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Health status and the Great Recession. Evidence from electronic health records

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Abstract

We investigate the impact of the Great Recession in Italy on the incidence of chronic diseases using new individual longitudinal data from Electronic Health Records. We exploit the exogenous shock in the economic conditions occurred in 2008 to estimate heterogeneous effects of an unprecedented rise in local unemployment rates in an individual fixed-effects model. Our results document that harsh economic downturns have a negative long-lasting effect on cardiovascular disease and a temporary effect on depression. This effect is heterogeneous across gender, increases with age and is stronger right before the retirement age. An important policy recommendation emerging from this study is that prolonged economic downturns constitute an additional external risk for individual health and not a temporary benefit.

KEYWORDS
depression, economic crisis, great recession, health status, unemployment

JEL CLASSIFICATION
I10, E32, J20

1 | INTRODUCTION

In virtually all societies, socio-economic conditions are a key determinant of health (Smith, 1999, among others). Individuals living in wealthier countries and individuals with high incomes are, on average, healthier and live longer. Moreover, those with better employment prospects are likely to enjoy better mental and physical health. Nevertheless, an influential body of research has shown how economic booms may be actually bad for health due to increasing environmental pollution and behavioral risks (McInerney & Mellor, 2012, Ruhm, 2000, 2003, 2005, Stevens et al., 2015, Toffolutti & Suhrcke, 2014, among others). The relationship between economic conditions and health is however multifaceted. It has changed over time and tends to be different in the short-versus long-term. Importantly, as recently shown, the relationship between economic conditions and health is also context dependent, where the severity of economic slumps and its interplay with the type of economy and the healthcare system have a substantial role as well (Birgisdóttir et al., 2020; Bonamore et al., 2015).

Before the coronavirus pandemic (COVID-19), the Great Recession (GR) was labeled the deepest global economic downturn since World War II. Gross Domestic Product fell significantly in most countries, with a dramatic increase in unemployment rate. The introduction of fiscal austerity to alleviate public debt favored a global slowdown, with important effects on several domains including health (OECD, 2016).

A number of studies have shown that the GR reduced mortality in many European countries and in the United States (Baker, 2014; Tapia Granados & Ionides, 2017). Yet, investigating the impact of economic downturns on mortality can be misleading, as many health complications first materialize as chronic diseases and may not lead to death in the short run.

Health technology has transformed several once deadly diseases into manageable chronic conditions, promoting longevity, but not disease free life expectancy (Stuckler et al., 2009). Thus disease diagnoses represent a more timely reflection of changes in individual health status and healthcare needs. Analyzing disease incidence due to changes in economic conditions is important from the perspective of policy-makers, as the costs deriving from chronic disease management are often borne by the healthcare system for a very long time.

While the effects of economic downturns on mortality have been extensively studied, a similar impact on mild health outcomes has been investigated to a narrower extent. Currie et al. (2016) and Tekin et al. (2013) use longitudinal and repeated cross sectional surveys to show that the rise in the United States unemployment rate during the GR worsened self-reported health status and behavioral outcomes, with stronger effects on the most fragile population groups, such as disadvantaged mothers and less educated individuals. These findings are confirmed by Wang et al. (2018), who exploit the Panel Study of Income Dynamics in the United States and find adverse effects on alcohol consumption, obesity, self-reported health and mental distress. In Europe, the main findings are summarized by Thompson et al. (2019), who consider 42 studies analyzing the associations between health and the GR in Europe, finding that more than 60% of these studies point to health declines. For Italy, Colombo et al. (2018) in a cross-sectional setting analyze the impact of economic fluctuations during the period 1993–2012, and show that higher unemployment rates are associated with a higher probability of experiencing self-reported chronic diseases. Despite these contributions, the analysis of the effect of unemployment during the GR on health shows some limitations, such as the use of self-reported health conditions in small samples, and the lack of a causal interpretation of the results.

In this paper we estimate the effect of the surge in unemployment rate during the GR on the incidence of chronic diseases, exploiting the heterogeneity in the province-level unemployment rise and analyzing how the slump in economic conditions affected individual-level incidence of cardio-vascular (CVD), liver, pulmonary and mental diseases. In particular, we focus on the sharp and unexpected decline in economic conditions in 2008 and the subsequent crisis characterized by unprecedentedly high unemployment rates. While a higher local unemployment during standard business-cycle fluctuations has been associated with lower mortality (Ruhm, 2000, 2003, 2005), a sharp and severe economic collapse is more likely to have detrimental effect on health (Birgisdóttir et al., 2020; Bonamore et al., 2015).

Our approach improves on previous contributions in several ways. First, we employ a very large longitudinal dataset collected by general practitioners (GPs) between 2004 and 2017 on 1.5 million patients nationally representative of the Italian population. This dataset offers several advantages and unique features. It tracks patient level clinical histories, enabling us to estimate the incidence of specific groups of diseases using within-patient variation by means of individual fixed-effects (FEs), ruling out potential confounding factors when analyzing the relationship between individual health and local unemployment. Moreover, the information is objectively assessed by physicians, providing more reliable indicators than self-reported health and mitigating measurement error.[1] In addition, our analysis benefits from the universal provision of healthcare, where GP visits are free of charge for all Italian residents. In many other studies instead individuals face heterogeneous costs of care, which may give rise to selection issues and measurement error. For the sake of completeness, one should highlight that the expected cost of treatment can also vary in the opportunity cost of time, which may depend on several factors such as the individual employment status and type of employment. While our study cannot rule out the latter, the free and universal access to GPs in Italy guarantees homogeneous access to healthcare among individuals. Finally, our large sample (over 16 million observations) allows us to explore heterogeneous effects by disease type, age, gender and region without loosing statistical power.

Our results point to a sharp and significant impact of the GR on the incidence of two major disease groups, namely CVDs and depression. We find that these effects are not evenly distributed in the population, being stronger for individuals close to retirement age (56–64). This pronounced effect among older individuals is plausibly driven by their drastically worsened employment prospects in the case of job loss. We also find that the effect on CVDs is stronger for women, while the effect on depression is mainly driven by men. We find no significant effects of the GR on pulmonary and liver disease incidence.

Our results also contribute to the literature on the health effects of job loss. Numerous authors have studied the effect of mass job displacement on health, and the results vary across countries, age groups and, most importantly, gender. These heterogeneities, to a reasonable extent, might be driven by differences in healthcare systems, generosity of welfare, but also by the underlying socio-economic health gradient. For instance, Sullivan and von Wachter (2009) find a strong increase in the mortality rate for displaced male workers, and this effect persists up to 20 years after job loss in the United States, while Browning and Heinesen (2012) find effects on overall mortality and mortality caused by circulatory disease, effects on suicides and suicide attempts, and on death and hospitalization due to traffic accidents, alcohol-related disease, and mental illness in Denmark. Black et al. (2015) show that job displacement promotes smoking in both men and women, while Brand et al. (2008) show that mass layoffs have a significant adverse effect on mental health of men, a finding confirmed also by Andreeva et al. (2015), who study downsizing episodes in Sweden. While our setting exploits aggregate labor market conditions, we contribute to the previous findings showing that older workers are more likely to bear the negative effects of a sharp decline in employment prospects. In particular, the psychological strain appears to be more pronounced for men due to their stronger labor market attachment.

In order to validate our findings, we run several robustness checks where we alter the treatment variable and the outcomes studied. First, we show that our results hold when we use employment rates instead of unemployment rates. While the two might diverge due to demographic factors and labor market participation, we find equivalent results for these alternative measures. Secondly, we conduct a falsification test where we study another major group of chronic diseases, cancers, which are less likely to respond to sudden economic slumps. In line with previous studies (Ruhm, 2000), we find that the surge in unemployment rates resulting from the GR did not cause significant changes in cancer incidence.

A number of studies examine the health impact of economically induced stress, where job loss is comparable to around 70% of the stress induced by the loss of a family member (see the review by Persson & Rossin-Slater, 2018). Since the literature shows that the onset of CVDs and mental disorders is directly related to stress (Colombo et al., 2018), our findings identify a relevant channel through which economic downturns are likely to affect not only individual health, but also the economic healthcare costs of unprecedentedly high unemployment. As improvements in health technology tends to delay the mortality risk for chronic patients, the monetary toll of future economic downturns is likely to impose an even greater burden on health expenditure. Back-of-the-envelope calculations suggest that the extra direct healthcare costs that can be attributed to the GR unemployment rise in between 2009 and 2014 amounts to nearly 135 million euro.

Until recently, the GR was seen as an extraordinary economic crisis, but the recent COVID-19 pandemic has overtaken the GR and has already become the largest global recession in our history. While policymakers are now struggling with direct COVID health consequences, they are also trying to offset the severe economic slump. Our paper contributes also to the cost-benefit analysis of COVID responses, shedding light on less striking but more subtle and persistent health effects of economic crises.

2 | DATA

2.1 | Medical records

All Italian residents are covered by the Italian National Healthcare System (Sistema Sanitario Nazionale [SSN] hereafter). The system requires all residents aged 15 and older to be registered with a GP practice, which is free of charge.[2] GPs act as the so-called "gatekeepers" of the SSN, as they issue all prescriptions allowing the patients to purchase drugs or access specialist visits and diagnostic procedures. The GPs keep track of this activity, together with all the diagnoses that they or the specialists make, in the patients' electronic records. Each GP thus runs a database containing records of all the patients (about 1500 for each GP), both sick and healthy, making it representative of the health status of the Italian population (Cricelli et al., 2003). These features are of paramount importance for our analysis since they ensure that our estimation sample is not affected by selection issues.

We exploit the Health Search (HS) database, which is a longitudinal observational dataset based on the Electronic Health Records (EHRs) collected by 795 GPs on over 1.5 million individuals representative of the Italian adult population by age and sex (Cricelli et al., 2003; Filippi et al., 2005).[3]

We focus on EHRs collected by GPs between 2004 and 2017. The panel of GPs is strongly balanced, while in a limited number of cases the corresponding panel of patients is unbalanced due to events such as mortality, migration or transitions from pediatricians to GPs.

The EHRs contain information collected by GPs during each visit. The HS maintains strict "up-to-standard" quality criteria in terms of coding levels and consistency in individual medical and clinical history. We focus on diagnosis of diseases relevant for both epidemiological characteristics potentially responsive to economic shocks in the short run and the cause-specific mortality statistics in the Italian population (Istat, 2017). Following the ICD-9 diseases classification, our health outcomes are thus represented by four chronic disease groups: CVDs, pulmonary, liver and depression.[4] In addition, we consider another disease group, cancers, that is not likely to reflect economic shocks in the short run, thus representing a suitable placebo outcome (Ruhm, 2000). This selection of outcomes is also in line with the literature analyzing the relationship between cause-specific mortality and economic cycles (see Gerdtham & Ruhm, 2006, Ruhm, 2000, 2015, among others). On top of that, in order to understand to what extent the effects on diagnosis might be driven by a change in patient care seeing behavior, we additionally analyze individual expenditure on diagnostic procedures and specialist visits.

For each individual i we combine their records into annual aggregates between 2004 and 2017. For each disease j we thus construct a binary indicator that assumes the value of one if, at any point in year t, individual i receives a diagnosis of disease j in her EHR. As all the diseases considered are of chronic nature, they are modeled as absorbing states. This implies that if patient *i* received a diagnosis of disease *j* in year *t*, in all the following periods she is automatically deemed affected by the disease.

We focus on individuals between ages 15 and 64 who represent the working-age population. We also require that our subjects are observed for at least 2 years in order to exploit the longitudinal dimension of the data.

Table 1 shows descriptive statistics for the health outcomes we examine and for the other relevant variables. The sample constructed according to this procedure includes 16,862,938 observations from approximately 1.5 million individuals. The prevalence rates of diseases are in line with the official Italian epidemiological statistics by age group (EpiCentro, 2016), with CVDs being the most frequent condition. On average, patients spend 107 euro/year for diagnostic procedures and specialist visits.

The objective nature of the HS data is one of the strengths of this study, allowing us to limit the measurement error often associated with self-reported health indicators. In this respect, Zajacova and Dowd (2011), Crossley and Kennedy (2002) and Dowd and Zajacova (2007) show that when compared with objective measures, measurement error in self-reported health data is substantial and correlated with both socio-economic disadvantage and age. Additionally, Baker et al. (2004) report that the number of false negatives reported in health surveys amounts to around 50% for most of the examined chronic conditions, including diabetes and hypertension. Moreover, Johnston et al. (2009) find that the probability of false negatives is significantly higher for low-income groups. If understating individual disease status is more likely for low-income patients, studies that attempt to measure the impact of economic variables on health using self-reported disease are likely to underestimate the true effect.

2.2 | Unemployment data and contextual controls

As is standard in this literature, we capture macroeconomic conditions with the unemployment rate. We use the Italian National Statistical Office data on province-level unemployment from 2004 to 2017. During that period, the unemployment rate varied substantially over time and across provinces, from a minimum of 1.9% to a maximum of 31.4%, with an average of 10.4%. Due to the economic collapse, the national average unemployment rate doubled, rising from 6.9% in 2007% to 13.9% in 2014, imposing a significant strain on individual lives. Minimum and maximum unemployment rates in 2007 were 2.2% and 16.9%, while in 2014 they increased to 4.4% and 27.2%. Figure 1 plots these annual rates.

By taking the national average unemployment rate as a reference, we identify three main sub-periods. The pre-GR period, going from 2004 to 2007, was characterized by a slight decline in unemployment. Subsequently, from the onset of the GR in Italy in 2008, the unemployment rates started to increase relatively slowly until 2010. Finally, during the third period, from 2011 to 2014, the GR had a more significant impact on Italian employment due to the Sovereign debt crisis (Neri & Ropele, 2015). In order to stop the spiral of distrust, the government adopted austerity measures, which made the unemployment slump strong and persistent. The maximum unemployment rate increased more rapidly, moving from 17.6% to 29%. In 2015, the Italian economy finally started to recover (Istat, 2016b).

Within this temporal dynamics, the GR was characterized by a highly heterogeneous pattern of unemployment changes across Italian provinces, which are displayed in Figure 2. The left panel shows that central and Southern regions faced the

TABLE 1 Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Women	0.53	0.499	0	1
Age	50.229	19.39	15	95
Share of graduated (province)	0.113	0.024	0.063	0.193
Unemployment rate (province)	10.429	5.93	1.873	31.456
Employment rate (province)	43.436	7.631	27.565	58.13
Cardio-vascular diseases (CVDs)	0.155	0.362	0	1
Liver diseases	0.007	0.085	0	1
Pulmonary diseases	0.032	0.175	0	1
Depression	0.045	0.207	0	1
Cancer	0.036	0.186	0	1
Expenditure (diagnostics and specialist visits)	106.68	226.7459	0	33,924.32

Note: Sample size is 16,862,938 observations.

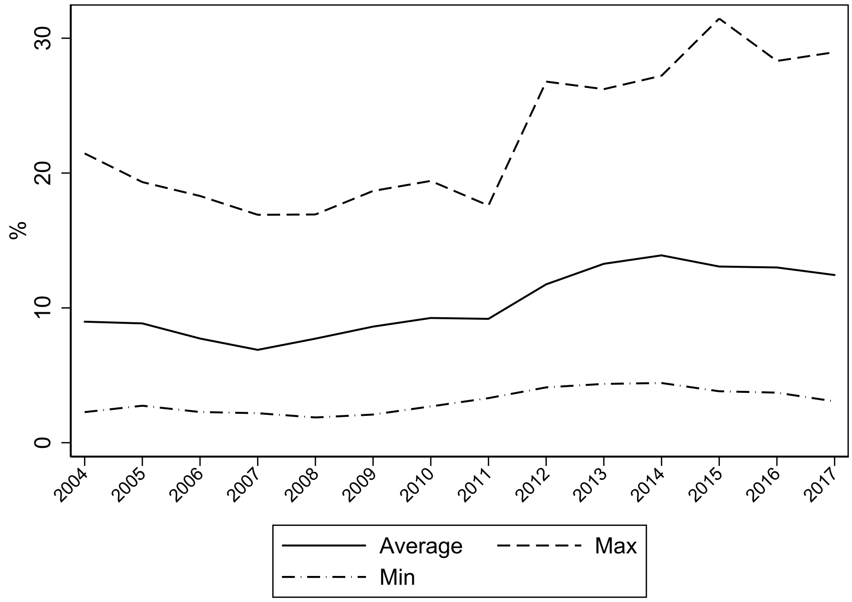

FIGURE 1 Minimum, average and maximum province unemployment rate in Italy. The graph shows the minimum, average and maximum province unemployment rate in Italy in between 2004 and 2017

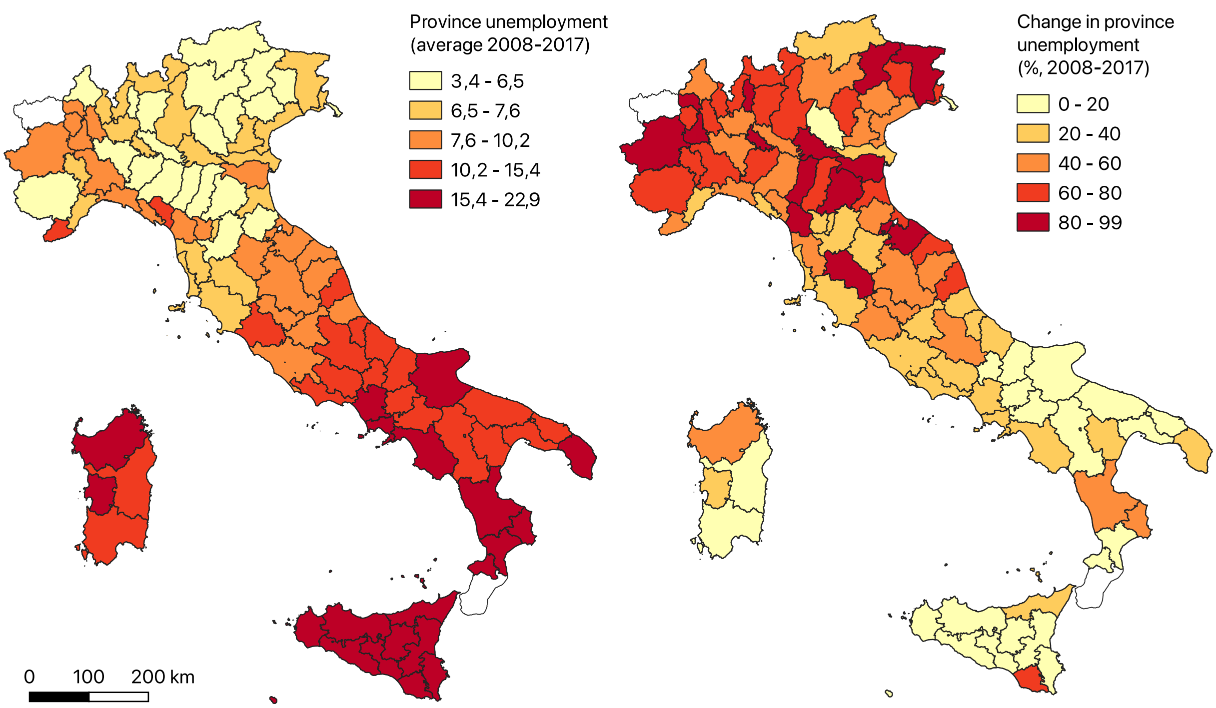

FIGURE 2 Unemployment levels and growth rates during the Great Recession (GR). The map displays the average province unemployment rate in the 2008–2017 (left panel) and the average growth rate of province unemployment rate (right panel) between the pre (2004/2007) and the post (2008–2017) GR periods [Colour figure can be viewed at wileyonlinelibrary.com]

highest unemployment levels in absolute terms as these provinces constitute the least-developed area of the country, also known as "Mezzogiorno". On the contrary, the most pronounced unemployment increase between 2004-2007 and 2008–2017 occurred in Northern regions, which instead include rich and productive areas (right panel). More specifically, the highest unemployment growth rates can be detected in the so-called "industrial triangle", which includes the three regions of Lombardia, Veneto and Emilia Romagna.

Along with the unemployment rate, we collect data on education attainment at the province level as a socio-economic control, measured by the fraction of the population with tertiary education (Istat, 2016a).

3 | EMPIRICAL STRATEGY

Our goal is to estimate the likelihood of developing a chronic condition as a result of an abrupt change in local unemployment rates during the GR. The sudden economic shock allows us to exploit plausibly exogenous variation in economic conditions over and above the typical business cycle fluctuations. We thus focus on measuring the impact of the unprecedentedly high levels of province unemployment in the GR period on individual health. While a higher unemployment during standard business-cycle fluctuations has been shown to exhibit a negative association with mortality (Ruhm, 2000, 2003, 2005), the effects of a harsh and persistent economic collapse are more likely to increase both mortality and the incidence of disease (Birgisdóttir et al., 2020; Bonamore et al., 2015; Guðjónsdóttir et al., 2012).

In particular, to capture the heterogeneity in the effects of unemployment over the crisis period with respect to the baseline fluctuations, we estimate an incidence model. This model restricts the sample to individuals who are not affected by disease j in the previous period. We interact the unemployment rate with year dummies as follows:

$$H_{ipt}^{j} = \alpha_i^j + \theta^j U_{pt} + \sum_{t=2005}^{2017} \beta_t^j D_t U_{pt} + \sum_{a=1}^{10} \delta_a^j AGE_{a,it} + \gamma^j EDU_{pt} + \\ + \sum_{t=2005}^{2017} \vartheta_t^j D_t + \varepsilon_{ipt} \quad \text{if } H_{ip,t-1}^{j} = 0 \; \& \text{ age } \leq 64, \tag{1}$$

where H_{ipt}^{j}, $j = 1, \ldots, 4$, is a dummy variable equal to one if individual i in province p starts suffering from the jth condition in period t, U_{pt} is the annual unemployment rate in province p, $AGE_{a,it}$, $a = 1, \ldots, 10$ are a set of 5-year age dummies, and EDU_{pt} measures the education attainment at province level as the fraction of the population with tertiary education. The terms α_i and ϑ_t control, respectively, for individual and year FEs, while ε_{ipt} is an idiosyncratic error term.

Our model thus focuses on the incidence of a disease, rather than its prevalence, being intended to focus on the events of transition into a diagnosis of a disease. As the outcomes are modeled as absorbing states, patients who receive a diagnosis of disease j in year t, are excluded from the estimation sample in all subsequent periods. Therefore, for each patient i, the sum of H_{ipt}^{j} over t is either zero or one.

In order to understand how the GR period affected the outcomes considered, in our key specification we focus on the differences in the effect of unemployment, captured by the interaction terms between the unemployment rate U_{pt} and a set of year dummies D_t, $t = 2005, \ldots, 2017$, with $t = 2008$ being the reference period.[5]

To begin with, we offer a simpler specification with a set of pre-post comparisons, where the year dummy variables are replaced with a single dummy variable - *Post* - equal to 1 after the GR onset (after 2008). In addition to this exercise, we also disaggregate the *Post* dummy variable into two dummies for the first and the second phase of the GR, namely 2009–2010 and 2011–2017.

In all the specifications, we estimate the parameters of interest using the within-group estimator. The unemployment rate, along with education, enters the model in levels and the associated coefficients represent an approximation of average marginal effects.[6] We cluster standard errors at the province level.[7]

Individual FEs α_i control for time-invariant patient characteristics that affect individual behavior and may be correlated with both unemployment and health. For instance, individuals may self-select by residing in provinces with specific characteristics, such as lower unemployment rates, or may engage in specific life styles determining their health, such as a healthy diet or regular exercise. Although the HS data do not provide information on individual level socio-economic status or life style preferences, the individual FEs control for this heterogeneity to the extent that these characteristics do not vary over time. Hence, when following individuals over the study period, individual FEs isolate the time variation in individual health status as a response to changes in the unemployment rate in the province of residence.

While our study focuses on objectively measured health outcomes, there is the lingering concern that individuals during the GR might undertake different patterns of care seeking, resulting in a selection bias. On the one hand, being unemployed might decrease the demand for healthcare due to reduced economic resources. The present setting is quite favorable to the extent that the universal nature of healthcare provision in Italy mitigates the access barriers to medical treatments, offering to low income individuals a wide set of exemptions even for secondary care.

On the other hand, a lower opportunity-cost of time for the unemployed might induce them to pursue more medical checks, hence potentially rise concerns about the validity of our estimates that may not only capture the insurgence of a disease but also the mere moment of its diagnosis. To begin with, GPs in Italy do not receive a pay-for-performance compensation, but a per-capita payment based on the number of patients they are in charge of. Acting as gate-keepers they prevent over-prescription of diagnostic procedures, which is likely to mitigate any undue excess demand for medical checks. In addition, all employees in Italy are obliged to pass an annual medical check in order to be complaint with the Italian regulation.[8] The checks can be more frequent for workers involved in high-risk occupations. Therefore, a potential threat of more care received from unemployed individuals is theoretically unlikely to hold. Still, in order to reassure for any possible remaining concern about selection to care, we directly check if the GR crisis had any relevant effect on patients' consumption pattern of diagnostic procedures and specialist visits (see Section 5).

4 | RESULTS

This section presents our estimates of the effect of the GR on disease incidence (Section 4.1). We begin by estimating a set of exploratory pre-and-post model specifications with province unemployment rate interacted with a dummy indicating the GR period as a whole (2008–2017), and subsequently with two dummies for the two sub-periods (2008–2010 and 2011–2017). We then present our main results of the effect of the change in unemployment on disease incidence in a fully interacted model, and its heterogeneous impacts by age class, gender and geographical area (Section 4.2). These results from the fully interacted model are presented graphically by plotting the interaction terms between unemployment rate and year dummy variables, while all the estimate tables are include in Tables B2–B5 and Tables B6–B9 in the Appendix B.

4.1 | Effects of the Great Recession on health

Column 1 of Table 2 shows that, with respect to the baseline association of unemployment with CVDs in a regular business cycle before 2009, one additional percentage point of unemployment surge in the GR caused an increase in the incidence of CVDs of 0.063% point (the average incidence rate of CVDs amounts to 0.536%). When considering the GR period in two separate phases (Column 2), a one percentage point increase in the unemployment rate in the first phase with respect to the pre-crisis period yields an additional 0.026% point in the incidence of CVDs, while a similar rise in the second period of the crisis with respect to the baseline adds an extra 0.076% point to the average incidence.

Table 2 also shows that net of the negative association between unemployment and the incidence of liver disease, pulmonary disease and depression in the pre-crisis period, the unemployment rate increase during the GR period caused a relative increase in the incidence of the conditions of 0.002, 0.013 and 0.021% point with respect to the pre-crisis period, respectively. This descriptive evidence points to a progressive increase in the magnitude of the effect and to a likely cumulative severity of the GR, due to both the persistent duration of the slump and the sharply worsening of the Italian economy.

In order to fully capture the heterogeneous effects of province unemployment over time, Figure 3 presents the coefficient estimates of our fully-interactive model specification described in Equation 2. In the top-left panel of Figure 3 we observe that

TABLE 2 Effect of local unemployment rate before and after the Great Recession (GR) onset

	CVDs		Liver		Pulmonary		Depression	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemp. Rate	−0.1113*** (0.0154)		−0.0042*** (0.0009)		−0.0168*** (0.0027)		−0.0319*** (0.0073)	
2009–2017 × Unemp.	0.0627*** (0.0086)		0.0020*** (0.0005)		0.0129*** (0.0021)		0.0215** (0.0067)	
Unemp. Rate		−0.1255*** (0.0200)		−0.0045*** (0.0012)		−0.0196*** (0.0034)		−0.0351*** (0.0091)
2009–2010 × Unemp.		0.0261*** (0.0071)		0.0012* (0.0005)		0.0065** (0.0019)		0.0128* (0.0049)
2011–2017 × Unemp.		0.0757*** (0.0096)		0.0023*** (0.0007)		0.0150*** (0.0022)		0.0245** (0.0074)
Obs.	9,204,718	9,204,718	9,993,871	9,993,871	9,940,976	9,940,976	9,702,948	9,702,948
Individuals	1,100,218	1,100,218	1,146,163	1,146,163	1,142,742	1,142,742	1,129,182	1,129,182

Note: All models control for individual and year fixed-effects, age group dummies and share of tertiary education at provincial level. Standard errors are clustered by province.

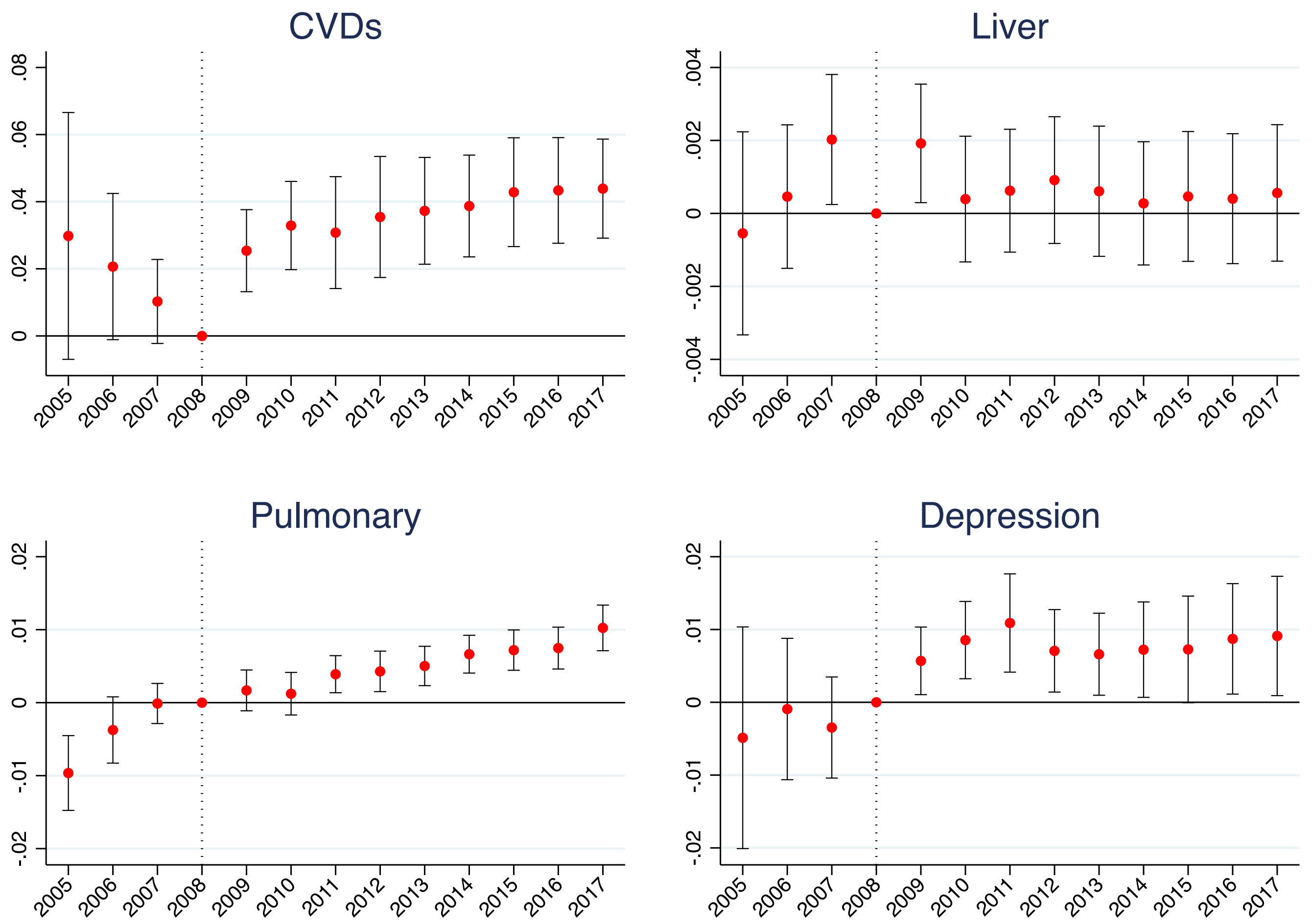

FIGURE 3 Changes in the effect of local unemployment rate on Cardio Vascular diseases (CVDs), liver, pulmonary and depression. The graph shows the changing effects of province unemployment with respect to the 2008 reference on CVDs, Liver disease, Pulmonary disease and Depression incidence. Bars represent confidence intervals at 95% [Colour figure can be viewed at wileyonlinelibrary.com]

during the years 2004–2007 before the onset of the GR, the effect of province unemployment rates on CVDs incidence is not significantly different from its baseline in 2008, pointing to a stable relationship with unemployment and CVDs incidence in the regular economic cycle. The association between incidence rate and unemployment changes with the GR onset, increasing significantly and progressively from 2009 onward. The impact of one additional percentage point of the GR-induced unemployment with respect to the baseline association in the pre-crisis period on the incidence rate of CVDs grows steadily and significantly by 0.025% point in 2009 to 0.044% point in 2017.

The right-top panel of Figure 3 shows the corresponding effect on liver disease, for which we find almost no statistically significant change in the role of unemployment rates after the GR. The left-bottom panel of Figure 3 signals also a significant change in the impact of unemployment rate on pulmonary disease, even though characterized by a significant pre-trend, with a relationship that changes progressively over time well in advance of the GR onset.

Notably, the right-bottom panel of Figure 3 shows a significant increase in the impact of unemployment on the incidence of depression since 2009. The increase shows a peak of 0.01% point in 2011 when Italy faced the second and much harsher wave of the crisis (see Section 2.2) and remains stable and significant up to the last year observed. The absence of a significant pre-trend signals that this increase can be interpreted as a response to changes in local unemployment during the GR.

4.2 | Heterogeneous effects by gender, age group and region

In analyzing the effects of economic cycles on health, the literature has identified some differences by gender, race, education, and age groups (Currie et al., 2016; Haaland & Telle, 2015; Ruhm, 2000; Tekin et al., 2013; Wang et al., 2018). In what follows, we disentangle the different impact of higher unemployment rates during the GR to identify the most fragile socio-economic groups in terms of observable characteristics such as gender, age and region of residence. In this heterogeneity analysis, we focus on CVDs and depression, the groups of diseases that emerge from our main specification as the most responsive to the short term economic collapse.[9]

Figure 4 shows estimates of the differences in the effects of the surge in unemployment rates on CVDs by gender: females in the left-hand Panel and males in the right-hand panel, controlling for age and individual FEs. Although the effect is persistent for both sexes, we find that woman are disproportionately affected by CVDs during the GR, with an average magnitude that varies between 0.029 and 0.044% points; the magnitude of these coefficients is higher than the effects for men over the period 2009–2017 (see Table B2 in Appendix B). The fact that higher unemployment rates during the crisis exert a larger effect on Italian women is in line with the literature on socio-economic gradients in health inequalities among Italians. In a statistical sense, education and labor force participation are stronger predictors of several health related outcomes for women than for men (Atella & Kopinska, 2014a). Moreover, Pirani and Salvini (2015) shows that greater job instability is more harmful for self-assessed health among females in Italy.

The occupational structure has undergone several changes during the GR, with many women joining the labor market in response to male employment loss. National official statistics show that the proportion of families relying on the sole income of male household heads fell during the GR, with women being more likely to work even during pregnancy (Istat, 2014). The gender-specific responses to the GR reflected in our estimates are thus supported by actual events in the labor market. These findings are in line with results obtained for the United States by Currie et al. (2016) and Wang et al. (2018).[10]

In the analysis by age class, we find that the change in the effect of unemployment rates is particularly strong for individuals just before retirement age, for whom labor market mobility is very low. Figure 5 shows the effects of the rise in unemployment with respect to its pre-crisis rates on CVDs for subsamples of 5-year age classes. For CVDs, we find significant coefficient estimates in all age groups, with large heterogeneity in the magnitude of the effects. The incidence of CVDs in younger individuals is less sensitive to changes in unemployment than for individuals aged 40.

The magnitudes of these effects are largest for individuals aged between 61 and 65, whose increase in the incidence of CVDs in response to increases in unemployment during the GR reaches 0.162% points in 2017, being almost four times larger with respect to the baseline estimate of 0.044% point in the same year. On the one hand, the effect being most pronounced at the verge of retirement age suggests that the detrimental effect of labor market instability is stronger when the potential for labor mobility is limited. On the other hand, this particular age group is more likely to develop chronic disease, making it also more vulnerable to the adverse effect of labor market downturns on CVDs.

Figure 6 shows estimates of the effects of the rise in unemployment rates on the incidence of depression for females and males, respectively. In this case, the coefficient estimates are only significant for men. According to the results, one additional percentage point in unemployment rate had the most detrimental impact in 2011, a year in which the GR effects on the economy were the most pronounced (see Table B5 in Appendix B).

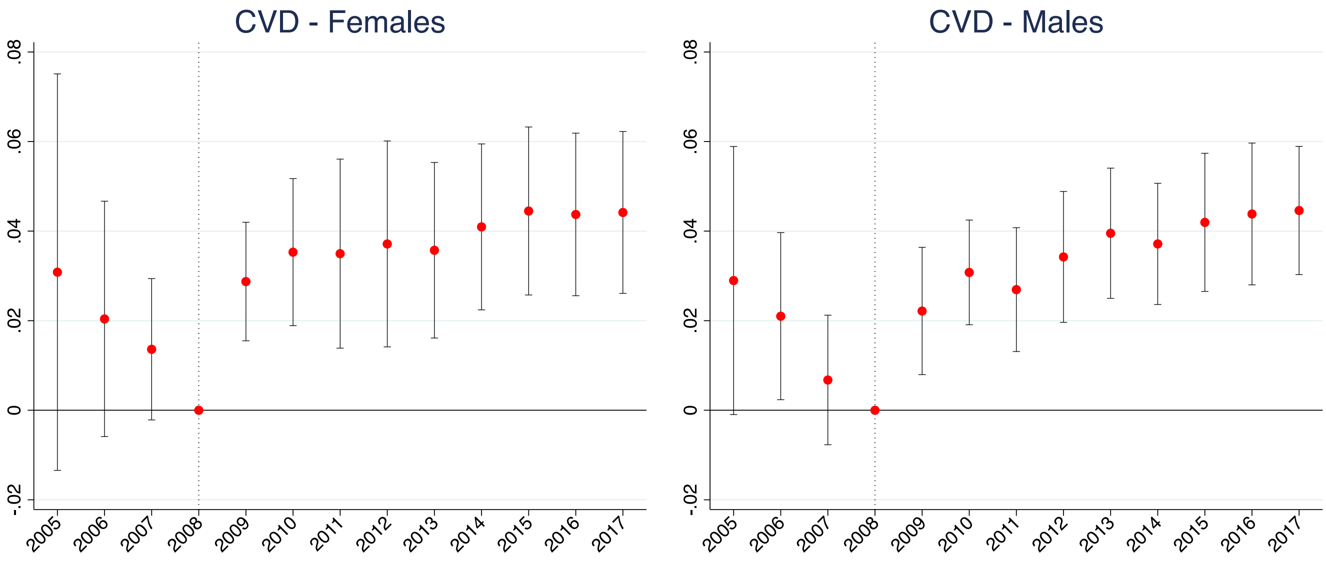

FIGURE 4 Changes in the effect of local unemployment rate on Cardio Vascular diseases (CVDs) by sex. The graph shows the effects of province unemployment on CVDs incidence by sex, assuming 2008 as a reference year. Bars represent confidence intervals at 95% [Colour figure can be viewed at wileyonlinelibrary.com]

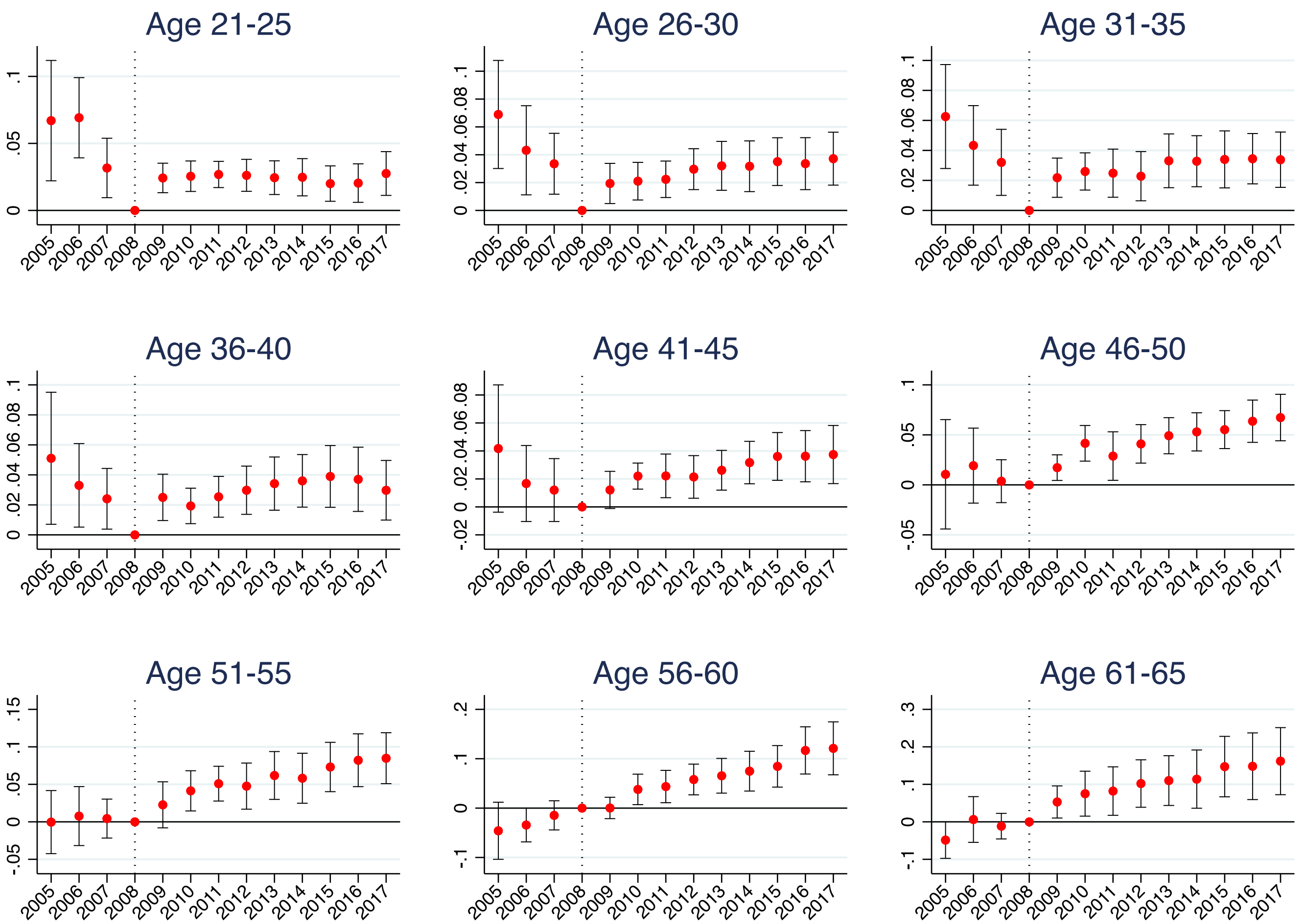

FIGURE 5 Changes in the effect of local unemployment rate on Cardio Vascular diseases (CVDs) by age class. The graph shows the effects of province unemployment with respect to the 2008 reference on CVDs incidence by age class. Bars represent confidence intervals at 95% [Colour figure can be viewed at wileyonlinelibrary.com]

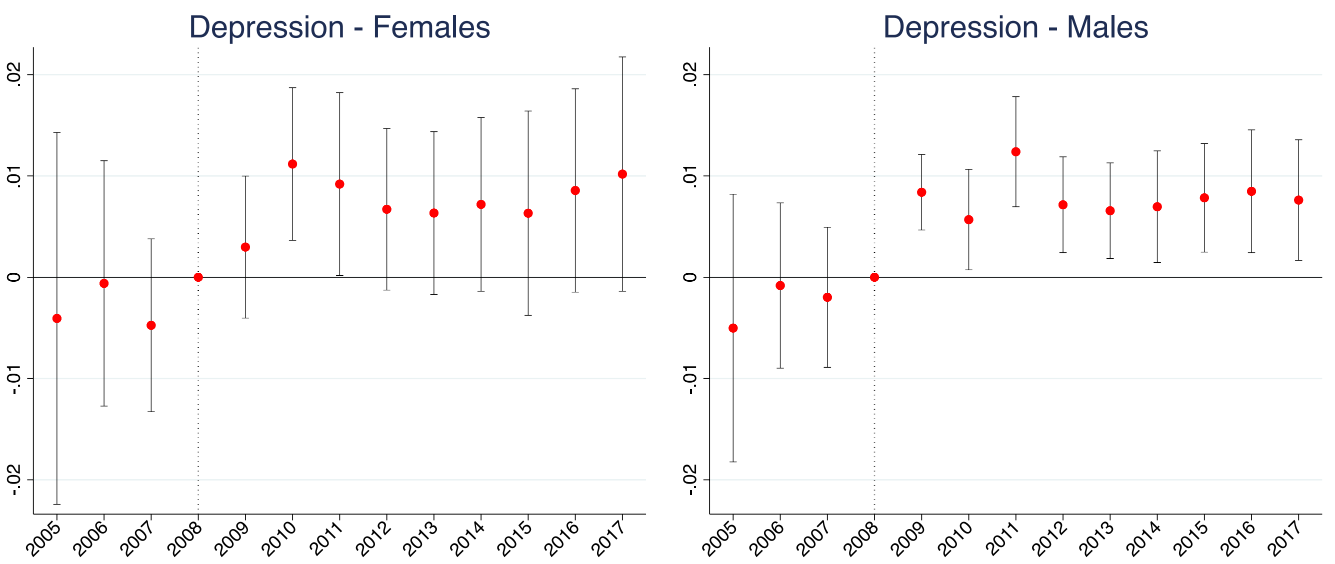

FIGURE 6 Changes in the effect of local unemployment rate on depression by sex. The graph shows the effects of province unemployment with respect to the 2008 reference on depression incidence by sex. Bars represent confidence intervals at 95% [Colour figure can be viewed at wileyonlinelibrary.com]

Men feature stronger labor market attachment and have more continuous employment career. It is thus plausible that a job loss for men results in a greater reduction in income and in well being, and as a result, a more adverse impact on mental health.

When exploring the effects on depression by age class, our estimates are largest for individuals between 56 and 65 years of age (Figure 7). Moreover, the effect is stable and persistent at around 0.04% points (see Table B9 in Appendix B). Hence, similar to CVDs, age becomes a major risk factor also for depression induced by the GR.

The finding on the age gradient in the relationship between job loss and mental health is in line with the existing literature. As argued by Green (2011), the detrimental effect of unemployment rates on mental health is stronger for individuals whose employability is weaker, which is the case of older workers. According to Farber (2015), individuals closer to the retirement age are more likely to face longer unemployment spells. Also according to Istat (2014), during the GR the share of individuals searching for employment without success was highest among those aged 50 and above. Economic downturns increase the need to relocate in the labor market, and younger workers are more likely to succeed in finding a new job.

Finally, when exploring the differences in the effect of unemployment rise by geographical area, we consider four different samples that correspond to four macro-regions: North-West, North-East, Center and South/Islands. Figure 8 and Figure 9 show the coefficient estimates respectively for CVDs and depression. From these figures we observe that, as in the case of age and gender, the impacts of the GR are not evenly distributed across geographical areas. Indeed most of the statistically significant estimates are found for the South and Islands. This heterogeneity pattern is in line with the employability prospects driving also the age gradient in the relationship between job loss and disease incidence. As shown in Figure 1, the South of Italy reached the highest absolute levels of unemployment during the GR, making the odds of re-employment particularly low for southern

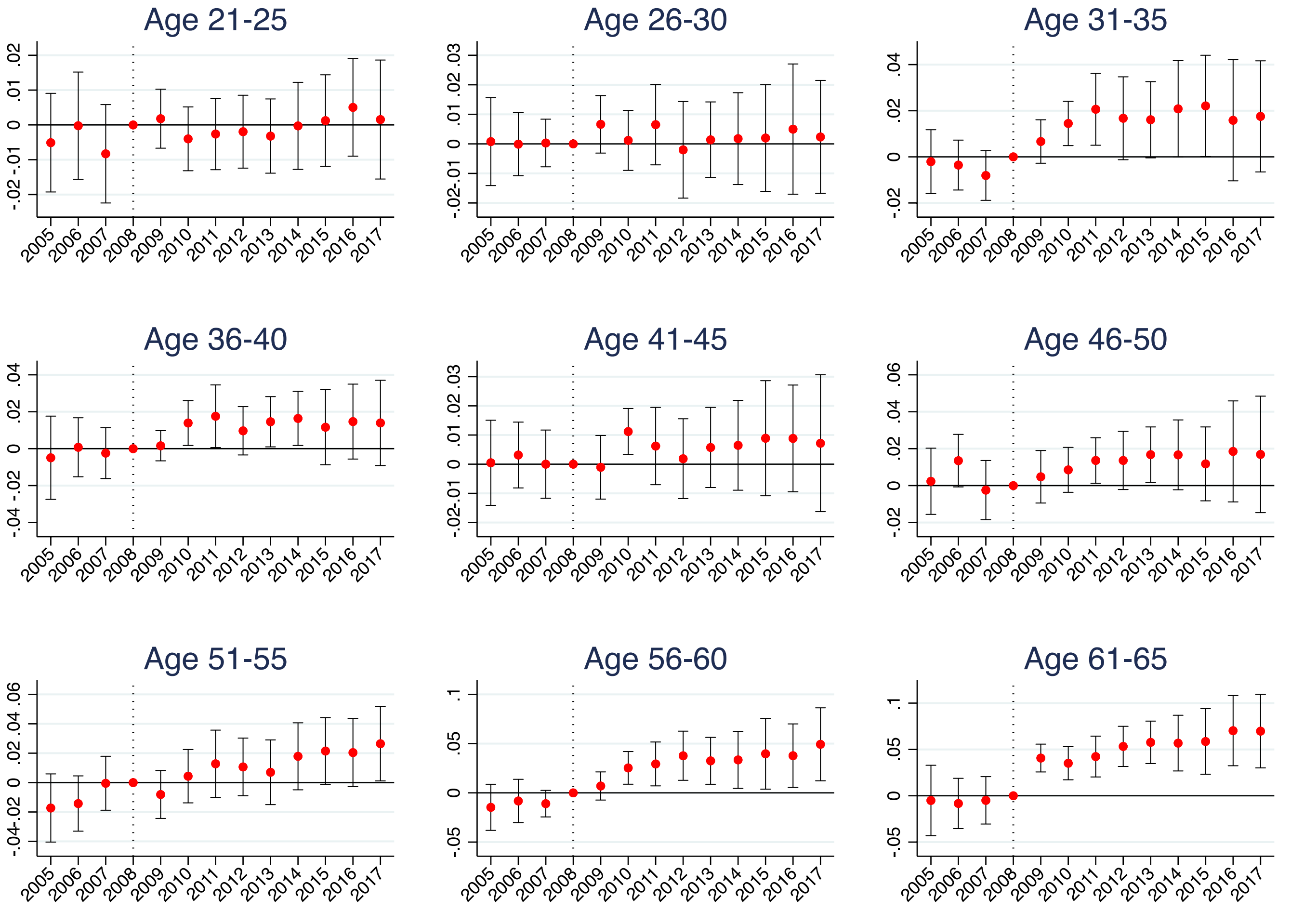

FIGURE 7 Changes in the effect of local unemployment rate on depression by age class. The graph shows the effects of province unemployment with respect to the 2008 reference on depression incidence by age class. Bars represent confidence intervals at 95% [Colour figure can be viewed at wileyonlinelibrary.com]

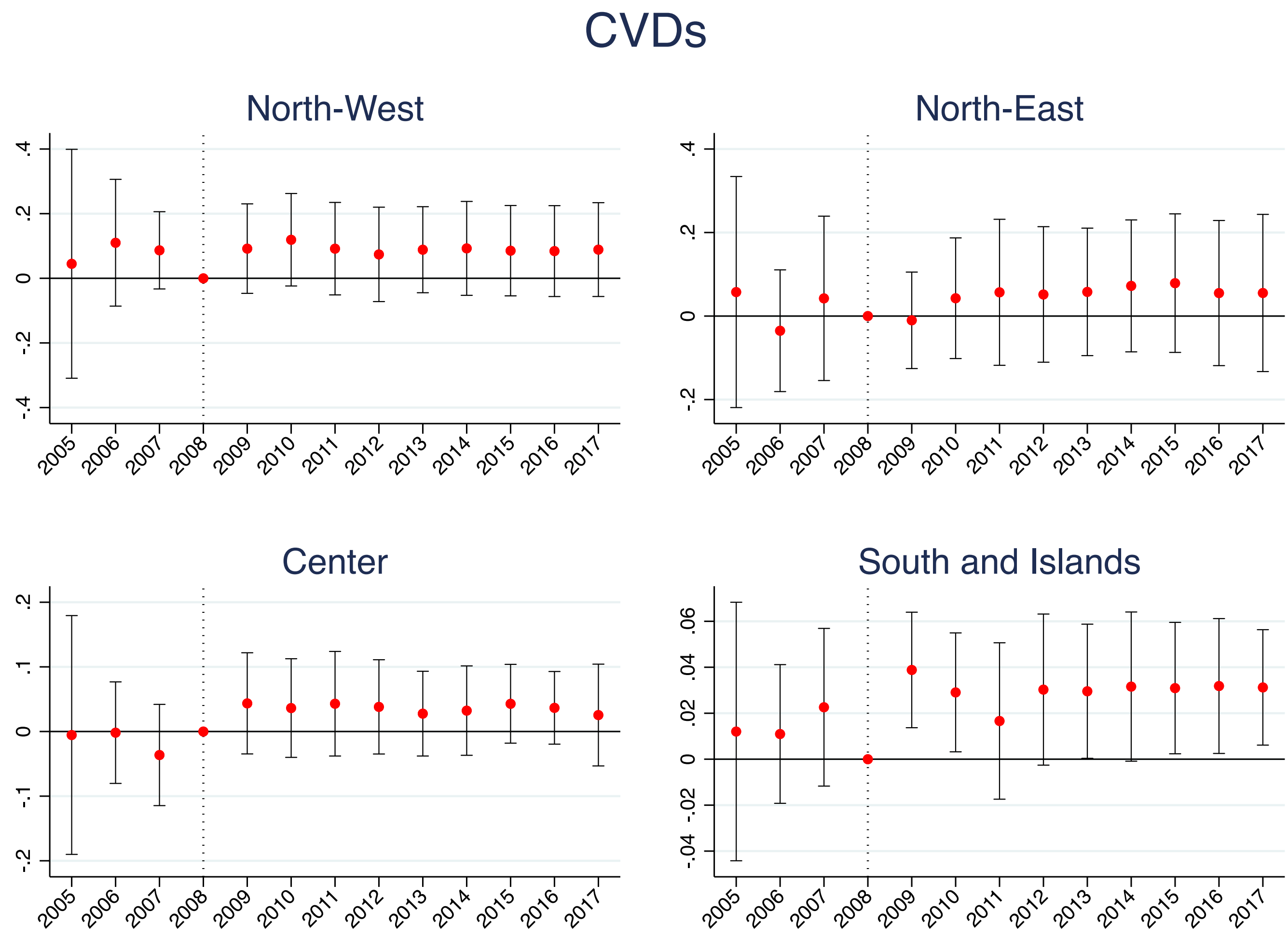

FIGURE 8 Changes in the effect of local unemployment on Cardio Vascular diseases (CVDs) by macro-area. The graph shows the effects of province unemployment on with respect to the 2008 reference CVDs incidence in four Italian macro-regions. Bars represent confidence intervals at 95% [Colour figure can be viewed at wileyonlinelibrary.com]

residents. Each additional increase in the unemployment rate during the GR is thus likely to have been more detrimental in this particular macro-area.

5 | ROBUSTNESS CHECKS

In this section we present a set of robustness checks supporting our main results. First, we re-estimate our model specification with employment rates, rather than unemployment rates. Employment and unemployment rates differ mainly due to demographic factors, labor market participation, and policies such as retirement legislation. While unemployment rate is more likely to capture labor market conditions in a timely manner, employment rate represents an alternative measure that accounts for the portion of the population not seeking employment. Table B10 and Figure 10 present the main estimates for the four groups of diseases.

The results are qualitatively identical to the previous set of estimates, with similar temporal evolution in the pattern of the impact of the GR rise in unemployment on the incidence of CVDs and depression with respect to the pre-crisis period. Overall, despite capturing slightly different characteristics of the labor market, both measures deliver equivalent results and confirm our main findings.

Second, we carry out a falsification test, based on another major group of diseases, cancers, which are not likely to respond to economic shocks in the short run. Figure 11 shows that the effect of province level surge in unemployment during the crisis does not change and is null for cancer incidence[11]; this evidence is also consistent with the previous studies, which do not find any effects of macroeconomic shocks on cancer mortality (Ruhm, 2000).

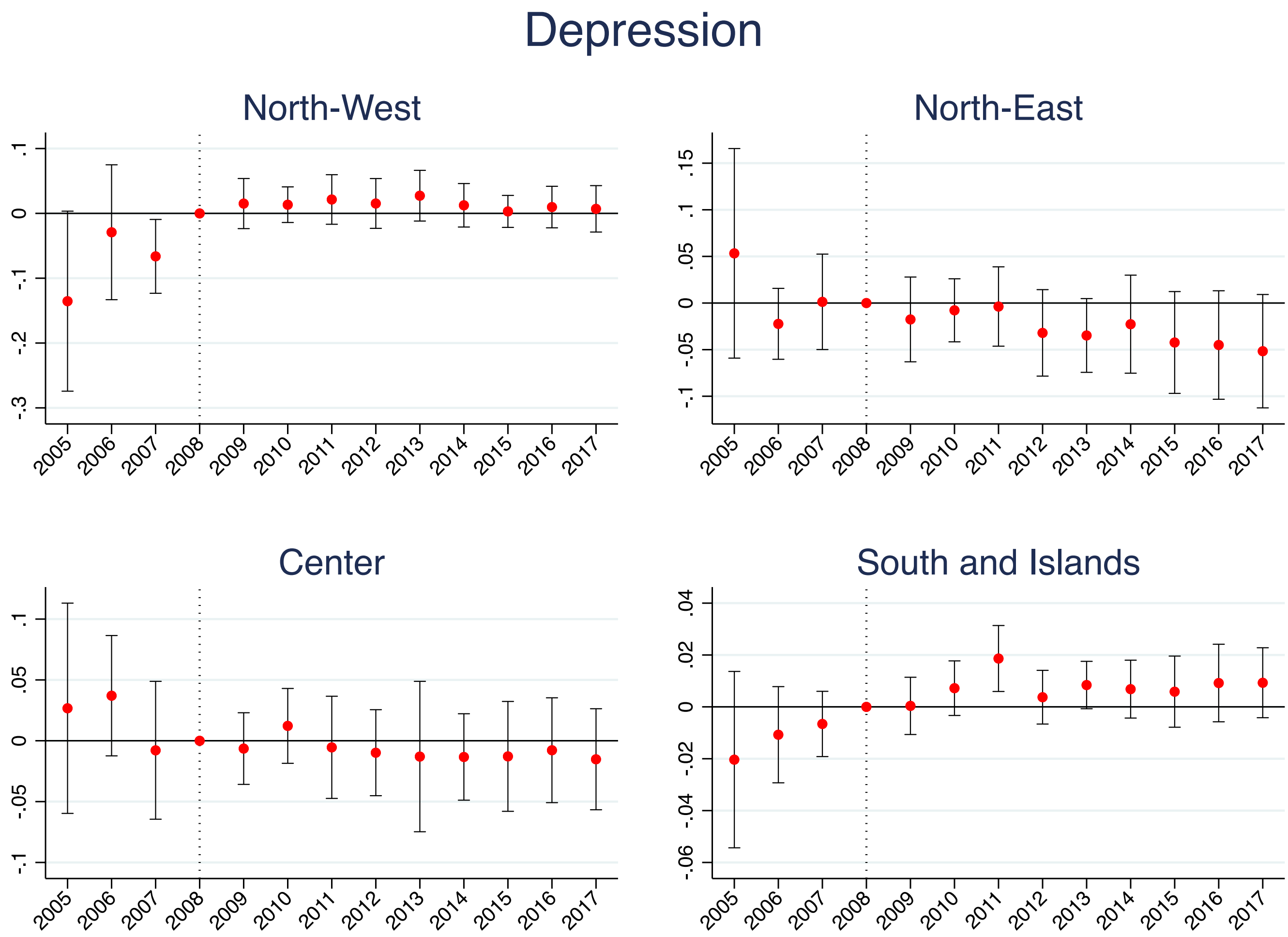

FIGURE 9 Changes in the effects of local unemployment on depression by macro-area. The graph shows the effects of province unemployment with respect to the 2008 reference on depression incidence in four Italian macro-regions. Bars represent confidence intervals at 95% [Colour figure can be viewed at wileyonlinelibrary.com]

Secondly, we address the concern for a potential difference in care-seeking patterns as a consequence of a higher local unemployment. On the one hand, unemployment might decrease the demand for healthcare due to reduced economic resources. This concern is to a large extent mitigated by the universal nature of healthcare provision in Italy, which minimizes access barriers to medical treatments, offering means-tested co-payment exemptions for a wide array of healthcare, spanning from drug purchases to secondary care. On the other hand, unemployed individuals could have a lower opportunity-cost of time that might induce them to pursue more medical checks. This could affect our estimates to the extent that unemployment would free up time to seek care, with the moment of diagnosis not necessarily coinciding with the onset of the disease. We study the presence of this potential confounding factor by looking at the consumption pattern of medical checks. The HS database provides information on healthcare costs of each patient devoted to medical specialist visits and diagnostic procedures. We thus re-estimate our main model specification as described in Equation 2 by substituting the dependent variable with patient-level yearly costs of medical checks.[12] The results are shown in Figure 12 and Appendix Table B12 and point to a non-statistically significant effect of the rise in province unemployment on this outcome. We take this evidence as reassuring on the fact that our estimates on the incidence of disease are capturing the effect on health status, rather than a differential pattern in healthcare demand.

Third, while our FE strategy inherently sorts out cross-sectional correlation, the evolution of unemployment in Italian provinces might be correlated with other time varying local characteristics. We thus check if and to what extent province level unemployment dynamics was correlated with the evolution of a set of characteristics, net of province specific FEs. We find statistically significant negative associations of unemployment with per-capita income and with the share of population aged 0–15, showing that, all else being equal, residents of provinces with greater unemployment experienced a relative drop in incomes and in birth rates (see Table B11). All other characteristics included, that is, share of migrants, all-cause mortality, neonatal mortality, are non-statistically associated with unemployment rate.

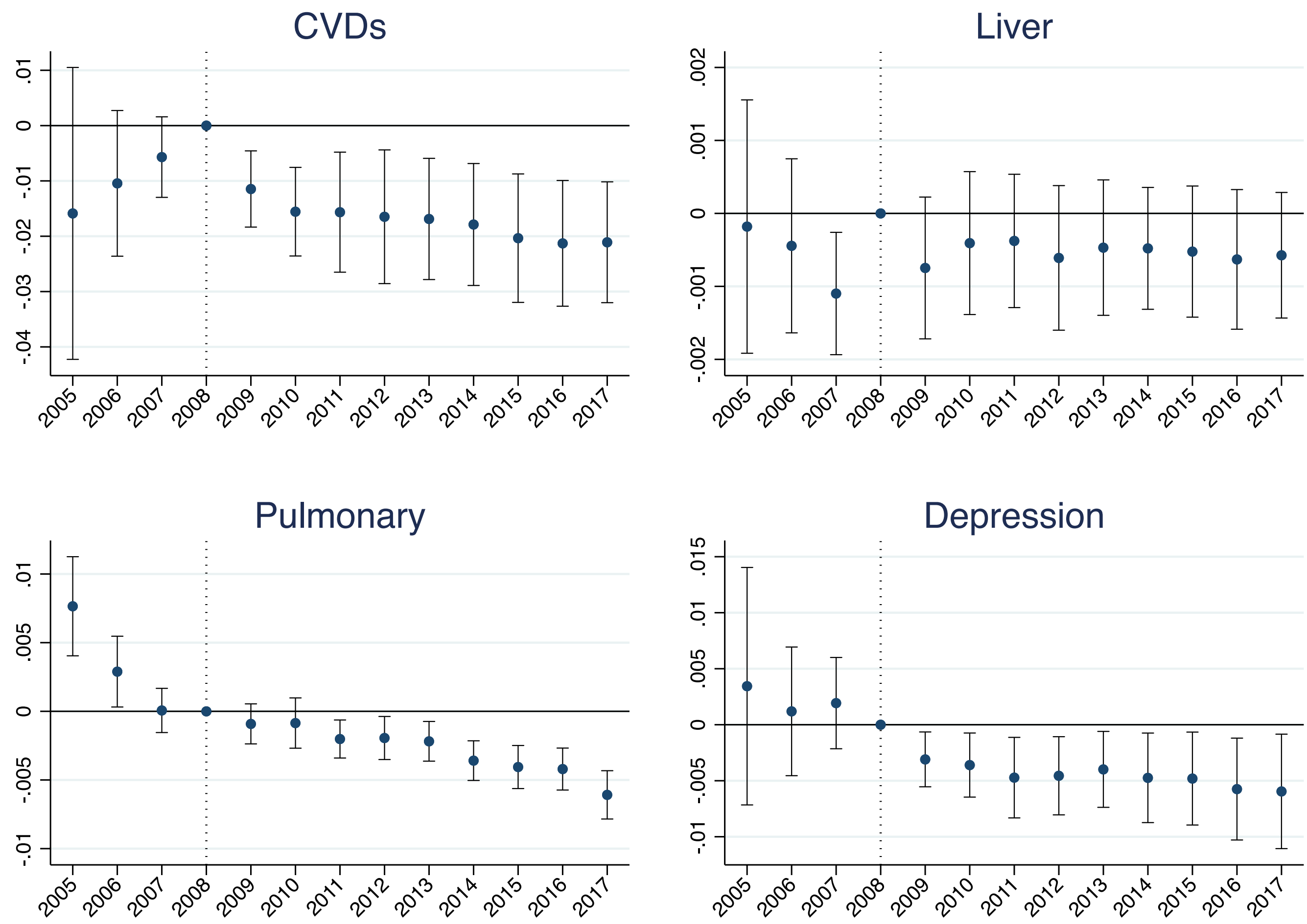

FIGURE 10 Changes in the effect of local employment rate on Cardio Vascular diseases (CVDs), liver, depression and pulmonary disease incidence. The graph shows the effects of province employment with respect to the 2008 reference on CVDs, liver disease, pulmonary disease and depression incidence. Bars represent confidence intervals at 95% [Colour figure can be viewed at wileyonlinelibrary.com]

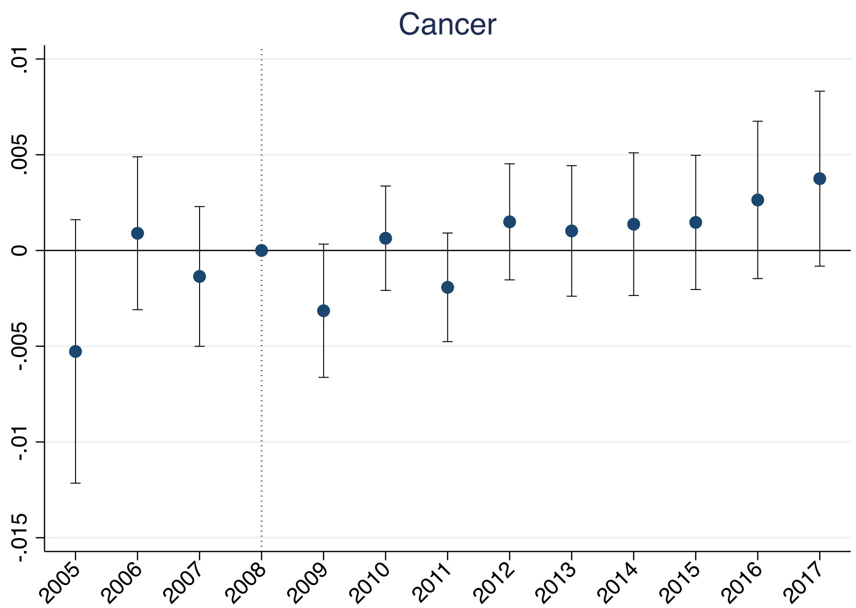

FIGURE 11 Changes in the effect of local unemployment on cancer as a placebo health outcome. The graph shows the effects of province unemployment with respect to the pre-crisis period on cancer incidence. Bars represent confidence intervals at 95% [Colour figure can be viewed at wileyonlinelibrary.com]

Moreover, in order to understand the robustness of our results with respect to other health indicators frequently correlated with CVDs, we additionally explore the changing effect of province unemployment upsurge during the GR on two additional outcomes, body mass index (BMI) and diabetes. Body mass index is considered one of the most common risk factors for a

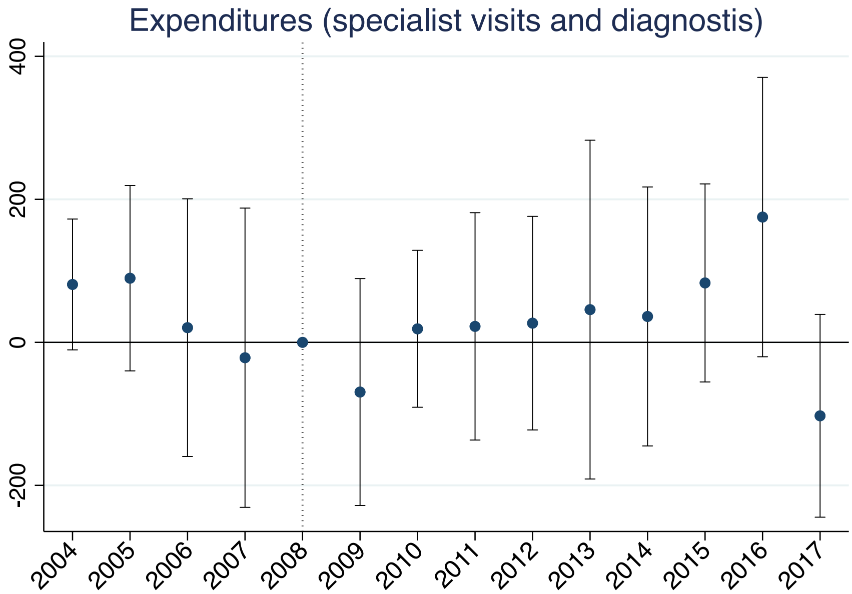

FIGURE 12 Changes in the effect of province unemployment on patient level costs of medical checks. The graph shows the effects of province unemployment with respect to the pre-crisis period on the expenditures (in euro) for medical specialist visits and diagnostic procedures. Bars represent confidence intervals at 95% [Colour figure can be viewed at wileyonlinelibrary.com]

large group of diseases, while diabetes represents one the most diffused chronic diseases and a frequent co-morbidity of CVDs. We find no statistically significant changes in the effect of unemployment on the evolution of BMI, and weakly statistically significant changes in the effect on the incidence of diabetes. The effect of the GR on diabetes is however not straightforward, as the association between the incidence and province level unemployment shows a time varying pattern throughout the entire period of the analysis, not only during the economic collapse (see Table B14).[13]

Finally, considering that different null hypotheses arise when estimating the effect of the GR on multiple health outcomes, we provide a step down bootstrap-based procedure for simultaneously testing multiple null hypotheses (Clarke, 2016; Romano & Wolf, 2016). The effects of the surge in the province unemployment rate during the GR persist significantly under this demanding inference criterion for testing the significance of our results. The Romano-Wolf adjusted p-values are presented in the Appendix Table B13.

6 | THE HEALTH EFFECTS OF THE GR: A BACK-OF-THE-ENVELOPE CALCULATION

Based on the estimates of Equation 2, displayed in Figure 2, we provide a back-of-the-envelope calculation of the number of extra incident individuals which can be attributed to the average annual changes in the unemployment rate. These calculations are presented in Table 3. First, we compute the number of individuals at risk of developing a specific disease in each year, pop_{jt}. We then compute for each disease j and year t, for which the coefficient estimates in our analysis are statistically significant, the additional number of incident patients as $extra_{jt} = pop_{jt}\hat{\beta}_{jt}\overline{\Delta U}_t$, where $\hat{\beta}_{jt}$ is the estimated difference in the unemployment effect on each disease j's incidence in each year t with respect to the onset of the crisis in 2008 (see Equation 2) and $\overline{\Delta U}_t = P^{-1}\sum_{p=1}^{P}\Delta U_{pt}$, with P indicating the number of provinces.

At the national level, the increase in unemployment rate has translated into approximately 63,000 additional individuals affected by CVDs between 2009 and 2014, and more than 13,000 additional individuals affected by depression in the same period.[14] We use estimates of the direct costs of both CVDs and depression in order to monetize the impact of the rise in incidence levels estimated in this study. Based on the estimates by Mennini (2017), the average annual cost of a patient affected by CVDs is 1668 euro, while the cost of assisting a patient with depression is 2236 euro, following Senese et al. (2018). The cost of the GR unemployment increase in terms of direct healthcare expenditures amounts to a total of nearly 135 million euro. Considering an annual basis, the total extra cost resulting from the unemployment surge during the 2009–2014 period is approximately 22.5 million euro, which represents 0.02% of the Italian National Healthcare Fund.

7 | CONCLUSIONS

Since the seminal paper by Ruhm (2000), a wide body of literature has investigated the effects of economic cycles on mortality, assuming that mortality is a proxy for the population's health. A major finding from these influential studies is the negative (procyclical) association between unemployment and mortality rates.

TABLE 3 Number of extra individuals diagnosed with Cardio Vascular diseases (CVDs) and depression due to increased unemployment rate

	CVDs		Depression		
Year	Extra incident	Share of total incident	Extra incident	Share of total incident	Δ Unemployment rate
2009	7203	3.23	1718	1.51	0.92
2010	6501	3.37	1797	1.69	0.64
2011	−710	0.37	−267	0.29	−0.07
2012	26,541	14.96	5626	6.64	2.51
2013	16,521	9.62	3108	3.88	1.51
2014	6799	3.93	1348	1.77	0.59
2015	−10,214	6.07	−1838	2.47	−0.81
2016	−1214	0.77	−259	0.39	−0.10
2017	−7509	5.01	−1654	2.76	−0.61

Note: The table reports the number of additional individuals diagnosed with CVDs and depression respectively, due to unemployment fluctuations in the GR period. The "extra incident" column represents the predicted additional number of patients that are diagnosed with CVDs and depression due a year-by-year change in unemployment. The "share of total incident" represents the proportion of extra incident patients with respect to the total number of incident patients in each year. *Δ* Unemployment rate is the year-by-year average change in the unemployment rate. The "extra incident" patients are computed as a product between the population at risk of CVDs and depression, the estimated difference in the unemployment effect on CVDs/depression's incidence in each year with respect to the onset of the crisis in 2008, and the average change in the unemployment rate. The estimates of the total number of incident patients in each year are obtained using population weights.

Using an individual FEs model, our analysis exploits the economic downturn experienced since the starting of the GR in 2008, which represents a discontinuity that allows us to identify the heterogeneous effects of increasing local unemployment on disease incidence. Our patient level analysis has several advantages. Unlike previous work, our analysis explores a wide and timely representation of the population health in terms of major chronic diseases. Moreover, our study exploits health information that are systematically and objectively measured by GPs in an individual FEs framework.

Our results show clear evidence of the detrimental health effects of the GR. In particular, we find significant effect on the incidence of CVDs and depression. We find no effects for liver disease, while for pulmonary disease the causal interpretation of the results is less clear-cut. These results complement the few studies that correlate individual self-reported health proxies with the unemployment dynamics during the GR (Currie et al., 2016, Tekin et al., 2013, among others). Our analysis shows that both the increased incidence of CVDs and depression are long-lasting and these impacts are characterized by large heterogeneity. Females and the elderly are the most affected by CVDs, while depression concentrates its effects on males and individuals close to the retirement age (56–64).

While our findings on CVDs contrast studies on general business cycle fluctuations and health (Cervini-Plá & Vall-Castelló, 2021, Ruhm, 2000, 2005), they are fully in line with recent findings by Birgisdóttir et al. (2020) on CVDs in Iceland. Moreover, the results on depression are more in line with previous studies that find a positive association between unemployment mortality due to suicide, a cause of death arguably linked strongly with depression (Vandoros et al., 2019).

Based on our empirical findings, we calculate that the during the GR the increase in local unemployment translated into nearly 63 thousand additional individuals affected by CVDs and over 13 thousand additional individuals affected by depression during the period 2009–2014. The healthcare costs necessary to treat those additional patients amount to 135 million euro for the years considered. More importantly, our cost estimates represent a lower bound since they do not account for indirect costs such as productivity loss and other social expenditures.

From an economic policy perspective, the social costs of health deterioration in terms of higher disease incidence due to the GR will be dumped on younger generations and on those to come. Moreover, the individuals affected by these severe chronic diseases are likely to face an increased risk of mortality in the future. An important recommendation emerging from this study is that policy makers should bear in mind that prolonged economic downturns constitute an additional external risk for individual health—and not a temporary benefit.

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CONFLICT OF INTEREST

The author declares no conflict of interest.

DATA AVAILABILITY STATEMENT

The individual health data employed in this study are originally collected and archived by HS - SIMG (Italian Association of General Physicians) (https://www.healthsearch.it). Given their clinical nature, they constitute sensitive data according to the Italian Law 101/2018. We have obtained these data under a strict confidentiality agreement with the HS – SIMG, which allows us to use the data only for specific research purposes. Health Search data can be only remotely accessed, following a Scientific Collaboration Agreement between CEIS Tor Vergata and SIMG signed in 2016. We commit to provide the Stata programming files (do files) with all steps of data preparation, cleaning and replication of the empirical analysis as supplementary material to the manuscript in case of publication. Unfortunately, we are not allowed to provide individual level data as this would represent a violation of the Scientific Collaboration Agreement between CEIS Tor Vergata and SIMG above mentioned. Nevertheless, in case of request, we will provide full assistance to anybody interested in getting the data from HS – SIMG for replication purposes. Data restrictions depend on the institutional review board, ethics committee and law. A "Data Access" or "Scientific Collaboration Agreement" for research/replication purposes has to be negotiated and signed with the owner of the data, HS - SIMG. The data owner can be contacted at: info@healthsearch.it I hope these information help facilitate the replication process.

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ENDNOTES

[1] The degree of measurement error is related to age, socio-economic status and income, hence correlated with the treatment variable in this type of analysis (Crossley & Kennedy, 2002; Johnston et al., 2009; Zajacova & Dowd, 2011).

[2] The choice of GP is based on geographical proximity since individuals must register with a GP practice located within their Local Health Authority (LHA) of residence. For individuals under 15 years of age, the same rules apply for registering with a pediatrician.

[3] More details on the extent to which the database represents the adult Italian population can be found in Appendix A and at https://www.health-search.it/ (Official website of the HS database). Numerous studies based on the HS data have been published in peer reviewed clinical and social sciences journals (see Atella et al., 2019, 2017, Atella & Conti, 2014, Atella & D'Amico, 2015, Atella & Kopinska, 2014b, Mazzaglia et al., 2009, among others).

[4] Appendix A reports the complete list of the included ICD-9 codes, together with their descriptions and aggregation into specific disease groups. In the Robustness Check section we also consider diabetes and BMI.

[5] One should stress that our setting might resemble a Difference-in-Differences (DiD) design with a continuous treatment, lacking untreated comparison units because all units are treated to some extent (Callaway et al., 2021). In such a framework a non-binary DiD could correspond to levels and slopes of the dose-response relationship, where, as the authors point out, a time varying treatment with time and unit fixed effects can cause the two-way fixed-effects (TWFE) estimands to have weights which may have undesirable properties in setups with heterogeneous treatment effects. This pitfall is cast in a DiD setting with variation in treatment timing, where the TWFE effects can perform poorly due to the presence of treatment effects dynamics or heterogeneous responses. It is however important to underline that by construction our setting cannot be defined a DiD design, as the GR timing was relatively homogeneous across provinces. The homogeneous treatment timing with a varying treatment intensity, sets apart our approach from treatment *vs*. Control comparisons, discussed in the literature presented above.

[6] We approximate the conditional probability of developing a chronic condition using a linear probability model (LPM) since we must consider the entire population of "at-risk" individuals each year. Even though the linear functional form is almost certainly wrong, fixed-effects binary models are not appropriate for our purposes since only transitioning individuals would be included in the estimation sample. Furthermore, LPM has the advantage of requiring neither the conditional independence of $y_{i1}, \ldots, y_{iT}$, $i = 1, \ldots, n$, nor any distributional assumption on the relationship between regressors and individual effects and, as pointed out by Wooldridge (2010), the within-group estimation of the LPM provides a reasonable approximation of the average marginal effects.

[7] Our dataset includes 83 out of 103 Italian provinces. The HS database does not include the provinces of two minor Italian regions, Valle d'Aosta and Molise.

[8] See Legislative Decree 626/1994 or the more recent Legislative Decree no. 81/2008.

[9] Full estimate tables for pulmonary and liver disease are reported in Appendix B.

[10] We also test if the coefficients obtained for females and males are significantly different by running the same model in Equation 2 for the two samples. We reject the null that the coefficients do not differ significantly. We repeat the same test when estimating the effect by age. The tests results are available upon request.

[11] We report full estimates in Table B1 in Appendix B.

[12] This model specification is no longer an incidence approach, hence as opposed to our baseline specification, we do not condition on any particular state of the dependent variable in the previous period.

[13] While diabetes is estimated following the incidence model described in Equation 2, estimates for BMI derive from a standard prevalence model.

[14] We restrict our calculations to the GR period, which goes from 2008 to 2014.

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APPENDIX A

Health Search database

The HS database contains detailed information on prescribed drugs, laboratory tests, outpatient visits and hospitalizations of more than two million patients, managed by over 1000 GPs overtime. Based on the data collected, a representative panel is constructed by selecting a longitudinal balanced sample of 900 GPs. The GPs are selected so as to reproduce the Italian distribution of GPs' patients by sex and region and on the basis of their capacity to deliver accurate and consistent records of their patients' medical history, diagnoses, diagnostic tests' results, specialist visits and hospitalizations. Each patient's visit to their GP gives rise to a record containing the data and type of the visit, the relative prescription of drugs, diagnostic tests, specialist visits and hospitalizations. The database constructed according to this procedure is representative of the population of Italian GPs' patients, with the only exception of the two smallest Italian regions, Molize and Valle d'Aosta, for whom the information collected are insufficient.

As mentioned before, the clinical information collected by GPs is further complemented with external sources. In particular, drug prices and tariffs for diagnostic tests and hospital DRGs are obtained from the Italian National Drug Agency (Agenzia Italiana del Farmaco - AIFA) and from the Department of Health (Ministero della Salute), respectively. This approach narrows possible GPs' errors in price imputation, and allows a consistent evaluation of health related expenditure. The data analysis is limited to individuals aged between 15 and 95. The restriction follows from the fact that, on the one hand, individuals under 15 are customary managed by pediatricians in the Italian health care system, while on the other hand, the sample of patients over 95 is extremely narrow leading to poor quality estimates. Expenditures are computed only for patients who have actually received a prescription of any type from their GPs. In order to assess the validity of the HSD data, several benchmark exercises have been carried out. In particular comparison of the data with the Italian National Statistical Institute (ISTAT) surveys confirmed the statistical representativeness of the data at regional level.

ICD9 codes for Cardiovascular diseases:

Ischemic Hert Disease:
410 411 412 413 414
Atrial fibrillation and flutter:
427.3
Diseases Of Arteries, Arterioles, And Capillaries:
440 441 442 443 444 445 446 447 448
Bypass or Coronary Angioplasty:
V45.81 V45.82
Cerebrovascular Disease:
430 431 432 433 434 435 436 437 438
Heart failure:
428
Hypertensive heart disease:
402.01 402.11 402.91
Hypertensive heart and chronic kidney disease:

404.01 404.91

ICD9 codes for Pulmonary diseases:

Chronic bronchitis:
491 496
Emphysema:
492

ICD9 codes for Depression disease:

Depression:
311 296.2296.3

ICD9 codes for Kidney diseases:

Chronic liver disease and cirrhosis:
5571.4 571.5 571.8 571.9

ICD9 codes for Cancer diseases:

Esophagus Cancer:
150
Stomach Cancer:
151
Rectum Cancer:
154
Breast Cancer:
174
Prostate Cancer:
185
Colon Cancer:
153
Lung Cancer:
162
Hodgkin and non-Hogdkin Diseases:
201 200.0 200.1 200.2 200.3 200.4 200.5 200.6 200.7 202.0 202.1 202.7
Leukemia:
204 205 206 207 208

TABLE B1 Effects of unemployment on cancer incidence

	Cancer
Unemployment rate	0.0035 (0.0027)
2005 × Unemp.	−0.0014 (0.0035)
2006 × Unemp.	0.0038 (0.0023)
2007 × Unemp.	0.0011 (0.0018)
2009 × Unemp.	−0.0026 (0.0019)
2010 × Unemp.	−0.0019 (0.0016)
2011 × Unemp.	−0.0027 (0.0015)
2012 × Unemp.	−0.0009 (0.0018)

TABLE B1 (Continued)

	Cancer
2013 × Unemp.	−0.0032 (0.0018)
2014 × Unemp.	−0.0025 (0.0020)
2015 × Unemp.	−0.0039 (0.0021)
2016 × Unemp.	−0.0021 (0.0022)
2017 × Unemp.	−0.0016 (0.0027)
Obs.	11,141,082
Individuals	1,182,457

Note: All models include individual and year fixed effects and control for age groups and share of tertiary education at province level. Standard errors are clustered at province level.

TABLE B2 Effects of unemployment on Cardio Vascular diseases (CVD) incidence by sex

	Male	Female
Unemployment rate	−0.0421*** (0.0083)	−0.0444*** (0.0097)
2005 × Unemp.	0.0290 (0.0150)	0.0308 (0.0223)
2006 × Unemp.	0.0210* (0.0094)	0.0204 (0.0132)
2007 × Unemp.	0.0068 (0.0073)	0.0136 (0.0079)
2009 × Unemp.	0.0222** (0.0072)	0.0287*** (0.0067)
2010 × Unemp.	0.0308*** (0.0059)	0.0353*** (0.0083)
2011 × Unemp.	0.0269*** (0.0069)	0.0350** (0.0106)
2012 × Unemp.	0.0342*** (0.0073)	0.0371** (0.0116)
2013 × Unemp.	0.0395*** (0.0073)	0.0357*** (0.0099)
2014 × Unemp.	0.0371*** (0.0068)	0.0409*** (0.0093)
2015 × Unemp.	0.0420*** (0.0078)	0.0445*** (0.0094)
2016 × Unemp.	0.0438*** (0.0080)	0.0437*** (0.0091)
2017 × Unemp.	0.0446*** (0.0072)	0.0442*** (0.0091)
Obs.	4,525,073	4,679,645
Individuals	536,395	563,823

Note: All models include individual and year fixed effects and control for age groups and share of tertiary education at province level. Standard errors are clustered at province level.

TABLE B3 Effects of unemployment on liver disease incidence by sex

	Male	Female
Unemployment rate	0.0007 (0.0022)	−0.0006 (0.0009)
2005 × Unemp.	−0.0010 (0.0020)	−0.0002 (0.0011)
2006 × Unemp.	−0.0000 (0.0015)	0.0009 (0.0009)
2007 × Unemp.	0.0016 (0.0014)	0.0024* (0.0010)
2009 × Unemp.	0.0022 (0.0012)	0.0016* (0.0007)
2010 × Unemp.	0.0006 (0.0015)	0.0002 (0.0008)
2011 × Unemp.	0.0008 (0.0014)	0.0005 (0.0008)
2012 × Unemp.	0.0003 (0.0015)	0.0015 (0.0008)
2013 × Unemp.	0.0002 (0.0015)	0.0010 (0.0007)
2014 × Unemp.	0.0002 (0.0014)	0.0004 (0.0007)
2015 × Unemp.	0.0004 (0.0015)	0.0006 (0.0007)
2016 × Unemp.	0.0002 (0.0014)	0.0006 (0.0008)

(Continues)

TABLE B3 (Continued)

	Male	Female
2017 × Unemp.	0.0004 (0.0015)	0.0008 (0.0008)
Obs.	4,891,773	5,102,098
Individuals	559,125	587,038

Note: All models include individual and year fixed effects, and control for age groups and share of tertiary education at province level. Standard errors are clustered at province level.

TABLE B4 Effects of unemployment on pulmonary disease incidence by sex

	Male	Female
Unemployment rate	−0.0067* (0.0028)	−0.0040 (0.0026)
2005 × Unemp.	−0.0132*** (0.0032)	−0.0064* (0.0029)
2006 × Unemp.	−0.0059* (0.0026)	−0.0018 (0.0023)
2007 × Unemp.	0.0016 (0.0015)	−0.0017 (0.0016)
2009 × Unemp.	0.0010 (0.0016)	0.0023 (0.0020)
2010 × Unemp.	0.0025 (0.0021)	0.0001 (0.0013)
2011 × Unemp.	0.0061** (0.0020)	0.0020 (0.0013)
2012 × Unemp.	0.0046* (0.0022)	0.0041** (0.0014)
2013 × Unemp.	0.0059** (0.0019)	0.0043** (0.0014)
2014 × Unemp.	0.0077*** (0.0022)	0.0058** (0.0018)
2015 × Unemp.	0.0088*** (0.0022)	0.0058** (0.0018)
2016 × Unemp.	0.0089*** (0.0023)	0.0062** (0.0018)
2017 × Unemp.	0.0123*** (0.0025)	0.0084*** (0.0017)
Obs.	4,863,256	5,077,720
Individuals	557,138	585,604

Note: All models include individual and year fixed effects, and control for age groups and share of tertiary education at province level. Standard errors are clustered at province level.

TABLE B5 Effects of unemployment on depression incidence by sex

	Male	Female
Unemployment rate	−0.0013 (0.0032)	0.0007 (0.0058)
2005 × Unemp.	−0.0050 (0.0066)	−0.0041 (0.0092)
2006 × Unemp.	−0.0008 (0.0041)	−0.0006 (0.0061)
2007 × Unemp.	−0.0020 (0.0035)	−0.0047 (0.0043)
2009 × Unemp.	0.0084*** (0.0019)	0.0030 (0.0035)
2010 × Unemp.	0.0057* (0.0025)	0.0112** (0.0038)
2011 × Unemp.	0.0124*** (0.0027)	0.0092* (0.0045)
2012 × Unemp.	0.0072** (0.0024)	0.0067 (0.0040)
2013 × Unemp.	0.0066** (0.0024)	0.0063 (0.0040)
2014 × Unemp.	0.0070* (0.0028)	0.0072 (0.0043)
2015 × Unemp.	0.0078** (0.0027)	0.0063 (0.0051)
2016 × Unemp.	0.0085** (0.0030)	0.0086 (0.0050)
2017 × Unemp.	0.0076* (0.0030)	0.0102 (0.0058)
Obs	4,819,439	4,883,509
Individuals	555,466	573,716

Note: All models include individual and year fixed effects, and control for age groups and share of tertiary education at province level. Standard errors are clustered at province level.

TABLE B6 Effects of unemployment on Cardio Vascular diseases (CVD) incidence by age class

	Age 21–25	Age 26–30	Age 31–35	Age 36–40	Age 41–45	Age 46–50	Age 51–55	Age 56–60	Age 61–65
Unemployment rate	−0.0213*	−0.0400***	−0.0396***	−0.0361***	−0.0251*	−0.0417***	−0.0629***	−0.0631***	−0.0841*
	(0.0092)	(0.0098)	(0.0113)	(0.0101)	(0.0100)	(0.0106)	(0.0119)	(0.0161)	(0.0406)
2005 × Unemp.	0.0670**	0.0689***	0.0626***	0.0511*	0.0417	0.0106	−0.0004	−0.0459	−0.0486
	(0.0226)	(0.0195)	(0.0174)	(0.0221)	(0.0229)	(0.0275)	(0.0211)	(0.0291)	(0.0245)
2006 × Unemp.	0.0692***	0.0432**	0.0433**	0.0330*	0.0167	0.0192	0.0077	−0.0342	0.0063
	(0.0150)	(0.0161)	(0.0133)	(0.0140)	(0.0137)	(0.0188)	(0.0198)	(0.0172)	(0.0306)
2007 × Unemp.	0.0317**	0.0335**	0.0320**	0.0241*	0.0120	0.0037	0.0043	−0.0147	−0.0115
	(0.0111)	(0.0110)	(0.0111)	(0.0102)	(0.0113)	(0.0108)	(0.0131)	(0.0148)	(0.0171)
2009 × Unemp.	0.0242***	0.0194**	0.0218**	0.0250**	0.0121	0.0172**	0.0227	0.0003	0.0530*
	(0.0055)	(0.0073)	(0.0066)	(0.0078)	(0.0067)	(0.0064)	(0.0154)	(0.0109)	(0.0215)
2010 × Unemp.	0.0255***	0.0210**	0.0260***	0.0193**	0.0220***	0.0416***	0.0413**	0.0378*	0.0751*
	(0.0057)	(0.0068)	(0.0062)	(0.0059)	(0.0047)	(0.0090)	(0.0135)	(0.0155)	(0.0301)
2011 × Unemp.	0.0268***	0.0224**	0.0248**	0.0254***	0.0222**	0.0288*	0.0509***	0.0437**	0.0821*
	(0.0049)	(0.0066)	(0.0081)	(0.0068)	(0.0078)	(0.0122)	(0.0117)	(0.0165)	(0.0325)
2012 × Unemp.	0.0262***	0.0296***	0.0228**	0.0298***	0.0214**	0.0410***	0.0476**	0.0579***	0.1022***
	(0.0060)	(0.0074)	(0.0082)	(0.0081)	(0.0077)	(0.0097)	(0.0155)	(0.0157)	(0.0318)
2013 × Unemp.	0.0244***	0.0320***	0.0331***	0.0342***	0.0262***	0.0492***	0.0618***	0.0654***	0.1100**
	(0.0063)	(0.0088)	(0.0090)	(0.0089)	(0.0071)	(0.0091)	(0.0160)	(0.0177)	(0.0333)
2014 × Unemp.	0.0247***	0.0317***	0.0328***	0.0360***	0.0317***	0.0530***	0.0581***	0.0748***	0.1139**
	(0.0070)	(0.0092)	(0.0086)	(0.0088)	(0.0076)	(0.0096)	(0.0167)	(0.0203)	(0.0390)
2015 × Unemp.	0.0200**	0.0351***	0.0340***	0.0390***	0.0361***	0.0553***	0.0731***	0.0846***	0.1473***
	(0.0066)	(0.0086)	(0.0096)	(0.0103)	(0.0086)	(0.0095)	(0.0165)	(0.0211)	(0.0405)
2016 × Unemp.	0.0204**	0.0336***	0.0345***	0.0370***	0.0362***	0.0637***	0.0821***	0.1168***	0.1483**
	(0.0072)	(0.0094)	(0.0084)	(0.0108)	(0.0092)	(0.0106)	(0.0177)	(0.0240)	(0.0447)
2017 × Unemp.	0.0275**	0.0372***	0.0338***	0.0297**	0.0374***	0.0673***	0.0848***	0.1211***	0.1619***
	(0.0082)	(0.0096)	(0.0093)	(0.0100)	(0.0104)	(0.0117)	(0.0171)	(0.0270)	(0.0450)
Obs.	752,076	828,584	970,666	1,100,924	1,186,168	1,143,060	1,031,841	909,235	792,630
Individuals	213,200	243,271	283,860	314,345	333,339	317,895	291,966	257,421	226,755

Note: All models include individual and year fixed effects, and control for share of tertiary education at province level. Standard errors are clustered at province level.

TABLE B7 Effects of unemployment on liver incidence by age class

	Age 21–25	Age 26–30	Age 31–35	Age 36–40	Age 41–45	Age 46–50	Age 51–55	Age 56–60	Age 61–65
Unemployment rate	0.0003 (0.0017)	0.0024 (0.0034)	0.0038 (0.0029)	−0.0001 (0.0028)	−0.0010 (0.0030)	0.0000 (0.0032)	−0.0020 (0.0026)	−0.0024 (0.0046)	−0.0043 (0.0046)
2005 × Unemp.	0.0012 (0.0015)	−0.0052 (0.0029)	−0.0004 (0.0025)	0.0050* (0.0022)	0.0073** (0.0025)	0.0007 (0.0040)	−0.0048 (0.0039)	−0.0046 (0.0054)	−0.0077 (0.0044)
2006 × Unemp.	0.0018 (0.0012)	−0.0043 (0.0028)	−0.0004 (0.0018)	0.0002 (0.0023)	0.0037 (0.0023)	0.0003 (0.0034)	−0.0052 (0.0040)	−0.0010 (0.0030)	−0.0016 (0.0070)
2007 × Unemp.	−0.0027* (0.0012)	−0.0027 (0.0021)	0.0055** (0.0021)	−0.0001 (0.0020)	0.0017 (0.0019)	0.0011 (0.0030)	−0.0006 (0.0033)	0.0102*** (0.0028)	0.0054 (0.0038)
2009 × Unemp.	0.0006 (0.0013)	0.0006 (0.0019)	0.0024 (0.0023)	0.0029 (0.0020)	0.0036 (0.0022)	0.0022 (0.0028)	0.0026 (0.0024)	0.0024 (0.0026)	0.0045 (0.0033)
2010 × Unemp.	−0.0024 (0.0015)	−0.0020 (0.0021)	0.0020 (0.0018)	−0.0015 (0.0025)	0.0030 (0.0021)	0.0026 (0.0025)	0.0009 (0.0024)	0.0023 (0.0020)	0.0050 (0.0034)
2011 × Unemp.	−0.0016 (0.0019)	−0.0023 (0.0022)	0.0008 (0.0027)	−0.0006 (0.0024)	0.0019 (0.0021)	−0.0004 (0.0024)	0.0004 (0.0028)	0.0042 (0.0027)	0.0092* (0.0045)
2012 × Unemp.	−0.0023 (0.0016)	−0.0014 (0.0022)	−0.0010 (0.0020)	−0.0005 (0.0023)	−0.0004 (0.0023)	0.0032 (0.0030)	0.0020 (0.0023)	0.0038 (0.0034)	0.0046 (0.0046)
2013 × Unemp.	−0.0016 (0.0018)	−0.0026 (0.0025)	−0.0006 (0.0023)	−0.0008 (0.0032)	0.0021 (0.0023)	0.0028 (0.0028)	0.0025 (0.0026)	0.0030 (0.0032)	0.0062 (0.0042)
2014 × Unemp.	−0.0033 (0.0017)	−0.0014 (0.0024)	−0.0008 (0.0022)	−0.0008 (0.0028)	−0.0005 (0.0027)	0.0031 (0.0032)	0.0029 (0.0023)	0.0027 (0.0035)	0.0053 (0.0043)
2015 × Unemp.	−0.0022 (0.0019)	−0.0008 (0.0026)	−0.0011 (0.0021)	−0.0018 (0.0032)	0.0002 (0.0024)	0.0006 (0.0033)	0.0024 (0.0030)	0.0034 (0.0037)	0.0050 (0.0045)
2016 × Unemp.	−0.0010 (0.0020)	−0.0020 (0.0023)	−0.0011 (0.0025)	−0.0009 (0.0033)	0.0023 (0.0030)	0.0004 (0.0030)	0.0012 (0.0026)	0.0025 (0.0040)	0.0085* (0.0041)
2017 × Unemp.	−0.0020 (0.0019)	−0.0021 (0.0025)	−0.0018 (0.0024)	0.0001 (0.0036)	0.0021 (0.0031)	−0.0002 (0.0032)	0.0000 (0.0028)	0.0045 (0.0038)	0.0081 (0.0050)
Obs.	802,606	889,912	1,035,606	1,170,578	1,261,929	1,226,777	1,130,881	1,036,152	958,536
Individuals	224,127	257,749	299,352	330,407	350,693	336,982	314,731	286,359	264,559

Note: All models include individual and year fixed effects, and control for share of tertiary education at province level. Standard errors are clustered at province level.

TABLE B8 Effects of unemployment on pulmonary incidence by age class

	Age 21–25	Age 26–30	Age 31–35	Age 36–40	Age 41–45	Age 46–50	Age 51–55	Age 56–60	Age 61–65
Unemployment rate	−0.0012 (0.0013)	−0.0017 (0.0014)	−0.0006 (0.0017)	−0.0055 (0.0034)	0.0013 (0.0033)	−0.0086 (0.0056)	−0.0179* (0.0073)	−0.0250*** (0.0073)	−0.0423*** (0.0122)
2005 × Unemp.	−0.0010 (0.0021)	−0.0032** (0.0011)	−0.0037 (0.0027)	−0.0089** (0.0028)	−0.0066* (0.0033)	−0.0150*** (0.0039)	−0.0170* (0.0074)	−0.0177* (0.0073)	−0.0367*** (0.0097)
2006 × Unemp.	0.0010 (0.0008)	0.0002 (0.0010)	−0.0000 (0.0018)	−0.0068* (0.0029)	−0.0029 (0.0031)	−0.0086* (0.0039)	−0.0112 (0.0063)	−0.0039 (0.0080)	−0.0202 (0.0108)
2007 × Unemp.	−0.0008 (0.0010)	−0.0007 (0.0014)	0.0009 (0.0015)	−0.0022 (0.0023)	0.0037 (0.0034)	−0.0047 (0.0040)	−0.0012 (0.0058)	0.0103 (0.0055)	−0.0249*** (0.0069)
2009 × Unemp.	0.0006 (0.0005)	0.0007 (0.0014)	−0.0006 (0.0012)	0.0004 (0.0013)	0.0011 (0.0027)	−0.0005 (0.0032)	0.0086* (0.0041)	0.0122 (0.0062)	0.0081 (0.0093)
2010 × Unemp.	0.0007 (0.0004)	0.0003 (0.0011)	−0.0007 (0.0013)	0.0054** (0.0019)	0.0004 (0.0019)	0.0005 (0.0038)	0.0040 (0.0051)	0.0125* (0.0061)	0.0177 (0.0090)
2011 × Unemp.	0.0009* (0.0004)	0.0006 (0.0017)	0.0036* (0.0015)	0.0026 (0.0019)	0.0021 (0.0028)	0.0056 (0.0052)	0.0153** (0.0047)	0.0280*** (0.0074)	0.0170 (0.0125)
2012 × Unemp.	0.0007 (0.0006)	0.0013 (0.0013)	0.0035* (0.0016)	0.0032 (0.0021)	0.0041 (0.0029)	0.0042 (0.0047)	0.0154** (0.0053)	0.0339*** (0.0065)	0.0315* (0.0142)
2013 × Unemp.	0.0002 (0.0007)	0.0006 (0.0015)	0.0030* (0.0014)	0.0047 (0.0028)	0.0012 (0.0026)	0.0065 (0.0054)	0.0149* (0.0057)	0.0368*** (0.0066)	0.0338* (0.0130)
2014 × Unemp.	−0.0004 (0.0008)	0.0012 (0.0016)	0.0015 (0.0014)	0.0053* (0.0025)	0.0028 (0.0025)	0.0101 (0.0064)	0.0220*** (0.0057)	0.0429*** (0.0068)	0.0421** (0.0129)
2015 × Unemp.	0.0000 (0.0010)	0.0019 (0.0014)	0.0025 (0.0016)	0.0068* (0.0030)	0.0039 (0.0028)	0.0134* (0.0064)	0.0247*** (0.0063)	0.0464*** (0.0074)	0.0474** (0.0161)
2016 × Unemp.	0.0003 (0.0008)	0.0019 (0.0016)	0.0017 (0.0015)	0.0081** (0.0026)	0.0050 (0.0035)	0.0143* (0.0060)	0.0255*** (0.0061)	0.0479*** (0.0076)	0.0520** (0.0173)
2017 × Unemp.	−0.0001 (0.0012)	0.0031* (0.0015)	0.0036* (0.0017)	0.0100*** (0.0029)	0.0058 (0.0033)	0.0186** (0.0064)	0.0289*** (0.0064)	0.0548*** (0.0076)	0.0612*** (0.0147)
Obs.	802,032	889,932	1,036,217	1,171,829	1,262,868	1,224,280	1,121,769	1,016,940	927,960
Individuals	223,962	257,749	299,501	330,750	351,012	336,542	312,963	282,293	257,625

Note: All models include individual and year fixed effects, and control for share of tertiary education at province level. Standard errors are clustered at province level.

TABLE B9 Effects of unemployment on depression incidence by age class

	Age 21–25	Age 26–30	Age 31–35	Age 36–40	Age 41–45	Age 46–50	Age 51–55	Age 56–60	Age 61–65
Unemployment rate	0.0050 (0.0062)	0.0018 (0.0067)	−0.0169* (0.0080)	−0.0035 (0.0072)	−0.0075 (0.0072)	−0.0139 (0.0095)	−0.0102 (0.0095)	−0.0195 (0.0124)	−0.0521*** (0.0104)
2005 × Unemp.	−0.0051 (0.0071)	0.0008 (0.0075)	−0.0021 (0.0070)	−0.0049 (0.0113)	0.0005 (0.0073)	0.0023 (0.0090)	−0.0173 (0.0117)	−0.0147 (0.0118)	−0.0051 (0.0191)
2006 × Unemp.	−0.0002 (0.0077)	−0.0001 (0.0054)	−0.0036 (0.0054)	0.0008 (0.0080)	0.0031 (0.0057)	0.0135 (0.0071)	−0.0143 (0.0095)	−0.0082 (0.0110)	−0.0083 (0.0136)
2007 × Unemp.	−0.0083 (0.0071)	0.0003 (0.0041)	−0.0081 (0.0054)	−0.0024 (0.0069)	−0.0000 (0.0059)	−0.0024 (0.0081)	−0.0005 (0.0092)	−0.0110 (0.0068)	−0.0049 (0.0129)
2009 × Unemp.	0.0018 (0.0043)	0.0066 (0.0049)	0.0067 (0.0047)	0.0016 (0.0041)	−0.0011 (0.0055)	0.0048 (0.0071)	−0.0081 (0.0082)	0.0070 (0.0072)	0.0407*** (0.0075)
2010 × Unemp.	−0.0040 (0.0046)	0.0012 (0.0051)	0.0145** (0.0048)	0.0139* (0.0061)	0.0112** (0.0040)	0.0085 (0.0061)	0.0043 (0.0091)	0.0253** (0.0083)	0.0351*** (0.0090)
2011 × Unemp.	−0.0026 (0.0052)	0.0065 (0.0068)	0.0206* (0.0079)	0.0176* (0.0085)	0.0062 (0.0067)	0.0136* (0.0062)	0.0128 (0.0115)	0.0293* (0.0112)	0.0423*** (0.0111)
2012 × Unemp.	−0.0019 (0.0053)	−0.0020 (0.0082)	0.0167 (0.0090)	0.0097 (0.0066)	0.0019 (0.0069)	0.0136 (0.0079)	0.0107 (0.0098)	0.0377** (0.0125)	0.0533*** (0.0109)
2013 × Unemp.	−0.0032 (0.0054)	0.0014 (0.0064)	0.0161 (0.0083)	0.0146* (0.0068)	0.0057 (0.0069)	0.0168* (0.0075)	0.0070 (0.0111)	0.0325** (0.0120)	0.0577*** (0.0115)
2014 × Unemp.	−0.0003 (0.0063)	0.0018 (0.0078)	0.0208 (0.0105)	0.0164* (0.0074)	0.0065 (0.0077)	0.0167 (0.0095)	0.0179 (0.0115)	0.0335* (0.0146)	0.0568*** (0.0151)
2015 × Unemp.	0.0012 (0.0066)	0.0020 (0.0091)	0.0221* (0.0110)	0.0116 (0.0102)	0.0089 (0.0099)	0.0118 (0.0101)	0.0215 (0.0114)	0.0397* (0.0180)	0.0586** (0.0178)
2016 × Unemp.	0.0050 (0.0070)	0.0050 (0.0111)	0.0159 (0.0132)	0.0147 (0.0102)	0.0088 (0.0092)	0.0185 (0.0138)	0.0204 (0.0116)	0.0378* (0.0162)	0.0703*** (0.0190)
2017 × Unemp.	0.0015 (0.0086)	0.0023 (0.0096)	0.0175 (0.0121)	0.0140 (0.0116)	0.0072 (0.0118)	0.0169 (0.0159)	0.0264* (0.0127)	0.0493** (0.0186)	0.0697*** (0.0199)
Obs.	795,678	876,712	1,014,506	1,140,433	1,223,418	1,182,698	1,083,797	987,332	909,926
Individuals	222,639	254,718	294,476	323,501	341,606	326,617	303,516	274,696	252,856

Note: All models include individual and year fixed effects, and control for share of tertiary education at province level. Standard errors are clustered at province level.

TABLE B10 Effects of employment on Cardio Vascular diseases (CVDs), liver, depression and pulmonary incidences

	CDVs	Liver	Pulmonary	Depression
Employment rate	0.0144 (0.0105)	−0.0003 (0.0010)	0.0026 (0.0022)	0.0002 (0.0049)
2005 × Emp.	−0.0159 (0.0133)	−0.0002 (0.0009)	0.0077*** (0.0018)	0.0034 (0.0053)
2006 × Emp.	−0.0104 (0.0066)	−0.0004 (0.0006)	0.0029* (0.0013)	0.0012 (0.0029)
2007 × Emp.	−0.0057 (0.0037)	−0.0011* (0.0004)	0.0001 (0.0008)	0.0019 (0.0020)
2009 × Emp.	−0.0115** (0.0035)	−0.0007 (0.0005)	−0.0009 (0.0007)	−0.0031* (0.0012)
2010 × Emp.	−0.0156***(0.0040)	−0.0004 (0.0005)	−0.0009 (0.0009)	−0.0036* (0.0014)
2011 × Emp.	−0.0156** (0.0055)	−0.0004 (0.0005)	−0.0020** (0.0007)	−0.0047* (0.0018)
2012 × Emp.	−0.0165** (0.0061)	−0.0006 (0.0005)	−0.0019* (0.0008)	−0.0046* (0.0018)
2013 × Emp.	−0.0169** (0.0055)	−0.0005 (0.0005)	−0.0022** (0.0007)	−0.0040* (0.0017)
2014 × Emp.	−0.0179** (0.0055)	−0.0005 (0.0004)	−0.0036*** (0.0007)	−0.0047* (0.0020)
2015 × Emp.	−0.0203*** (0.0058)	−0.0005 (0.0005)	−0.0041*** (0.0008)	−0.0048* (0.0021)
2016 × Emp.	−0.0213*** (0.0057)	−0.0006 (0.0005)	−0.0042*** (0.0008)	−0.0057* (0.0023)
2017 × Emp.	−0.0211*** (0.0055)	−0.0006 (0.0004)	−0.0061*** (0.0009)	−0.0060* (0.0026)
Obs.	10,405,323	11,229,979	11,176,444	10,922,795
Individuals	1,137,706	1,182,512	1,179,134	1,166,196

Note: All models include individual and year fixed effects, and control for age groups and share of tertiary education at province level. Standard errors are clustered at province level.

APPENDIX B

TABLE B11 Correlation between province-level characteristics and unemployment rate

	Province unemployment (1)
Occupation in agriculture	−0.0590 (0.0717)
Per-capita income	−0.0017*** (0.0005)
Share of foreign residents	−0.0003 (0.0010)
Share of females	−0.5141 (0.4025)
Total population	−0.0022* (0.0012)
Share of pop. Age 0/15	−1.0319*** (0.2664)
Share of pop. Age 66/75	0.5559 (0.4026)
Share of pop. Age 76/85	−0.5045 (0.6132)
Share of pop. Age 86+	−0.5021 (1.2044)
Population density	0.0682 (0.0578)
Mortality	−0.0053 (0.0171)
Neonatal mortality	0.0079 (0.0091)
Province FEs	Yes
Year FEs	Yes
Obs.	1,050
R2	0.75

Note: These estimates show the associations between the province-level unemployment rate and several characteristics based on official province-level data provided by the Italian National Institute of Statistics (ISTAT). The model includes province and year fixed effects. ISTAT data are accessible at `data.istat`

TABLE B12 Effect of province unemployment on patient level costs of medical checks

	Medical checks costs
	(1)
Unemployment rate	197.6798 (115.4621)
2004 × Unemp.	24.6065 (82.0804)
2005 × Unemp	100.9105 (71.6066)
2006 × Unemp.	187.9951** (70.0018)
2007 × Unemp.	46.1326 (60.7775)
2009 × Unemp.	−54.5377 (39.9304)
2010 × Unemp.	−34.5122 (51.9795)
2011 × Unemp.	−5.0379 (67.2477)
2012 × Unemp.	−42.5172 (70.5589)
2013 × Unemp.	−130.3052 (71.0521)
2014 × Unemp.	−100.8961 (82.2448)
2015 × Unemp.	−53.8226 (93.9657)
2016 × Unemp.	−94.9455 (104.8917)
2017 × Unemp.	−81.8655 (130.3537)
Obs	10,852,704
Individuals	1,186,900

Note: All models control for individual and time fixed effets, age groups and share of tertiary education at provincial level. Standard errors are clustered by province.

TABLE B13 Multiple hypotheses test - Romano & Wolf *p*-values

	CVDs	Depression	Liver	Pulmonary
	(1)	(2)	(3)	(4)
2005 × Unemp.	0.735	1.000	1.000	0.005
2006 × Unemp.	0.565	1.000	1.000	0.735
2007 × Unemp.	0.735	0.970	0.345	1.000
2009 × Unemp.	0.000	0.225	0.280	0.925
2010 × Unemp.	0.000	0.040	1.000	0.990
2011 × Unemp.	0.010	0.040	1.000	0.060
2012 × Unemp.	0.000	0.210	0.960	0.060
2013 × Unemp.	0.000	0.300	1.000	0.005
2014 × Unemp.	0.000	0.365	1.000	0.000
2015 × Unemp.	0.000	0.525	1.000	0.000
2016 × Unemp.	0.000	0.325	1.000	0.000
2017 × Unemp.	0.000	0.365	1.000	0.000

Note: All models control for individual and time fixed-effects, age groups and share of tertiary education at provincial level. Romano & Wolf *p*-values based on 10,000 bootstrap replications clustered at province level.

TABLE B14 Effect of province unemployment on Diabetes and BMI

	Diabetes	BMI
Unemployment rate	−0.0134* (0.0051)	−0.0003 (0.0067)
2004 × Unemp.		−0.0010 (0.0073)
2005 × Unemp.	−0.0207*** (0.0048)	−0.0008 (0.0057)
2006 × Unemp.	−0.0119* (0.0054)	0.0016 (0.0043)
2007 × Unemp.	−0.0101* (0.0040)	0.0023 (0.0027)
2009 × Unemp.	−0.0008 (0.0025)	−0.0074* (0.0030)
2010 × Unemp.	0.0058 (0.0032)	−0.0090* (0.0041)
2011 × Unemp.	0.0052 (0.0033)	−0.0104* (0.0047)
2012 × Unemp.	0.0096** (0.0034)	−0.0086 (0.0052)
2013 × Unemp.	0.0099** (0.0037)	−0.0052 (0.0065)
2014 × Unemp.	0.0120** (0.0040)	−0.0018 (0.0086)
2015 × Unemp.	0.0122** (0.0040)	−0.0053 (0.0083)
2016 × Unemp.	0.0146*** (0.0039)	−0.0048 (0.0101)
2017 × Unemp.	0.0165*** (0.0042)	−0.0098 (0.0104)
Obs.	9,712,951	1,894,516
Individuals	1,124,004	445,031

Note: All models control for individual and time fixed-effects, age groups and share of tertiary education at provincial level. Standard errors are clustered by province.