Social Science & Medicine 158 (2016) 86–95

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

The impact of precarious employment on mental health: The case of Italy

F. Moscone [a,*], E. Tosetti [a], G. Vittadini [b]

[a] *Brunel University London, UK*
[b] *University of Milan, Bicocca, Italy*

ARTICLE INFO

Article history:
Received 17 May 2015
Received in revised form
4 March 2016
Accepted 9 March 2016
Available online 13 April 2016

Keywords:
Italy
Precarious employment
Mental health
Psychotropic medication
Prescription
Probit

ABSTRACT

Although there has been a sizeable empirical literature measuring the effect of job precariousness on the mental health of workers the debate is still open, and understanding the true nature of such relationship has important policy implications.

In this paper, we investigate the impact of precarious employment on mental health using a unique, very large data set that matches information on job contracts for over 2.7 million employees in Italy followed over the years 2007–2011, with their psychotropic medication prescription. We examine the causal effects of temporary contracts, their duration and the number of contract changes during the year on the probability of having one or more prescriptions for medication to treat mental health problems. To this end, we estimate a dynamic Probit model, and deal with the potential endogeneity of regressors by adopting an instrumental variables approach. As instruments, we use firm-level probabilities of being a temporary worker as well as other firm-level variables that do not depend on the mental illness status of the workers.

Our results show that the probability of psychotropic medication prescription is higher for workers under temporary job contracts. More days of work under temporary contract as well as frequent changes in temporary contract significantly increase the probability of developing mental health problems that need to be medically treated. We also find that moving from permanent to temporary employment increases mental illness; symmetrically, although with a smaller effect in absolute value, moving from temporary to permanent employment tends to reduce it. Policy interventions aimed at increasing the flexibility of the labour market through an increase of temporary contracts should also take into account the social and economic cost of these reforms, in terms of psychological wellbeing of employees.

1. Introduction

Mental health has become a priority in the agenda of policy makers in many western countries, both in terms of meeting the needs of people with mental illness as well as improving the mental wellbeing of the population. According to a recent OECD report, half of the population will develop a mental illness at some point in their lives, with adverse effects on their productivity, wage, and employment opportunities (OECD, 2014). A strand of literature has been focusing on evaluating the impact of mental health problems on firm productivity (see, among others, Stewart et al., 2003). However, it is also true that employment instability may have a major influence on psychiatric disorders. As also documented by a recent ILO report (ILO, 2011), the phenomenon of employment instability has emerged in the early 1980s, when the proportion of individuals employed in flexible work has steadily increased in all western countries. This trends could be in part explained by the need of a more flexible labour market, where entrepreneurs facing higher competition are able to quickly adapt their production to shifts in supply and demand conditions. According to ILO (2008), precarious employment is also associated with the use of new technologies, which allow fragmenting the production process and outsourcing certain tasks. The recent global crisis has exacerbated employment instability, reducing the bargaining power of many employees and offering fewer possibilities to obtain permanent jobs. As emphasized by the ILO (2012) World of Work Report, in many countries where growth of employment has resumed after the economic recession, the majority of the new contracts are

* Corresponding author.
E-mail address: francesco.moscone@brunel.ac.uk (F. Moscone).

http://dx.doi.org/10.1016/j.socscimed.2016.03.008

short-term, with increasing shares of involuntary part-time and temporary employment.

There is still no universally agreed definition of precarious employment, given its multidimensional nature that differs across countries and the economic and social structure of the labour market. However, precarious employment can be seen as employment relations characterized by high uncertainty, low income, and reduced social benefits and statutory entitlements (Vosko, 2010; Benach et al., 2014). Physically heavy work, poor working conditions and higher risk of accidents have also been associated with precarious employment (Gash et al., 2007). These characteristics are likely to have a negative impact on workers' physical and mental health, ultimately resulting in absenteeism, lost firm productivity and lost employment.

The study on the impact of precarious employment on the mental health of workers is complicated by the presence of a bidirectional relationship between job instability and health. As pointed by a consistent body of literature, individuals with mental illness, such as depression, are less likely to be in employment, have lower productivity levels, lower salaries, and more absenteeism than workers without mental illness (see, among others, OECD, 2011, and Frijters et al., 2014). Hence, individuals suffering from mental health problems may also have a lower propensity to find a stable work than others. However, most empirical studies have investigated the link between health and forms of precarious employment without taking into account such reverse causality problem.

In this paper, we implement an original Instrumental Variable (IV) approach to estimate the causal impact of precarious employment on the mental health of people. In our analysis, rather than using, as in most studies, a measure of self-reported psychological health, we assume that mental health problems occur when the worker has been dispensed one or more prescriptions of psychotropic drugs, for two or more consecutive quarters within a year. We identify precarious employment with temporary employment, namely, all employment relations other than those of unlimited duration, including fixed-term and subcontracted jobs, as well as work done on projects, on call and through temporary-help agencies. As also pointed by Benach et al. (2014), one can consider temporary workers to be in an objective state of job insecurity. We also investigate the impact on the mental health of workers of the number of changes in temporary job contract observed over time, and the number of days worked under temporary contract within the year. In fact, we expect these variables to significantly affect the degree of precariousness of employees, and hence their mental health status.

We match a very large administrative data set from the Ministry of Labour in Italy on a set of employee resident in the Lombardy region, in Italy, with data on their psychotropic drug prescriptions for the years between 2007 and 2011. The resulting data set, with over 13 million observations, offers a unique opportunity to assess the precariousness of job contracts, and investigate its role in developing mental health disorders. In Italy, full-time permanent work was the most common form of employment around which labour law has been developed. However, the past decade has witnessed a growth in non-standard employment, in the form of temporary, part-time or informal employment, with seven employees out of ten recruited on fixed-term contracts in 2012. Badly designed employment regulations have been pointed, among other reasons, as discouraging employers from recruiting under permanent contracts in Italy (ILO, 2008).

We assume that the mental health status follows a dynamic process where mental health systematically varies across individuals. To control for unobserved heterogeneity in the context of a dynamic nonlinear panel, we follow Wooldridge (2005b) and use the Chamberlain (1980) device to obtain a distribution of the outcome variable conditional on initial values and exogenous explanatory variables. To deal with the reverse causality problem between job instability and health, we adopt a two-step control function approach, a method recently advanced by Wooldridge (2014) to estimate nonlinear models with endogenous explanatory variables, within the Probit specification. For a given worker in the data set, we take as instruments firm-level probabilities of being precarious and other variables characterizing job precariousness within the firm where she is employed. These are valid instruments as long they do not directly affect the mental health status of the worker, but rather only indirectly through their impact on the labour variables. It is plausible to think that these firm-level variables are not influenced by the mental health of a single worker, but rather reflect to a large extent the recruiting policy of firms.

We believe that our rich data set combined with the use of recently advanced econometric methods allows us to estimate more accurately than previous studies the effect of employment instability on mental health.

The rest of the paper is organized as follows. Section 2 reviews existing literature on this topic, while Section 3 describes the data and presents a preliminary exploratory data analysis. Section 4 introduces our regression model and explains our econometric approach. Section 5 comments on regression results, while Section 6 explores the mental health consequences of moving to precarious employment. Finally, Section 7 concludes.

2. Literature review

There is a growing empirical literature measuring the effect of job precariousness on the mental health of people, although the debate is still open. Based on cross-sectional survey data from 15 European countries, Benavides et al. (2000) found that precarious employment, in the form of fixed term, temporary contract and sole traders, is positively correlated with job dissatisfaction, although negatively associated with absenteeism and stress. In a meta-analysis, Virtanen et al. (2005) found greater psychological morbidity among temporary employees relative to permanent employees. However, the analysis showed high heterogeneity across studies, in part due to differences in exposure to temporary employment, as well as in mental health outcomes and contextual factors.

More recently, Quesnel-Vallee et al. (2010) performed a propensity score analysis on a cohort of American people followed from 1979 to 2010, finding more severe depressive symptoms for those individuals who had been exposed to temporary work in the two years preceding the outcome measurement. Similar adverse effects on mental health are reported by Cottini and Lucifora (2010) by performing a panel data analysis based on three waves of the European Working Conditions Survey. The authors addressed the potential endogeneity of working condition by exploiting the variation across countries and over time in workplace, health and safety regulations as well as in regulations on working time flexibility. They showed that job characteristics such as working in shifts, performing complex and intensive tasks and having restricted job autonomy increases the probability of reporting mental health problems, and also found that adverse overall working conditions increase mental health distress. Waenerlund et al. (2011), focusing on a sample of workers aged 42 years old in Sweden, found that workers under temporary contracts have higher risk of experiencing psychological distress and non-optimal self-rated health. A negative influence on psychological well-being exerted by certain contractual and working conditions is also found by Robone et al. (2011), using twelve waves of the British Household Panel Survey. The problem of reverse causality is addressed by including previous health status, lagged one period, in the empirical models. To deal with potential endogeneity of job insecurity, Caroli and Godard (2014) adopt an IV approach taking as instruments the natural layoff rate in the sector where the individual is employed interacted with the stringency of the employment protection legislation in her country. Using cross-country data from the 2010 European Working Conditions Survey, the authors showed that, after controlling for endogeneity bias, job insecurity has health-deteriorating impact only on a small number of mental health outcomes, namely suffering from headaches or eyestrain and depression or anxiety. Dawson et al. (2015) used a sample of individuals drawn from the British Household Panel Survey in the years between 1991 and 2008 to investigate the relationship between three indicators of mental health (psychological distress, psychological anxiety and life satisfaction), an indicator of general health and transitions between temporary and permanent employment. The authors found that permanent employees with poor mental health select into temporary employment, with this selection effect mediated by greater job dissatisfaction, thus suggesting that previous cross section research may have overestimated the influence of employment type on mental health.

There is also research according to which temporary or atypical employment does not have long-lasting detrimental effects on the mental health of workers. Virtanen et al. (2002), using cross sectional survey from 8 Finnish towns, reported that both men and women with fixed-term employment had better self-rated health compared to their permanent counterparts. Focusing on the first 10 waves of the British Household Panel Study, Bardasi and Francesconi (2004) found that atypical employment does not have long-lasting detrimental effects on the mental health of workers. To deal with the issue of reverse causality, the authors adopt various strategies, such as including individual fixed effects, controlling for previous employment status, as well as analysing the effects of changes in labour market status on changes in health outcome to sweep out unobserved heterogeneity. Artazcoz et al. (2005) reported no differences for Spain in mental health between workers with fixed-term and permanent contracts. A cross sectional study by Keuskamp et al. (2013), while pointing at strong correlation between casual full-time employment and poor physical health, found no significant relationship between casual full-time or part-time employment and poor mental health, in a sample of Australian workers in 2009.

Few works investigate this relationship with regard to the Italian context. Focusing on three waves of the Bank of Italy Survey on Household Income and Wealth, Ponzo (2011) pointed at lower reported levels of happiness for workers with fixed-term contracts. Carrieri et al. (2014) investigated the influences of temporary contracts along various dimensions of well-being, including physical and mental health, self-assessed health and happiness using the ISTAT cross-sectional survey for the Italian population in 2004–2005. The authors found that temporary contracts have detrimental effects on mental health and happiness, in particular for young men and individuals without family economic support.

To sum up, a large number of studies have investigated the impact of short-term employment or employment conditions on mental health, mostly using survey data for one or more countries. Some studies deal with the endogeneity problem by including in the empirical model previous health or employment status, or by adopting an IV approach where instruments are usually aggregate variables, such as new regulations in terms of working time flexibility or unemployment rate.

Contrary to previous research, this paper uses a very large data set coming from the matching of labour and health care administrative data sources, which allows us to build innovative instruments that exploit information within firms where workers in the sample are employed.

3. Data and sample construction

Our empirical analysis uses data on the workforce resident in the Lombardy region of Italy. This region is the most densely populated and the main industrial area of the country, workers from this region represent around 18.5 percent of national employment, 25 percent if focusing on the industrial sector only, and produce more than 20 percent of Italian Gross Domestic product. One important reason for taking this region is that it has the highest concentration of workers with non-standard labour contracts in Italy, amounting to 23.8 percent of total fixed term contracts in Italy in 2008 (INPS, 2008). A further advantage of focusing the analysis on only one region rather than the entire nation is that we mitigate the significant heterogeneity existing across Italian regions, arising from differences in their socio-demographic factors and economic structure, as well as the variety of forces governing different regional health care systems. The Italian territory is divided into 20 regions that are extremely varied in terms of size, population and age distribution, levels of economic development as well as industrial structure (European Observatory on Health Systems and Policies, 2014). In addition, the Italian health-care system is a regionally based national health service where regions are responsible for organizing and delivering health care services, as well determining payment rates for hospital and outpatient care.

We collected data from different sources. First, we gathered administrative data on workforce resident in the region, in the years from 2007 to 2011 from the Italian Ministry of Labour. Since 2007, it is mandatory for Italian firms to notify electronically all hires and separations, extensions or conversions of job contracts. The data system known as Compulsory Communications (CC) records each workforce movement in private and public Italian firms. For each worker movement, it provides information on the date of the event, the identity of the worker, the identity of the firm and a set of worker characteristics including her age, gender, nationality, educational level, and residence. It also includes information on the type of contract and the sector of activity of the firm according to the European Statistical Classification of Economic Activities NACE Rev. 2. The data set provides information on whether the contract is temporary, meaning that the job is not permanent in one of the following ways: fixed period contract, agency temping, casual work, seasonal work or other fixed-term work. Clearly, our data set excludes information on people into self-employment, such as freelancers, or professionals who work as consultants. This data set, which registers work-related events, contains 20,122,437 over the years 2007–2011.

It is important to stress some limitations of this source of data. First, we observe that it does not contain information on all existing workforce, but rather only on those workers that have started or terminated an employment contract anytime after the year 2007. Therefore, the data set does not include workers having a permanent or temporary position that has not changed over the 5-year sample period. By construction, the data set is unbalanced towards young workers as it captures all workers that enter in the labour market for the first time during the sample period, while it does not include older workers having a stable position since before 2007. Another limitation of these data is that it is not possible to know what happens to the workers once her contract is terminated, whether she becomes unemployed, self-employed, or rather moves outside the labour force; we only know that she is not anymore under a job contract.

We have then collected information on antidepressant, mood stabilizer and antipsychotic prescriptions dispensed by General

Practitioners or specialists to any of the workers appearing in the CC data set. We have focused on this set of medications as these are used to treat major psychiatric disorders of Axis I (Clinical Disorders) in the Diagnostic and Statistical Manual of Mental Disorders. Following the advice of a psychiatrist, some psychotropic antiepileptic drugs were excluded because they are usually not used for psychiatric disorders; a list of medications included in the analysis is available upon request. Data on prescriptions have been extracted from the electronic register PSICHE, collecting prescriptions and epidemiological characteristics of all people resident in the Lombardy region. This data set contains 75,688 prescriptions over the years 2007–2011.

The two data sets, namely the CC and the prescription data set, have been matched in a two-step procedure. First, the two data sets have been converted into person-year data sets. Since for one individual, two or more work-related events can be registered within the same year, a decision had to be made on which contract this individual had within the year. In this paper we have decided to assign to each individual in the CC data set the so-called "prevalent" contract within the year, i.e., the contract for which she has worked the longest period of time within the year. For each individual in the CC data set, the variables number of days worked within the year under the prevalent contract, and number of contract changes within the year by contract type have also computed. As for the prescription data set, in the person-year data set a variable counting the prescriptions for each year, and a variable stating if a prescription has been issued for two or more consecutive quarters have been calculated. Once obtained our person-year data sets, these have been merged using the person identifiers known as Fiscal Code and the year of reference as matching keys. Similar to a Social Security Number card in the United States or the National Insurance Number issued in the United Kingdom, the fiscal code identifies unambiguously individuals residing in Italy, irrespective of residency or employment status. After this matching process, we have obtained a data set of around 16 million observations. In order to find suitable instruments to deal with the endogeneity of our key variables, we need to have enough observations within each firm so that we can exploit firm-level information on job contracts. To this end, we have dropped all observations related to firms having 10 or less job contracts active within a year. We have also dropped individuals younger than 18 and older than 65 years old. After this cleaning procedure, we have obtained a person-year data set of around 2.6–2.7 million workers observed over 2007 to 2011 (see Table 2).

Finally, we have gathered information on gender-specific unemployment rate in the region from the Italian Office of National Statistics, and on the amount of redundancy funds transferred to the sector where the various firms operate in order to cover the loss in production due to adverse economic conditions from the Social Security Institution. The latter variable is expressed in number of hours paid by the pension institute to each firm within each sector of activity, according to the NACE Rev. 2 classification.

Table 2
Descriptive statistics on labour data.

	2007	2008	2009	2010	2011
n. workers					
18–34	1,412,792	1,293,179	1,220,880	1,158,338	1,080,092
35–49	951,277	951,515	984,037	1,024,469	1,063,719
50 and over	368,357	388,997	426,098	469,871	513,093
All sample	2,732,426	2,633,691	2,631,015	2,652,678	2,656,904
% in population:(*)					
18–34	74.20	69.23	66.52	64.57	61.13
35–49	41.51	40.79	41.55	42.83	44.12
50 and over	19.45	20.45	22.21	24.17	26.00
All sample	44.87	43.16	42.97	43.28	43.19
n. of firms	120,779	164,235	175,660	185,646	232,114

(*): Population in the same age group, source: Eurostat.

We refer to Table 1 below for a list of the variables appearing in the matched data set, together with their definition and some descriptive statistics. We remark that our variable for mental health (h_{it}) takes value of 1 if the person has received at least one medical prescription for two or more consecutive quarters within year t, as an indication that this person is affected by mental health problems. The variable Milan is a dummy variable indicating whether the individual is resident in Milan, which is the largest city of the Lombardy region as well as the main industrial, commercial, and financial centre of Italy. We also observe that in our matched data set we do not have information on what employees working under their prevalent contract for less than 365 days a year do during the rest of the year, whether they are employed under other types of contract or are unemployed. However, the statistics in Table 1 show that workers in the data set work under their (prevalent) contract a consistent part of the year (on average, 219.5 days a year).

Table 2 gives some summary statistics on the sample. In our regression analysis, we classify individuals into three age groups in order to distinguish workers that have recently accessed the labour market (aged 18 to 34), from those that have been in the labour market presumably for a longer time (aged 35 to 49), and from those workers that are closer to retirement age (aged 50 and over). We observe that in Italy before 2011 a worker could retire at any age provided that she paid 20 years of social security contributions. According to INPS (2014), in the year 2011, 21.6 percent of people aged between 55 and 64 were retired, so that we expect part of workers in the third age group to be in the process of leaving the labour market. It is likely that these three groups of workers have different expectation towards their job career, and react in a different manner to job precariousness, which in turn may affect

Table 1
Definition of variables and descriptive statistics.

Variable	Description	Mean(+)	Std. Dev.
h_{it}	1 if person i is affected by mental health problems in year t	3.60	–
Temporary$_{it}$	1 if person i holds a temporary contract in year t	39.74	–
N. days empl.$_{it}$	n. of days worked over the year t	219.5	151.5
N. of contract changes$_{it}$	n. of new contracts held by person i in year t	0.323	0.800
Age$_{it}$	Age of person i in year t	37.70	11.19
Female$_i$	1 if person i is female	45.20	–
High school$_{it}$	1 if person i has completed high school in year t	51.93	–
University degree$_{it}$	1 if person i has a university degree in year t	11.71	–
Non-Italian citizenship$_{it}$	1 if person i has non-Italian citizenship in year t	22.58	–
Milan$_{it}$	1 if person i is resident in Milan in year t	29.21	–
Redundancy pay$_{st}$	n. of hours paid by the pension institute to sector s in year t (in 1,000,000)	2.750	6.51
Unemployment rate$_t$	Gender-specific unemployment rate in the region in year t	4.775	1.31

Notes: (+) percentage where relevant.

their mental health status. The second panel in Table 2 reports the sample size by year/age group expressed as percentage over the total population in the same year/age group, resident in the Lombardy region. These figures clearly show that, as expected, young workers are over-represented in the data set, when compared to older workers. This table also reports the number of firms in the sample, as in our empirical analysis a number of variables will be computed at firm-level.

Table 3 reports a set of descriptive statistics for the health and labour variables, as well as a set of socio-demographic variables, for all sample and for the sample divided into age groups. We do not report statistics on unemployment rate as this variable only varies across gender and years. As expected, the percentage of people with at least one prescription increases with age. As for the labour variables, around 35 to 47 percent of the workers have a temporary contract, and work on average, over 200 days a year. A worker changes job contract on average around 0.2 to 0.4 times during the year, depending on their age.

Table 4 reports statistics for our precariousness variables for the subset of healthy workers, and the subset of workers under medical prescription. Our statistics show that for the latter group workers hold on average more temporary contracts (except for the youngest group), work more days under temporary contracts and have more contract changes in temporary contracts. In the next section we introduce a regression model where we condition on individual-specific characteristics.

4. The empirical model and estimation strategy

As also pointed by a consistent medical literature, mental illness has a strong recursive component, as the occurrence of a mental health problem for an individual at a point in time is likely to increase the likelihood of having mental health problems in the future. Recurring episodes are often due to the presence of symptoms that persist after an episode ends (Roy and Schurer, 2013). Accordingly, we assume that the mental health status follows a dynamic panel data regression. In addition, we include worker-specific effects to account for significant heterogeneity across individuals in mental health status, due to a set of characteristics that may be time invariant (e.g., genetic factors, etc.). Let h_{it}^* be the latent (unobserved) mental health status of worker i at time t, with $i = 1, \ldots, N$ and $t = 1, \ldots, T$. We assume the following dynamic model for h_{it}^*:

$$h_{it}^* = \alpha_i + \lambda h_{i,t-1} + \beta' \mathbf{x}_{it} + u_{it}, \tag{1}$$

Table 3
Descriptive statistics on health and labour data.

	18–34	35–49	50 and over
Health variables			
% with medical prescriptions	2.29	4.25	5.47
Labour variables			
Temporary (%)	46.51	34.14	35.18
N. of days empl. (average)	202.8	234.5	227.5
N. of contract changes (average)	0.401	0.284	0.215
Redundancy pay (average)	2.675	2.77	2.875
Socio-demographic variables			
Age (average)	27.51	41.168	55.73
Female (%)	46.03	46.09	41.08
High school (%)	47.91	53.89	58.12
University degree (%)	13.44	11.17	8.29
Non-Italian citizenship (%)	25.71	23.33	12.95
Milan	34.39	35.96	34.92

$$h_{it} = 1_{[h_{it}^* > 0]}, \tag{2}$$

where α_i is an unobserved, individual-specific effect, u_{it} is an idiosyncratic, serially uncorrelated error term, x_{it} is a vector of worker-specific covariates, and $1_{[.]}$ is an indicator function. As also explained in Section 3, when estimating the above model, we assume that $h_{it} = 1$ if the person has received at least one medical prescription for two or more consecutive quarters within year t.

The above model allows the occurrence of mental health problems at time t to depend not only on unobserved heterogeneity, α_i, but also on the mental health state at time $t-1$. Suppose initially that $\mathbf{x}_{it}$ contains only strictly exogenous variables. Within the Probit specification, Wooldridge (2005b) has suggested an approach for dealing with the initial conditions problem in nonlinear dynamic random effects models that consists of obtaining a joint distribution of $(h_{i1}, h_{i2}, \ldots, h_{i,T})$ conditional on the initial value, h_{i0}, and any exogenous explanatory variables. For this method to work, Wooldridge (2005b) proposes to specify a density for α_i given $(h_{i0}, \mathbf{x}_{i1}, \ldots, \mathbf{x}_{iT})$ using the Chamberlain (1980) device:

$$\alpha_i = \pi_0 + \pi_1 h_{i0} + \boldsymbol{\pi}_2' \overline{\mathbf{x}}_{i.} + \eta_i, \tag{3}$$

where $\overline{\mathbf{x}}_{i.} = \frac{1}{T}\sum_{t=1}^{T} \mathbf{x}_{it}$, is the time average of the (time-varying) regressors, and η_i is assumed to be distributed $N(0, \sigma_\eta^2)$, independent of the regressors, the error term u_{it}, and the initial conditions. Plugging (3) into (1), under the Probit specification, it is possible to derive the joint distribution of outcomes after the initial period, conditional on the initial value and any strictly exogenous variables (see, also, Wooldridge, 2005a, 2010). Such likelihood has exactly the same structure as the standard random effects Probit model, except for the regressors, which will be now

$$\mathbf{x}_{it}^* = (1, h_{i,t-1}, \mathbf{x}_{it}, h_{i0}, \overline{\mathbf{x}}_{i.}).$$

Hence, with this approach it is possible to add h_{i0} and $\overline{\mathbf{x}}_{i.}$ as additional explanatory variables in each time period and use standard random effects Probit software to estimate β, λ, π_0, π_1, and $\boldsymbol{\pi}_2$. This approach only works if $\mathbf{x}_{it}$ is made up of strictly exogenous variables. However, as also previously explained, the variables characterizing the job precariousness of workers, included in $\mathbf{x}_{it}$ are potentially endogenous. Suppose that $\mathbf{x}_{it}$ is made up of two sub-vectors, namely:

$$\mathbf{x}_{it} = (\mathbf{z}_{1,it}, \mathbf{w}_{it}),$$

where $\mathbf{z}_{1,it}$ is a k-dimensional vector of strictly exogenous covariates, and $\mathbf{w}_{it}$ is p-dimensional vector of variables characterizing the job precariousness of worker i at time t, potentially correlated with u_{it}. We observe that some studies lag the variables in w one period to account for delays in the impact of contractual conditions on health (see, for example, Bardasi and Francesconi (2004), and Robone et al. (2011)). However, we note that failing to include the current job contract can lead to an omitted-variable problem as precariousness experienced by the worker within the current year is likely to impact on her mental health. To deal with the endogeneity of $\mathbf{w}_{it}$, in this paper we adopt a control function approach, as outlined in Wooldridge (2014), which consists of two steps. Let $\mathbf{z}_{2,it}$ be a set of exogenous variables, our instruments, affecting $\mathbf{w}_{it}$, and let $\mathbf{z}_{it} = (\mathbf{z}_{1,it}, \mathbf{z}_{2,it})$. In the *first step*, we regress each variable belonging to $\mathbf{w}_{it}$ on $\mathbf{z}_{it}$, and obtain the corresponding residuals, $\widehat{e}_{k,it}$. Hence, in a *second step* we include $\widehat{e}_{k,it}$ as additional regressor in model (1)–(2). Given the endogeneity of $\mathbf{w}_{it}$, in this second step we relate the heterogeneity only to the strictly exogenous variables, $\mathbf{z}_{it}$, and assume that

Table 4
Mental health and temporary contracts.

Age class	% Temporary	N. of days empl. in temp. contracts	N. changes in temp. contracts
Workers with no medical prescription			
18–34	51.48	96.2	0.390
35–49	37.39	109.7	0.290
50 and over	37.72	97.2	0.214
Workers with medical prescriptions			
18–34	51.15	113.7	0.499
35–49	39.92	118.4	0.355
50 and over	38.50	95.3	0.211

$$\alpha_i = \pi_0 + \pi_1 h_{i0} + \boldsymbol{\pi}_2' \overline{\mathbf{z}}_{i.} + \eta_i. \tag{4}$$

We include in the vector $\mathbf{z}_{1,it}$ the gender and age of worker i, whether at time t she holds a university degree or rather has completed high school, if she has Italian citizenship, a variable indicating whether she lives in Milan and a dummy for the sector of economic activity of the firm where worker i is employed at time t (according to the NACE Rev. 2 European classification). It is well known that social and demographic factors such as gender, age and education are important predictors of mental health (WHO, 2014). We have included the dummy variable for being resident in Milan as living in an urban environment is often associated with increased exposure to social stress, which is known to be a risk factor for psychiatric disease (see, for example, Lederbogen et al., 2013). In our regression, we have also incorporated the amount of redundancy fund transferred to the sector where the firms operates in order to cover the loss in production due to adverse economic conditions, the regional, gender-specific unemployment rate, and time dummies. The reason for including these variables in our model is to control for economy-wide conditions which may affect mental health of workers. This is important also in consideration that our sample period covers the 2007–08 financial crisis and consequent global recession. We have excluded from $\overline{\mathbf{z}}_{i.}$ the variable gender, given that it is time invariant and the education variables which could be affected by the past mental health of workers, hence not strictly exogenous.

The vector w_{it} contains three key variables to proxy the job precariousness experienced by individual i at time t: a dummy indicating whether the prevalent contract of worker i in year t is temporary ("Temporary"), the number of days worked within the year t under temporary job contract ("N. days empl. – temporary"), and the number of changes in temporary job contracts for worker i within the year t ("N. contract changes – temporary"). In our regression, we also include the number of days worked within the year t under the prevalent job contract ("N. days empl."), and the number of changes in job contracts for worker i within the year t ("N. contract changes"), irrespective of whether this is temporary or permanent contracts. In fact, one could change job contract also when this is permanent for a variety of reasons, such as progress in career, changes in preferences, or redundancy, which we do not include in our definition of precariousness. While holding a temporary contract is a clear indicator of job precariousness, it is important to clarify the role of the other two key variables in determining job precariousness and their expected impact on the mental health of workers. On one hand, we would expect more days worked under a temporary contract to make the employment relation more stable and hence improve the wellbeing of the employee. On the other hand, more days of temporary employment could be seen as exacerbating the precariousness of the worker and her dissatisfaction. As for the number of changes in temporary job contracts, we expect job precariousness to be worsened by frequent changes in fixed-term contracts, thus impacting on the mental health of workers.

In our empirical exercise we also look at what happens to the mental health of workers, when they face a change in their employment conditions, by including dummies indicating a change in the type of contract. We observe that for these further regressions the first-stage regression is identical as the above regression. Finally, we also provide some descriptive statistics on workers that experience a change in their employment status, moving from a permanent to a temporary contract over the sample period. To build these statistics, we use the predicted outcomes from the first-stage regression in our previous analysis, rather than observed values. In fact, predicted values identify workers that have a temporary or a permanent contract only because of their exogenous characteristics, and not because they are depressed.

As instruments, in all our regressions we take a set of variables, $\mathbf{z}_{2,it}$, that are specific to the firm where worker i is employed at time t. More specifically, $\mathbf{z}_{2,it}$ contains the percentage of workers having the same contract (either temporary or permanent) in the firm where i is employed at time t, the average number of days worked within the year by workers in the firm where i is employed at time t, and the percentage of changes in contract for these workers. These variables are valid instruments as long they do not directly affect the mental health status of worker i, but rather only indirectly through their impact on the labour variables, $\mathbf{w}_{it}$. It is plausible to think that these variables are not affected by the mental health of worker i, but rather they reflect to a large extent the recruiting policy of firms. Table 5 shows some summary statistics on the selected instruments. We note a consistent average number of active job contracts by firm in one year, although when looking at the median number of contracts by firm, most firms have less than 58 contracts open in a particular year. The large discrepancy between mean and median is due to the presence in the data set of few, very large companies. We also observe that workers within a firm on average change contract less than once in a year (0.454), a figure that is consistent to the average values reported both in Tables 1 and 3. Noting that all firms in the data set have at least 10 contracts open in any given year, we believe we hold enough information at firm level on the type of contracts open to use it for instrumentation.

5. Empirical results

Table 6 shows results for the estimation of model (1)–(2), using the approach outlined above, for different age groups. To provide an indication of the magnitude of the association between mental health and the regressors we present average partial effects (APEs). For continuous variables, such as age, these are obtained by taking the derivative of the Probit probabilities with respect to the variable in question. For discrete regressors, such as lagged health status, they are obtained by taking differences.

The coefficient attached to $h_{i,t-1}$ is positive and significant across all age groups, ranging between 0.0787 for younger workers to

Table 5
Descriptive statistics on the selected instruments.

Average number of contracts by firm	439.10
Median number of contracts by firm	58
Average % of workers with the same type of contract by firm	57.23
average n. of changes in contract for workers in the same firm	0.454
average n. of days worked for workers in the same firm, same contract	267.46

Table 6
Regression results, average partial effects.

	18–34		35–49		50 and over	
	Par.	Std.err.	Par.	Std.err.	Par.	Std.err.
$h_{i,t-1}$	0.0787*	0.0003	0.1197*	0.0003	0.1358*	0.0005
Temporary$_{it}$	0.0061*	0.0005	0.0071*	0.0007	0.0037*	0.0013
N. contract changes − Temporary$_{it}$	−0.0005*	0.0002	−0.0001	0.0002	0.0018*	0.0005
N. contract changes$_{it}$	0.0008*	0.0002	0.0004	0.0003	−0.0011	0.0006
N. days empl.$_{it}$ − Temporary$_{it}$	0.0001*	0.0000	0.0001*	0.0000	0.0002*	0.0000
N. days empl.$_{it}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Age$_{it}$	0.0071*	0.0003	0.0185**	0.0034	−0.0053*	0.0015
Female$_i$	0.0118*	0.0023	0.0165**	0.0030	0.0004	0.0050
High school$_{it}$	−0.0002	0.0002	−0.0003	0.0002	−0.0002	0.0003
University degree$_{it}$	−0.0049*	0.0002	−0.0042**	0.0003	0.0001	0.0006
Non-Italian citizenship$_{it}$	−0.0117*	0.0002	−0.0192*	0.0003	−0.0266*	0.0007
Milan$_{it}$	−0.0009*	0.0002	−0.0007**	0.0002	0.0000	0.0003
Redundancy pay$_{st}$	−0.0002	0.0002	0.0004**	0.0002	0.0000	0.0004
Unemployment rate$_t$	−0.0033*	0.0013	−0.0036*	0.0017	0.0062**	0.0029
VAT endogeneity tests:						
Temporary	0.0888*	0.0053	0.0801*	0.0051	0.0872*	0.0078
N. contract changes	−0.0004*	0.0000	−0.0003*	0.0000	−0.0004*	0.0000
N. days empl.	0.0044	0.0037	−0.0009	0.0039	−0.0242*	0.0074
First-stage χ^2 test:						
Temporary	825,411*	[0.00]	759,243	[0.00]	108,331.5	[0.00]
N. contract changes	14,800,000*	[0.00]	15,600,000	[0.00]	392,124.0	[0.00]
N. days empl.	1,150,000*	[0.00]	618,592	[0.00]	158,208.11	[0.00]
Pseudo-R^2	0.3489		0.3909		0.3983	

Notes: (*),(**),(***) mean significant at the 1, 5, 10 percent significance level, respectively.

0.1358 for the elderly. This coefficient measures how persistent psychotropic drug prescription (and, hence, mental illness) is over time, and it is likely to reflect the endurance of mental disorders, both observable and not observable. The elderly may suffer from more severe forms of depression, perhaps linked to (unobserved in our data set) physical health, explaining the difference in persistence in psychotropic drug prescription over time across age groups. More permanent mental health outcomes as one grows old are also confirmed in previous studies (see, for example, Roy and Schurer, 2013).

Looking at our key variables for job precariousness, the coefficient attached to the variable "Temporary" is positive and significant for all age groups, corroborating our hypothesis that temporary contracts, being more precarious than permanent contracts, are more likely to increase mental illness that needs to be medically treated. To have an idea of the size of these coefficients, suppose for example, that all workers in a temporary contract in the data set work under this contract one extra year, holding all other variables fixed. Under this assumption, the number of workers with temporary contract in the sample increases around 8–10 percent, depending on the age group. Then, using the predicted outcomes from the estimated regression with this new variable, the number of individuals under psychotropic medication would increase by around 1, 2.3, 0.8 percent, for the young, middle and older aged groups, respectively.

For the elderly, frequent changes in temporary contracts seems to increase psychotropic drug prescription, while an opposite effect is observed for younger workers. Suppose for example that workers experience one additional change in temporary contracts than what is in the data set. In this case, all other variables being constant, the number of (predicted) individuals under medication for the oldest age group would rise by 1.3 percent. While the "N. of days empl." is not significant in all regression, when focusing only on temporary contracts all coefficients attached to "N. of days empl. − temporary" are positive and significant across the age groups, thus suggesting that more days of work under temporary contracts significantly increase the probability of being under psychotropic medication. To sum up, our findings confirm that holding temporary contracts significantly increases the probability of developing mental health problems such as anxiety and depression that need to be medically treated. In addition, we find that more days worked under temporary contracts is associated with higher probabilities of being under medication for employees, while frequent changes in temporary contracts seem to affect only the elderly.

As for the socio-demographic characteristics, despite the division in age groups, it is interesting to note that age still plays an important role in explaining variations in the probability of psychotropic drug prescription across individuals; for the first two age groups, being one year older increases such probability by 0.007 and 0.018, respectively, while for the age group 50 and over it decreases such probability by 0.005, indicating that the relation between age and psychotropic prescriptions has an inverted U-shape. A negative coefficient for the older age group could be explained by more negative attitude of older people toward mental health treatment, or the risk for adverse reactions from psychotropic medications, which increases dramatically with the number of medications taken and with age (Lindsey, 2009).

The coefficient attached to the variable female is positive and significant across all age groups. This result is in line with consistent evidence from epidemiological, and clinical studies that mental disorders are more common in women (Sullivan et al., 2000; WHO, 2014). Table 6 also shows that holding a university degree diminishes the probability of suffering from mental health problems requiring psychotropic medications, relative to workers with less than secondary school (the excluded dummy), for the first two age groups. This result may be explained by the fact that highly educated employees have more opportunities in the labour market compared to those with lower education, and this is reflected in their health and mental health status (see Robone et al., 2011).

The coefficient attached to having "Non-Italian citizenship" has a negative sign and is statistically significant, implying lower probabilities of psychotropic drug prescription for these individuals. This result supports evidence that non-Italian citizens living in Italy are in a better mental health status than Italian people (ISTAT, 2005). Another explanation for this result is that non-Italian workers may have less access to health care, due for example to the lack of information on the availability of different treatments, possibly linked to poor education, cultural difference, and/or language barrier. Living in Milan decreases the probability of being under psychotropic medication, which is in contrast with results in the literature pointing at more mental illness for people residing in large urban areas (Lederbogen et al., 2013). This result may be explained by a higher concentration of social services in the city, or perhaps by the fact that people living in Milan have a better network. Finally, it is interesting to observe that more hours of redundancy pay seem to exacerbate mental illness within the middle age group, while a higher unemployment rate has a negative impact on prescription probabilities for the first two age classes. The negative effect of the gender-specific unemployment rate could indicate that an increase in unemployment for all workers makes workers more tolerant towards their employment conditions, hence impacting on their mental health.

The bottom part of Table 6 reports variable addition tests for endogeneity (VAT) for each variable suspected to be endogenous (Wooldridge, 2014). The VAT test for the null hypothesis that a variable in $\mathbf{w}_{it}$ is exogenous is a robust t-test on the residuals (obtained in the first stage regression) included in the second stage equation. Most VAT tests indicate that our proxies for precariousness have a significant impact, and hence are endogenous, thus confirming the appropriateness of the instrumental variable approach adopted in this empirical analysis. Finally, the Table reports the χ^2 test for overall significance of estimated parameters in the first-stage regression. Taken jointly, the coefficients of the first-stage regression are highly significant, thus indicating the relevance of our instruments.

6. Exploring the consequences of moving to precarious employment

The above regression results shows that being precarious increases the probability of having one or more prescriptions for medication to treat mental health problems. We now focus on what happens to the mental health of workers, when they face a change in their employment conditions. Specifically, in the regression we include three dummies: "Permanent to temporary$_{it}$" is a dummy equal to one when worker i faces a change from a permanent to a temporary contract between $t-1$ and t, and zero otherwise; "Temporary to permanent$_{it}$" is equal to one only when worker i faces a change from a temporary contract to another temporary contract between $t-1$ and t; "Stable temporary$_{it}$" is equal to one when worker i keeps a temporary contract in both periods $t-1$ and t. It follows that the excluded dummy depicts a situation in which a worker i does not change her situation of permanent contract between $t-1$ and t, i.e., he could change contract, but only for another permanent contract. Results are reported in Table 7. It is interesting to observe that moving from permanent to temporary contract significantly increases the probability of suffering from mental health problems that require psychotropic medications, while, symmetrically, although with a smaller effect in absolute value, moving from temporary to permanent contract tends to reduce it, for all age groups. Finally, not being able to move from a situation of temporary contracts increases such mental health problems, when compared to a condition of stable permanent contracts. All other variables have coefficients that are similar in terms of size and significance to those reported in the previous regression.

It is important however to interpret with caution these results. In fact, the change from permanent to temporary contract might have been forced because the worker has been made redundant due to economic difficulties of their employer, and hence the worsening in mental health may reflect the fact of having been made redundant rather than the movement to precarious employment. Unfortunately, our data do not give us information on the reason for changing job contract.

Table 8 shows some descriptive statistics on workers that experience a change in their employment status, moving from a permanent to a temporary contract over the sample period, using the procedure outlined in Section 4. As expected, the percentage of workers moving from permanent to temporary contracts decreases with age, while the percentage of workers with first episode of psychotropic medication prescription before or after moving from permanent to temporary rises with age. This result is supported by our descriptive statistics, which indicate that a large proportion of people belonging to the older age group hold a permanent contract, and, on average, tend to have less contract changes than younger workers. One explanation for this result is that current legislation in Italy, while very strict for workers on permanent contracts, does not adequately protect workers on non-regular forms of employment, with the result is that older workers on permanent contracts may be reluctant to move to other jobs.

It is interesting to observe that the average number of contract changes after movement from permanent to temporary is higher for workers that develop a mental health episode, although the number of days worked is roughly the same. This result seems to corroborate the hypothesis that a mental illness occurring after a movement to precariousness in turn impacts on future precariousness pattern, by increasing average future contract changes. Thus, our findings seem to indicate that mental health deterioration in precarious workers may permanently affect future job trajectories. However, we observe that the time span of our analysis is too short to fully investigate the job trajectories of workers due to the mental illness triggered by job precariousness.

7. Concluding remarks

The main objective of this paper was to study the effects of precarious employment on the mental health of employees during a period of economic recession. After having identified a set of attributes attached to precarious employment, we find that, *ceteris paribus*, being in a status of temporary employment tends to increase the likelihood of developing mental health problems, such as anxiety and depression that need to be medically treated. More days of work under temporary contracts, as well as frequent changes in temporary contracts significantly increase the probability of being depressed, especially for older workers. Finally, we observe that moving from permanent to temporary contract tends to deteriorate mental health; symmetrically, shifting from temporary to permanent jobs improves the mental health status,

Table 7
Regression results: moving to precarious employment. Average partial effects.

	18–34		35–49		50 and over	
	Par.	Std.err.	Par.	Std.err.	Par.	Std.err.
$h_{i,t-1}$	0.0787*	0.0003	0.1198*	0.0003	0.1358*	0.0005
Permanent to temporary$_{it}$	0.0053*	0.0005	0.0024*	0.0007	0.0029**	0.0013
Temporary to permanent$_{it}$	−0.0009**	0.0003	−0.0011*	0.0003	−0.0009***	0.0005
Stable temporary$_{it}$	0.0049*	0.0004	0.0033*	0.0005	0.0042*	0.0008
N. contract changes$_{it}$	0.0006*	0.0001	0.0012*	0.0002	0.0006	0.0005
N. days empl.$_{it}$	0.0000	0.0000	−0.0001*	0.0000	0.0000	0.0000
Age$_{it}$	0.0064*	0.0004	0.0182*	0.0034	−0.0043*	0.0015
Female$_{i}$	0.0121*	0.0023	0.0164*	0.0030	−0.0003	0.0050
High school$_{it}$	−0.0002	0.0002	−0.0002	0.0002	0.0000	0.0003
University degree$_{it}$	−0.0047*	0.0002	−0.0039*	0.0003	0.0004	0.0006
Non-Italian citizenship$_{it}$	−0.0118*	0.0002	−0.0196*	0.0003	−0.0272**	0.0007
Milan$_{it}$	−0.0009*	0.0002	−0.0008*	0.0002	0.0001	0.0003
Redundancy pay$_{st}$	−0.0002	0.0002	0.0004**	0.0002	0.0000	0.0004
Unemployment rate$_{t}$	−0.0035**	0.0013	−0.0036**	0.0017	0.0065**	0.0029
Pseudo-R^2	0.3488		0.3908		0.3982	

Notes: (*),(**),(***) mean significant at the 1, 5, 10 percent significance level, respectively.

Table 8
Descriptive statistics on the mental health of workers before and after movement to precarious employment.

	18–34	35–49	50 and over
% workers moving from permanent to temporary contract:	8.64	6.44	5.17
Av. n. contract changes after movement	0.417	0.298	0.208
Av. n. days worked after movement	194.0	234.5	226.2
% workers with mental health episode before moving from permanent to temporary contract	2.44	4.69	5.22
% workers with first with mental health episode after moving from permanent to temporary contract:	2.79	5.11	6.53
Av. n. contract changes after movement	0.456	0.319	0.207
Av. n. days worked after movement	201.7	228.7	219.9

although with a milder effect. An exploratory data analysis corroborates the hypothesis that mental illness developed after a movement to precarious employment may permanently affect future job trajectories.

One lesson to learn for policy makers is that interventions aimed at increasing the flexibility of the labour market through an increase of temporary contracts should also take into account the social and economic cost of these reforms, in terms of psychological wellbeing of employees. Policy makers may consider providing a mechanism that encourages employers to transform temporary contracts into permanent ones, for example, through financial incentives, or rather penalties for employers having low conversion rates. These interventions should aim at strengthen the perceived security among non-permanent employees. On the other hand, policy tools designed to alleviate mental health stress caused by job precariousness and better management of mental health problems linked to job instability could not only improve the health of workers but also increase firms' productivity, thus impacting on the wider economy. From a point of view of public health, it would be important to design campaigns of prevention of mental health problems due to job instability. For example, one effective intervention could be implementing NHS direct lines that can be contacted by employees who suspect early signs of stress due to their work conditions (e.g., being trapped in low-paid, low-productivity temporary contracts).

Although our data set is extremely rich, one limitation is its short time span that does not allow us to follow the job trajectories of the workers, to better estimate the complex interaction between job precariousness and mental health problems. Further, we know little about the characteristics of the firms where workers are employed, as well as other important socioeconomic characteristics of the workers, such as income, marital status or the presence of children in the household, which are certainly important determinant of their mental health status. Another limitation of our data is that we are not able to estimate the costs of precarious employment. The challenge ahead is to estimate the economic costs due to a higher use of mental health services associated with temporary work as well as linked to lost productivity, to be able to quantify the burden of precarious employment on the economy and the wider society.

Acknowledgments

We thank Jonathan Skinner, Catia Nicodemo and two anonymous reviewers for helpful comments on a previous version of this paper.

References

Artazcoz, L., Benach, J., Borrell, C., Cortes, I., 2005. Social inequalities in the impact of flexible employment on different domains of psychosocial health. J. Epidemiol. Community Health 59, 761–767.
Bardasi, E., Francesconi, M., 2004. The impact of atypical employment on individual wellbeing: evidence from a panel of British workers. Soc. Sci. Med. 58, 1671–1688.
Benach, J., Vives, A., Amable, M., Vanroelen, C., Tarafa, G., Muntaner, C., 2014. Precarious employment: understanding an emerging social determinant of health. Annu. Rev. Public Health 35, 229–253.
Benavides, F.G., Benach, J., Diez-Roux, A., Roman, C., 2000. How do types of employment relate to health indicators? Findings from the second European survey on working conditions. J. Epidemiol. Community Health 54, 494–501.
Caroli, E., Godard, M., 2014. Does job insecurity deteriorate health? A causal approach for Europe. In: PSE Working Papers n. hal-00784777.
Carrieri, V., Di Novi, C., Jacobs, R., Robone, S., 2014. Insecure, sick and unhappy? Well-being consequences of temporary employment contracts. In: Research in Labour Economics (IZA).
Chamberlain, G., 1980. Analysis of covariance with qualitative data. Rev. Econ. Stud. 47, 225–238.
Cottini, E., Lucifora, C., 2010. Mental Health and Working Conditions in European Countries. Cornell University ILR Review, Special Issue on Job Quality, p. 66.
Dawson, C., Veliziotis, M., Pacheco, G., Webber, D.J., 2015. Is temporary employment

a cause or consequence of poor mental health? A panel data analysis. Soc. Sci. Med. 134, 50–58.
European Observatory on Health Systems and Policies, 2014. Italy: Health System Review. Health Systems in Transition, p. 16.
Frijters, P., Johnston, D.W., Shields, M.A., 2014. The effect of mental health on employment: evidence from Australian panel data. Health Econ. 23, 1058–1071.
Gash, V., Mertens, A., Romeu Gordo, L., 2007. Are fixed-term jobs bad for your health?: a comparison of West-Germany and Spain. Eur. Soc. 9, 429–458.
ILO, 2008. Impact of changing work patterns on income inequality. In: Discussion Paper n. 193.
ILO, 2011. Policies and Regulations to Combat Precarious Employment. Geneva.
ILO, 2012. World of Work Report. Geneva.
INPS, 2008. Stabilmente precari? Rapporto 2008 sui lavoratori parasubordinati iscritti alle Gestione Separata INPS. Report. Available at: www.radioarticolo1.it/userdata/articoli/allegati/200806rapportonidil-ireslavoratoriprecari_8782.pdf.
INPS, 2014. Statistiche della previdenza e dell'assistenza sociale, I trattamenti pensionistici – Anno 2011.
ISTAT, 2005. Stranieri residenti in Italia: rapporto Istat 2005 su salute e ricorso ai servizi sanitari available at: www3.istat.it/salastampa/comunicati/non_calendario/20081211_00/testointegrale20081211.pdf.
Keuskamp, D., Ziersch, A.M., Baum, F.E., Lamontagne, A.D., 2013. Precarious employment, psychosocial working conditions, and health: cross-sectional associations in a population-based sample of working Australians. Am. J. Ind. Med. 56, 838–844.
Lederbogen, F., Haddad, L., Meyer-Lindenberg, A., 2013. Urban social stress – risk factor for mental disorders. The case of schizophrenia. Environ. Pollut. 183, 2–6.
Lindsey, P.L., 2009. Psychotropic medication use among older adults: what all nurses need to know. J. Gerontol. Nurs. 35, 28–38.
OECD, 2011. Sick on the job? Myths and realities about mental health and work. Ment. Health Work. http://dx.doi.org/10.1787/9789264124523-en. OECD Publishing.
OECD, 2014. Making Mental Health Count: the Social and Economic Costs of Neglecting Mental Health Care. OECD Publishing. www.oecd.org/els/health-systems/Focus-on-Health-Making-Mental-Health-Count.pdf.
Ponzo, M., 2011. Status occupazionale e benessere soggettivo in Italia. In: QA-Rivista dell' Associazione Manlio Rossi Doria, vol. 65, pp. 75–106.
Quesnel-Vallee, A., De Haney, S., Ciampi, A., 2010. Temporary work and depressive symptoms: a propensity score analysis. Soc. Sci. Med. 70, 1982–1987.
Robone, S., Jones, A.M., Rice, N., 2011. Contractual conditions, working conditions and their impact on health and well-being. Eur. J. Health Econ. 12, 429–444.
Roy, J., Schurer, S., 2013. Getting stuck in the blues: persistence of mental health problems in Australia. In: IZA Discussion Paper n. 7451.
Stewart, W.F., Ricci, J.A., Chee, E., Hahn, S.R., Morganstein, D., 2003. Cost of lost productive work time among US workers with depression. JAMA 289, 3135–3144.
Sullivan, P.F., Neale, M.C., Kendler, K.S., 2000. Genetic epidemiology of major depression: review and meta-analysis. Am. J. Psychiatry 157, 1552–1562.
Virtanen, P., Vahtera, J., Kivimaki, M., Pentti, J., Ferrie, J., 2002. Employment security and health. J. Epidemiol. Community Health 56, 569–574.
Virtanen, M., Kivimaki, M., Joensuu, M., Virtanen, P., Elovainio, M., Vahtera, J., 2005. Temporary employment and health: a review. Int. J. Epidemiol. 34, 610–622.
Vosko, L., 2010. Managing the Margins: Gender, Citizenship, and the International Regulation of Precarious Employment. Oxford University Press, Oxford.
Waenerlund, A.K., Virtanen, P., Hammarström, A., 2011. Is temporary employment related to health status? Analysis of the northern Swedish Cohort. Scand. J. Public Health 39, 533–539.
WHO, 2014. Social Determinants of Mental Health. WHO Press.
Wooldridge, J.M., 2005a. Unobserved heterogeneity and estimation of average partial effects. In: Andrews, D.W.K., Stock, J.H. (Eds.), Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg. Cambridge University Press, pp. 27–55.
Wooldridge, J.M., 2005b. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. J. Appl. Econ. 20, 39–54.
Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data, second ed. MIT Press, Cambridge, MA.
Wooldridge, J.M., 2014. Quasi-maximum likelihood estimation and testing for nonlinear models with endogenous explanatory variables. J. Econ. 182, 226–234.