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Original Article

Is it Easier to Be Unemployed When the Experience Is More Widely Shared? Effects of Unemployment on Self-rated Health in 25 European Countries with Diverging Macroeconomic Conditions

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Abstract

The economic crisis in Europe since 2008 has led to high unemployment levels in several countries. Previous research suggests that becoming unemployed is a health risk, but is job loss and unemployment easier to cope with when unemployment is widespread? Using EU-SILC panel data (2010–2013), this study examines short-term effects of unemployment on self-rated health (SRH) in 25 European countries with diverging macroeconomic conditions. Ordinary least squares regressions show that the unemployed are in worse health than the employed throughout Europe. The association is reduced considerably, but remains significant in several countries when time-invariant personal characteristics are accounted for using individual-level fixed-effects models. Propensity score kernel matching shows that both being and becoming unemployed are associated with slightly worse SRH. There is a weak tendency towards less health effects of unemployment in countries where the experience is widely shared. In particular, countries with a very low unemployment rate stand out with larger health effects. The results overall suggest that a changed composition of the unemployed population is an important explanation for the weaker unemployment—health association in high-unemployment countries.

Introduction

During the Great Recession, average unemployment rates in the EU-28 countries rose from 7.0 per cent in 2008 to 10.8 per cent in 2013 (Eurostat, 2016a). Unemployment is clearly undesirable, since it involves both income loss and human capital devaluation, but is it also detrimental for health? And will negative health effects be less pronounced when unemployment is high?

The present study addresses these issues, with special attention paid to the relationship between country-level unemployment rates and health effects of unemployment. We use panel data from EU-SILC (harmonized surveys of level of living conducted across Europe; cf. Eurostat, 2016b) and examine 25 countries with different levels of, and trends in, unemployment. The analysed outcome is self-rated general health (SRH), which is likely to be sensitive to the material and psychological stress which unemployed people could experience (Singh-Manoux *et al.*, 2006).

The aim is to contribute to the existing literature in three ways. First, a cross-national comparative approach through analyses of 25 countries with diverging unemployment rates will extend our knowledge about the unemployment—health association. Secondly, the complex issue of causal effects of unemployment is addressed by applying three statistical methods: ordinary least squares regression (OLS), individual-level fixed-effects (FE) models, and propensity score kernel matching. Thirdly, we try to disentangle between different explanations of why health effects of unemployment could vary with unemployment levels.

Previous Research and Theory

Previous Research

It is well documented that the employed tend to have better health than the unemployed do, but whether this association varies with macroeconomic conditions is disputed. Several studies indicate *less* negative health effects of unemployment during economic downturns. A Swedish study found no excess mortality due to suicide among the unemployed during a recession, the opposite being the case when the economy was improving (Garcy and Vågerö, 2013). Using the Finnish recession in the 1990s as a natural experiment, Martikainen and Valkonen (1996) found a weaker unemployment—mortality association when overall unemployment increased. Another Finnish study showed that mortality was lower among individuals working in strongly downsizing firms (Martikainen, Mäki and Jäntti, 2007). In Britain, Clark (2003) showed that well-being among unemployed was better if unemployment was high in the area (or affected other household members), while Gathergood (2013) showed that people entering unemployment in high unemployment areas deteriorated less in psychological health. Finally, an Australian study found worse health among young unemployed when unemployment was low (Scanlan and Bundy, 2009).

Other studies give scant support, however, to the hypothesis that health effects are less pronounced when unemployment is high. Swedish studies on somatic and psychological symptoms (Novo, Hammarström and Janlert, 2000) and mortality risk (Åhs and Westerling, 2006) among the unemployed did not find any noticeable variation with overall unemployment level. A Greek study even found *worse* health effects of being unemployed when unemployment is common (Drydakis, 2015), and a Canadian study could not confirm that effects of unemployment on health vary with unemployment rates (Beland, Birch and Stoddart, 2002). Noelke and Beckfield (2014) found increased mortality among older American workers who lost their jobs during recessions, while job loss in booming economic conditions was not associated with higher mortality. Recessionary labour market conditions have also been found to correspond to increased risk of cardiovascular disease among older Americans experiencing job loss (Noelke and Avendano, 2015).

The above-mentioned studies have only used data from one specific country, and unemployment rates varied much between the research contexts. This could explain the mixed findings, since a deep recession (e.g. Finland in the 90s) could have other implications than 'normal' business cycle fluctuations. A cross-national approach may provide more insight into the relationship between health and unemployment during 'busts and booms', but comparative studies are rare. Oesch and Lipps (2012), analysing German and Swiss data, did not find that life satisfaction among the unemployed was better when regional unemployment was higher. Likewise, two studies examining 27 and 16 countries, respectively, did not find any moderating effect of country-level (Buffel, Dereuddre and Bracke 2015) or regional-level unemployment (Buffel, Missinne and Bracke, 2017). In summary, previous studies have not produced clear-cut results as to how health effects of unemployment vary with macroeconomic conditions.

Theory and Hypotheses

Two main mechanisms could explain a weaker unemployment—health association during an economic crisis. There may be *less stigma* and *self-blame* when the unemployment experience is widely shared. Clark and Oswald (1994: p. 657) commented that their findings 'indicate that it is harder to put up with unemployment if one lives in a place where few people are without a job'. Turner (1995: p. 215) suggested that unemployed '...would be more likely to attribute their job loss to some sort of personal failing...' if the unemployment rate in the area is low. When unemployment increases, people will probably view their unemployment more as a structural problem and less of a personal disgrace. Unemployment may also be easier to cope with if also friends and relatives are unemployed.

A *changed composition* of the unemployed population could also be of importance. When labour demand is high, individuals who are disadvantaged as to education and health—and perhaps personality traits and cognitive abilities as well—may constitute a considerable part of the unemployed population. When unemployment rises, this could change. Productive and highly skilled workers will lose their jobs because of downsizing and firm closures. Such unemployed individuals could have better coping skills and better health-related behaviours compared to the typical unemployed when unemployment is low, and they could be less likely to have had physically demanding work in the past. Their health when becoming unemployed may therefore be relatively good, and their resources for withstanding health deterioration could be better. Accordingly, research has suggested that the unemployed are healthier on average in countries with a severe economic crisis (Heggebø and Dahl, 2015).

However, the mixed findings suggest possibilities for the opposite pattern, namely, that unemployment has *worse* health consequences when unemployment is high. Being unemployed could be especially damaging during an economic slump because there is no apparent way out of the situation. When labour demand is low, more jobless people will compete for fewer available job openings (Noelke and Beckfield, 2014), causing *low re-employment likelihood*. Unemployment during an economic crisis could therefore be associated with more deteriorated health among the unemployed because feelings of hopelessness could be more widespread.

In line with the discussion above, the present study will examine three hypotheses.

Hypothesis 1. Unemployment has negative effects on self-rated health (SRH), irrespective of national context and macroeconomic conditions. The present study uses data from 25 European countries to examine this well-known hypothesis.

Hypothesis 2. Negative health effects of unemployment are less pronounced in high-unemployment countries, compared to countries with an intermediate or low overall unemployment rate. The assumption here is that widespread unemployment will make the experience hurt less, but changes in the composition of the unemployed population could also generate this empirical pattern.

Hypothesis 3. Negative health effects of unemployment are larger in countries with a high and growing unemployment rate, compared to countries where the unemployment rate is high, but falling. This hypothesis focuses on the 'economic climate'; being unemployed could be easier to deal with when the economy is improving.

Data and Methods

Classification of 25 European Countries

The present study utilizes EU-SILC panel data 2010–2013 (described below), which were available for 25 European countries. They were classified according to two dimensions: average *level* of unemployment 2010–2013, and unemployment *trend*. Table 1 shows that average unemployment level was above 10 per cent in 8 countries (Spain, Latvia, Lithuania, Portugal, Ireland, Slovakia, Estonia, and Bulgaria), less than 5 per cent in 5 countries (Iceland, The Netherlands, Luxembourg, Austria, and Norway), and fairly high (7.6–10 per cent) or intermediate (5.1–7.5 per cent) in the remaining 12 countries.

With respect to the third hypothesis, countries' combination of *trend* and *level* in unemployment is relevant. The experience of unemployment may be less harmful when the economy is improving. To examine this possibility, countries with high and rising unemployment (Spain, Portugal, and Bulgaria) will be compared with countries with high and falling unemployment (Latvia, Lithuania, and Estonia).

Survey Data

The European Union Statistics on Income and Living Conditions (EU-SILC) panel data are collected by a rotational method: a new sample of households/persons is introduced each year to replace roughly 25 per cent of the existing panel (Verma, Betti and Gagliardi, 2010: p. 15). Some have participated in all four survey years 2010–2013, but the data collection procedure, as well as attrition, implies that many panel respondents provide observations in only two or three waves.

Respondents aged 18–65 years have been analysed. The number of respondents and person-years (overall and by employment status) per country are given in Table A1. The analysed samples consist of respondents who were either in employment or outside employment but in the labour force and actively defining themselves as unemployed. Individuals who were not asked health questions, and people who reported—in any of the panel waves—that they were disabled, retired, inactive, students, in military service, or had domestic tasks as their main activity, were excluded. The assumption is that the employed will be the most relevant control group when estimating health effects of unemployment (cf. Roelfs et al., 2011: p. 850). However, negative health effects of unemployment could be upwardly biased if continuously employed people are positively selected on health characteristics. Therefore, analyses that included the disabled, retired, inactive, etc., were also performed, with similar findings (available on request).

Table 1. Unemployment rates in 25 European countries, 2010–2013

Country	2010	2011	2012	2013	Trend[a]	2010–2013[b]
Spain	17.8	19.2	22.5	23.8	+	20.8
Latvia	17.4	14.6	13.6	10.7	–	14.1
Lithuania	16.1	13.9	12.2	10.9	–	13.3
Portugal	10.5	11.3	13.9	14.7	+	12.6
Ireland	12.0	12.9	12.9	11.6	=	12.4
Slovakia	12.5	11.8	12.2	12.5	=	12.3
Estonia	14.9	11.2	8.9	7.6	–	10.7
Bulgaria	9.2	10.1	11.0	11.8	+	10.5
Hungary	10.0	9.9	9.7	8.9	=/–	9.6
Cyprus	5.1	6.4	10.2	13.6	+	8.8
Poland	8.1	8.0	8.5	8.8	=/+	8.4
Italy	6.9	6.9	8.9	10.2	+	8.2
France	7.7	7.7	8.2	8.7	=/+	8.1
Slovenia	6.5	7.5	7.9	9.2	+	7.8
Belgium	7.0	6.0	6.4	7.1	=	6.6
Finland	6.6	6.1	6.1	6.5	=	6.3
Denmark	6.3	6.3	6.3	5.9	=	6.2
Czech Republic	6.4	5.9	6.0	6.1	=	6.1
United Kingdom	5.8	5.8	5.7	5.4	=	5.7
Malta	5.6	5.0	4.9	5.2	=	5.2
Iceland	5.8	5.5	4.5	4.3	–	5.0
The Netherlands	3.9	4.0	4.7	6.1	+	4.7
Luxembourg	3.8	4.1	4.2	5.1	=/+	4.3
Austria	4.1	3.9	4.2	4.7	=/+	4.2
Norway	2.7	2.4	2.3	2.6	=	2.5

Notes:
[a]Unemployment trend: + (growing), – (falling), = (stable).
[b]Average unemployment rate for the years 2010–2013.
Source: Eurostat (2016a).
EU-SILC 2013 longitudinal data not available for Croatia, Germany, Greece, Romania, Sweden, and Switzerland.

Variables

The outcome measure is SRH, with response categories 'very bad', 'bad', 'fair', 'good', and 'very good', coded 0–4 (higher values indicating better health). *Level* of SRH was indicated by the last available observation, while *change in* SRH was indicated by subtracting the last available SRH observation from the first (cf. Böckerman and Ilmakunnas, 2009: p. 172). SRH is a generic health indicator widely used in research; although simple, it is associated with mortality risk (Mackenbach et al., 2002) and reflects both functional limitations, chronic disease, psychological malaise, and psychiatric conditions (Singh-Manoux et al., 2006; Präg et al., 2013).

Being unemployed is derived from a question on current economic status (unemployed = 1, employed = 0). The variable *becoming unemployed* signifies change from employment to unemployment in the past year (becoming unemployed = 1, else = 0). *Gender* is measured by a dummy variable for women (=1). *Age* is coded into five categories (16–25, 26–35, 36–45, 46–55, and 56–65 years), with 36–45 years as reference. Being *married* (yes = 1) is indicated by a dummy variable. Education is measured by a question on highest attained educational level and classified into *primary* (pre-primary, primary, and lower secondary), *secondary* (upper secondary and post-secondary non-tertiary), and *higher*, the latter being the reference category. *Years in paid employment* (and its square) measures labour market experience, while dummy variables for *part-time work*, having a *temporary work contract*, and being *self-employed* account for differences in work conditions.

Table A2 shows descriptive statistics on selected covariates for the country samples, split by employment status. In all 25 countries, the unemployed were less likely to hold higher education and to be married. The unemployed were significantly younger than the employed in all countries except for Finland, The Netherlands, and Slovenia.

Table 2. List of variables included in the propensity score analysis

Covariates	Two educational level dummies (higher education omitted), five age dummies (36–45 years omitted), gender, marital status, years in paid employment, years in paid employment squared, part-time work, temporary work contract, self-employed, bad health, LLSI
Treatment	Unemployed (being or becoming)
Outcome	SRH (level and change)

Statistical Methods

This study will examine effects of being/becoming unemployed on SRH in different macroeconomic contexts (i.e. country-level unemployment rates), and we will try to assess whether the estimated coefficients represent *causal* effects in line with the potential outcome understanding of causality (Angrist and Pischke, 2009; Morgan and Winship, 2010). The well-known challenge when investigating this issue is that employed and unemployed will typically differ on multiple characteristics, such as previous health trajectories, educational levels, and work histories (i.e. selection bias), making estimations of the effect of unemployment *per se* difficult. Several statistical techniques provide ways of dealing with this problem, but each of them has potential limitations. Here, we approach the causality issue by comparing findings from different statistical models and assess results in view of each model's characteristics.

First, we present results from OLS analyses, which show overall associations between employment status and SRH adjusted for gender, age, marital status, and education. A possible problem with the OLS results is that they may suffer from omitted variable bias, i.e. coefficients could be distorted when important confounders are not included in the model.

This difficulty can partly be addressed by *individual-level fixed effects* (FE) regression models (Angrist and Pischke, 2009: p. 221–227; Firebaugh, Warner and Massoglia, 2014). SRH is measured at least twice in the EU-SILC panel data, enabling adjustment for unobserved *time-invariant* characteristics, such as ability or motivation. FE models provide a wider adjustment for potential confounders than OLS, but bias may arise if important *time-varying* characteristics are unobserved. FE estimates are also 'notoriously susceptible to attenuation bias'; misreporting in only one panel wave may invalidate the measures of within-individual change used by FE models (Angrist and Pischke, 2009: p. 225). In the present study, estimates may moreover be imprecise when based on relatively few within-respondent changes in some of the country samples (see Supplementary Table S6).

An alternative to regression is *propensity score matching* (PSM). In general, causal analysis with matching methods consists in comparing outcomes between a treatment sample (those exposed to the assumed cause) and a control sample (the non-treated). If the two samples are 'matched' sufficiently well, differences in outcomes(s) can plausibly be ascribed to the treatment. In PSM, matching is attained by using propensity scores, defined as the probability of treatment assignment conditional on observed baseline covariates (Rosenbaum and Rubin, 1983). By weighting control cases so that propensity scores are distributed equally among treated and control subjects, causal effects may be credibly estimated if baseline characteristics used for calculating propensity scores cover all relevant differences between treated and non-treated (Morgan and Winship, 2010: pp. 98–109).

Most matching estimators can be written as nonparametric regressions (Morgan and Winship, 2010: p. 155), indicating basic similarities between PSM and regression methods. However, PSM estimations put most weight on 'covariate cells containing those who are most likely to be treated', while regression relies more on 'cells where the conditional variance of treatment status is largest', usually implying cells with equal numbers of treated and controls (Angrist and Pischke 2009: p. 76). Thus, PSM and regression may yield differing results, even if the same covariates are included in the models.

In our application, propensity scores (i.e. probability of being/becoming unemployed) were estimated with logistic regression (Angrist and Pischke, 2009: p. 83) adjusted for covariates known to be associated with unemployment (Austin, 2011). These covariates (listed in Table 2) were measured at the first year the respondent participated in the panel. Next, untreated respondents (the employed) were matched to the treated (the unemployed). Different algorithms exist for choosing and weighting matches (Morgan and Harding, 2006: pp. 30–33). We chose *kernel* matching (Morgan and Winship, 2010: p. 109) which uses all untreated respondents as matches, but each is weighted according to how close his/her propensity score is to the matched treated individual.[1] A successful 'balancing' of untreated with treated subjects was obtained (see Tables A2 and A3): all significant employed—unemployed differences in gender, age, education, and marital status were removed (exception: mean age in Hungary).

Analyses and Interpretations

Analyses are performed separately for the 25 countries. The OLS results will indicate overall unemployed—employed health differences adjusted for gender, age, marital status and education. To some extent, these estimates will probably reflect causal effects of unemployment, for instance among the long-term unemployed (e.g. respondents losing their job before 2010), but they are also likely to be contaminated by reverse causation (i.e. that respondents with ill health are more prone to unemployment).

From a causal inference perspective, the FE models are better, as time-invariant personal characteristics are accounted for. Moreover, the potential difference between OLS and FE results may be informative as to why health effects could vary with countries' unemployment level. If such country-variation occurs primarily because of less *stigma and self-blame*, one should observe smaller coefficients in high-unemployment countries in both OLS and FE models. The *compositional change* explanation, on the other hand, implies that the unemployed deviate more from the employed as to (unfortunate) individual characteristics in low-unemployment countries, compared to high-unemployment countries. FE models are better able than OLS to adjust for unemployed—employed health differences due to such variations in individual characteristics. In consequence, FE estimates will vary less with country-level unemployment rates than OLS estimates if compositional change is the chief explanation for larger health disparities in low-unemployment countries.

Similar reasoning applies to the PSM analyses. When *being* unemployed is the treatment variable, long-term unemployed people—including those who became unemployed because of ill health—will be included in the models, and estimated effects of unemployment on SRH may in part reflect reverse causation. When *becoming* unemployed is used as treatment, the analysed treatment is restricted to those who lost their job during 2010–2013, and more selection bias is accounted for by excluding the long-term unemployed. Again, if the less stigma/self-blame explanation is valid, both PSM models should show smaller effect sizes in high-unemployment countries. If, however, health effects vary less with country-level unemployment rates when using *becoming* unemployed instead of being unemployed as treatment, the compositional change explanation gains support.

Furthermore, the PSM analyses will also use SRH change scores—differences between first and last observation of SRH—as outcomes. With SRH change as outcome, trends in SRH within matched unemployed/employed 'pairs' are compared, adjusted for unobserved time-invariant traits. This amounts to a *difference-in-difference* model (Guo and Fraser, 2015: p. 298), which is similar to the FE model in focusing on within-individual changes adjusted for time-invariant confounders. Results may still differ, however, because PSM uses matched employed (for which health status can improve) as the control group, whereas FE uses the unemployed individual him/herself as controls.

One can argue that the PSM difference-in-difference model with *becoming* unemployed as treatment and SRH *change* as outcome is the model best suited to reveal causal effects of unemployment. In this specification, treatment and control samples are balanced on a wide set of observed covariates, time-invariant personal characteristics are adjusted for, and long-term unemployed are excluded since the analysis constrains unemployment occurrences to 2010–2013. However, statistical uncertainty rises in this model because relatively few individual-level changes are analysed in many of the country samples (Supplementary Table S6). Coefficients may also be attenuated because of misreporting (Angrist and Pischke, 2009: p. 225), and long-term health consequences of unemployment will be disregarded. We will therefore draw on results from all the above-mentioned models to assess the three hypotheses.

Results

OLS and FE Models

Table 3 presents results from OLS and FE regressions, both with standard errors clustered on individuals. The countries are listed according to average unemployment rates in 2010–2013 (highest to lowest, see Table 1). The OLS results, adjusted for gender, age, marital status, and education, indicate significantly worse SRH (using the P-value <0.05 criterion) among the unemployed in all 25 countries. However, the unemployed–employed difference is quite small in most countries, varying from -0.085 (Malta) to -0.588 (Austria) on the five-point scale (0–4).

Regarding Hypothesis 2—that health effects of unemployment will vary with unemployment levels—the quite large coefficients in several low-unemployment countries (e.g. Luxembourg, Austria, and Norway) are noteworthy. In the eight countries with highest average unemployment rate, the average OLS coefficient was less than half of the average in the five countries with lowest unemployment rates (-0.162 vs. -0.389).

Results from FE models[2] are reported in the right part of Table 3. In every country except for Malta, the FE coefficients are smaller—often much smaller—than

Table 3. Results from OLS and individual-level FE regression of SRH, by unemployment and covariates

Country	(1) OLS	(2) FE
Spain	−0.125*** (0.010)	−0.040*** (0.015)
Latvia	−0.154*** (0.015)	−0.047** (0.019)
Lithuania	−0.168*** (0.023)	−0.015 (0.030)
Portugal	−0.168*** (0.019)	−0.063*** (0.022)
Ireland	−0.159*** (0.022)	−0.024 (0.034)
Slovakia	−0.176*** (0.024)	−0.053** (0.023)
Estonia	−0.193*** (0.023)	−0.012 (0.027)
Bulgaria	−0.156*** (0.019)	−0.071*** (0.022)
Hungary	−0.285*** (0.016)	−0.048*** (0.018)
Cyprus	−0.119*** (0.019)	−0.089*** (0.026)
Poland	−0.154*** (0.016)	−0.075*** (0.016)
Italy	−0.132*** (0.012)	−0.064*** (0.018)
France	−0.182*** (0.017)	−0.032* (0.018)
Slovenia	−0.321*** (0.029)	−0.062* (0.036)
Belgium	−0.383*** (0.031)	−0.079* (0.041)
Finland	−0.272*** (0.029)	0.010 (0.031)
Denmark	−0.429*** (0.070)	0.077 (0.058)
Czech Republic	−0.353*** (0.032)	−0.069* (0.036)
United Kingdom	−0.287*** (0.026)	−0.013 (0.037)
Malta	−0.085** (0.035)	−0.112** (0.049)
Iceland	−0.170** (0.074)	0.003 (0.079)
The Netherlands	−0.286*** (0.037)	0.043 (0.036)
Luxembourg	−0.399*** (0.044)	−0.038 (0.054)
Austria	−0.588*** (0.039)	−0.079* (0.041)
Norway	−0.504*** (0.075)	−0.221*** (0.079)

Significance level: ***$P = 0.01$; **$P = 0.05$; *$P = 0.1$; NS/(empty) => 0.1.

Covariates: (1) OLS: Gender dummy, marital status dummy, two educational-level dummies (reference: higher education), and four age dummies (reference: 36–45 years).

(2) FE: Calendar year dummies.

Notes: Standard errors clustered at the individual for both OLS and FE models. Only unemployment coefficients shown. Full models available on request.

Number of observations in Table A1.

the OLS coefficients. FE estimated health effects of unemployment are nonetheless *negative* in 21 of the 25 countries. Thus, detrimental health effects appear also when time-invariant personal characteristics are accounted for, but effect sizes are mostly quite small, and the FE coefficients are significant (P-value <0.05) in only 11 countries.

Furthermore, the average FE coefficient in the eight high-unemployment countries was quite small (−0.041) and very similar to the average for the five low-unemployment countries (−0.058). When excluding the 'outlier' Norway, the average coefficient for low-unemployment countries declines to −0.018. This suggests, as discussed above, that *compositional change* could be a main reason for the tendency, found in the OLS analyses, towards larger unemployed–employed health differences in low-unemployment countries.

An improving economy with better re-employment likelihood could make it easier to cope with unemployment (Hypothesis 3). This issue can be assessed by comparing 'high and growing' unemployment countries (Spain, Portugal, and Bulgaria) with 'high and falling' countries (Latvia, Lithuania, and Estonia). Coefficients in the 'high and growing' category (−0.040, −0.063, −0.071) suggest slightly more negative health effects than in the latter category (−0.047, −0.015, −0.012), but coefficients are often small and insignificant.

PSM Estimates

PSM results are presented in Table 4 (four models), with *being* and *becoming* unemployed as treatment, and SRH *level* and SRH *change* as outcome.

The PSM model to the left in the table with *being* unemployed as treatment shows significant associations with SRH level in 23 countries, with insignificant, but nevertheless negative, coefficients in Hungary (−0.015) and Cyprus (−0.059). Average coefficients in the eight countries with high overall unemployment was −0.109, but twice as large (−0.223) in the five low-unemployment countries. This corresponds to the findings in the OLS models that health differences were larger in countries with low unemployment. These results are shown graphically in Figure 1 (Panel A): the country-level correlation between unemployment rates and PSM coefficients is significant ($R = 0.571$, $P = 0.003$).

The 'economic climate' Hypothesis 3 is not supported, however, since coefficients for Spain, Portugal, and Bulgaria (−0.061, −0.069, −0.154) were hardly different from the coefficients for Latvia, Lithuania, and Estonia (−0.091, −0.141, −0.139).

Indications of negative health effects of being unemployed appear also in the PSM analysis with SRH *change* as outcome (the second column in Table 4). The coefficient is negative in 24 of 25 countries, but statistically significant (P-value <0.05) in only eight. Effect sizes are rather small, except for Iceland (−0.191) and Austria (−0.106).

In the models using *becoming* unemployed as treatment, effects on SRH level tend to be smaller than in the corresponding PSM model with *being* unemployed as treatment. Nevertheless, the coefficient is negative in 22 countries (exceptions Ireland, Finland, and Malta), but significantly so in only 14. These results are displayed in Panel B in Figure 1, which illustrates that in many countries, effects fluctuate around −0.100 with a very slight tendency for less health effects in high unemployment

Table 4. Average treatment effect on SRH of being and becoming unemployed among the treated. Results from kernel matching, 25 European countries

	(1) Being unemployed		(2) Becoming unemployed	
	Outcome		Outcome	
Country	SRH	SRH change	SRH	SRH change
Spain	−0.061*** (0.021)	−0.031 (0.021)	−0.015 (0.022)	0.029 (0.027)
Latvia	−0.091*** (0.017)	−0.034* (0.018)	−0.075*** (0.024)	−0.047* (0.025)
Lithuania	−0.141*** (0.023)	−0.063*** (0.022)	−0.111*** (0.027)	0.080** (0.031)
Portugal	−0.069*** (0.021)	−0.034* (0.020)	−0.058** (0.025)	−0.043* (0.023)
Ireland	−0.073*** (0.026)	−0.033 (0.027)	0.012 (0.035)	0.005 (0.040)
Slovakia	−0.140*** (0.022)	−0.061** (0.026)	−0.109*** (0.038)	−0.038 (0.029)
Estonia	−0.139*** (0.023)	−0.065*** (0.022)	−0.136*** (0.031)	−0.055** (0.027)
Bulgaria	−0.154*** (0.021)	−0.056*** (0.018)	−0.094*** (0.026)	−0.042 (0.030)
Hungary	−0.015 (0.022)	−0.037 (0.023)	−0.006 (0.025)	−0.033 (0.027)
Cyprus	−0.059* (0.033)	−0.032 (0.035)	−0.066** (0.031)	−0.041 (0.035)
Poland	−0.115*** (0.013)	−0.051*** (0.014)	−0.082*** (0.020)	−0.035** (0.017)
Italy	−0.079*** (0.013)	−0.036*** (0.013)	−0.066*** (0.019)	−0.018 (0.024)
France	−0.063*** (0.018)	−0.006 (0.018)	−0.033 (0.020)	0.011 (0.021)
Slovenia	−0.116*** (0.029)	−0.041 (0.029)	−0.102** (0.041)	−0.049 (0.037)
Belgium	−0.176*** (0.038)	−0.050 (0.031)	−0.086* (0.048)	−0.039 (0.048)
Finland	−0.125*** (0.035)	−0.038 (0.030)	0.025 (0.064)	−0.015 (0.065)
Denmark	−0.314*** (0.067)	−0.084 (0.064)	−0.076 (0.064)	0.030 (0.050)
Czech Republic	−0.147*** (0.028)	−0.048 (0.031)	−0.188*** (0.035)	−0.052 (0.035)
United Kingdom	−0.172*** (0.030)	−0.037 (0.025)	−0.107*** (0.032)	−0.027 (0.034)
Malta	−0.090** (0.040)	−0.083 (0.052)	0.137** (0.060)	0.111 (0.082)
Iceland	−0.186*** (0.070)	−0.191*** (0.072)	−0.159 (0.118)	−0.080 (0.114)
The Netherlands	−0.137*** (0.037)	0.022 (0.040)	−0.080 (0.051)	0.064 (0.043)
Luxembourg	−0.228*** (0.042)	−0.067 (0.046)	−0.187*** (0.061)	−0.026 (0.052)
Austria	−0.276*** (0.034)	−0.106*** (0.034)	−0.195*** (0.042)	−0.028 (0.035)
Norway	−0.289*** (0.067)	−0.005 (0.062)	−0.166* (0.094)	0.018 (0.088)

Notes: Significance levels: $***P = 0.01$; $**P = 0.05$; $*P = 0.1$; NS/(empty) = > 0.1.
Bootstrapped standard errors (100 replications) in parenthesis.
Bandwidth = 0.02.

countries ($R = 0.281$, $P = 0.173$). The average coefficient for the eight countries with highest unemployment (−0.073) is lower than the average in the five countries with lowest unemployment (−0.157), implying some support for Hypothesis 2. The results do not favour Hypothesis 3, however, as Latvia, Lithuania, and Estonia (−0.075, −0.111, −0.136) have more negative coefficients than Spain, Portugal, and Bulgaria (−0.015, −0.058, −0.094).

As discussed earlier: if *compositional change* explains larger negative health effects in low-unemployment countries, cross-national variation in coefficients should be smaller when *becoming* unemployed, instead of *being* unemployed, is used as treatment in the PSM models. This is actually what emerges in Figure 1. The plotted line is clearly less steep, and the correlation coefficient is considerably lower, in Panel B than in Panel A.

Finally, the column to the very right in Table 4 presents results from the difference-in-difference analysis with *becoming* unemployed as treatment and SRH *change* as outcome. The coefficients in this model specification are negative in 17 countries, but most often of a very small size. Only in two countries—Poland (−0.035) and Estonia (−0.055)—are the coefficients both negative and statistically significant (*P*-value <0.05).

Sensitivity Tests

Different algorithms for constructing a control sample of untreated are available in PSM, and tests have shown that they may yield different results (Morgan and Winship, 2010: pp. 109–116). The analyses were performed using the *nearest neighbour* algorithm[3] as well, with four

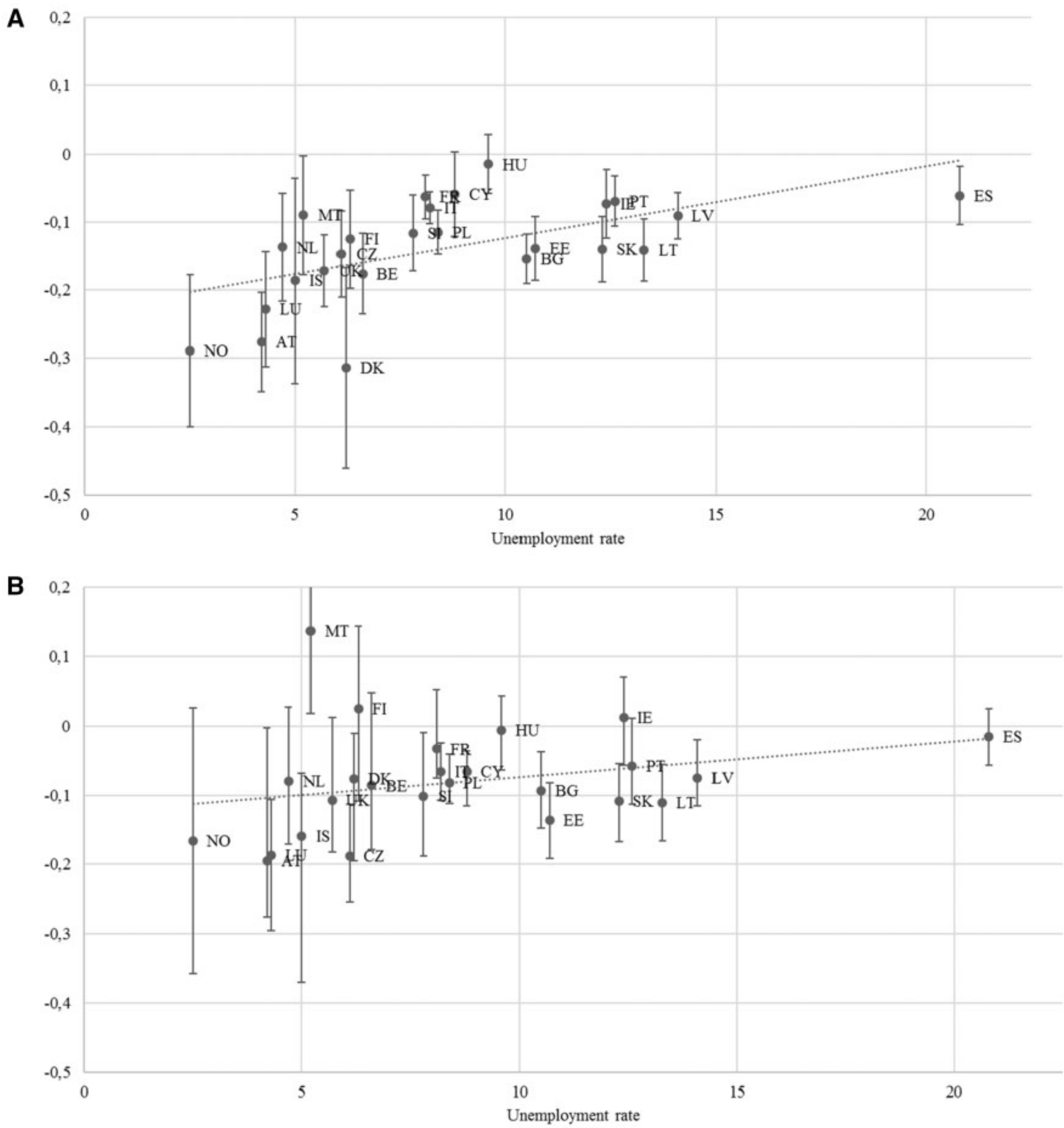

Figure 1. Average treatment effect of being (**A**) or becoming (**B**) unemployed on respondents' level of SRH in 25 European countries; results from PSM with kernel method

Notes: 95 per cent confidence intervals presented. Pearson's $R = 0.571$ ($P = 0.003$) in panel A, 0.281 ($P = 0.173$) in panel B.

matches per treated individual. These results were similar to the kernel results (see Supplementary Table S1).

In the EU-SILC data, a variable indicating *limiting long-standing illness* (LLSI) is available, and the analyses were also run with this outcome (Supplementary Tables S2 and S3). The results were basically similar to the SRH results, but effect sizes were smaller. This was not surprising, since LLSI is often due to chronic somatic diseases which would more seldom develop in the short run because of unemployment.

Effects could differ by gender, perhaps with men more inclined to health deterioration due to unemployment because of the traditional 'male breadwinner model'. Gender split results (Supplementary Tables S4 and S5) do not indicate that this is the case, however. Overall, results are similar for men and women, although some exceptions appear (see e.g. FE coefficients for Portugal, Malta, and Cyprus).

By analysing each country sample separately, relatively detailed insight into variations between countries is achieved. An alternative would be to pool all the EU-SILC country samples and utilize multilevel analysis, but a sample of 25 countries is barely large enough for this approach (Bryan and Jenkins, 2016). A linear multilevel model with country-level unemployment rate as the only level-two variable has nonetheless been estimated (Table A4, left column). An overall association between unemployment and worse SRH (coefficient −0.201) emerged, as well as a weak, but significant, tendency towards smaller employed–unemployed differentials in high-unemployment countries, in line with the OLS results and first PSM model reported above.

In this study, respondents' exposure to macroeconomic conditions has been indicated by the average country-level unemployment rate 2010–2013, but there may be considerable regional variation in unemployment within each country. Unfortunately, EU-SILC panel data provide few possibilities for analysing regions, but it is possible for Spain and France[4]. Results from four models analysing the Spanish and French samples are shown in Table A4. Overall, noticeable health effects of unemployment appear, but no ameliorating effect of higher regional unemployment. The regional unemployment coefficient is actually negative (suggesting more negative health effects the higher regional unemployment, contrary to Hypothesis 2), but very small (−0.001 and −0.020) in all models. However, even the 'best' regions in these countries had relatively high unemployment rates (13.8 per cent in País Vasco, Spain; 7.0 per cent in Limousin, France), suggesting that these regional findings should not be generalized to low-unemployment countries.

Discussion

The Three Hypotheses

Overall, the results are in line with Hypothesis 1 that unemployment has negative effects on respondents' SRH, regardless of unemployment levels and national contexts. In the OLS model, the unemployed reported significantly worse SRH than the employed in each of the 25 analysed countries. When using FE models, effect sizes were reduced considerably, but negative coefficients were nevertheless present in 21 of 25 countries, among which 11 statistically significant (P-value <0.05). Propensity score kernel matching indicated similar widespread, although small, negative health consequences both when using *being* and *becoming* unemployed as treatment. The most 'demanding' model, the PSM *difference-in-difference* analysis with *becoming* unemployed as treatment and *change* in SRH as outcome, resulted in rather small effects, but negative coefficients emerged in 17 countries. Thus, in every statistical model, negative health effects appeared in all, or at least in a majority, of the 25 countries.

Whether these findings should be interpreted as *causal effects* can be considered in view of the different model characteristics. Generally, the estimated health effects of *being* unemployed became lower the more controls that were included in the models. Average coefficients across the 25 countries were −0.250 for OLS, −0.138 for PSM, and −0.051 for the PSM difference-in-difference model with *being* unemployed as treatment (Figure 2, Panel A). The OLS results, with limited control for possible confounders, are probably exaggerated estimates of causal effects. It is, on the other hand, debateable whether the PSM difference-in-difference results should be regarded as optimal approximations to the causal effects. Adjusting for time-invariant personal characteristics is important to reduce selection bias, but analyses restricted to within-individual changes implies uncertainties about the estimates due to fewer analysed observations and a vulnerability to attenuated effects because change scores are more susceptible to measurement errors. A conjecture is therefore that the average causal effect of *being* unemployed is somewhere between the PSM (−0.138) and the PSM difference-in-difference coefficients (−0.051), i.e. noticeable, but overall rather small negative effects on SRH.

The FE model (which gave an average coefficient of −0.047 across the 25 countries, see Figure 2, Panel A) and the two PSM models with *becoming* unemployed as treatment (average coefficients −0.081 and −0.013, respectively) showed even smaller coefficients, as expected since long-term consequences of unemployment are disregarded in these models.

Figure 2, Panel B, summarizes the findings regarding Hypothesis 2—that negative health effects of unemployment will be smaller when unemployment rates are higher. The OLS results suggest systematically larger effects with lower levels of unemployment, but the FE models, in contrast, show no such pattern. The results from PSM models with SRH level as outcome and *being* and *becoming* unemployed as treatment suggest that negative health effects of unemployment are especially pronounced in low-unemployment countries. Thus, Hypothesis 2 is supported in the sense that countries with particularly low unemployment rates (e.g. Norway,

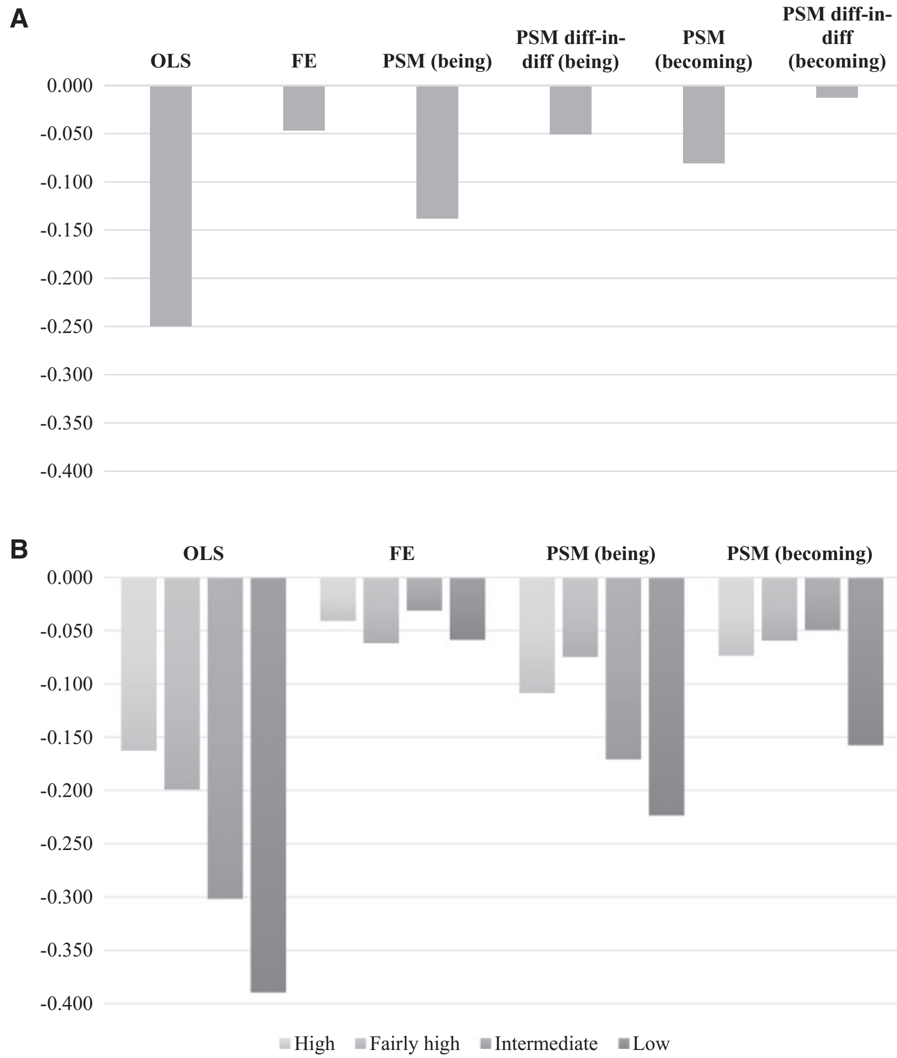

Figure 2. The relationship between unemployment and SRH. Average coefficients derived from OLS regression, individual-level FE models, and PSM with kernel method

Panel A. Average for 25 countries.

Panel B. Average for countries with a high, fairly high, intermediate, and low unemployment level (see page 3 and Table 1 for classification).

Austria, Luxembourg) seem to deviate markedly from the other countries.

Two possible explanations for such a pattern were proposed in the introduction: either that unemployment will hurt less in high-unemployment countries, since its commonness makes it *less stigmatizing*, or a *compositional change* explanation (i.e. a 'positively selected' unemployment population in high-unemployment countries). The findings that low-unemployment countries stand out empirically suggest compositional change as an important mechanism. In countries with low unemployment rates, selective processes in the labour market could contribute to a population of unemployed who has less satisfactory health and less coping resources. The diverging results between the different models support this interpretation: country-level variation in health effects is considerably larger in the more 'naïve' models (e.g. OLS, PSM *being* unemployed) than in models which account better for selection bias (e.g. FE, PSM *becoming* unemployed).

Hypothesis 3, suggesting that the unemployment experience would be more harmful when unemployment was high and growing compared to high and falling, received scant support in the analyses. Thus, *re-employment likelihood* is probably not an important explanatory factor for cross-national differences in health effects of unemployment.

Limitations

In the analysed panel data, the maximum follow-up period is 4 years, but many included respondents participated in merely two consecutive surveys. Thus, long-term health deterioration in consequence of unemployment could not be examined thoroughly (the OLS coefficients will probably include such long-term effects, but they will also be contaminated by reverse causation). Unfortunately, the EU-SILC data have no information on mental health problems, which are likely to be more sensitive in the short-run to stress and feelings of inadequacy accompanying unemployment. However, the subjective nature of the SRH indicator implies that it is associated with psychosocial well-being and other psychological conditions (Singh-Manoux et al., 2006; Präg et al., 2013).

Findings in the models which rely on observations of within-individual changes, suggest that the negative health effects of unemployment are often very small (and statistically insignificant) in many countries. However, because of possibly attenuated coefficients due to measurement errors, these estimates could be biased towards zero. Findings will also be plagued by statistical uncertainty, since relatively few within-individual changes were available for analyses in several of the country samples.

Another limitation in these data is the possible discrepancy between the country-level unemployment rate and what the unemployed actually experience. An unemployed individual might encounter few other unemployed in the local area, and re-employment chances may be good even when the national unemployment rate is high. This is of relevance for Hypothesis 3, where our interpretation depends on the uncertain assumption that a high and rising national unemployment rate will somehow be observed and experienced by most respondents.

As regards the PSM models, the kernel procedure seems to have been successful. Omitted variable bias is still a concern, however, as unobserved cognitive abilities or certain personality characteristics could be important for both the probability of exposure to unemployment and to how well a person deals with the experience. A potential problem with the treatment measurement is that the exact duration of unemployment cannot be determined in these data. There is also a possibility that negative health effects are downwardly biased towards zero if also the employed (i.e. the control group) experience deteriorated health during an economic downturn, for instance due to fear of job loss.

Conclusions

Unemployment tends to hurt SRH, whatever unemployment rates and national contexts. OLS models indicate that the unemployed are in worse health than the employed throughout the 25 analysed countries. The association is reduced considerably, but remains significant in several countries when time-invariant personal characteristics are accounted for in individual-level FE models. Models applying propensity score kernel matching show that both being and becoming unemployed is associated with worse SRH in the short run, although effect sizes are small. The analyses indicate a slight tendency towards less health effects of unemployment in countries where the experience is more widely shared. In particular, countries with a very low unemployment rate stand out with larger coefficients. The findings overall suggest that variations in the composition of the unemployed population are important for explaining cross-national differences in the unemployment–health association.

Notes

1 PSM enables different (causal) effects to be estimated. ATE is the average effect—at the population level—of moving an entire population from untreated to treated, whereas the ATT is the average effect on those subjects who received the treatment. ATT is most relevant in the present study, since we wish to examine the health effects of unemployment among people who have actually experienced it. ATT is estimated in kernel matching with the following equation:

$$ATT = \frac{1}{N^T} \Sigma_{i \in T} \left\{ Y_i^T - \Sigma_{j \in C} Y_j^C K\left(\frac{e_j(x) - e_i(x)}{h_n}\right) / \Sigma_{k \in C} K\left(\frac{e_k(x) - e_i(x)}{h_n}\right) \right\}.$$

Here, N^T is the number of treatment cases, $Y$is SRH (level or change), i is an index of treatment cases, and j is an index of control cases. $e_j(x)$ is the propensity score of case j in the control group, $e_i(x)$ is the propensity score of case i in the treated group, and $e_j(x) - e_i(x)$ is the distance of the propensity scores (Li, 2013: p. 204). In kernel matching, all untreated respondents are used as matches, but each untreated is weighted (denoted K) according to how close his/her propensity score is to the matched treated individual. How differences in propensity scores translate into weights are determined by the 'bandwidth' parameter (denoted h_n), in our case set to

0.02. Bootstrapped standard errors (100 replications) are reported for the PSM analyses.

2 Only calendar year dummy variables are included in the FE models. The results were similar with potentially time-varying covariates (e.g. marital status, income) included.

3 Nearest neighbour matching was performed with replacement, and the range of available matches was restricted by a caliper of 0.01. Nearest neighbour matching indicated somewhat more negative health effects of *being* unemployed in France, but less in Cyprus, Malta, Slovenia, and the United Kingdom. More health effects of *becoming* unemployed were found in Hungary, but less in The Netherlands and Malta.

4 Spain and France are the only countries included in EU-SILC with detailed information on residential region (19 and 22 regions, respectively). For 15 of the 25 countries analysed in this study, the number of regions is either one, or missing. For the remaining eight countries, the number of regions is low (2–5), and/or there is a large discrepancy between the number of observed regions and the actual number of regions in the country.

Supplementary Data

Supplementary data are available at *ESR* online.

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Appendix

Table A1. Number of individuals and person-years for 25 European countries, overall, and by employment status

	Overall		Employed		Unemployed	
Country	Individuals	Person-years	Individuals	Person-years	Individuals	Person-years
Spain	15,638	35,014	12,139	25,939	5,662	9,071
Latvia	7,044	16,369	5,949	13,069	2,131	3,300
Lithuania	4,726	11,278	4,089	9,569	1,016	1,709
Portugal	6,37,0	15,932	5,314	12,696	1,921	3,230
Ireland	4,942	9,979	3,991	7,949	1,312	2,028
Slovakia	6,648	17,079	5,967	15,005	1,222	2,074
Estonia	5,533	11,445	4,915	9,919	1,055	1,526
Bulgaria	5,874	15,138	4,901	12,089	1,600	3,049
Hungary	12,466	28,850	11,067	24,788	2,672	4,062
Cyprus	6,478	15,817	5,775	13,538	1,532	2,279
Poland	14,672	35,381	12,982	30,585	2,945	4,796
Italy	21,179	44,053	18,270	37,323	4,469	6,730
France	15,745	42,062	14,502	37,698	2,677	4,361
Slovenia	5,394	11,779	4,593	9,824	1,259	1,952
Belgium	6,535	14,389	5,868	12,797	1,003	1,584
Finland	6,459	15,061	5,931	13,579	951	1,482
Denmark	2,044	5,269	1,972	4,943	203	281
Czech Republic	6,590	15,316	6,155	14,063	798	1,253
United Kingdom	13,448	24,140	12,660	22,700	1,172	1,426
Malta	4,466	10,751	4,233	10,148	381	603
Iceland	1,611	3,763	1,540	3,552	155	208
The Netherlands	6,362	15,052	6,154	14,471	451	561
Luxemburg	4,985	10,904	4,722	10,167	533	737
Austria	6,537	14,813	6,146	13,733	764	1,080
Norway	3,848	8,669	3,734	8,416	190	234

Notes: Only participants answering health questions are included in the sample.
Individuals with missing information on health variables were dropped.
Only people in the labour force included (disabled, retired, inactive, students, in military service, and fulfilling domestic tasks are dropped).
People aged over 65 and under 18 years are excluded from the sample.
Source: EU-SILC Panel Data 2013.

Table A2. Descriptive statistics on selected covariates, by employment status

	Higher education (per cent)		Mean age		Married (per cent)		Woman (per cent)	
Country	Employed	Unemployed	Employed	Unemployed	Employed	Unemployed	Employed	Unemployed
Spain	38.21	19.90***	43.52	40.59***	62.92	48.29***	44.78	47.96***
Latvia	32.78	12.59***	43.29	41.74***	49.30	34.48***	53.58	43.79***
Lithuania	39.88	14.04***	46.25	44.14***	72.77	53.72***	56.93	46.93***
Portugal	18.50	9.05***	42.92	41.06***	63.25	47.99***	49.53	49.85
Ireland	52.37	29.39***	41.87	39.05***	61.31	40.25***	48.66	29.34***
Slovakia	25.40	10.82***	41.90	37.20***	61.85	40.52***	48.10	50.34*
Estonia	36.47	16.20***	43.65	40.66***	50.71	34.86***	55.63	43.97***
Bulgaria	28.01	9.81***	43.80	40.62***	63.36	47.88***	48.12	42.05***
Hungary	25.00	7.25***	42.72	39.29***	56.45	37.84***	48.33	47.24
Cyprus	37.66	31.55***	41.95	37.64***	71.62	51.95***	50.07	46.16***
Poland	26.19	9.95***	41.71	39.35***	72.11	54.30***	45.90	53.86***
Italy	19.37	10.88***	43.42	37.59***	59.58	37.24***	42.79	42.33
France	37.17	19.58***	42.45	38.85***	52.64	33.35***	48.76	49.05
Slovenia	32.38	13.24***	41.75	41.85	54.47	44.98***	48.59	49.85
Belgium	47.56	20.89***	42.14	41.61*	54.25	37.14***	48.16	49.31
Finland	45.06	19.94***	45.06	45.71**	55.69	34.89***	46.52	37.65***
Denmark	43.95	26.47***	47.22	46.08*	68.44	50.18***	48.82	51.25
Czech Republic	19.50	5.12***	43.86	42.39***	59.79	44.37***	50.30	56.42***
United Kingdom	44.19	25.13***	42.99	38.11***	58.41	29.17***	48.99	41.87***
Malta	22.57	5.47***	39.80	35.31***	59.25	29.52***	36.82	25.87***
Iceland	35.68	17.31***	45.00	38.05***	57.79	37.81***	48.56	40.38**
The Netherlands	43.17	30.98***	44.54	45.90***	54.75	36.90***	49.51	48.48
Luxembourg	28.27	15.04***	41.09	36.56***	57.06	32.84***	45.48	46.27
Austria	23.30	9.72***	41.75	40.48***	54.28	36.67***	46.36	47.41
Norway	45.91	23.14***	44.27	37.22***	52.38	29.06***	44.33	38.89*

Notes: Pooled data. Full descriptive statistics available on request.
T-test on the difference between unemployed and employed.
Significance levels: $^{***}P = 0.01$; $^{**}P = 0.05$; $^{*}P = 0.1$; NS/(empty) = > 0.1.

Table A3. Covariate balancing, derived from kernel matching (treatment = being unemployed, outcome = SRH level)

Country	Higher education (per cent)		Mean age		Married (per cent)		Woman (per cent)	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control
Spain	26.40	26.78	41.69	41.37	58.29	57.76	43.55	43.45
Latvia	14.20	14.32	42.82	42.76	38.32	38.60	46.56	46.35
Lithuania	16.41	16.75	44.66	44.85	61.23	61.48	47.15	46.75
Portugal	8.99	8.30	42.47	42.46	54.19	54.86	50.54	50.04
Ireland	31.62	31.80	40.90	41.17	45.06	45.93	32.21	31.58
Slovakia	9.73	10.34	41.91	41.52	55.47	54.63	51.70	52.31
Estonia	19.64	20.25	42.29	42.22	41.54	41.73	45.06	45.83
Bulgaria	10.82	10.64	44.01	44.05	57.24	56.53	42.93	42.35
Hungary	5.52	6.07	41.04	42.42***	42.54	42.39	48.30	47.97
Cyprus	27.64	28.31	41.32	40.91	68.84	66.99	41.20	42.37
Poland	10.33	10.48	41.03	40.90	61.70	60.86	53.21	52.94
Italy	11.02	10.70	39.54	39.52	44.08	44.08	46.44	46.25
France	21.83	22.70	39.33	39.60	36.09	36.88	50.61	50.50
Slovenia	13.86	14.93	44.34	44.32	51.19	52.24	48.81	49.15
Belgium	22.26	22.52	41.84	41.51	40.66	41.09	49.75	49.46
Finland	23.50	25.04	46.98	46.75	37.75	38.35	39.74	40.02
Denmark	24.56	25.58	47.01	46.75	56.14	58.30	49.12	49.57
Czech Republic	5.81	7.19	43.35	43.45	49.86	50.50	57.79	57.54
United Kingdom	28.45	30.44	40.95	40.95	33.17	36.27	42.49	43.04
Malta	6.69	9.17	38.26	38.67	37.01	39.93	30.32	31.15
Iceland	17.52	21.04	38.56	39.10	37.23	37.70	40.15	40.77
The Netherlands	28.01	29.67	47.59	47.16	41.18	42.93	47.90	48.86
Luxembourg	13.90	15.63	39.26	38.83	41.12	41.17	48.88	48.76
Austria	10.69	11.91	40.63	40.52	39.74	41.96	47.69	47.74
Norway	23.08	24.56	36.82	37.51	26.92	31.67	39.56	39.38

Notes: *T*-test on the difference between treated and control subjects.
Significance levels: ****P* = 0.01; NS/(empty) = > 0.1.

Table A4. Results from multilevel and regional analyses of SRH, by unemployment, unemployment rate (country/region), and covariates

Variables/country	(1) Multilevel (linear)	(2) OLS	(3) OLS regional FE	(4) Individual FE	(5) Individual and regional FE
Unemployment	−0.201*** (0.003)				
Country-level unemployment	0.022*** (0.003)				
N observations/countries	443,650/25				
Spain					
Unemployment		−0.125*** (0.010)	−0.125*** (0.010)	−0.039*** (0.015)	−0.039*** (0.015)
Regional unemployment		−0.001** (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.020 (0.019)
N observations		34 224	34 224	35 010	35 010
France					
Unemployment		−0.182*** (0.017)	−0.182*** (0.017)	−0.032* (0.018)	−0.032* (0.018)
Regional unemployment		−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.000 (0.001)
N observations		41,888	41,888	42,058	42,058

Significance level: ***$P = 0.01$; **$P = 0.05$; *$P = 0.1$; NS/(empty) = > 0.1.

Covariates: Models 1–3: Gender dummy, marital status dummy, two educational-level dummies (reference: higher education), and four age dummies (reference: 36–45 years).

Models 4–5: Calendar year dummies.

Notes: Only unemployment and unemployment rate (country/region) coefficients shown. Full models available on request.

Only country-level unemployment rate included at Level 2 in Model 1. See Table 1 for 2010–2013 average unemployment rates (varying from 2.6 to 23.8).

2010–2013 average of regional unemployment rate varies from 13.83 (País Vasco) to 32.13 (Andalucía) in Spain, and from 7.03 (Limousin) to 13.38 (Languedoc-Roussillon) in France.

Source: Eurostat.

There are 19 and 22 regions in Spain and France, respectively. The region with largest sample size is the reference group in Models 3 and 5: Andalucía ($N = 4{,}185$) and Île de France ($N = 5{,}719$).

Standard errors clustered at the individual for Models 2–5.