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ABSTRACT

The Effects of Unemployment on Health, Hospitalizations, And Mortality – Evidence from Administrative Data*

Linking health to the employment history of the whole Slovenia's workforce, this paper employs three innovative features. First, it utilizes a novel "double proof" approach of addressing the reverse causality that tracks only healthy individuals, making sure that any unemployment spell that individual may undergo precedes the occurrence of a disease, and relies on mass-layoffs to provide an additional layer of exogeneity to unemployment. Second, it is one of the first papers using data on drug prescriptions to infer information about the health status of individuals and link it labor market outcomes. And third, it treats the health effects of unemployment as part of a dose–response relationship, with the share of time spent in unemployment (as opposed to other labor market states) reflecting the "unemployment dose". The paper finds that, in comparison to employed persons with permanent contracts, persons experiencing unemployment face increased hazard of all three studied groups of diseases – cardiovascular diseases, diabetes, and mental disorders – as well as of hospitalizations caused by these diseases, with the effects stretching over a 15-year horizon. Moreover, the results also show that unemployment significantly increases the probability of death due to cardiovascular diseases and mental disorders, as well as death of any cause.

JEL Classification: J64, I12, C23

Keywords: unemployment, health, hospitalization, mortality, cardiovascular diseases, diabetes, mental disorders, prescriptions, duration analysis

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1. Introduction

Economists sometimes associate unemployment with "adjustment costs" – costs needed to reduce the level of output or introduce new technologies. Yet treating unemployment purely as a reallocation problem grossly underestimates the true costs of unemployment. Beyond rendering workers temporarily jobless, unemployment results in losses of income, decreases productivity once individuals become reemployed (as witnessed, for example, through lower reemployment wages of displaced workers) – and as it is becoming increasingly clear, also affects their health.

The health effects of unemployment have been well documented in the literature, although many of the earlier studies suffer from methodological limitations that prevent them from confirming whether the effect of unemployment on health is causal (see Stauder, 2009, for discussion). Recent studies that address causality more thoroughly show that exposure to unemployment increases the risk of cardiovascular diseases (CVDs) – for example, Ardito et al. (2017). Studies also show that unemployment affects mental health (see McKee-Ryan et al., 2005, and Paul and Moser, 2009, for meta-analyses). Strong evidence is provided also by empirical studies that address the causality problem by studying the health effects of involuntary job loss due to plant closures or mass layoffs. These studies show that job loss increases risk of mental disorders, risk of hospitalization for mental disorders, suicidal intentions or increased use of antidepressants and related drugs (Kuhn et al., 2009; Eliason and Storrie, 2009a, 2010; Browning and Heinesen, 2012). In contrast, no causal effect of job loss on mental health or hospitalizations for stress-related diseases was found by Browning et al (2006), Salm (2009), and Schmitz (2011). Moreover, empirical studies also show that unemployment increases the risk of mortality (Eliason and Storrie, 2009b; Browning and Heinesen, 2012; Bloemen et al., 2018).

The mechanism through which unemployment or job loss affect health is as follows. Long-term exposure to stressful, threatening circumstances associated with unemployment and job loss creates wear and tear on the cardiovascular, metabolic, and immune systems. This increases susceptibility to infectious diseases, contributes to the early onset of chronic diseases such as hypertension, diabetes, morbid obesity, and metabolic syndrome, as well as to the development of mood disorders, functional limitations, and even to early death (McEwen, 1998, 2000, 2003; Seeman et al., 2001; Havranek et al., 2015). While ultimately the mechanism is always physiological, there are distinct types of stressors at work. Financial stressors – emerging from the loss of income connected to unemployment – increase the frequency of stressful life events such as incurring debt, having worse diet, and lower quality of home environment (Jacobson et al., 1993; Couch and Placzek, 2010; Eliason, 2011). Psychosocial stressors, arising from fewer opportunities for social contact and for defining individual's social identity, damage individual's self-esteem and self-confidence, and have adverse effects on cognition and emotion (Jahoda, 1982). And unemployment can also trigger a change in behaviour – often because of perceiving unemployment as a threat that a person cannot confront with – that results in smoking, inactivity, unhealthy diets and alcohol use, less frequent visits to the doctor, and medication nonadherence (Havranek et al., 2015).[1]

This paper rigorously evaluates the health and mortality effects of unemployment for Slovenia, relying on three innovative features. First, it uses a new, "double proof" approach of addressing the reverse causality that tracks only healthy individuals, making sure that any unemployment spell that individual may undergo precedes the occurrence of a disease, and relies

[1] Some aspects of unemployment – particularly if combined with generous income support – can conceivably also contribute to improved health, partly depending on the stressors typically present in the individual's working environment.

on mass-layoffs to provide additional layer of exogeneity to unemployment. Second, it is one of the first papers that uses data on drug prescriptions to infer information about the health status of individuals and link it labor market outcomes.[2] Third, it treats the health effects of unemployment as part of a dose–response relationship, with the share of time spent in unemployment (as opposed to other labor market states) reflecting the "unemployment dose".

Other strengths include the reliance on a powerful methodological tool – duration models, and on exceptionally rich, administrative data that enables the use of such a methodology. By linking health and labor market data, we can track individual employment and health history of the entire Slovenia's workforce continuously over two decades. Such coverage also allows the estimation of long-term, not just short-term effects of unemployment on health. Moreover, we examine a rich range of health and health-related outcomes: morbidity of CVDs, diabetes, and mental disorders, hospitalizations related to these groups of diseases, and mortality from these groups. Our data also capture objective rather than self-reported health outcomes. This is particularly important because self-reported information is affected by the perception of overall well-being and life satisfaction, so it is likely that self-reported health outcomes of unemployed workers are biased.

Our hazard rate model estimates show that being unemployed in the past – sometimes stretching up to 15 years back – significantly increases the hazard of the three studied groups of diseases as well as of hospitalizations caused by these diseases. For example, for both sexes experiencing unemployment in the past 6–10 years by the younger group (35–50 year olds) or in the past 11–15 years by the older group (for 51–65 year olds) increases the hazard of CVDs as

[2] The only other paper we are aware of that uses drug prescription data is Caliendo et al. (2020) that studies the (unintended) health consequences of two labor market policies – participation in training and unemployment benefit sanctions.

compared to employed workers with permanent contract. Moreover, for men unemployment in the past 5 years, and for the older group, also in the past 6 to 11 years, significantly increases hazard of CVD-caused hospitalization. Moreover, the results confirm that unemployment in the past 5 years significantly affects hazard of diabetes, and for men, also diabetes-caused hospitalizations. The experience of unemployment also significantly increases the hazard of mental disorders and mental-disorder-caused hospitalizations, particularly for younger workers of both sexes. Our results also show that unemployment in the past 5 years significantly increases the probability of death due to CVDs and mental disorders, as well as death of any cause for both sexes. While both the broad and narrow definitions of unemployment – the narrow being preferred, as it introduces additional assurance of exogeneity – yield qualitatively similar results, fewer estimates remain significant when using the narrow definition of unemployment.

The organization of the paper is as follows. We start with a brief literature review of the effects of unemployment and displacement on health outcomes and mortality. We continue with presenting our empirical strategy to estimate the health effects of unemployment, describing data source, and explaining how we construct key variables used in the regression analysis. We then present the results, both of the descriptive analysis that compares the prevalence of the selected groups of diseases and related hospitalizations among the employed and unemployed persons, as well as estimates of hazard rate models. The last section concludes.

2. Literature review of the health effects of unemployment

There is substantial evidence that the risk of CVD is related to unemployment, although only a few studies address the problem of reverse causality. Based on time-series analysis for Brazil, Katz et al. (2016) show that there is a positive relationship between unemployment rate and hospital admission for acute myocardial infarction. Dupre et al. (2012) find that in the U.S., job loss increases the risk of acute myocardial infarction by 35% within the first year after the loss, and that the risk depends on the number of unemployment episodes. Similarly, Gallo et al. (2006) show for the U.S. that older workers who lost jobs had more than twofold increase in the risk of subsequent myocardial infarction than employed. In a nation-wide longitudinal study for France, Meneton et al. (2014) report that the risk of fatal and non-fatal cardiovascular event increased by 80% for unemployed compared to employed workers. These findings are of special importance as they refer to middle-aged socially privileged individuals who were not likely to have had very unhealthy lifestyles.

Ardito et al. (2017) also find that Italian workers who were unemployed for more than 3 years had 2.8 times higher risk ratio of hospitalization due to ischemic heart disease in comparison to continuously employed workers, and that those unemployed who decided to become self-employed had a 2.2 higher risk ratio for hospitalization. Moreover, by comparing the values of biomarkers, Michaud et al. (2016) find that workers who became unemployed had significantly higher C-reactive protein (and also heart rate) than continuously employed workers. In contrast to the above studies, Yarnell and others (2005) find no statistically significant relation between unemployment and risk of coronary heart disease in a cohort study in France and Northern Ireland. Similarly, Eliason and Storrie (2009a) find no evidence that job loss increased the risk of severe CVDs in Sweden.

There is some evidence that the exposure to unemployment increases also the risk of diabetes. Most studies in this field are based on survey data and report prevalence rates among the unemployed or associations with unemployment. For example, Chung and Pérez-Escamilla (2009) and Sabanayagam et al. (2009) report higher prevalence of diabetes among unemployed in Korea and Singapore, respectively. Similarly, Müller et al. (2013) and Brož et al. (2016) find a positive association between unemployment rate and prevalence of diabetes at the neighbourhood or regional level in Germany and Czech Republic, respectively. Müller et al. (2013) also find that unemployed women in five German regions had 1.73 times higher odds of having type 2 diabetes than employed women. One of the few studies that uses objective data was performed by Rautio et al. (2017). They show that in Finland, men who were unemployed for more than 1 year during the 3-year period had a 1.6-fold higher risk for pre-diabetes and 2.6-fold higher risk for screen-detected type 2 diabetes than employed men (but they lack the baseline assessment of the health status of individuals prior to the exposure of unemployment).

There is also evidence that the loss of job, and unemployment per se, results in a deterioration of mental health.[3] In a meta-study based on the 237 cross-sectional and 87 longitudinal studies, Paul and Moser (2009) show that unemployment negatively affects mental health. They find that the effect is stronger for men, blue-collar workers, and the unemployed in less developed countries. In a nation-wide study, Kondo et al. (2008) conclude that the subjective reporting about feeling unwell is twice as frequent among unemployed Japanese. Similarly, Kaspersen et al. (2016) find that there was a significant increase in risk of purchasing psychotropic drugs by Norwegian workers who experienced unemployment and that the risk decreased with the approaching re-employment. Urbanos-Garrido and Lopez-Varcarcel (2015) show that in comparison to employed workers, the overall health and mental health of Spanish unemployed workers were more adversely affected by the economic crisis that started in 2008. Similar findings for Spain are reported by Farré et al. (2018), who find that an increase of the unemployment rate by 10 percentage points due to the collapse of the construction sector raised poor health and mental

[3] The effects can also be "transmitted" to spouses of the unemployed. For example, for Germany Marcus (2013) notes that, one year after the episode of the unemployment, deterioration of the mental health affected both the person unemployed as well as his or her partner.

disorders in the affected population by 3 percentage points. In a study covering the U.S. and 13 European countries, Riumallo-Herl et al. (2014) find that with job loss, the symptoms of depression in older people who are approaching retirement age increased by 4.8% in the U.S. and 3.4% in European countries. Based on a panel analysis for individual workers in five countries (Australia, Canada, Korea, Switzerland and United Kingdom), OECD (2008) also confirms that mental health suffers when individuals move from employment to unemployment or inactivity, and that the impact of duration of nonemployment differs across countries and by gender.

Studies also show that unemployment is linked to hospitalizations due to mental disorders as well as suicides. Eliason and Storrie (2010) show that involuntary job loss increased the risk of psychiatric hospitalization among Swedish women by 17%. Similarly, Browning and Heinesen (2012) report that job loss increases the risk of hospitalization for mental diseases by 63% in the first year of unemployment; the cumulative hazard ratio decreases to 1.32 four years after and to 1.19 20 years after the job loss. Using Austrian health insurance data, Kuhn et al. (2009) show that job loss increases expenditures for hospitalizations due to mental health problems and for antidepressants and related drugs for men. As for suicides, for Western European countries Laanani and others (2015) conclude that a 10-percent change in unemployment on average increases the rate of suicides by 0.3%. Short-run effects of job loss on suicide are confirmed also by Browning and Heinesen (2012) for Denmark, and Eliason and Storrie (2009a) for Sweden.

There are also studies that fail to confirm the link between job loss and health. Salm (2009) and Schmitz (2011) find no evidence of worsening of the mental health among the U.S. or German workers, respectively, who lost their job because of plant closures. Similarly, Browning et al. (2006) find that in Denmark, worker displacement does not cause hospitalizations for stress-related diseases.

There is ample evidence that unemployment increases the risk of mortality. For Sweden, Gerdtham and Johannesson (2003) find that unemployment increases risk of mortality by nearly 50% and that it has significant impact on suicides and mortality from other diseases except on cancer and CVDs. For the Netherlands, Bloemen et al. (2018) find that job loss due to firm closure increased the probability to die within five years by 34% to 46%. Sullivan and Wachter (2009) report both short-and long-run effects for Pennsylvanian male displaced workers with long job tenure. Their mortality rates in the first year after unemployment were 50% to 100% higher than for workers who have not experienced displacement, and the effect was observed also 20 years after job loss. Similar findings are reported for Sweden by Eliason and Storrie (2009b), who find that in the first 4 years after plant closure the overall mortality risk among men increased by 44%, but they do not confirm effects beyond this period. Using Danish data, Browning and Heinesen (2012) find that in the first year after job loss the risk of overall mortality is 79% higher and remains statistically significant even after 20 years. For Italy, d'Errico and others (2019) show that the overall risk of mortality is 2–3 times higher among unemployed men relative to employed men and do not find statistically significant effects for women. Among causes of death, they stress elevated risk of mortality from neoplasms, CVDs, and suicides. Similarly for Scotland, Clemens and other (2015) find that unemployed men had 1.9 times higher mortality risk than employed men, and also do not confirm the mortality effects for unemployed women. In a meta-study, Roelfs et al. (2011) also confirm that unemployment is associated with higher mortality risk for persons in their early and middle careers.

3. Empirical strategy, data sources, and construction of key variables

The paper draws on extremely rich administrative dataset that covers the entire population of Slovenia and provides continuous labor market and health history of every individual, often for several decades. Below we describe the empirical strategy used in the paper, including how we address the reverse causality – ill-health of the worker influencing the occurrence of his/her unemployment, one of the key methodological problems in evaluating the effects of labor market events on health. We also describe data sources and explain how we construct health and health-related variables used in the regression analysis, and how we identify unemployment spells due to mass layoffs or bankruptcies.

3.1 Empirical strategy

Based on data availability, our empirical strategy of estimating health effects of unemployment consists of estimating hazard rate models. In these models, we include the exposure to various labor market states – in our case, unemployment being of key interest – in the preceding 15 years as the key explanatory variables (we include separate variables for the exposure in the past 5 years, in the past 6–10 years, and in the past 11–15 years). We have chosen a 15-year horizon to be able to capture also the long-term health and mortality effects of unemployment, as one can hypothesize – and many studies, including the ones cited above, corroborate – that such effects may only manifest themselves over a prolonged time horizon. We measure labor market exposure as share of time spent in a certain state. Note that our measure of unemployment – "unemployment dose" – is thus invariant to the pattern of unemployment spells as long as its combined duration is the same. Health effects of unemployment are measured in relative terms, via comparison of hazard rates of certain diseases (or other outcomes) between unemployed and employed workers.

Hazard rate models have distinct advantages over the linear mixed effects models commonly used in the literature. Taking advantage of continuous recording of events, the hazard rate models not only reflect more completely the effects of labor market events on health status than models based on individuals being followed via successive panels, but they are also better adjustable to possible nonlinearities as well as to the changes of covariates and effects in time. They allow individuals to enter and exit the estimation sample without biasing the results.

To address reverse causality, we employ a new, "double proof" approach of tackling the problem. One way of addressing it is by tracking individuals until they develop a certain disease. That is, we ignore parts of the employment history of individuals that occur after the onset of a (studied) disease, thus making sure that any unemployment spell that an individual may undergo *precedes* the occurrence of a disease. In other words, because we stop tracking individuals at the point of developing a disease, we eliminate occurrences of unemployment that could have been provoked by ill health. Therefore, if we can establish a systematic relationship between the onset of unemployment and subsequent occurrence of disease, doing so would indeed prove the causal effect of unemployment on health.

However, this strategy – following individuals until they develop a certain disease – may be susceptible to individual health status being identified imperfectly, or information about illness being recorded with a lag, or not at all. There are three reasons for that:

(a) Individuals may develop another disease that we do not control for (if we do not take into account information about all three groups of diseases for which we have information) or for which we do not have information (such as musculoskeletal disorders or cancer).

(b) There is a “behavioural lag” affecting our recording of the onset of the illness. In our prescription records we learn about a person becoming ill upon the prescribed medication being filled. But for that to happen, two prior steps are needed: the person needs to (i) go to the doctor, and (ii) take a prescription to the pharmacy to be filled. Obviously, some individuals may be more proactive than others – and to make things worse, this lag may be affected by their labor market status. For example, it is likely that an unemployed individual is less proactive in visiting a doctor or obtaining a medication, or both. Note, however, that hospitalization – being urgent events beyond the control of individuals – are free of such behavioural lags.

(c) Individuals may be ill – and their actions may be affected by their illness – before they themselves know that.

Under this strategy, the estimated coefficients of our variable representing the exposure to unemployment in the estimated hazard rate models may thus still be contaminated – endogenous. As explained above, the unemployed retained in our estimation may not be “randomly selected’ as far as their health status is concerned – that is, their health status may contribute to their unemployment status. If this is the case, the estimated effects of unemployment on health will be overestimated.

To provide additional layer of exogeneity, we adopt a common approach in the literature that relies on identification of subgroups of the unemployed for whom there is reason to believe that their unemployment is exogenous: unemployed due to the mass layoff, and as a variant, unemployed due to the bankruptcy. In our estimated models, we thus include exposure to unemployment as experienced by two separate groups: unemployed due to mass layoffs (alternatively, due to bankruptcy), and unemployed due to other reasons.

3.2 Data sources

The study draws on extremely rich administrative data that provides both labor market and health information on the entire population of Slovenia, with employment spells being linked to their employers. Data from various sources are merged based on a personal identifier. Note that the source of data on unemployment is unemployment registry at Employment Service of Slovenia.

Given the large array of benefits registered unemployed are entitled to or eligible for (OECD, 2016), the coverage of unemployment in the registry is solid.[4]

The dataset is built from the following sources, all having countrywide coverage:

Labor-market related databases (available 1991 – 2017, wages until 2015)

- *Work history database*. It contains the information on the starting and ending date of an employment spell, the type of appointment, occupation, regular number of hours of work, employer identification code, and personal characteristics (gender, age, and education). (Through the employer identification code, employment spells could also be linked to accounting and other data on the current employers.) Source: Statistical Office of Slovenia.
- *Workers' earnings database*. It contains information on earnings associated with each employment spell of an individual (amount of earnings, number of hours worked, starting and ending date of earnings period). Source: Pension and Disability Institute of Slovenia.
- *Database on registered unemployment, unemployment benefit receipt and active labor market program participation (ALMP)*. It contains starting and ending date of each unemployment spell, destination of exit, information about the receipt of unemployment insurance benefits, information on an individual's participation in ALMPs, and personal and family characteristics. Source: Employment Service of Slovenia.

Health and health-related databases (source: National Institute of Public Health)

[4] Apart from unemployment benefits, other benefits available to registered unemployed include personalized help with job search, reimbursement of transportation costs associated with job search, participation in active labor market programs, and eligibility to certain means-tested cash transfers. Note also that a common shortcoming of registry data on unemployment – inaccurate end date of unemployment spell upon finding a job, given the lack of incentives of reporting the date by the unemployed – is not a problem in our case, because we can impute the information about the end of unemployment spell from the information on the first post-unemployment employment spell.

- *Outpatient prescription drugs database* (available 2009 – 2017). It includes information about the person being prescribed the medication and about the filled prescription, including the type of medication and the date of filling (redeeming) the prescription.
- *National Hospital Health Care Statistics Database* (available 2005 – 2017). It includes key information about the patient, the health care provider (hospital), the main and secondary causes of hospitalization (diagnoses according to ICD-10), therapeutic and diagnostic procedures, and duration of hospitalization.
- *Database on deceased persons* (available 2000 – 2017). It includes key information about the deceased person, including a personal identifier, the basic cause of death, the external cause of death, and the date and place of death.

3.3 Construction of key variables used in the regression analysis

Below we explain how we use the information from our administrative data sources to measure health and labor market variables used in the regression analysis. Let us stress that morbidity indicators for all three groups of studied diseases – CVDs, diabetes, and mental disorders – are based on the information about the filling of prescriptions, while information on hospitalizations and deaths is taken directly from respective administrative registers.

Construction of health and health-related indicators

For each group of diseases studied – CVDs, diabetes, and mental disorders – we formed morbidity, mortality, and hospitalization indicators. As mentioned, morbidity indicators are formed based on the information about the filling of prescriptions. For CVDs, for example, the person's indicator is set to zero just before the start of the period for which we have the information about prescriptions (January 2009) and the value is changed to one at the time of the first occurrence of the disease as evidenced by filling the prescription of a certain type. The indicators for diabetes and mental disorders are formed in a similar way (see classifications underlying the formation of these, as well as mortality and hospitalization indicators, in Appendix 1). As these indicators relate to chronic diseases, changes in their values are irreversible. The mortality indicator is set to one at the time of death as recorded in the database of deceased persons. Indicators on hospitalizations show the timing of hospitalizations and which group of studied diseases is the main cause for hospitalization. The universe of individuals for which the indicators are formed consists of all those born before or on December 31, 2002.

The task of determining the population at risk is hindered by the lack of direct, explicit information about onset of the disease. That is, for persons having a prescription filled in the initial period as recorded in our database, we do not know whether it is truly the first prescription filling of that person – indicating, in our set-up, the onset of the disease – or it is a repeated filling, in which case the disease must have occurred earlier. To overcome this glitch in our data, we use the initial period for which we have information about prescription to separate prior from new occurrences of a disease. In particular, we use the initial three years (2009 – 2012) as the "onset-observation window" to determine the true onset of the disease: only for persons who are during this period clear of any prescription fillings of certain type, we treat the first occurrence of such filling after this period as the onset of the disease.

Identification of unemployment spells due to mass layoffs or bankruptcies

Trying to avoid treating cases of spurious exit as mass layoffs, we identify unemployment spells due to mass layoffs in three steps. First, for every firm (uniquely determined by the business registry identification code) in every year, we determine the most common firm identifier for its workers in the next year. Note that for most firms, the firm identifier for its workers will not change from one year to the next, but in cases of spurious exit and entry, the most common identifier in the next year will be the one of the successor entity (or, in case of an acquisition, the acquiring entity). We then construe cases of mass layoffs to arise when less than 20% of workers are still employed at the most common firm identifier in the next year.[5] Second, we identify workers who separated from the firm experiencing a mass layoff in the three-year period centered around the timing of the mass layoff. And third, we identify mass-layoff provoked unemployment spells as those unemployment spells of workers, identified in the second step, which immediately follow separations from the firms experiencing mass layoffs as identified above. This procedure applies a strict criterion for determining when a mass-layoff event occurs – at least 80% of workers being laid off – but recognizes that the precise timing of layoffs may be more spread out. In particular, employment protection legislation stipulates additional procedures in cases of mass layoffs, which firms may attempt to avoid by staggering their layoffs. Also, differences in advance notice periods may result in the staggered departure of workers who were notified of their termination on the same date.

The identification of unemployment spells due to bankruptcies is also done based on observed employment. We identify firms whose employment is reduced to zero, and its timing; we identify workers who separated from the firm in the year before the employment is reduced to zero; and we identify unemployment spells of these workers which immediately follow such separations.[6] Note that, in contrast to the measure of mass-layoff induced unemployment, this

[5] Cases of spurious exit – a firm disappearing and a new firm entering, the latter taking over many of the workers previously employed in the firm which exited – are not considered mass layoffs unless they involve layoffs of more than 80% of workers of the firm exiting.

[6] Although we have data from the firm registry which could also be used to determine bankruptcy, the bankruptcy data is problematic because of the lag between formal bankruptcy and when individual workers stop working at the firm. In the case of large firms, most have virtually none of their employees still employed at the firm at the time when the firm has been declared to cease operations in the firm registry.

definition does not take into account the spurious entry or exit of firms due to e.g. changes in accounting entities.

The number of unemployed and employed workers included in empirical analysis is presented in Table 1. The number of employed workers on permanent contracts – the group used as a baseline when presenting our hazard ratio results – remained relatively stable at around 600,000 throughout the observation period (1997–2017), although its share in total employment declined from 78.2 to 72.4%. Reflecting the business cycle, the number of unemployed strongly increased during 2009–2013, following the 2008 recession. Note that throughout the observation period, the number of unemployed due to mass layoffs is sizeable, reaching the lowest number in 2008 (6,721) and the highest in 1997 (11,832), thus offering a sample of workable size to determine health effects of unemployment as experienced by this group alone.

4. Descriptive analysis

As an initial exploration, we compare the prevalence of the studied groups of diseases, and hospitalizations attributable to them, among the employed and unemployed persons. We also compare the prevalence across educational groups. Because age is an obvious determinant of health status and health-provoked outcomes, we present all prevalence rates by age groups. Unsurprisingly, our results mostly show that lower age is associated with better health – with lower prevalence of diseases or hospitalizations. Because age-related diseases are not the focus of this study, we do not discuss these relationships in detail below. Note that, as mentioned above, the health status of individuals is determined from the information on prescriptions (at the point of filling, not writing, the prescription).

Our results show that the prevalence of the studied groups of diseases is considerably higher among unemployed compared to employed workers. This finding applies particularly for mental disorders, but also for CVDs and diabetes. For mental disorders, the prevalence rate for the unemployed 20–29 and 30–39 olds is more than double the rate for the employed – see Figure 1, panel (a). For older groups, the difference becomes relatively smaller, but it remains sizable – for example, for 50–59 olds the prevalence rate among the employed is 19%, compared to 30% among the unemployed. In contrast, for CVDs and diabetes the difference in prevalence between unemployed and employed workers is less pronounced for younger groups and it becomes larger for persons older than 50 (for CVDs) or 40 years (for diabetes).

A very similar picture emerges for the prevalence of hospitalizations. The difference in the prevalence rates between the unemployed and employed is particularly dramatic for hospitalizations for mental reasons – see Figure 1, panel (b). For example, the prevalence rates for the younger three groups of the unemployed range from 1.6% to 2.3%, compared to prevalence rates of 0.2–0.3% for the younger three groups of the employed. Paralleling the differences in prevalence of mental disorders, the difference in prevalence of hospitalizations for mental reasons also becomes smaller at older age – and interestingly, the prevalence rates of hospitalizations themselves becomes smaller for both employed and unemployed workers after the age of 50 (possibly because workers most at risk in this age category retire on disability grounds). The prevalence of hospitalizations attributable to CVDs and diabetes is also higher among the unemployed compared to the employed workers, with differences becoming notable at the age of 40 and older.

Our results also show that higher education is associated with a lower prevalence of the studied groups of diseases as well as hospitalizations attributable to them – see Figure 2, panels (a) and (b). This relationship is more pronounced for the prevalence of hospitalizations, and, in case of diseases, at ages higher than 40 (higher prevalence of mental disorders and CVDs among

60–69 workers with tertiary education is an exception, probably attributable to higher pensionable age of this group due to delayed entry to the labor force, and hence less health-based selection among those still working at this age).

Clearly, the above findings show that compared to the employed, the unemployed are more likely to be of ill health and more likely to be hospitalized, pretty much at all ages. Of course, the question remains how much of this difference can be attributed to unemployment causing ill health, as opposed to workers of ill health losing jobs or entering unemployment disproportionally – a question we turn to below.

5. The estimation model and regression results

Below we describe our hazard rate estimation model and the results of applying this model to our Slovenia's datasets, with health and health-related outcomes relating to 2012–2017. We present the results of the effects of unemployment on the hazard of CVDs, diabetes and mental disorders, as well as on the hazard of hospitalizations caused by these diseases. We also present the results of the effects of unemployment on mortality, as well as some other effects.

5.1 The estimation model and summary statistics of the samples

We estimate the following Cox proportional hazard model:

$$h(t, \boldsymbol{S}, \boldsymbol{X}) = h_0(t)e^{\boldsymbol{\alpha S}_t + \boldsymbol{\beta X}_t}$$

with the dose response to historical exposure (for up to 15 years prior to time *t*) in the different labor market states contained in vector $\boldsymbol{\alpha}$ (with the corresponding shares of time spent in the various states contained in vector $\boldsymbol{S_t}$) and control variables contained in vector $\boldsymbol{X_t}$. Individuals are included in the regression (i.e., considered in the risk set) as long as they are healthy, with a failure event defined as having a medical condition related to CVDs, diabetes or mental disorders based on prescriptions, hospitalization, or death (for the latter, either cause-specific or due to any cause).

The key coefficients of interest are those relating to the labor market states contained in vector $\boldsymbol{S_t}$. For each point in analysis time *t* and for every individual in the risk set, the vector $\boldsymbol{S_t}$ contains labor market information on the share of that individual's time spent in the following 7 categories for the 15 years preceding time *t* (the categories are mutually exclusive and jointly exhaustive):

(1) Permanent employment (*baseline category in regressions)*

(2) Unemployment due to exogenous shock – that we identify either as unemployment due to mass layoffs or, alternatively, due to bankruptcy of the employer – with an option of distinguishing between the receipt and non-receipt of unemployment benefits

(3) Unemployment <u>not</u> due to exogenous shock, again with an option of distinguishing between the receipt and non-receipt of unemployment benefits

(4) Fixed-term employment

(5) Other regular employment (mostly self-employed, but may also include other legal categories such as farmers)

(6) Inactive (out of the labor force) and residing in Slovenia

(7) Not residing in Slovenia (employment/unemployment status unknown)

The variables contained in vector $\boldsymbol{S_t}$ denote the share of time spent in each of the above 7 labor market states in the preceding 0–5, 6–10, and 11–15 years, respectively.[7] They are continuous variables spanning [0,1], with the sum of the vector $\boldsymbol{S_t}$ summing to exactly 3 (specifically, totaling 1 for each of the variables relating to the share of time spent in each of the labor market states in

[7] Distinguishing yearly lags over a 15-year horizon failed to produce consistent results, so we opted for 5-year lags of the labor market status variables (similar to Eliason and Storrie, 2009b, who also model the effect as constant within three periods, each of four years of length, thus covering a 12- year horizon).

the preceding three 5-year periods).[8] Additional explanatory variables are education (distinguishing primary, general secondary, vocational secondary, and tertiary), ethnicity (Slovenian or non-Slovenian), region of residence, and calendar year. These may also vary over time.

Other features of the estimation are as follows. First, analysis time is each individual's age, with events measured daily. To differentiate between the health effects of younger and older individuals, we estimate models separately for two age groups: 35–50 and 50–65. Second, individuals are considered at risk in periods, delineated in days, when they are (i) not affected by the disease being analyzed (e.g., diabetes) or not hospitalized, (ii) aged either 35–50 or 50–65, and (iii) residents of Slovenia. Individuals not affected by the disease thus enter the risk set upon fulfilling both conditions (ii) and (iii). If they develop the disease being analyzed, or die – technically speaking, if the "event" or "failure" happens – they are subsequently dropped from the risk set. Alternatively, individuals who exceed the age limit (50 or 65), or emigrate from Slovenia, are right censored. And third, reported are estimated coefficients from Cox proportional hazard regressions – the implied hazards ratios associated with a given variable as compared to the baseline group are calculated by the exponentiating the coefficients.

Summary statistics of variables used in the regression analysis are presented in Tables 2 and 3. The incidence rates of the studied groups of diseases are mostly in the double digits, except for diabetes (Table 2). Of course, they are much larger for the older group (aged 51 to 65). For CVDs, for example, the incidence rate for both men and women of the older group is about 22%, and it is less than half of that for the younger group (aged 35 to 50). Except for mental disorders,

[8] The coefficients for unemployment thus show the effect of being exposed to a 5-year duration of unemployment in the preceding 0–5,6–10, and 11–15 years, respectively, compared to the baseline of being employed under a permanent contract.

the incidence rates for men and women are rather similar. Also the incidence rates of hospitalizations are considerable – for example, nearly 6% of individuals included in our risk set of men aged 51 to 65 are hospitalized due to CVDs. The incidence rate of hospitalizations due to mental disorders is about one percent for all studied groups of individuals, and due to diabetes are still smaller, for example, a mere 0.06% to 0.1% for the younger groups of women and men, respectively. Mortality rates, of course, are the smallest – the mortality rate from CVDs for the older groups are 0.3% and 0.1% for men and women, respectively, and from mental disorders (reflecting suicides) are 0.1% and 0.02%, respectively.

As for explanatory variables, the mean share of time spent in unemployment (any cause for unemployment except mass layoffs) is in the range of 4.2% to 8.8%, with no particular pattern across the work history periods and gender (Table 3). Unemployment due to mass layoffs is, understandably, a much less frequent phenomenon, with the mean share ranging from 0.2% to 1.2%, with the mean share of the older group (those aged 51 to 65) exceeding the mean share of the younger group (those aged 35 to 50) by two to three times. The mean share spent in fixed-term employment varies from 5.6% to 14.4%, and it is considerably higher among men. The largest mean shares of both men and women come pertain to those with secondary education. The mean share of both men and women with tertiary education among the younger groups strongly exceed the corresponding share of the older groups, particularly among women.

5.2 The effects of unemployment on health and hospitalizations

(a) Hazard of CVDs and CVD-caused hospitalizations

Our results show that being unemployed in the past – stretching up to 15 years back – significantly increases the hazard of CVDs and CVD-caused hospitalizations, particularly for men. Sticking to the broad definition of unemployment (any cause for unemployment except mass layoffs), our results show that for men aged 35 to 50, the hazard of CVDs is significantly affected by unemployment in the past 5 years and 6–10 years (Table 4). For the older group (men aged 50 to 65), more distant unemployment – that occurred during past 6–10 and 11–15 years – is found to significantly affect the hazard of CVDs. Estimated coefficients that are statistically significant imply hazard ratios of 1.10 to 1.26, reflecting the elevation of hazard rates associated with unemployment in the past 6–10 or 11–15 years compared to hazard rates of permanently employed workers. The hazard of CVD-caused hospitalization mirrors almost precisely the hazard of CVDs, except that for the older group, coefficients for all three past periods of unemployment are significant. The hazard ratio for CVD-caused hospitalization, in the periods when they are significant, range from 1.20 to 1.63. Similarly, the results for women confirm significant effects of past unemployment on both CVDs and CVD-caused hospitalizations. In comparison to men, the most notable difference is that none of the estimated coefficients for unemployment in the period up to 5 years is significant.

Turning to the measure of unemployment that reflects an additional assurance of exogeneity – unemployment due to mass layoffs – the results remain qualitatively similar, but less significant. For both sexes, unemployment in the past 6–10 and 11–15 years increases the hazard of CVDs, for the younger and older group, respectively. Moreover, for men unemployment in the past 5 years, and for the older group, also in the past 6 to 11 years, significantly increases hazard of CVD-caused hospitalization. For women, this measure of unemployment is not shown to increase the hazard of CVD-caused hospitalization. Overall, for men 5 out of 9 coefficients that are significant under the broad unemployment definition remain significant also under a more stringent measure of unemployment, and for women, 2 out 6 (none for hospitalizations). The results based on the alternative measure of a more restrictive, exogenous unemployment – unemployed due to bankruptcies – are qualitatively very similar.[9]

(b) Hazard of diabetes and diabetes-caused hospitalizations

The results confirm that past unemployment also significantly affects hazard of diabetes and diabetes-caused hospitalizations. As with CVDs, the effects appear to be present across more groups, time periods, and types of hazard when using a broad definition of unemployment, but they can be confirmed also for the exclusive, mass-layoff- or bankruptcy-based definition of unemployment.

Using the broad definition of unemployment, hazards of diabetes as well as diabetes-caused hospitalizations show prolonged effects of unemployment, for both men and women (Table 5). The effects of the unemployment occurring in the past 5 years are present across all groups and studied types of hazard except for the group of older men, the coefficient of more distant occurrence of unemployment – in the past 6–10 and 11–15 years – are significant in just below half of the cases.

Using mass-layoff definition of unemployment (Table 5), the effects of unemployment tend to appear more strongly in the immediate past, that is, within the past 5 years (the results obtained from bankruptcy definition of unemployment are similar). For men, both hazard of diabetes and diabetes-caused hospitalizations is significantly affected – in the case of bankruptcy-based definition, for both age groups, and the case of mass-layoff definition, only hospitalizations for older men. For women, the coefficients are less significant, with only the hazard of diabetes for younger women being significantly affected by unemployment in the past 5 years.

[9] Because estimation results of hazard rate models obtained using bankruptcy-based definition of unemployment are very similar to those obtained by using mass-layoff definition of unemployment, due to space considerations we do not present them.

(c) Hazard of mental disorders and mental-disorder-caused hospitalizations

Our results also show that the experience of unemployment significantly increases hazard of mental disorders and mental-disorder-caused hospitalizations. This applies particularly for men – for women, results are less clear-cut.

Similar to other two groups of diseases, the effects appear to be weakened when using a narrow definition of unemployment. Indeed, under the broad definition of unemployment, all coefficients of unemployment – pertaining to different distance to the occurrence of unemployment, age groups, and type of hazards studied – turned out to be positive and significant, with the exception of the hazard of mental disorder for younger women (Table 6)**.** Moving to the narrow, mass-layoff definition of unemployment, most – but not all – of the estimated hazard coefficients lose significance. For men, the effects of unemployment on both the hazard of mental disorders and mental-disorder-caused hospitalizations remain significant. For the group of younger men, the impact is significant for non-distant unemployment – up to 5 years – only, and for the group of older men, the impact extends to more distant unemployment (past 6 to 10 years). For women, only the hazard of mental disorders for younger women is affected via unemployment in the past 6 to 10 years.[10]

5.3 The effects of unemployment on mortality

Our results show that the exposure to unemployment also significantly affects mortality. Using a broad definition of unemployment, unemployment in the past 5 years significantly increases the probability of death due to CVDs and mental disorders, as well as death of any cause for both men

[10] The above results suggest that studies of mental disorders – if they do not account for reverse causality – may be particularly susceptible to bias health effects of unemployment. Namely, while for all three studied groups of diseases the confirmed health effects are weakened when using the narrow as compared to broad definition of unemployment, this applies even more for mental disorders. Adhering to the interpretation that under the broad definition of unemployment we may still capture individuals who enter unemployment of ill-health, our results suggest that such a bias is present more than proportionally among workers with mental disorders.

and women (Tables 7A and 7B).[11] Coefficients of more distant occurrences of unemployment – in the past 6–10 and 11–15 years – are also significant in several cases. As with the estimated effects on diseases, the estimated effects on mortality become somewhat less significant when we use a narrow definition of unemployment – unemployment due to mass layoffs. Nonetheless, coefficient of unemployment in the past 5 years remains significant in all estimated models. The effects are quite large: for the group of older workers, in comparison to employed workers the hazard of death for all causes for the unemployed is 2.8 and 3.4 times higher (for men and women, respectively), and for the younger group, the estimated effects are even much larger.[12]

5.4 Other effects

Our estimated hazard rate models also offer an opportunity to examine the association between health and work under precarious circumstances – in our case, proxied by employment under fixed-term contract. To the extent fixed-term workers are facing increased stress as compared to workers under permanent contracts, one can hypothesize a positive sign of the coefficient pertaining to the variable "Fixed-term employment" in the estimated hazard rate models (as with other labor market statuses, we distinguish the share spent in fixed-term employment in three periods – in the preceding 0–5, 6–10, and 11–15 years). Our results weakly confirm this hypothesis in the case of CVDs and mental disorders, but not of diabetes. In the case of hazard of CVDs and CVD-caused hospitalizations, the coefficients related to "Fixed term employment" are positive and significant in 10 out of 24 cases, and negative (that is, "wrongly" signed) and significant in 3 cases (Table 4). In the case of mental disorders and mental-disorder-caused hospitalizations, they are positive and

[11] Note that in our dataset, there were too few deaths to estimate models of mortality due to diabetes for both men and women, as well as for models of mortality due to CVDs and mental disorders for the younger group of women.
[12] Note that that the number of deaths due to diseases-specific causes of death, and also for the younger group of women in case of death for all causes is below 1000, sometimes in the double digits, and thus too small to provide reliable estimates.

significant in 12 out of 24 cases, and "wrongly" signed and significant in 3 cases (Table 6); and in the case of diabetes and diabetes-cause hospitalizations, they are positive and significant in only 2 out of 24 cases, and "wrongly" signed and significant in 5 cases (Table 5).[13] Of course, the effects associated with the variable "Fixed-term employment" may well reflect forces responsible for the selection into that status and not necessarily the additional stress of working under the fixed-term as compared to permanent contract.

Another interesting question that can be addressed with our estimating framework is whether the receipt of unemployment benefits mitigates the stress of unemployment. To examine this question, in Tables 8–10 we included variables: "Unemployment in past 5 years – with benefits" and "Unemployment in past 5 years – without benefits", for both broad and narrow definitions of unemployment. Assuming that stress is reduced, we can expect the coefficients of variables indicating the receipt of benefits to be smaller than those indicating no receipt of benefits (or insignificant), reflecting a smaller hazard of the studied groups of diseases or hospitalizations caused by them faced by the group in receipt of the benefits.

The estimated coefficients support the above expectations that the studied hazards are smaller for individuals receiving benefits as compared to hazards of those not receiving benefits, with the caveat that for CVDs and mental disorders, the receipt of the benefit actually reduces the studied hazards. For example, under the broad definition of unemployment the hazards of CVDs and CVD-caused hospitalizations for individuals receiving benefits are smaller compared to hazards of those not receiving benefits in all eight cases where such comparisons can be made (that is, when at least one of the two coefficients being compared is statistically significant, see Table

[13] The magnitude of these effects is relatively modest – for example, the 10 positive coefficients in the hazard rate models of mental disorder or mental-disorder-disorder imply the average increase of 30% in the hazard of mental disorder or related hospitalizations due to working under fixed-term as compared to permanent employment for five years, and 4% increase for working under fixed-term as compared to permanent employment for one year.

8). Under the narrow definition, the same observation applies, although the comparison can be made only for in three cases. Interestingly, all of the significant coefficients for the receipt of the benefits are negative, implying that unemployed individuals receiving benefits face lower hazard of CVDs and CVD-caused hospitalizations than employed workers under permanent contract (the baseline group). Similar results apply to hazard rate models of mental disorders and mental-disorder-caused hospitalizations that include the receipt of unemployment benefits (Table 10). In interpreting the above results, however, the same caveat applies as with fixed-term employment: the effects of the variables indicating the receipt or non-receipt of benefits may reflect the effects of having that status – or forces responsible for the selection into that status, with estimated models unable to separate between the two.

Alternatively, the results may indicate that unemployment, combined with generous income support, can in fact conceivably also contribute to improved health: that stressors present at an individual's previous job become are greater than the stress experienced during unemployment. This may be particularly true if unemployment results in an increase in leisure time, due to lax activation requirements or a long period of potential unemployment benefit receipt. The fact that Slovenia scores relatively poorly in an international comparison of "job strain", which compares the demands placed on workers with the resources made available to them (OECD, 2021), combined with the relative generosity of unemployment benefits, supports this line of thought.

5.5 Comparison of the results with other studies

How do our results compare with other studies? Answering this question is complicated by the fact that the relevant comparators – mostly studies which adjust for causality and report effects spanning over longer time horizon – take bankruptcy or mass-layoffs as the event which triggers health effects. We are thus faced with the task of contrasting two very different "treatments": job loss/displacement – a one-time event that (in principle) can be collapsed to one moment, and unemployment – a continuous event which intensity depends on a "dose", that is, on the duration of unemployment an individual is exposed to. Therefore, in order to make our, unemployment-based results roughly comparable to the job loss/displacement results, we calculated a representative "unemployment dose" individuals experiencing unemployment spells in Slovenia are exposed to, and scaled coefficients from the estimated hazard rate models accordingly.[14] These hazard ratios – representing the effect of the exposure to one-year unemployment compared to employment under a permanent contract – are presented in Tables 11 and 12.

For the risk of mortality and hospitalization, our results seem to be broadly consistent with those found in the literature. For example, for all-cause mortality Browning an Heinesen (2012) report hazard ratios of 1.79 in the first year and 1.30 in the fourth year, in comparison with our past 5-year average of 1.54 (according to the broad definition of unemployment – other reasons for unemployment) and 1.46 (according to the narrow definition of unemployment – unemployment due to mass layoffs – see Table 12). In the 10th and 15th year, Browning an Heinesen (2012) find hazard ratios of 1.1 and 1.07, and while our average of 1.14 (1.06 under the narrow definition of unemployment) for the past 11–15 years accords well to their estimate, our average of 0.9 (0.89 under the narrow definition of unemployment) for the past 6–10 years deviates somewhat. Our results are also consistent with Eliason and Storrie (2009b), who find that overall

[14] Assuming a linear dose-response effect in rescaling coefficients, we calculate hazard ratios as exp(α/5), where α denotes the corresponding coefficient from the estimated hazard rate models. Note that these models are estimated from 5-year intervals, and thus coefficients reflect the effects of being in a certain state for 5 years (compared to the baseline of being employed under a permanent contract). The scaling factor of 1/5 was chosen so that the applied "unemployment dose" corresponds to the representative unemployment dose experienced in Slovenia. This dose is calculated as the median duration of unemployment in 5-year intervals of individuals experiencing unemployment spells in Slovenia in the last 15 years and in 2017, it amounted to 0.96 years (the median duration was 0.65 and 0.88 years for 35–50 year old men and women, and 1.04 and 1.27 years for the 51–65 year old men and women, respectively). Upon rounding, we arrive at one year as the representative "unemployment dose".

mortality risk for men is increased by 44% during the first four years following job loss, as well as with Bloemen et al (2018), who find that job loss due to firm closure increased the probability to die within five years by 34% (controlling for worker characteristics) or 46% (not controlling for these characteristics).

As for mortality results by groups of diseases, for circulatory diseases Browning an Heinesen (2012) report hazard ratios of 2.28 in the first year and 1.46 in the fourth year, in comparison with our past 5-year average of 1.38 (according to the broad definition of unemployment) and 1.54 (according to the narrow definition of unemployment), and lowering of hazard ratios in subsequent years, the finding reflected also in our results (comparison is based on our results for CVDs). Similar scale of effects, as well as their dynamics, as reported by Browning an Heinesen (2012) is reflected also in our results on mortality from mental illness, and also in hospitalization results both due to CVDs (again compared to hospitalizations due to circulatory diseases reported by Browning an Heinesen, 2012) and due to mental disorders.[15]

We found very few studies reporting the hazard of developing various diseases following the exposure to unemployment. Among those related to CVDs, Dupre et al (2012) report that one year of cumulative unemployment increases the hazard of acute myocardial infarction by 27% to 35%, and Ardito et al. (2017) find that the relative risk for workers unemployed for more than three years is 2.8 times higher compared to continuously employed workers. Both estimates,

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[15] For example, for hospitalizations due to circulatory diseases Browning and Heinesen (2012) report hazard ratios of 1.07 in the first year and 1.03 in the fourth year, in comparison with our past 5-year average of 1.07 (according to the broad definition of unemployment) and 1.09 (according to the narrow definition of unemployment), with subsequent lowering of hazard ratios, the finding reflected also in our results (comparison is based on our results for hospitalizations due to CVDs). Similarly, for hospitalizations due to mental illness Browning and Heinesen (2012) report hazard ratios of 1.63 in the first and 1.22 in the fourth year, in comparison with our past 5-year average of 1.20 (according to the broad definition of unemployment) and 1.25 (according to the narrow definition of unemployment). Their hazard ratios are subsequently reduced, as are our (Table 11).

particularly the latter one, are considerably above our estimates for hazard of CVDs, ranging from 2% to 15% (Table 11). We have found no studies to compare our diabetes results with.

6. Concluding remarks

We study the impact of unemployment on a large range of health, hospitalization, and mortality outcomes. We find that that, in comparison to employed persons under permanent contracts, persons experiencing unemployment face increased hazard of all three studied groups of diseases – CVDs, diabetes, and mental disorders – as well as of hospitalizations caused by these diseases, with the effects stretching over a 15-year horizon. Moreover, our results show that unemployment significantly increases the probability of death due to CVDs and mental disorders, as well as death of any cause, again often with the effects stretching over a 15-year horizon. As for the reliability of our results, it is reassuring that the results are consistent across two groups of unemployed with very different underlying source of unemployment: those that become unemployed as part of the mass layoff or bankruptcy, and those becoming unemployed for other reasons. In areas that have been studied by other researchers – mortality of various types of diseases and hospitalizations caused by such diseases – our results are broadly comparable to those of others. We also provide results about a range of outcomes that we have not found suitable comparators in the literature (related to, above all, longer-term effects on health of the three studied groups of diseases).

To our knowledge, our paper is the first one that uses drug prescription data to study the causal effects of unemployment on health status of individuals. Such data allows to track individuals over long periods, thus enabling the estimation of long-term effects. Moreover and very importantly, its long, continuous coverage allows to eliminate from the risk set the individuals who have developed a certain disease (or to eliminate parts of work histories of such individuals), making sure that any unemployment spell that an individual may undergo precedes the occurrence of a disease. This creates a new, powerful way of controlling for reverse causality (particularly when combined with a standard approach in the literature using worker displacement as the source of unemployment). Another important advantage of using drug prescription data is the ability to examine a broad range of diseases – in our case, three groups of leading non-communicable diseases – within a single framework, thus producing consistent estimates over a range of health outcomes. And drug prescription data offers an objective measure of health and easily allows for a wide coverage, in our case, the whole population of the country.

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Appendix 1. Classifications underlying the formation of health and health-related indicators

A. Morbidity of CVDs

Information on morbidity of the individual is obtained from filling of the prescription for a drug of the following groups according to the Anatomical Therapeutic Chemical (ATC) classification system (WHO Collaborating Centre for Drug Statistics Methodology, 2021):

- C02 Antihypertensives
- C03 Diuretics
- C04 Peripheral vasodilators
- C07 Beta blocking agents
- C08 Calcium channel blockers
- C09 Agents acting on the renin-angiotensin system

Hospitalization: Person is admitted to hospital with the primary diagnosis I00-I99 (with the exception of I51, I78, and I97) according to ICD-10 (World Health Organization, 2015)

Death: Person dies due to underlying code of death I00-I99 (with the exception of I51, I78, and I97) according to ICD-10 (World Health Organization, 2015)

B. Morbidity of diabetes mellitus

Information on morbidity of the individual is obtained from filling of the prescription for a drug of ATC group A10 (WHO Collaborating Centre for Drug Statistics Methodology, 2021)

Hospitalization: Person is admitted to hospital with the primary diagnosis E10-E14 according to ICD-10 (World Health Organization, 2015)

Death: Person dies due to underlying code of death diabetes (E10-E14) according to ICD-10 (World Health Organization, 2015)

C. Morbidity of mental disorders

Information on morbidity of the individual is obtained from filling of the prescription for a drug of the following groups according to the ATC classification system (WHO Collaborating Centre for Drug Statistics Methodology, 2021):

- N05 Psycholeptics (including N05B Anxiolytics)
- N06 Psychoanaleptics (including N06A Antidepressants)
- N07 Other nervous system drugs

Hospitalization: Person is admitted to a psychiatric hospital under the primary diagnosis F00-F99 (F64 and F65 were excluded) according to ICD-10 (World Health Organization, 2015)

Death: Person dies due to suicide (external code of death X60-X84) according to ICD-10 (World Health Organization, 2015)

Tables and Figures

Table 1: The number of unemployed and employed workers, Slovenia, 1997-2017

	Unemployed		Employed		
	Except due to mass layoffs	Due to mass layoffs	Permanent	Fixed term	Other
1997	106,725	11,832	602,106	65,282	102,562
1998	106,195	11,434	602,895	69,631	99,243
1999	101,122	11,511	607,469	70,963	104,960
2000	89,293	10,513	613,912	74,970	106,125
2001	85,490	9,996	619,104	77,598	105,728
2002	88,673	10,837	617,423	76,125	103,117
2003	84,826	10,181	618,492	75,519	101,955
2004	80,655	9,239	621,266	79,125	104,451
2005	83,687	9,412	624,025	84,883	107,051
2006	80,030	9,176	625,912	90,989	109,076
2007	66,203	7,526	629,035	111,912	111,483
2008	57,340	6,721	631,512	131,224	113,343
2009	76,725	10,070	622,739	112,184	117,359
2010	83,032	13,292	609,919	104,125	118,208
2011	87,847	15,778	587,003	112,711	120,689
2012	85,417	17,274	577,962	114,493	117,635
2013	91,662	18,792	574,618	102,518	118,427
2014	91,191	17,665	589,283	93,697	120,019
2015	79,628	16,495	595,360	100,111	121,775
2016	55,786	12,438	603,477	110,517	112,871
2017	46,658	9,215	617,122	121,862	113,805

Table 2: Incidence rates of diseases and hospitalizations, and mortality rates, population included in regression analysis (in percent)

	Men		**Women**	
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65
Incidence rates of groups of diseases				
CVDs	9.53	21.96	10.24	22.47
Diabetes	1.01	3.79	0.99	2.52
Mental disorders	7.84	11.60	15.17	20.17
Incidence rates - hospitalizations				
CVDs	1.61	5.95	1.54	3.79
Diabetes	0.11	0.45	0.06	0.23
Mental disorders	1.04	1.12	0.97	1.03
Mortality rate				
CVDs	0.02	0.30	0	0.09
Mental disorders	0.02	0.10	0	0.02
Any cause of death	0.17	1.80	0.08	0.96

Note: The statistics are calculated using the same risk set and the same definitions of censoring and failure as in the Cox proportional hazard rate regressions presented in Tables 4–6 and Tables 7A and 7B.

Table 3: Means of explanatory variables used in regression analysis

	Men		Women	
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65
Employment history				
Unemployment (except due to mass layoffs)				
In past 5 years	0.053	0.087	0.071	0.078
With benefits	0.012	0.039	0.013	0.030
Without benefits	0.041	0.048	0.057	0.048
In past 6-10 years	0.042	0.055	0.071	0.075
In past 11-15 years	0.057	0.053	0.088	0.078
Unemployment due to mass layoffs				
In past 5 years	0.004	0.012	0.004	0.009
With benefits	0.002	0.007	0.002	0.004
Without benefits	0.002	0.005	0.003	0.005
In past 6-10 years	0.002	0.006	0.003	0.009
In past 11-15 years	0.002	0.007	0.003	0.011
Fixed-term employment				
In past 5 years	0.091	0.043	0.079	0.026
In past 6-10 years	0.095	0.046	0.103	0.036
In past 11-15 years	0.091	0.041	0.099	0.035
Other employment				
In past 5 years	0.138	0.127	0.090	0.061
In past 6-10 years	0.105	0.144	0.073	0.074
In past 11-15 years	0.073	0.142	0.056	0.076
Inactive				
In past 5 years	0.083	0.246	0.066	0.330
In past 6-10 years	0.086	0.126	0.069	0.151
In past 11-15 years	0.097	0.086	0.079	0.061
Unknown				
In past 5 years	0.037	0.017	0.018	0.006
In past 6-10 years	0.085	0.041	0.044	0.012
In past 11-15 years	0.184	0.071	0.141	0.021
Education				
Unknown	0.026	0.044	0.020	0.031
Primary	0.134	0.210	0.111	0.263
Vocational secondary	0.318	0.349	0.174	0.203
General secondary	0.304	0.239	0.319	0.290
Tertiary	0.218	0.158	0.377	0.213
Nationality				
Slovenian	0.866	0.886	0.954	0.961
Other	0.134	0.114	0.047	0.039
Years				
2012	0.164	0.164	0.168	0.162
2013	0.166	0.165	0.167	0.163
2014	0.170	0.167	0.169	0.166
2015	0.162	0.165	0.164	0.167
2016	0.167	0.169	0.166	0.170
2017	0.171	0.170	0.166	0.172
Individuals	360,657	324,466	304,815	282,126

Note: The statistics refer to the regressions estimating hazard of death for any cause.

Table 4: Estimates of hazard rate model of CVDs and CVD-caused hospitalizations, by gender and age groups, 2012–2017– coefficients from Cox proportional hazard regressions

	Men				Women			
	CVDs		CVD-caused hospitalizations		CVDs		CVD-caused hospitalizations	
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65
Employment history (omitted group: past employment on a permanent contract)								
Unemployment (except due to mass layoffs)								
In past 5 years	**0.097** **(0.045)**	-0.037 (0.030)	**0.492***** **(0.090)**	**0.181***** **(0.042)**	0.060 (0.040)	-0.008 (0.032)	-0.040 (0.096)	0.052 (0.059)
In past 6-10 years	**0.234***** **(0.059)**	**0.133***** **(0.041)**	**0.286**** **(0.120)**	**0.249***** **(0.054)**	**0.199***** **(0.047)**	**0.079**** **(0.037)**	**0.217*** **(0.111)**	0.063 (0.065)
In past 11-15 years	0.014 (0.047)	**0.166***** **(0.037)**	0.082 (0.097)	**0.240***** **(0.049)**	**0.108***** **(0.039)**	**0.097***** **(0.032)**	-0.025 (0.093)	**0.121**** **(0.055)**
Unemployment due to mass layoffs								
In past 5 years	0.023 (0.150)	-0.033 (0.068)	**0.637**** **(0.279)**	**0.206**** **(0.093)**	0.134 (0.134)	0.048 (0.079)	-0.181 (0.359)	0.021 (0.148)
In past 6-10 years	**0.680***** **(0.222)**	0.137 (0.106)	0.541 (0.435)	**0.318**** **(0.136)**	**0.525***** **(0.163)**	0.134 (0.086)	0.452 (0.400)	0.022 (0.163)
In past 11-15 years	0.164 (0.189)	**0.162*** **(0.084)**	-0.394 (0.429)	0.086 (0.105)	0.031 (0.167)	**0.147**** **(0.069)**	-0.140 (0.351)	-0.106 (0.125)
Fixed-term employment								
In past 5 years	-0.014 (0.038)	**0.149***** **(0.041)**	-0.023 (0.088)	**0.154**** **(0.069)**	**-0.151***** **(0.040)**	-0.077 (0.055)	-0.150 (0.099)	-0.146 (0.117)
In past 6-10 years	**0.074*** **(0.039)**	**0.072*** **(0.043)**	**0.198**** **(0.089)**	0.071 (0.068)	**0.169***** **(0.038)**	**0.108**** **(0.048)**	**0.219**** **(0.090)**	**-0.219**** **(0.103)**
In past 11-15 years	**0.083**** **(0.036)**	**-0.085**** **(0.041)**	0.006 (0.084)	-0.068 (0.066)	0.061 (0.037)	0.018 (0.047)	-0.091 (0.092)	**0.170*** **(0.093)**
Additional controls for past status?	YES	YES	YES	YES	YES	YES	YES	YES
Education (omitted group: general secondary education)								
Primary	**0.162***** **(0.019)**	**0.139***** **(0.015)**	**0.149***** **(0.042)**	**0.070***** **(0.022)**	**0.264***** **(0.020)**	**0.276***** **(0.015)**	**0.366***** **(0.046)**	**0.257***** **(0.027)**
Vocational secondary	**0.090***** **(0.015)**	**0.092***** **(0.013)**	0.033 (0.034)	**0.036*** **(0.020)**	**0.097***** **(0.018)**	**0.120***** **(0.015)**	**0.286***** **(0.041)**	**0.168***** **(0.029)**
Tertiary	**-0.134***** **(0.017)**	**-0.186***** **(0.016)**	**-0.177***** **(0.040)**	**-0.131***** **(0.025)**	**-0.166***** **(0.016)**	**-0.161***** **(0.015)**	**-0.252***** **(0.040)**	**-0.238***** **(0.032)**
Additional covariates?	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,801,653	1,425,886	3,369,126	2,597,637	2,451,817	1,196,790	2,967,945	2,232,472
Number of individuals	315,154	194,557	356,604	310,679	263,922	167,100	300,885	273,303
Number of failures	30,027	42,727	5,744	18,474	27,016	37,541	4,619	10,366
Log-likelihood	-337,076	-457,134	-65,467	-208,637	-300,087	-398,202	-52,065	-116,181
Total time at risk	1,203,050	714,307	1,416,499	1,266,788	1,045,605	631,405	1,234,241	1,151,104

Notes: Analysis time is defined as an individual's age. Failure is defined as the filling of a prescription for a CVD-related drug, or CVD-caused hospitalization, occurring the first time. "Additional controls for past status" include time shares spent in the following states (three variables for each state, relating to share of time in past 0-5, 6-10, and 11-15 years, respectively): (i) self-employed, (ii) inactive resident of Slovenia, (iii) non-resident of Slovenia. Additional covariates include dummies for calendar year (5), region (13), and non-Slovene citizenship. Standard errors clustered by individuals are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5: Estimates of hazard rate model of diabetes and diabetes-caused hospitalizations, by gender and age groups, 2012–2017 – coefficients from Cox proportional hazard regressions

	Men				Women			
	Diabetes		Diabetes -caused hospitalizations		Diabetes		Diabetes -caused hospitalizations	
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65
Employment history (omitted group: past employment on a permanent contract)								
Unemployment (except due to mass layoffs)								
In past 5 years	**0.408*** (0.114)**	0.021 (0.054)	**0.887*** (0.318)**	**0.769*** (0.140)**	**0.399*** (0.106)**	**0.130* (0.070)**	**1.424*** (0.417)**	**0.551** (0.221)**
In past 6-10 years	0.039 (0.156)	0.120 (0.073)	0.516 (0.410)	0.264 (0.171)	**0.291** (0.129)**	0.098 (0.078)	0.531 (0.541)	**0.392* (0.233)**
In past 11-15 years	**0.257** (0.123)**	0.096 (0.066)	**0.474* (0.288)**	0.119 (0.152)	**0.456*** (0.108)**	**0.198*** (0.064)**	0.250 (0.371)	**0.618*** (0.183)**
Unemployment due to mass layoffs								
In past 5 years	0.419 (0.319)	0.076 (0.121)	1.332 (0.944)	**1.096*** (0.273)**	**0.908** (0.374)**	**0.320** (0.160)**	-1.572 (1.950)	0.362 (0.569)
In past 6-10 years	0.601 (0.575)	0.036 (0.190)	-1.491 (1.642)	0.550 (0.423)	0.001 (0.519)	0.239 (0.170)	-0.561 (2.327)	-0.885 (0.659)
In past 11-15 years	0.558 (0.447)	0.051 (0.145)	1.029 (1.160)	-0.486 (0.361)	0.183 (0.497)	0.157 (0.133)	0.450 (1.149)	**1.273*** (0.352)**
Fixed-term employment								
In past 5 years	-0.153 (0.111)	0.138 (0.085)	0.057 (0.339)	**-0.593** (0.297)**	**-0.237** (0.118)**	**-0.458*** (0.154)**	-0.503 (0.542)	**-1.005* (0.593)**
In past 6-10 years	0.017 (0.116)	0.030 (0.086)	0.492 (0.320)	0.208 (0.242)	**0.280** (0.110)**	**0.212* (0.115)**	-0.871 (0.531)	-0.601 (0.440)
In past 11-15 years	0.164 (0.106)	0.044 (0.080)	0.205 (0.299)	-0.094 (0.234)	-0.007 (0.113)	0.019 (0.111)	**-1.253** (0.570)**	-0.661 (0.436)
Additional controls for past status?	YES	YES	YES	YES	YES	YES	YES	YES
Education (omitted group: general secondary education)								
Primary	**0.462*** (0.051)**	**0.259*** (0.028)**	**0.448*** (0.148)**	**0.313*** (0.080)**	**0.393*** (0.061)**	**0.560*** (0.034)**	**0.711*** (0.215)**	**0.395*** (0.110)**
Vocational secondary	**0.267*** (0.044)**	**0.122*** (0.025)**	0.112 (0.134)	**0.240*** (0.074)**	**0.161*** (0.055)**	**0.228*** (0.037)**	0.230 (0.214)	0.129 (0.122)
Tertiary	**-0.434*** (0.059)**	**-0.337*** (0.034)**	**-0.407** (0.188)**	**-0.465*** (0.116)**	-0.021 (0.049)	**-0.257*** (0.044)**	-0.197 (0.220)	**-0.446*** (0.159)**
Additional covariates?	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,381,006	2,576,038	3,448,431	2,835,798	2,971,222	2,247,239	3,042,647	2,369,971
Number of individuals	355,529	300,603	360,287	323,352	299,663	269,854	304,566	281,623
Number of failures	3,578	11,394	394	1,442	2,968	6,799	183	636
Log-likelihood	-40,676	-128,443	-4,406	-16,199	-33,402	-75,754	-1,992	-6,990
Total time at risk	1,418,480	1,239,572	1,441,780	1,355,774	1,233,339	1,147,019	1,258,947	1,208,016

Notes: Analysis time is defined as an individual's age. Failure is defined as the filling of a prescription for a diabetes-related drug, or diabetes-caused hospitalization, occurring the first time. "Additional controls for past status" include time shares spent in the following states (three variables for each state, relating to share of time in past 0-5, 6-10, and 11-15 years, respectively): (i) self-employed, (ii) inactive resident of Slovenia, (iii) non-resident of Slovenia. Additional covariates include dummies for calendar year (5), region (13), and non-Slovene citizenship. Standard errors clustered by individuals are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 6: Estimates of hazard rate model of mental disorders and mental-disorder-caused hospitalizations, by gender and age groups, 2012–2017 – coefficients from Cox proportional hazard regressions

	Men				Women			
	Mental disorders		Mental-disorder-caused hospitalizations		Mental disorders		Mental disorder-caused hospitalizations	
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65
Employment history (baseline: past employment on a permanent contract)								
Unemployment (except due to mass layoffs)								
In past 5 years	**0.389*** (0.046)**	**0.064* (0.034)**	**1.433*** (0.091)**	**0.767*** (0.087)**	0.050 (0.036)	**-0.156*** (0.036)**	**1.056*** (0.096)**	**0.288*** (0.104)**
In past 6-10 years	**0.499*** (0.058)**	**0.379*** (0.045)**	**0.693*** (0.120)**	**0.430*** (0.115)**	**0.255*** (0.041)**	**0.170*** (0.040)**	**0.455*** (0.117)**	**0.565*** (0.122)**
In past 11-15 years	**0.322*** (0.045)**	**0.318*** (0.040)**	**0.413*** (0.093)**	**0.509*** (0.097)**	**0.212*** (0.034)**	**0.123*** (0.033)**	**0.496*** (0.097)**	**0.377*** (0.104)**
Unemployment due to mass layoffs								
In past 5 years	0.237 (0.176)	-0.075 (0.085)	**1.121*** (0.291)**	0.230 (0.231)	-0.050 (0.139)	-0.098 (0.090)	0.433 (0.385)	-0.534 (0.361)
In past 6-10 years	0.267 (0.284)	0.197 (0.129)	0.216 (0.595)	**0.612** (0.307)**	**0.274* (0.156)**	-0.073 (0.097)	0.239 (0.476)	0.536 (0.331)
In past 11-15 years	0.281 (0.220)	0.086 (0.093)	-0.297 (0.488)	-0.056 (0.247)	0.127 (0.155)	0.088 (0.075)	-0.192 (0.513)	0.077 (0.227)
Fixed-term employment								
In past 5 years	-0.056 (0.041)	0.038 (0.051)	0.096 (0.109)	**-0.582*** (0.165)**	-0.031 (0.034)	0.008 (0.055)	**-0.325*** (0.123)**	**-1.077*** (0.234)**
In past 6-10 years	**0.204*** (0.040)**	**0.118** (0.051)**	**0.522*** (0.105)**	**0.491*** (0.142)**	**0.171*** (0.032)**	**0.143*** (0.049)**	**0.312*** (0.110)**	0.242 (0.167)
In past 11-15 years	**0.232*** (0.037)**	**0.138*** (0.048)**	**0.175* (0.099)**	**0.345*** (0.128)**	**0.162*** (0.031)**	0.056 (0.049)	-0.025 (0.114)	-0.037 (0.168)
Additional controls for past status?	YES	YES	YES	YES	YES	YES	YES	YES
Education (baseline: general secondary education)								
Primary	**0.104*** (0.021)**	**0.104*** (0.018)**	**0.333*** (0.051)**	**0.165*** (0.051)**	**0.278*** (0.018)**	**0.194*** (0.015)**	**0.229*** (0.059)**	0.031 (0.053)
Vocational secondary	**0.037** (0.016)**	**0.034** (0.015)**	**0.190*** (0.043)**	**0.078* (0.046)**	**0.137*** (0.015)**	**0.076*** (0.016)**	0.023 (0.053)	0.009 (0.054)
Tertiary	-0.030 (0.018)	-0.025 (0.019)	**-0.376*** (0.058)**	**-0.167*** (0.061)**	**-0.130*** (0.014)**	**-0.099*** (0.015)**	**-0.357*** (0.051)**	**-0.208*** (0.059)**
Additional covariates?	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,809,309	2,035,949	3,365,559	2,780,632	2,009,885	1,155,859	2,979,842	2,320,466
Number of individuals	319,553	261,356	356,297	320,154	235,948	174,386	301,733	278,756
Number of failures	25,057	30,323	3,705	3,574	35,789	35,176	2,915	2,859
Log-likelihood	-281,738	-335,965	-41,172	-40,205	-391,918	-375,030	-32,499	-32,050
Total time at risk	1,218,615	1,023,530	1,418,383	1,336,788	895,160	655,036	1,241,304	1,190,100

Notes: Analysis time is defined as an individual's age. Failure is defined as the filling of a prescription for a mental-disorder-related drug, or mental-disorder-caused hospitalization, occurring the first time. "Additional controls for past status" include time shares spent in the following states (three variables for each state, relating to share of time in past 0-5, 6-10, and 11-15 years, respectively): (i) self-employed, (ii) inactive resident of Slovenia, (iii) non-resident of Slovenia. Additional covariates include dummies for calendar year (5), region (13), and non-Slovene citizenship. Standard errors clustered by individuals are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7A: Estimates of hazard rate model of mortality due to CVDs and mental disorders for men, by age groups, 2012–2017– coefficients from Cox proportional hazard regressions

	Men					
	CVDs		Mental disorders		Any cause of death	
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65
Employment history (omitted group: past employment on a permanent contract)						
Unemployment (except due to mass layoffs)						
In past 5 years	**2.420***** **(0.620)**	**1.102***** **(0.191)**	**4.581***** **(0.713)**	**1.643***** **(0.322)**	**2.890***** **(0.219)**	**1.221***** **(0.074)**
In past 6-10 years	0.093 (0.844)	**0.523***** **(0.179)**	-0.468 (0.678)	0.444 (0.309)	0.006 (0.262)	**0.207***** **(0.076)**
In past 11-15 years	0.579 (0.642)	**0.427***** **(0.151)**	-0.300 (0.515)	**1.384***** **(0.249)**	0.256 (0.201)	**0.635***** **(0.064)**
Unemployment due to mass layoffs						
In past 5 years	**3.092**** **(1.535)**	**1.066**** **(0.419)**	**4.278***** **(1.104)**	**2.048***** **(0.637)**	**2.464***** **(0.675)**	**1.028***** **(0.163)**
In past 6-10 years	0.555 (1.259)	-0.832 (0.631)	-1.025 (2.626)	0.302 (0.688)	-0.165 (0.825)	0.219 (0.186)
In past 11-15 years	**2.089*** **(1.156)**	0.443 (0.323)	-19.030 (11.901)	0.212 (0.488)	0.202 (0.680)	**0.278**** **(0.130)**
Fixed-term employment						
In past 5 years	**-3.085**** **(1.206)**	-0.590 (0.575)	0.338 (1.413)	-0.976 (1.200)	0.097 (0.379)	**-0.591***** **(0.219)**
In past 6-10 years	**2.245***** **(0.745)**	-0.095 (0.377)	-1.758 (1.138)	-1.067 (0.754)	0.202 (0.304)	-0.150 (0.153)
In past 11-15 years	0.667 (0.820)	-0.090 (0.317)	0.315 (0.693)	-0.033 (0.550)	0.228 (0.255)	0.009 (0.126)
Additional controls for past status?	YES	YES	YES	YES	YES	YES
Education (omitted group: secondary general education)						
Primary	0.573 (0.395)	**0.398***** **(0.101)**	**1.392***** **(0.468)**	0.102 (0.174)	**0.686***** **(0.127)**	**0.350***** **(0.041)**
Vocational secondary	0.127 (0.389)	**0.247**** **(0.099)**	0.591 (0.492)	0.114 (0.169)	**0.290**** **(0.124)**	**0.167***** **(0.040)**
Tertiary	0.041 (0.517)	**-0.476***** **(0.172)**	-45.192 (0.000)	**-1.084***** **(0.404)**	-0.314 (0.204)	**-0.344***** **(0.066)**
Additional covariates?	YES	YES	YES	YES	YES	YES
Observations	3,456,323	2,857,210	3,456,323	2,857,210	3,456,323	2,857,213
Number of individuals	360,657	324,463	360,657	324,463	360,657	324,466
Number of failures	64	986	63	340	605	5,839
Log-likelihood	-629	-10,859	-559	-3,558	-6,146	-64,339
Total time at risk	1,444,136	1,363,225	1,444,136	1,363,225	1,444,136	1,363,225

Notes: Analysis time is defined as an individual's age. Failure is defined as the death of the person (in cause-specific models, death for other causes is treated as the point of data censoring). "Additional controls for past status" include time shares spent in the following states (three variables for each state, relating to share of time in past 0-5, 6-10, and 11-15 years, respectively): (i) self-employed, (ii) inactive resident of Slovenia, (iii) non-resident of Slovenia. Additional covariates include dummies for calendar year (5), region (13), and non-Slovene citizenship. Standard errors clustered by individuals are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7B: Estimates of hazard rate model of mortality due to CVDs and mental disorders for women, by age groups, 2012–2017– coefficients from Cox proportional hazard regressions

	Women			
	CVDs	Mental disorders	Any cause of death	
	Age 51 to 65	Age 51 to 65	Age 35 to 50	Age 51 to 65
Employment history (omitted group: past employment on a permanent contract)				
Unemployment (except due to mass layoffs)				
In past 5 years	**1.243*** (0.414)**	**1.760* (1.021)**	**3.112*** (0.270)**	**1.007*** (0.122)**
In past 6-10 years	0.352 (0.351)	-0.037 (1.036)	**-1.415*** (0.352)**	-0.168 (0.111)
In past 11-15 years	**0.683** (0.285)**	**1.584** (0.737)**	**0.715** (0.279)**	**0.594*** (0.088)**
Unemployment due to mass layoffs				
In past 5 years	**2.141** (0.862)**	**4.811*** (1.547)**	**2.660*** (0.650)**	**1.219*** (0.299)**
In past 6-10 years	-0.575 (0.777)	-41,036 (0.000)	-2.012 (1.243)	**-0.568* (0.306)**
In past 11-15 years	**0.861* (0.504)**	1.198 (1.416)	0.903 (0.828)	0.188 (0.198)
Fixed-term employment				
In past 5 years	-2.533 (2.216)	-40,265 (0.000)	-0.028 (0.554)	**-0.686* (0.380)**
In past 6-10 years	0.030 (0.866)	-0.902 (2.148)	0.309 (0.452)	0.258 (0.214)
In past 11-15 years	0.638 (0.693)	-0.036 (1.525)	-0.565 (0.512)	0.095 (0.193)
Additional controls for past status?	YES	YES	YES	YES
Education (omitted group: secondary general education)				
Primary	0.080 (0.176)	0.528 (0.499)	**0.316* (0.181)**	**0.196*** (0.054)**
Vocational secondary	0.076 (0.192)	0.590 (0.522)	0.127 (0.180)	0.092 (0.059)
Tertiary	**-0.542* (0.311)**	-0.965 (1.045)	-0.338 (0.225)	**-0.250*** (0.079)**
Additional covariates?	YES	YES	YES	YES
Observations	2,378,269	2,378,269	3,047,037	2,378,270
Number of individuals	282,125	282,125	304,815	282,126
Number of failures	249	45	254	2,722
Log-likelihood	-2,712	-449	-2,583	-30,066
Total time at risk	1,211,459	1,211,459	1,260,329	1,211,459

Notes: Analysis time is defined as an individual's age. Failure is defined as the death of the person (in cause-specific models, death for other causes is treated as the point of data censoring). "Additional controls for past status" include time shares spent in the following states (three variables for each state, relating to share of time in past 0-5, 6-10, and 11-15 years, respectively): (i) self-employed, (ii) inactive resident of Slovenia, (iii) non-resident of Slovenia. Additional covariates include dummies for calendar year (5), region (13), and non-Slovene citizenship. Standard errors clustered by individuals are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 8: Estimates of hazard rate model of CVDs and CVD-caused hospitalizations – receipt of unemployment benefits, by gender and age groups, 2012–2017

	Men				**Women**			
	CVD		CVD-caused hospitalizations		CVD		CVD-caused hospitalizations	
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65
Employment history (omitted group: past employment on a permanent contract)								
Unemployment (except due to mass layoffs)								
In past 5 years – with benefits	**-0.611***** **(0.186)**	**-0.083*** **(0.050)**	-0.280 (0.383)	-0.096 (0.070)	**-0.372**** **(0.188)**	**-0.150**** **(0.059)**	**-0.754*** **(0.437)**	-0.137 (0.111)
In past 5 years – without benefits	**0.196***** **(0.051)**	-0.011 (0.038)	**0.594***** **(0.101)**	**0.340***** **(0.052)**	**0.117**** **(0.046)**	0.057 (0.039)	0.055 (0.110)	**0.133*** **(0.070)**
Unemployment due to mass layoffs								
In past 5 years – with benefits	-0.382 (0.382)	-0.089 (0.112)	-0.708 (0.824)	0.195 (0.151)	**-0.939**** **(0.472)**	-0.021 (0.150)	**-1.862*** **(1.077)**	-0.456 (0.300)
In past 5 years – without benefits	0.167 (0.199)	0.016 (0.103)	**1.038***** **(0.341)**	0.197 (0.139)	**0.391**** **(0.161)**	0.084 (0.106)	0.234 (0.389)	0.261 (0.187)
Additional covariates?	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,801,653	1,425,886	3,369,126	2,597,637	2,451,817	1,196,790	2,967,945	2,232,472
Number of individuals	315,154	194,557	356,604	310,679	263,922	167,100	300,885	273,303
Number of failures	30,027	42,727	5,744	18,474	27,016	37,541	4,619	10,366
Log-likelihood	-337,067	-457,133	-65,463	-208,624	-300,081	-398,197	-52,062	-116,177
Total time at risk	1,203,050	714,307	1,416,499	1,266,778	1,045,605	631,405	1,234,241	1,151,104

Notes: The table presents the estimates of the same models as presented in Table 4, except that the variable “Unemployment in the past 5 years” is substituted by the following two variables: “Unemployment in past 5 years – with benefits” and “Unemployment in past 5 years – without benefits”, under both Unemployment (except due to mass layoffs) and Unemployment due to mass layoffs. Only coefficients of variables related to the receipt and non-receipt of benefits are presented (see notes of Table 4).

Table 9: Estimates of hazard rate model of diabetes and diabetes-caused hospitalizations – receipt of unemployment benefits, by gender and age groups, 2012–2017

	Men				**Women**			
	Diabetes		Diabetes -caused hospitalizations		Diabetes		Diabetes -caused hospitalizations	
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65
Employment history (omitted group: past employment on a permanent contract)								
Unemployment (except due to mass layoffs)								
In past 5 years – with benefits	0.002 (0.457)	0.001 (0.089)	1.948 (1.470)	**0.482*** **(0.255)**	0.559 (0.548)	-0.143 (0.139)	1.434 (2.206)	-0.220 (0.468)
In past 5 years – without benefits	**0.467***** **(0.125)**	0.033 (0.070)	**0.770**** **(0.362)**	**0.898***** **(0.168)**	**0.377***** **(0.117)**	**0.231***** **(0.081)**	**1.408***** **(0.482)**	**0.766***** **(0.246)**
Unemployment due to mass layoffs								
In past 5 years – with benefits	-0.773 (0.985)	0.076 (0.193)	0.988 (2.615)	0.759 (0.514)	**2.418**** **(1.054)**	0.222 (0.326)	3.572 (3.257)	-2.711 (1.727)
In past 5 years – without benefits	**0.769*** **(0.419)**	0.075 (0.186)	1.440 (1.195)	**1.290***** **(0.368)**	0.550 (0.471)	**0.364*** **(0.206)**	**-7.191*** **(4.057)**	**1.373**** **(0.607)**
Additional covariates?	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,381,006	2,576,038	3,448,431	2,835,798	2,971,222	2,247,239	3,042,647	2,369,971
Number of individuals	355,529	300,603	360,287	323,352	299,663	269,854	304,566	281,623
Number of failures	3,578	11,394	394	1,442	2,968	6,799	183	636
Log-likelihood	-40,674	-128,443	-4,405	-16,197	-33,401	-75,752	-1,992	-6,985
Total time at risk	1,418,480	1,239,572	1,441,780	1,355,774	1,233,339	1,147,019	1,258,947	1,208,016

Notes: The table presents the estimates of the same models as presented in Table 5, except that the variable "Unemployment in the past 5 years" is substituted by the following two variables: "Unemployment in past 5 years – with benefits" and "Unemployment in past 5 years – without benefits", under both Unemployment (except due to mass layoffs) and Unemployment due to mass layoffs. Only coefficients of variables related to the receipt and non-receipt of benefits are presented (see notes of Table 5).

Table 10: Estimates of hazard rate model of mental disorders and mental-disorder-caused hospitalizations – receipt of unemployment benefits, by gender and age groups, 2012–2017

	Men				**Women**			
	Mental disorders		Mental-disorder-caused hospitalizations		Mental disorders		Mental disorder-caused hospitalizations	
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65
Employment history (omitted group: past employment on a permanent contract)								
Unemployment (except due to mass layoffs)								
In past 5 years – with benefits	-0.263 (0.201)	**-0.207*** (0.059)**	**1.912*** (0.407)**	0.212 (0.176)	**-0.347** (0.168)**	**-0.275*** (0.065)**	**1.974*** (0.480)**	-0.055 (0.235)
In past 5 years – without benefits	**0.471*** (0.051)**	**0.210*** (0.043)**	**1.393*** (0.098)**	**0.959*** (0.101)**	**0.102** (0.041)**	**-0.097** (0.043)**	**0.969*** (0.108)**	**0.388*** (0.117)**
Unemployment due to mass layoffs								
In past 5 years – with benefits	**-1.463*** (0.469)**	**-0.249* (0.135)**	0.643 (1.158)	-0.303 (0.423)	**-1.324*** (0.419)**	**-0.552*** (0.173)**	-0.090 (1.633)	-1.086 (0.685)
In past 5 years – without benefits	**0.832*** (0.208)**	0.071 (0.130)	**1.251*** (0.363)**	**0.533* (0.323)**	**0.294* (0.167)**	0.171 (0.119)	0.550 (0.428)	-0.302 (0.433)
Additional covariates?	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,809,309	2,035,949	3,365,559	2,780,632	2,009,885	1,155,859	2,979,842	2,320,466
Number of individuals	319,553	261,356	356,297	320,154	235,948	174,386	301,733	278,756
Number of failures	25,057	30,323	3,705	3,574	35,789	35,176	2,915	2,859
Log-likelihood	-281,724	-335,948	-41,171	-40,197	-391,910	-375,022	-32,497	-32,048
Total time at risk	1,218,615	1,023,530	1,418,383	1,336,788	895,160	655,036	1,241,304	1,190,100

Notes: The table presents the estimates of the same models as presented in Table 6, except that the variable "Unemployment in the past 5 years" is substituted by the following two variables: "Unemployment in past 5 years – with benefits" and "Unemployment in past 5 years – without benefits", under both Unemployment (except due to mass layoffs) and Unemployment due to mass layoffs. Only coefficients of variables related to the receipt and non-receipt of benefits are presented (see notes of Table 6).

Table 11: Hazard ratios implied by hazard rate models presented in Tables 4 – 6 (only statistically significant coefficients from these tables are accounted for)

	Men				Women				Row average
	Hazard ratios of developing a disease		Hazard ratios of hospitalization		Hazard ratios of developing a disease		Hazard ratios of hospitalization		
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	
CVDs									
Unemployment (except due to mass layoffs)									
In past 5 years	1.02		1.10	1.04					1.05
In past 6-10 years	1.05	1.03	1.06	1.05	1.04	1.02	1.04		1.04
In past 11-15 years		1.03		1.05	1.02	1.02		1.02	1.03
Unemployment due to mass layoffs									
In past 5 years			1.14	1.04					1.09
In past 6-10 years	1.15			1.07	1.11				1.11
In past 11-15 years		1.03				1.03			1.03
Diabetes									
Unemployment (except due to mass layoffs)									
In past 5 years	1.09		1.19	1.17	1.08	1.03	1.33	1.12	1.14
In past 6-10 years					1.06			1.08	1.07
In past 11-15 years	1.05		1.10		1.10	1.04		1.13	1.08
Unemployment due to mass layoffs									
In past 5 years				1.25	1.20	1.07			1.17
In past 6-10 years									
In past 11-15 years								1.29	1.29
Mental disorders									
Unemployment (except due to mass layoffs)									
In past 5 years	1.08	1.01	1.33	1.17		0.97	1.24	1.06	1.12
In past 6-10 years	1.10	1.08	1.15	1.09	1.05	1.03	1.10	1.12	1.09
In past 11-15 years	1.07	1.07	1.09	1.11	1.04	1.02	1.10	1.08	1.07
Unemployment due to mass layoffs									
In past 5 years			1.25						1.25
In past 6-10 years				1.13	1.06				1.09
In past 11-15 years									

Notes: The above hazard ratios represent the effect of the exposure to one-year unemployment compared to permanent-contract employment. Each is calculated as $\exp(\alpha/5)$, where α denotes the corresponding coefficient from Tables 4 – 6 in which all coefficients were estimated from 5-year intervals. The estimates thus assume a linear dose-response effect in rescaling coefficients. The scaling factor of 1/5 was chosen so that the "unemployment dose" corresponds to the empirically determined median duration of unemployment in 5-year intervals of individuals experiencing unemployment spells in Slovenia, which is just under one year.

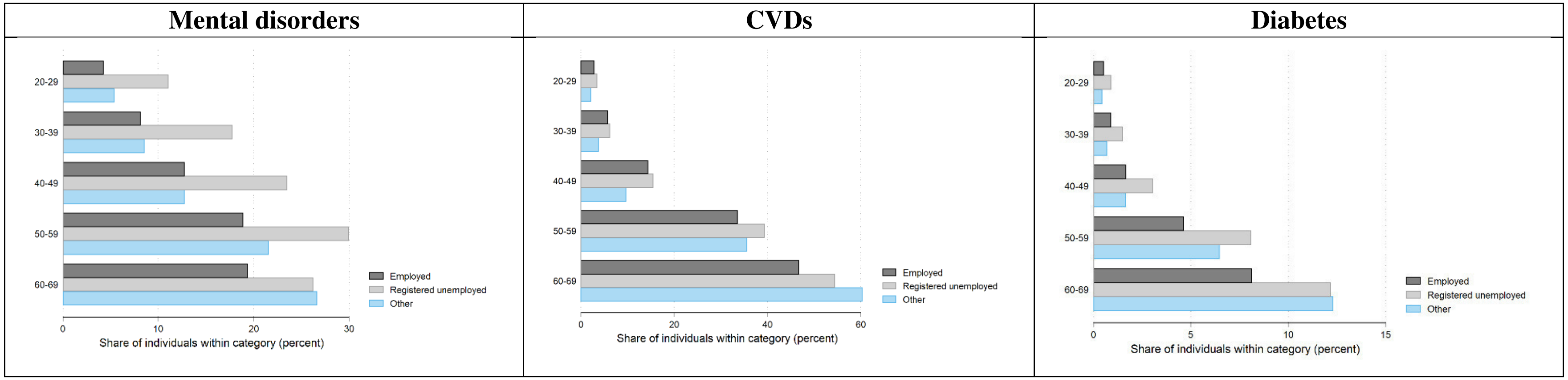
Table 12: Mortality hazard ratios implied by hazard rate models presented in Tables 7A and 7B (only statistically significant coefficients from these tables are accounted for)

	Men		**Women**		**Row average**
	Age 35 to 50	Age 51 to 65	Age 35 to 50	Age 51 to 65	
CVD					
Unemployment (except due to mass layoffs)					
In past 5 years	1.62	1.25		1.28	1.38
In past 6-10 years		1.11			1.11
In past 11-15 years		1.09		1.15	1.12
Unemployment due to mass layoffs					
In past 5 years	1.86	1.24		1.53	1.54
In past 6-10 years					
In past 11-15 years	1.52			1.19	1.35
Mental disorders					
Unemployment (except due to mass layoffs)					
In past 5 years	2.50	1.39		1.42	1.77
In past 6-10 years					
In past 11-15 years		1.32		1.37	1.35
Unemployment due to mass layoffs					
In past 5 years	2.35	1.51		2.62	2.16
In past 6-10 years					
In past 11-15 years					
Any cause of death					
Unemployment (except due to mass layoffs)					
In past 5 years	1.78	1.28	1.86	1.22	1.54
In past 6-10 years		1.04	0.75		0.90
In past 11-15 years		1.14	1.15	1.13	1.14
Unemployment due to mass layoffs					
In past 5 years	1.64	1.23	1.70	1.28	1.46
In past 6-10 years				0.89	0.89
In past 11-15 years		1.06			1.06

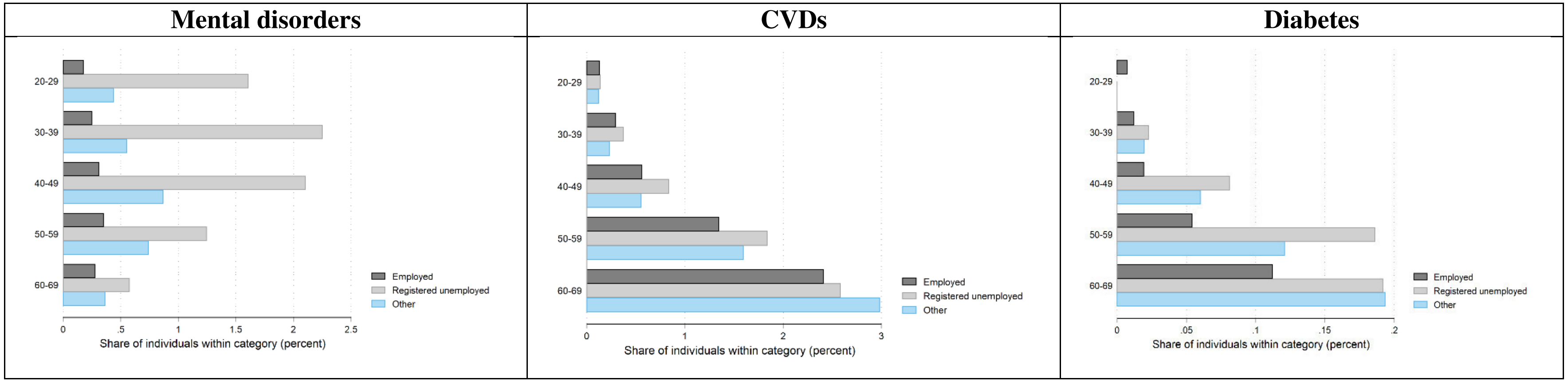
Notes: The above hazard ratios represent the effect of the exposure to one-year unemployment compared to permanent-contract employment. Each is calculated as exp(α/5), where α denotes the corresponding coefficient from Tables 7A and 7B in which all coefficients were estimated from 5-year intervals. The estimates thus assume a linear dose-response effect in rescaling coefficients. The scaling factor of 1/5 was chosen so that the "unemployment dose" corresponds to the empirically determined median duration of unemployment in 5-year intervals of individuals experiencing unemployment spells in Slovenia, which is just under one year.

Figure 1: The prevalence of groups of studied diseases, and hospitalizations attributed to them, by labor market status and age groups

(a) Prevalence of groups of studied diseases (July 2016 – December 2017)



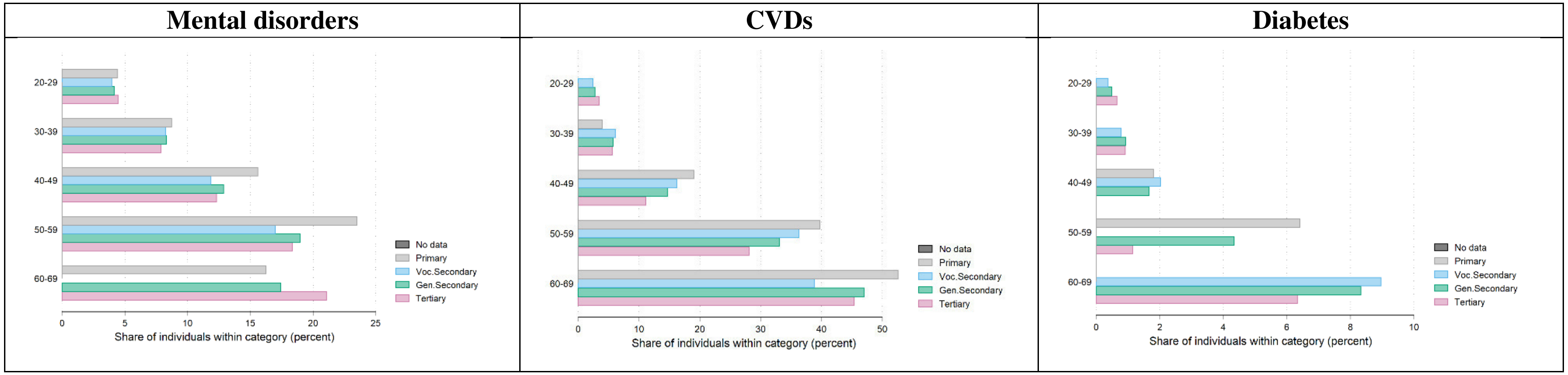
(b) Prevalence of hospitalizations attributed to the groups of studied diseases (December 2016 – December 2017)



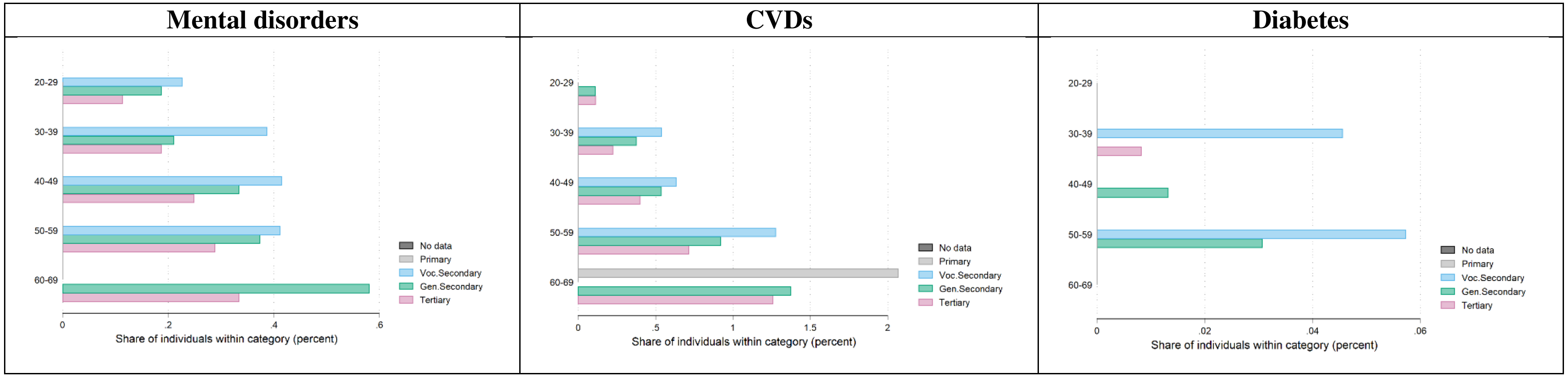
Note: Health status of individuals is determined from prescriptions (at the point of filling the prescription).

Figure 2: The prevalence of groups of studied diseases, and hospitalizations attributed to them, by education and age groups

(a) Prevalence of groups of studied diseases (July 2016 – December 2017)



(b) Prevalence of hospitalizations attributed to the groups of studied diseases (December 2016 – December 2017)



Note: Health status of individuals is determined from prescriptions (at the point of filling the prescription).