered in the labour market as self-employed after a period of unemployment (Table 5).

***Table 5 PSM estimation results, Relative Risks of CHD for Unemployed & Self-employed VS Continuously Employed***

| | RR | ATT | ATT S.E. | Factual | Counter-factual | n° T | n° C | n° matches | STD diff. %success | Sianesi Test |
|---|---|---|---|---|---|---|---|---|---|---|
| Base Selection | 1.695* | 0.007 | 0.004 | 0.016 | 0.009 | 1,492 | 55,914 | 1,492 | 100% | Pass |
| Selection 1 | 1.905** | 0.009 | 0.004 | 0.018 | 0.010 | 1,093 | 52,701 | 1,093 | 100% | Pass |
| Selection 2 | 2.150** | 0.010 | 0.004 | 0.019 | 0.009 | 1,068 | 52,000 | 1,068 | 100% | Pass |
| Selection 3 | 2.159** | 0.011 | 0.005 | 0.020 | 0.009 | 945 | 46,785 | 945 | 100% | Pass |

*Note: For* Unemployment & Self-employed *we mean an unemployment of any duration followed by self-employment. Analysis are adjusted for: age and age-square; modal sector of activity (32 cat.); firm size (5 cat.); 5 macro regions (5 cat.); entry wage and average wage; total number of unemployment weeks; total number of unemployment subsidy; total number of sick leave weeks; occupational injuries; professional diseases. All controls variables are related to pre-treatment period.* Legend: * p<0.10, **p <0.05, *** p<0.01

Workers with this kind of career pattern (blue-collar employee – unemployed – self-employed) display a high RR of CHD without selecting only those with long periods of unemployment[10]. The probability of CHD for these individuals is more elevated than those who were continuously employed in the treatment window, once all the characteristics in the pre-treatment period were controlled for by the matching algorithm. The RRs specific to the different selections follow the usual pattern: in the base selection we have a RR of 1.70 (p<.10), and the risk increases when the criteria for being included in the sample become more severe in terms of prior health and labour market attachment. In the most severe selection the treated have more than twice the probability of being hospitalized for CHD than the control group (RR=2.16, p<.01)[11]. The usual post-estimation diagnostic tests have been performed, and they showed good balance of the observable covariates and propensity score overlap among treated and control. Results are confirmed also using a Poisson model (Table 6)[12].

***Table 6 Poisson model, Relative Risks of CHD for Unemployed & Self-employed VS Continuously Employed***

| | RR | S.E. | P>\|z\| |
|---|---|---|---|
| Base Selection | 1.73*** | 0.372 | 0.010 |
| Selection 1 | 1.93*** | 0.445 | 0.005 |
| Selection 2 | 1.99*** | 0.460 | 0.003 |
| Selection 3 | 2.18*** | 0.520 | 0.001 |

*Note: For* Unemployment & Self-employed *we mean an unemployment of any duration followed by self-employment. Analysis are adjusted for: age and age-square; modal sector of activity (32 cat.); firm size (5 cat.); 5 macro regions (5 cat.); entry wage and average wage; total number of unemployment weeks; total number of unemployment subsidy; total number of sick leave weeks; occupational injuries; professional diseases. All controls variables are related to pre-treatment period. The model includes also an offset variable, for the time occurred between the end of the treatment and the realization of the CHD event.* Legend: * p<0.10, **p <0.05, *** p<0.01

A possible explanation for this finding could be that autonomous work is a stressful event, especially for those workers who spent most of their working career employed under a dependent work relationship and have not acquired the needed experiences to cope with the new challenge. Blanchflower (2004) showed for OECD countries that self-employed individuals work under a lot of pressure, find their work stressful, lose sleep over worry and place more weight on work than they do on leisure. However, this hypothesis does

[10] Remember that without conditioning on the type of transition out of unemployment, the "ever unemployed" did not show a higher risk of CHD (Table 3). The sample size for the treatment pattern "employee-unemployed-self-employed" was not sufficiently large to stratify also the according to the length of the unemployment period.

[11] The matching procedure passes the standardized differences test (see appendix for details) and the test proposed by Sianesi (2004).

[12] It is worth to say that the results we got for the whole population of unemployment (Table 3) are not fully driven by the subpopulation of unemployed re-entering the labour market as self-employed. In fact, the increased relative risk of CHD persists if this subpopulation is excluded, confirming also the usual pattern: RRs are positive and not significant in the Base Selection (RR=1.47, t=1.22) and in Selection 1 (RR=1.61, t=1.28); significant in Selection 2 (RR=2.19, t=1.94) and significant and bigger in Selection 3 (RR=2.26, t=2.17).

not to fit our data as we checked whether becoming self-employed in itself, without any intermediate period of unemployment, produced some negative effect on health, and we did not find any association between becoming self-employed and subsequent increased risk of CHD[13].

A more plausible interpretation relies on the so-called "push theory" (Dawson et al. 2012). The push hypothesis states that under worsening economic conditions and increased levels of unemployment, the perspective for finding dependent work opportunities reduces. This adverse economic context would act pushing individuals towards self-employment[14]. Empirical works found supportive evidence for this hypothesis, suggesting furthermore that the "push" to become self-employed would be even stronger for vulnerable groups. Using longitudinal data from Spain and Canada, Carrasco Raquel (1999) and Moore (2002) found that unemployment (versus wage employment) favours self-employment, particularly for those who experienced a longer period of joblessness and who did not collect unemployment benefits.

Following these insights, we explored the presence of heterogeneity among the unemployed and we actually found that those individuals experiencing this specific career path (blue-collar employee – unemployed – self-employed) have different characteristics (Table 7). They are younger; come more from the North of Italy (where undocumented employment is less common); earn less, already at labour market entry and on average; they are employed in smaller firms (where employment protection is typically lower); have a longer cumulated unemployment and, when unemployed, receive less frequently unemployment benefits. Regarding health, interestingly, available measures for sick weeks, professional diseases and injuries do not show any statistical difference at the baseline. This profile together fits with the identification of this group as more disadvantaged among the unemployed.

***Table 7 Description of Unemployed with and without a self-employed career after the unemployment episode***

| | **Unemployed without Self-employed** | **Unemployed and after Self-employed** | **p-value** |
|---|---|---|---|
| Age | 40.17 | 37.37 | *** |
| Entry weekly wage | 317.10 | 300.02 | *** |
| Mean weekly wage | 365.23 | 352.39 | *** |
| Weeks worked | 568.08 | 559.33 | *** |
| Weeks unemployed | 24.34 | 30.13 | *** |
| Weeks subsidy | 3.19 | 1.55 | *** |
| Weeks sickness absence | 8.51 | 8.40 | |
| Sickness absence intensity | 0.02 | 0.02 | |
| Employment intensity | 0.95 | 0.94 | *** |
| Total injuries | 0.21 | 0.21 | |
| Severe injuries | 0.04 | 0.04 | |
| Professional diseases | 0.00 | 0.00 | |
| Firm size (0/1) | | | |
| 0-9 | 0.29 | 0.42 | *** |
| 10-19 | 0.11 | 0.13 | ** |
| 20-199 | 0.33 | 0.30 | *** |

[13] Results available upon request.

[14] Dawson et al. (2012) report that in the *push theory* literature, the adopted "[...] terminology may vary; for example Gilad and Levine (1986) and Amit and Muller (1994) refer to "push" vs "pull" entrepreneurship, Hessels et al. (2008) refer to "necessity entrepreneurship", and Thurik et al. (2008) coin the term "refugee entrepreneurship".

| | | | |
|---|---|---|---|
| 200-999 | 0.13 | 0.09 | *** |
| >=1000 | 0.14 | 0.07 | *** |
| Area of work (0/1) | | | |
| North | 0.48 | 0.61 | *** |
| Centre | 0.19 | 0.19 | |
| South and Islands | 0.34 | 0.20 | *** |
| N. Obs | 12,296 | 1,492 | |

*Note: For Unemployment & Self-employed we mean an unemployment of any duration followed by self-employment. Sample used: Base Selection. All variables are related to pre-treatment period. Legend: * p<0.10, **p <0.05, *** p<0.01*

## Section 5: CONCLUSIONS

The paper has analysed the causal effect of unemployment on coronary heart diseases (CHD), using Italian Administrative data for years 1985-2008. Adopting a Propensity Score Matching technique and a Poisson model for longitudinal data as robustness check, we found that a cumulated unemployment longer than 3 years increases significantly the probability of hospitalization for CHD, making the risk for long unemployed almost three times higher than those continuously employed (RR=2.8, p<.01). An interesting pattern emerged from the analysis, i.e. the healthier and more labour market attached were the workers at the baseline, the bigger the detrimental effect of unemployment on the CHD risk.

Another source of heterogeneity emerged among the treated, which to our knowledge is not yet investigated: the unemployed who re-entered in the labour market as self-employed suffered more the detrimental effect of unemployment. Their choice to start an autonomous work activity seems to be driven by an urgent need to find out a way to escape from unemployment, to make ends meet. In fact, those who follow this particular career path (employees as blue-collar – unemployed – self-employed) are on average more disadvantaged, as they are younger, experienced longer unemployment periods, were less covered less by the welfare, were working in small firms (having hence less secure and protected jobs).

A strength of our study rests in the very large representative sample of the male population employed as manual worker in the private sector (n=69,937) and the deep longitudinal dimension of the data (1985-2008), which allowed us to minimize the risks of health selection and unemployment misclassification, in several ways. First, the longitudinal design imposed the desired temporality to the sequence of the events, that is, we could observe whether health in *t+1* were affected by a labour market event occurred in *t*, once the baseline characteristics were taken into account in the pre-treatment period *t-1*. Moreover, the implementation of a definition of unemployment corrected some undercoverage and misclassification issues that affects studies based on a purely administrative definition of it. As a further robustness check, we considered different selections of individuals who at the baseline were highly labour market attached and in good health. However, differences between the results obtained from the Base model and the other Selections, where stricter selection rules for health and labour market attachment were applied, revealed that baseline health status was not an important confounder of the association between unemployment and CHD risk in this study, at least not in the expected direction.

In conclusion, for Italian manual men workers, unemployment is an exceptionally stressful career event with the potential for provoking long-lasting harmful consequences for their health. Workers who stuck in long-term unemployment (>3 years) experience a worryingly high relative risk of myocardial infarction and other severe form of coronary heart diseases. The magnitude of this effect has been never pointed out in previous studies and much less in Italy.

Health care professionals who treat individuals who lose their jobs should therefore pay attention to the vulnerability of their status and consider the loss of employment a risk factor for coronary hearth diseases. Similarly, policy makers also should be aware of the high social and public cost associated to job loss, and should intervene with urgency to implement effective programmes designed to support and return unemployed to work.

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## Appendix

***Appendix 1***

***Standardized Differences for Long Unemployment VS Continuously Employed (Table 3)***

| | Base Selection | | Selection 1 | | Selection 2 | | Selection 3 | |
|---|---|---|---|---|---|---|---|---|
| | Pre Match | Post Match | Pre Match | Post Match | Pre Match | Post Match | Pre Match | Post Match |
| Age | 25.61 | -0.39 | 28.85 | -1.53 | 28.58 | -1.51 | 28.91 | -1.95 |
| $Age^2$ | 25.07 | -0.62 | 28.55 | -1.48 | 28.27 | -1.57 | 28.54 | -1.77 |
| Work area: North-East IT | -59.07 | -10.85 | -54.34 | -4.28 | -54.42 | -6.57 | -55.12 | -6.99 |
| Central IT | -1.78 | -0.56 | -1.62 | 1.65 | -2.24 | 2.79 | -2.50 | -1.71 |
| South IT | 83.48 | 6.66 | 78.85 | 1.50 | 79.18 | 2.08 | 79.78 | 4.39 |
| Islands IT | 37.13 | 0.56 | 37.31 | 0.23 | 37.73 | -0.44 | 38.56 | 1.37 |
| Entry weekly wage | -16.70 | 4.65 | -13.65 | -10.56 | -14.13 | -4.20 | -14.82 | -8.13 |
| Mean weekly wage | -44.92 | 5.62 | -40.64 | -5.89 | -40.14 | -2.87 | -41.14 | 1.11 |
| Weeks unemployed | 62.44 | -3.72 | 32.26 | -4.64 | 32.45 | -4.58 | 33.94 | -4.35 |
| Weeks subsidy | 54.10 | -5.02 | 36.18 | -3.80 | 35.25 | -0.70 | 37.02 | -4.59 |
| Weeks worked | -61.03 | 5.58 | -36.33 | 0.44 | -36.70 | 4.72 | -40.31 | 8.09 |
| Weeks sick (1989-1996) | 18.62 | 0.57 | 20.95 | -1.84 | 17.93 | -1.44 | 12.72 | 2.31 |
| Professional diseases (1994-1996) | -0.84 | 1.44 | 0.70 | 0.80 | 1.05 | -0.59 | -1.06 | 0.64 |
| Severe injuries (1994-1996) | -1.13 | 1.65 | -2.40 | -3.02 | -3.87 | 2.57 | -1.77 | -1.32 |
| Firm size: 10-19 | -12.02 | -6.25 | -12.00 | 2.48 | -12.06 | 5.63 | -11.10 | 0.86 |
| 20-199 | 33.52 | 3.60 | 29.13 | 3.86 | 29.98 | -1.11 | 29.67 | 0.27 |
| 200-999 | 3.45 | -0.67 | 5.98 | -3.04 | 5.87 | -2.95 | 7.04 | -3.39 |
| >=1000 | -17.75 | 0.20 | -14.33 | -2.51 | -15.00 | -0.60 | -18.04 | 3.84 |
| Sector of activity: Agriculture & Fishing | -0.07 | -3.23 | -0.40 | 2.92 | -0.30 | 0.00 | -0.04 | -2.27 |
| Extraction of fuel minerals | -3.49 | -36.83 | -3.54 | 0.00 | -3.40 | 0.00 | -3.33 | 0.00 |
| Extraction of non-fuel minerals | 9.28 | 1.19 | 7.83 | -0.84 | 8.12 | -2.13 | 6.72 | -0.53 |
| Food | 6.65 | 3.36 | 7.14 | -0.20 | 6.25 | 1.85 | 3.74 | 3.16 |
| Textile | 7.02 | -4.79 | 11.58 | 2.25 | 12.39 | 2.33 | 11.13 | 3.69 |
| Hide and leather | 17.39 | -1.77 | 14.07 | 2.18 | 14.51 | -1.15 | 13.19 | 1.36 |
| Wood | 1.83 | 0.48 | 4.52 | -0.05 | 4.94 | 1.60 | 5.26 | -1.13 |
| Paper, printing and publishing | -3.73 | 2.23 | -5.08 | 0.48 | -5.58 | 2.67 | -7.97 | 1.78 |
| Coke manufacturing and refineries | 1.21 | -2.65 | 3.01 | 1.36 | 3.25 | -1.73 | 1.88 | 2.28 |
| Chemical product manufacturing | 9.89 | -0.81 | 13.15 | -5.06 | 13.00 | -0.55 | 12.14 | 0.88 |
| Rubber and plastics | -0.01 | 3.14 | -2.91 | 0.64 | -3.63 | 3.35 | -5.13 | -1.44 |
| Processing of non-metallic minerals | 19.73 | 0.45 | 15.99 | 2.66 | 16.25 | 1.07 | 16.12 | -5.39 |
| Metal and metallic products | -10.53 | -3.08 | -7.68 | 1.28 | -8.44 | -0.24 | -7.63 | -2.23 |
| Manufacturing and repair of machinery | -18.97 | -0.50 | -17.21 | 3.00 | -16.62 | 2.93 | -14.01 | 4.77 |
| Manufacturing of electrical machinery | 13.90 | -2.10 | 17.78 | -2.74 | 16.78 | -1.72 | 19.33 | -0.29 |
| Vehicle manufacturing | -16.29 | 0.83 | -20.03 | -2.97 | -19.27 | -0.33 | -19.85 | -0.41 |
| Other manufacturing industries | 2.30 | -0.11 | 3.33 | -2.76 | 3.83 | -2.87 | 3.47 | -2.69 |
| Electrical energy, gas and water | -8.69 | -1.18 | -6.93 | -2.38 | -6.87 | -2.07 | -6.72 | -2.97 |
| Construction | 7.58 | 3.40 | 6.38 | -1.58 | 7.21 | -2.51 | 8.18 | 1.94 |
| Commerce | -7.08 | 2.08 | -6.06 | 2.19 | -6.86 | 2.46 | -5.08 | -3.30 |
| Hotels and restaurants | 12.34 | -0.62 | 6.73 | -1.97 | 7.13 | -0.33 | 9.07 | 5.23 |
| Transport and communications | -31.54 | -3.43 | -31.83 | 0.69 | -31.66 | -2.26 | -31.43 | -0.75 |
| Financial intermediation | -0.24 | 1.50 | 0.25 | 0.92 | 0.91 | -0.16 | -0.41 | 0.94 |
| Business services | 13.87 | 2.12 | 11.13 | -1.17 | 10.37 | -5.33 | 10.85 | -2.82 |
| Public administration, defense and compulsory social security | -3.98 | 1.53 | -8.12 | 0.00 | -8.15 | 0.00 | -8.49 | 0.00 |
| Education | -1.12 | -3.55 | 0.14 | 2.36 | 0.26 | 2.99 | 0.93 | -0.64 |
| Health and social work | -6.76 | 1.08 | -5.28 | 0.00 | -5.09 | 0.85 | -4.38 | 0.46 |
| Other community and social services | -8.89 | 1.53 | -11.79 | 0.00 | -11.82 | 0.00 | -12.14 | 0.00 |

***Appendix 2***

***Standardized Differences for Unemployment & Self-employment VS Continuously Employed (Table 5)***

| | Base Selection | | Selection 1 | | Selection 2 | | Selection 3 | |
|---|---|---|---|---|---|---|---|---|
| | Pre Match | Post Match | Pre Match | Post Match | Pre Match | Post Match | Pre Match | Post Match |
| Age | -52.83 | 4.21 | -55.66 | 5.93 | -55.58 | 1.53 | -53.70 | 2.30 |
| Age$^2$ | -53.43 | 4.51 | -56.17 | 5.99 | -56.09 | 1.57 | -54.28 | 2.36 |
| Work area: North-East IT | -3.11 | -1.84 | -0.51 | -0.57 | -0.58 | 0.68 | -0.14 | -0.86 |
| Central IT | 3.49 | 1.19 | 0.93 | -1.85 | 0.97 | -3.39 | 1.37 | -0.38 |
| South IT | 2.36 | -0.62 | 1.23 | 3.86 | 2.13 | 0.22 | 2.60 | -0.02 |
| Islands IT | 5.82 | -0.27 | 5.08 | -0.12 | 5.77 | 0.94 | 5.03 | 0.22 |
| Entry weekly wage | -35.07 | 2.93 | -33.45 | -2.02 | -33.50 | 1.14 | -32.95 | -1.61 |
| Mean weekly wage | -51.89 | 3.54 | -50.04 | -1.10 | -50.03 | 2.05 | -49.48 | 0.26 |
| Weeks unemployed | 75.33 | 3.97 | 53.07 | 2.72 | 52.80 | 2.78 | 53.34 | 2.58 |
| Weeks subsidy | 12.64 | 0.81 | 12.44 | 1.71 | 12.43 | 2.88 | 13.06 | 1.62 |
| Weeks worked | -69.18 | -1.65 | -48.24 | -1.90 | -48.46 | -1.72 | -48.07 | -3.11 |
| Weeks sick (1989-1996) | 7.38 | -1.50 | 8.01 | -1.73 | 5.38 | 0.29 | 3.29 | 0.67 |
| Professional diseases (1994-1996) | -3.70 | 2.31 | -4.87 | -0.42 | -4.66 | -0.43 | -7.23 | 0.00 |
| Severe injuries (1994-1996) | -0.03 | 0.10 | -1.54 | 4.97 | -3.20 | 2.69 | -0.27 | -0.18 |
| Firm size: 10-19 | 4.81 | -1.28 | 8.32 | 0.28 | 8.46 | -0.14 | 8.59 | 0.95 |
| 20-199 | -9.81 | -0.27 | -8.69 | -2.08 | -8.95 | 1.29 | -11.00 | -2.10 |
| 200-999 | -20.81 | -1.65 | -17.81 | -0.80 | -17.66 | 0.39 | -18.49 | 1.71 |
| >=1000 | -35.97 | 3.30 | -34.87 | 1.80 | -36.11 | 1.50 | -35.29 | 2.43 |
| Sector of activity: Agriculture & Fishing | 1.07 | 2.61 | 1.30 | -1.14 | 1.38 | -1.34 | 1.57 | 0.61 |
| Extraction of fuel minerals | -3.49 | 0.00 | -3.54 | 0.00 | -3.40 | 0.00 | -3.33 | 0.00 |
| Extraction of non-fuel minerals | -1.94 | -0.68 | -3.59 | 1.91 | -3.50 | 1.72 | -2.59 | 3.20 |
| Food | 5.96 | -1.29 | 4.64 | 0.35 | 5.11 | 1.30 | 5.45 | -0.73 |
| Textile | -1.75 | -1.29 | 0.84 | -0.25 | -0.07 | 1.13 | -1.01 | -0.62 |
| Hide and leather | -0.54 | -2.30 | 1.79 | 0.69 | 1.95 | -1.02 | 0.97 | -0.12 |
| Wood | 3.43 | 0.29 | 6.36 | 1.40 | 6.68 | -0.97 | 7.84 | 1.15 |
| Paper, printing and publishing | -1.90 | 0.70 | -2.26 | 0.73 | -1.83 | 2.66 | -2.41 | -2.70 |
| Coke manufacturing and refineries | -3.94 | -1.53 | -2.88 | 0.30 | -2.76 | -0.30 | -4.41 | -1.81 |
| Chemical product manufacturing | -4.98 | 2.95 | -2.99 | -0.74 | -4.68 | 0.19 | -5.03 | 0.89 |
| Rubber and plastics | -3.42 | -1.79 | -2.77 | 2.06 | -2.43 | -0.50 | -2.84 | 1.25 |
| Processing of non-metallic minerals | -2.70 | -1.17 | -1.07 | 0.40 | -0.55 | -1.70 | 0.53 | -2.06 |
| Metal and metallic products | -20.14 | 1.21 | -20.73 | 0.20 | -19.91 | 0.44 | -20.50 | 2.83 |
| Manufacturing and repair of machinery | -10.08 | 2.15 | -8.87 | 0.29 | -9.50 | 1.13 | -9.96 | 0.00 |
| Manufacturing of electrical machinery | 2.49 | -0.43 | 2.57 | -1.34 | 2.60 | -1.14 | 4.07 | 1.31 |
| Vehicle manufacturing | -20.32 | 2.23 | -18.84 | 0.00 | -21.03 | 1.57 | -20.37 | 2.32 |
| Other manufacturing industries | 1.92 | -2.54 | -1.00 | -1.02 | -0.68 | 0.79 | 0.75 | -2.14 |
| Electrical energy, gas and water | -9.55 | 1.30 | -9.11 | 2.55 | -9.12 | 1.29 | -9.33 | 1.60 |
| Construction | 29.13 | 1.03 | 26.46 | -0.61 | 25.92 | 0.60 | 24.24 | 0.45 |
| Commerce | 19.38 | 0.23 | 18.18 | -0.74 | 18.89 | -1.54 | 18.67 | 0.17 |
| Hotels and restaurants | 14.75 | -0.57 | 14.18 | -2.32 | 14.55 | -0.14 | 14.95 | -0.12 |
| Transport and communications | -14.70 | 0.99 | -14.23 | -1.94 | -13.88 | -1.51 | -14.35 | -3.58 |
| Financial intermediation | -4.34 | -2.73 | -2.53 | 2.10 | -3.31 | -1.29 | -1.60 | 0.20 |
| Business services | -1.76 | -1.41 | -1.51 | -0.52 | -1.26 | 0.00 | -1.79 | 0.00 |
| Public administration, defense and compulsory social security | 5.75 | 1.23 | 5.56 | 2.42 | 5.71 | -0.58 | 5.16 | -3.24 |
| Education | -1.05 | -0.51 | -2.15 | -0.42 | -2.09 | -1.71 | -1.70 | -0.91 |
| Health and social work | -4.49 | 0.44 | -6.54 | -0.24 | -6.41 | 0.74 | -5.96 | 0.79 |
| Other community and social services | 5.16 | -2.85 | 7.49 | 2.14 | 7.72 | 0.43 | 8.80 | 1.49 |

***Appendix 1***

***Propensity score distribution and Kernel approximation***