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Why are the unemployed in worse health? The causal effect of unemployment on health

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ABSTRACT

We analyse the effect of unemployment on health using information from the German Socio-Economic Panel of the years 1991–2008. To establish a causal effect we rely on fixed-effects methods and plant closures as exogenous entries into unemployment. Although unemployment is negatively correlated with health, we do not find a negative effect of unemployment due to plant closure on health across several health measures (health satisfaction, mental health, and hospital visits). For this subgroup of the unemployed, unemployment does not seem to be harmful and selection effects of ill individuals into unemployment are likely to contribute to the observed overall correlation between poor health and unemployment.

1. Introduction

The association between unemployment and health is well documented in the empirical literature. Various studies report a strong negative correlation between individual health and the experience of unemployment, or, more generally, between health and low income (see, e.g., Adams et al., 2003). However, the direction of causality is not yet well understood. There are at least three pathways that can lead to the observation of a less healthy stock of unemployed compared to the stock of employed. First, there is a selection of ill workers from work into unemployment. García-Gómez et al. (2010), Arrow (1996), Riphahn (1999), and Lindholm et al. (2001) provide evidence that the likelihood of becoming unemployed is higher for ill workers. Second, poor health causes longer unemployment spells, as shown by Stewart (2001). Both points – selection of ill workers into unemployment and selection of healthy workers out of unemployment – increase the probability of observing an ill individual in the stock of unemployed and, thus, lead to a lower average health status of the stock of unemployed.

Third, unemployment itself might lead to a deterioration in health. The causal effect of unemployment on health is probably the most difficult of the three to show. There are most likely individual unobservable effects that both affect health and the probability of becoming unemployed, for instance a general frailty or other genetic factors. Usually, panel data help to control for this unobserved heterogeneity. Moreover, the health-related selection into unemployment needs to be considered. Since there might be reversed causality (e.g., a health shock that both decreases health and leads to unemployment), a causal effect can only be established if this selection effect is controlled for.

If unemployment indeed deteriorates health the individual and social costs of unemployment are higher than usually assumed and policymakers should try even harder to get the unemployed back into the labour market. An additional motivation to examine this third point is to find out more about the nature of unemployment. The life satisfaction literature concludes that unemployment is involuntary if it causally reduces life satisfaction (Winkelmann and Winkelmann, 1998). Similar arguments hold for health. It can be assumed that unemployment negatively affects health especially if it is involuntary.[1]

There are only a few studies that analyse the effect of unemployment on health with German data. Romeu Gordo (2006) finds a negative effect of short-term unemployment on health

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[1] This is true at least in countries where unemployment does not imply the loss of health insurance and leads to only a moderate drop in income, like in Germany.

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satisfaction for men but no effect for women with SOEP data from 1984–2001. Moreover, long-term unemployment decreases health satisfaction of both men and women. However, although Romeu Gordo (2006) uses panel data and can therefore control for unobserved heterogeneity, the author cannot exclude that reversed causality may have biased the result. Huber et al. (2010) focus on welfare recipients (usually long-term unemployed) as a subgroup of unemployed and restrict their analysis to exit from unemployment. They find positive effects of returning to work on health, in particular the mental health of males.

The contribution of this paper is the following: First, in contrast to most of the international literature (Salm, 2009 being among the exceptions), we do not only use one health measure as an outcome variable but several different ones. In addition to health satisfaction (as in Romeu Gordo, 2006) these are the probability of a hospital visit within four years after the interview as a more objective health measure, and a measure of mental health. Moreover, we use the appropriate econometric methods by accounting for the ordered nature of the health satisfaction variable. Third, and most importantly, we extend the analysis by Romeu Gordo (2006) by accounting for the possible endogeneity of the entry into unemployment. In principle, this can be done by estimating a simultaneous equations model with health and the labour market status as endogenous variables (see Cai, 2010). Here, we rely on an alternative approach by using plant closures as an exogenous reason for unemployment. Doing this, reversed causality (from poor health to unemployment) is ruled out.

We find that the reason of unemployment entry has a strong impact on the results. Using data from the German Socio-Economic Panel for the years 1991–2008 and including *all* unemployed in the analysis, we find that unemployed are less healthy than employed according to all health measures. However, this is not causally due to unemployment, since there is no effect at all if unobserved heterogeneity is controlled for and exogenously unemployed are considered. In this latter group, unemployment does not deteriorate health. Thus, the worse health status of the unemployed might only be a selection effect into unemployment.

The results are in line with several international studies in the recent literature that either use plant closures or mass lay-offs to rule out a health-driven selection into unemployment. Browning et al. (2006) find no causal effect of job loss on the probability of entering a hospital due to symptoms caused by mental stress after four years with Danish register data. Salm (2009) finds no effect on several subjective and objective health measures with data from the HRS. Kuhn et al. (2009) do not find short-run effects of job loss on public health costs associated with health care utilisation. However, they do find that job loss increases hospitalisations for mental health reasons and prescriptions for antidepressants (both for males only). There are also studies that do find strong effects of involuntary job loss on subsequent mortality (e.g., Sullivan and von Wachter, 2009; Eliason and Storrie, 2009). A difference in our study is that we analyse the effect of actually being unemployed instead of the mere job loss on health. Also doing this, Böckerman and Ilmakunnas (2009) do not find negative effects of unemployment on self-assessed health for Finland, although they do not restrict their analysis to mass lay-offs or plant closures as reasons for unemployment.

The next section presents the data used in the analysis. Section 3 explains the econometric strategy while Section 4 reports the regression results. Section 5 presents robustness checks and Section 6 concludes.

2. Data

The database for the empirical analysis is the German Socio-Economic Panel (SOEP), which started in 1984 with more than 12,000 individuals in West Germany and was extended to East Germany in June 1990. There were several refreshments resulting in a sample size of more than 20,000 adult individuals living in about 13,000 households that participated in the SOEP survey in 2006 (see, e.g., Wagner et al., 2007).[2]

The SOEP contains information on the current labour force status in each wave. We collapse full-time and part-time employment to the category "working". In case of a job termination, the SOEP asks for the reason. Possible reasons include own resignation, dismissal, plant closure, and end of a temporary job. Because the question differed somewhat before 1991 and we rely on the reason of the job loss later in the econometric analysis, we only use data from 1991 to 2008 in the analysis. We exclude all individuals above the age of 58 because of special regulations that allowed for possible voluntary unemployment in combination with early retirement at around this age in the past.

Individuals who are out of the labour force are dropped from the sample at the time they leave the labour force. This is done irrespective of their previous labour force status (work or unemployment due to any reason). Due to the age restriction of 58 in our analysis this does not affect many observations. Individuals that return to the labour force (or into unemployment) after having left the labour market re-enter the sample. This, however, only applies to a couple of observations.[3] Over the whole sample period we get a panel of up to 180,117 observations in person-year form, resulting from 23,734 individuals.

We use three different health measures. The first one, satisfaction with health, is a self-stated measure on an 11-point scale, ranging from 0 (totally unhappy) to 10 (totally happy). It refers to the day of the interview and, thus, reflects the current health status. This variable is widely used in the literature to proxy the health status, e.g. by Frijters et al. (2005) or Jones and Schurer (2010). It is a subjective measure but this kind of measures has been shown to have high predictive power for morbidity and subsequent mortality (see, e.g., Idler and Benyamini, 1997, for a review of studies which use self-rated health as a health variable).[4] Furthermore, it gives a more complete picture of overall health than many single objective measures can do. It combines physical and mental health and might be the preferred measure when we think of health in terms of the utility derived from it.

The second measure, the Mental Component Summary Scale (MCS), is a measure of mental health. It is based on the SF12v2-questionnaire in the SOEP that includes several questions about health quality and health satisfaction of individuals. The exact questions which include questions about phases of melancholy, emotional problems or social limitations due to mental health problems are presented in Table A1 in the Appendix A. All questions refer to mental health problems within the period of four weeks before the interview. Thus, they reflect the current mental health status. The Mental Component Summary Scale is provided by the SOEP-group and calculated using explorative factor analysis. It ranges from 0 to 100, with a higher value indicating a better health status. The mean value of the SOEP 2004 population is set to 50 with a standard deviation of 10 (see Andersen et al., 2007, for a description).

[2] The data used in this paper were extracted using the Add-On package PanelWhiz v3.0 (Jul 2008) for Stata. PanelWhiz was written by Dr. John P. Haisken-DeNew (john@panelwhiz.eu). The PanelWhiz generated Do file to retrieve the SOEP data used here and any Panelwhiz Plugins are available upon request. Any data or computational errors in this paper are my own. Haisken-DeNew and Hahn (2006) describe PanelWhiz in detail.

[3] As an example, someone who appears in the panel in ten waves and is out of the labour force in three of the ten years contributes to the analysis with seven observations in person-year form. Including observations that are out of the labour force in the analysis and controlling for this state with a dummy does not affect the results at all.

[4] We do not use the five-point-scaled self-rated health status since it is not available for all years. For the years it is available, its correlation with health satisfaction is 0.77. Moreover, robustness checks that use self-rated health as an outcome measure do not lead to different conclusions.

The third measure is a more objective indicator of individual health. It is the binary variable for having at least one overnight hospital stay in the next four years after the interview. In order to make it comparable to the other two measures with a higher value meaning a better health status, we define the variable as *no* hospital visit. The SOEP asks about the hospital visits in the *last* twelve months, therefore we use information from the four future waves after the current interview. Hospital visits are a fairly crude measure of health, but also widely used in the literature. However, in contrast to Browning et al. (2006) we do not know the reason of the hospital visit and cannot, therefore, distinguish between hospital visits due to symptoms that arise from mental stress and other reasons.[5]

While health satisfaction is available for all waves between 1991 and 2008, the question about hospital visits was not asked in 1993. Therefore, and because of the prospective nature of the variable, we cannot use the years 1991–1992 and 2005–2008 for this measure. The mental health score is only available for the years 2002, 2004, 2006, and 2008. Hence, more observations for health satisfaction than for the other two indicators can be used. The three measures reflect different aspects of the individual health status. While health satisfaction is an overall measure, the Mental Component Summary Scale only represents mental health. The hospital visits are objective but can be seen as an indicator of bad health only. For instance, this measure does not discriminate between forms of very good and good health if for both types no hospital visit at all is necessary. No measure can thus *per se* be preferred to the other ones and a complete picture of the effects of unemployment on health can be achieved when all indicators are used together in the analysis. The three variables are significantly and positively correlated in the data with health satisfaction and mental health showing the strongest correlation (0.32). Since (no) hospital visits are given as a binary variable only, the correlation coefficient of this one and the other two measures is naturally smaller (0.14 with health satisfaction and 0.07 with mental health).

When analysing the effect of unemployment on health there is the potential problem of reversed causality or endogenous unemployment. It may well be that we observe a working individual in good health in one year in the sample and in bad health and unemployment in the following one. Because we only have the information on the health status at two points in time (before and after the day of the job loss) we cannot exclude the case that the individual first became ill and then lost her job (or quit) due to bad health. In order to identify the causal effect of unemployment on health we need an exogenous reason for unemployment, especially one that is not related to the individual health status.

In this study we rely on plant closures as an exogenous reason for unemployment (see Salm, 2009; Browning et al., 2006, or Kuhn et al., 2009 for a similar argumentation).[6] Table 1 reports the number of observations for the different health measures. Only about 5% of all the unemployed (in person-year observations) are unemployed due to plant closure. This means a reduction of identifying observations for the estimation of the effect of unemployment on health. However, we still have enough individuals for a reasonable analysis.

Table 1 also reports the means of the three health measures for all working individuals, all unemployed and the subgroup of unemployed due to plant closures. According to all measures, the stock of unemployed consists of less healthy individuals than the stock of employed. Although being a special group, the unemployed due to plant closure do not differ significantly from the other unemployed with respect to their health status. They have a slightly lower health satisfaction and a slightly higher likelihood of a hospital visit but a better mental health (all differences not significant). However, these are only raw means without controlling for observable and unobservable individual effects that may be correlated with both health and the labour market status. Thus, the table does not reflect a causal relationship between health and unemployment. We try to answer this question with a regression analysis, the strategy of which is outlined in the next section.

To get a better idea of the (potentially health-related) dynamics of unemployment in the data, Table 2 reports transitions of individuals who are unemployed at one point in time in the following year. Four states are possible: (a) individuals are still unemployed one year after, (b) they are back on the labour market, (c) they left the labour force (mainly due to retirement or homemaking), or (d) they are right censored. Censoring mostly appears because individuals reach the age

Table 1
Means of the health measures.

	Health satisfaction	No hospital visit	Mental health
Means All	7.01	71.28%	49.74
Observations All	180,117	90,562	45,664
Means Unemployed	6.38	65.47%	47.50
Observations Unemployed	15,780	7987	3936
Means Unemployed PC	6.26	65.28%	48.62
Observations Unemployed PC	899	527	200
Means of other covariates (full sample)			
$28 \leq \text{Age} \leq 32$	0.127	0.127	0.098
$33 \leq \text{Age} \leq 37$	0.146	0.154	0.136
$38 \leq \text{Age} \leq 42$	0.155	0.161	0.170
$43 \leq \text{Age} \leq 47$	0.147	0.149	0.170
$48 \leq \text{Age} \leq 52$	0.129	0.126	0.151
$53 \leq \text{Age} \leq 58$	0.128	0.131	0.144
Male	0.543	0.556	0.531
Foreign	0.114	0.107	0.070
West	0.741	0.715	0.756
Years of education	12.072	12.002	12.527
Married	0.625	0.649	0.611
Children in household	0.430	0.447	0.400
Private insurance	0.118	0.108	0.156
Education/Vocational training	0.078	0.078	0.068
Blue collar	0.346	0.358	0.291
Self-employed	0.085	0.079	0.097
Civil servant	0.060	0.059	0.071
Other position	0.053	0.054	0.044
Quarter of interview = 2	0.254	0.219	0.255
Quarter of interview = 3	0.066	0.055	0.058
Quarter of interview = 4	0.006	0.007	0.001

Source: SOEP 1991–2008. The three health measures imply three different samples. Therefore, the lower part reports means of the covariates for the three samples used.

Table 2
Transitions of unemployed in the next period.

All unemployed	Share in %	Health satisfaction	No hospital visit	Mental health
Unemployed	44.61	6.17	64.5%	47.18
Working	33.19	6.88	70.1%	48.64
Censored	14.72	6.19	61.3%	47.58
Out of labour force	7.48	5.83	53.0%	45.12
Unemployed due to plant closure				
Unemployed	51.28	6.10	64.7%	47.37
Working	33.70	6.76	69.0%	50.41
Censored	9.57	5,.98	65.5%	50.47
Out of labour force	5.45	5.20	48.5%	42.20

Source: SOEP 1991–2008.

5 We do, however, exclude women who gave birth within the 4-year-period from the analysis since it is most likely that they had a hospital visit due to this reason not being related to bad health.

6 "Plant closure" does *not* include job loss of self-employed who had to close down their own business. The questionnaire explicitly allows for this reason as well, allowing us to distinguish between both reasons and use only the category "plant closure" in the SOEP.

of 58 and are dropped from the sample or because it is the last year in the panel (mostly 2008).

Out of 100% of all who were unemployed in the base period, 44.61% were still unemployed one year after, 33.19% returned to work, and 7.48% left the labour force. Apparently, healthy individuals are more likely to find a job after unemployment according to all three health measures.[7] In contrast, unhealthy individuals are more likely to leave the labour force. Note, however, that these means are not conditional on other covariates. Therefore, the worse health status of those who left the labour market might also be due to their higher age compared to the remaining sample.

The lower panel of Table 2 repeats the statistics for unemployed due to plant closure. Two findings are notable. First, the transition rates into work do not differ strongly for this subgroup. Thus, this group does not find a job after unemployment faster than the average unemployed irrespective of the reason. Second, the health differences between those who found a job one year after and those who did not are also similar to those found for all unemployed. Thus, the results in the regression analysis below do not seem to be driven by the fact that unemployment durations are much shorter for the unemployed due to plant closure.

3. Econometric model

Health satisfaction is an ordinal measure, hence ordered logit or ordered probit seems to be the appropriate estimation method instead of ordinary least squares which assumes cardinality of the outcome variable. The general notion of ordered models in our context is that there is a latent health status y^*_{it}, unobserved by the researcher. Respondents report a health satisfaction of $y_{it}=j$ if y^*_{it} falls within the range of the unobserved thresholds α_{j-1} and α_j. Assuming the linear relationship $y^*_{it}=X'_{it}\beta+u_{it}$ and that u_{it} follows a logistic distribution, the parameters β and the thresholds α can be estimated by ordered logit models.

When estimating the relationship between health and unemployment it is essential to control for other factors that affect both health and the likelihood of becoming (and staying) unemployed. Although we include several variables to control for observed heterogeneity, a great deal of unobservable heterogeneity is likely to remain. Possibly, parts of the unobserved factors are correlated with the labour force status (or other covariates) rendering the estimated coefficients inconsistent. These unobserved effects could be genetic factors or a general frailty of the individuals, i.e., a potentially bad baseline health status. Likewise, one might think of risk aversion, or time preferences as important unobserved factors. Less risk averse individuals might be more likely to find a job (but also to lose it) and less likely to be in a good health status due to less preventive efforts and a more risky behaviour.

Since the mentioned unobserved effects can be assumed to be time invariant – at least over a limited period of time – we rewrite u_{it} as $u_{it}=\varepsilon_i+\nu_{it}$ and assume that these factors are captured by ε_i. Likewise, we assume strong exogeneity of the explanatory variables, i.e. no correlation of X_{it} with the time-varying error term ν_{ik} also for periods $t\neq k$. If both identifying assumptions hold, fixed-effects methods are capable of solving the endogeneity problem resulting from omitted variable bias. Ferrer-i-Carbonell and Frijters (2004) develop a fixed-effect ordered logit estimator which collapses the ordered variable into a binary one with the thresholds that determine whether the original ordered variable is transformed to a one or a zero being individual-specific. Since implementation of this estimator is not trivial and convergence time is very long, the authors point to an easily implementable approximation of their estimator which works pretty well and is widely used in the recent literature.[8] In the approximation, the information on health satisfaction is collapsed into a binary variable that takes on the value 1 if health satisfaction exceeds the within-individual average over time, and 0 if it is below.

$$\tilde{y}_{it} = \begin{cases} 0 & \text{if} \quad y_{it}<\bar{y}_i \\ 1 & \text{if} \quad y_{it}\geq\bar{y}_i \end{cases} \text{ where } \bar{y}_i = \frac{1}{T_i}\sum_{t=1}^{T_i} y_{it}$$

The model is estimated as the traditional conditional logit model (Chamberlain, 1980) that conditions on a sufficient statistic (namely $\sum_{j=1}^{T_i}\tilde{y}_{it}$), leading to the following likelihood function in which the fixed-effect ε_i cancels out:

$$L\left[\tilde{y}_{i1},\dots,\tilde{y}_{iT_i} \mid \sum_{t=1}^{T_i}\tilde{y}_{it} = W_i\right] = \prod_{i=1}^{N} \frac{exp\left(\sum_{t=1}^{T_i}\tilde{y}_{it}X'_{it}\beta\right)}{exp\left(\sum_{\tilde{y}_i\in S(W_i)}\tilde{y}_{it}X'_{it}\beta\right)}$$

where $\tilde{y}_i=[\tilde{y}_{i1},\dots,\tilde{y}_{iT_i}]'$ and $S(W_i)$ denotes the set of possible realisations of $\tilde{y}_i$ such that $\sum_{t=1}^{T_i}\tilde{y}_{it}=W_i$. Since the conditional likelihood function does not contain the fixed-effect ε_i we can estimate the parameters β consistently even if ε_i is correlated with the X_{it}. Observations that do not vary over time in $\tilde{y}_{it}$ do not contribute to the likelihood function. Thus, only individuals who change their health status at least once in the observed period can be included in the conditional logit regression. This, however, is the case for most of the individuals in the sample. A drawback of this estimator (as well as with the normal fixed-effects logit estimator) is that one cannot calculate marginal effects without imposing further assumptions on the fixed effect. We therefore show parameter estimates only.

Since the mental health score lies between 0 and 100, we use the linear fixed-effects model here, while the conditional logit model is again used for the binary hospital visit variable. The fixed-effects estimation also removes the possible problem of selection of healthy workers out of unemployment – which might be a problem when we look back at Table 2 – because we only consider the within differences. Therefore, if we assume that the *changes* in health due to unemployment are the same for healthy and ill unemployed, it does not bias the analysis if healthy individuals are more likely to find their way back into the labour market. However, if there are negative effects of unemployment and they are stronger for already ill individuals, we might overestimate the negative effects of unemployment even with the use of fixed-effects estimation. This assumption does not need to be made when job loss instead of unemployment is the explanatory variable because this one treats all individuals who lost their job equally, irrespective of their later duration of unemployment. In a robustness check below we will show that the main results are not sensitive to the choice of job loss as an explanatory variable. Thus, our assumption does not seem to be too restrictive.

Because, in general, blue collar workers are more likely to lose their job due to plant closures than white collar workers and they are – on average – less healthy than the latter, we also control for job characteristics (blue collar, white collar, self-employed, civil servant, other position). Since there is no information in the data on the job characteristics of unemployed, we include the job position prior to unemployment for this group. Furthermore, we include a full set of dummies for the type of industry (2 digit NACE codes).

[7] Similar results hold when we look at the health measures in the base period of those who will work/be unemployed in the next year.

[8] See e.g. Böckerman and Ilmakunnas (2009), Kassenböhmer and Haisken-DeNew (2009), or Brenner (2007). Jones and Schurer (2010)) report that the differences in the estimates between the original estimator and the approximation are negligible.

4. Results

Table 3 reports estimation results for the three health measures when pooled estimation models without fixed effects are used. Since the estimated coefficients of the unemployment dummies are likely to be biased, they should not be interpreted as causal effects. Table 3 rather serves as a first benchmark and descriptive analysis. Note that in all specifications, income is not included as a regressor. Hence, the possible effects (or associations as in Table 3) of unemployment are combinations of monetary and non-monetary effects on health. According to all health measures, the unemployed are less healthy than working individuals. This holds both for unemployed due to plant closure and those due to other reasons. However, first, unemployment due to other reasons is associated with worse health than unemployment due to plant closure. Second, hospital visits are not significantly associated with unemployment due to plant closure and mental health is significant only at the 10% level.

Although unemployment is the most interesting variable in this study, we briefly discuss the results of the other covariates. Males, foreigners, and better educated individuals report a better health status than the respective base categories. West Germans have a better health satisfaction and mental health but not less hospital visits than East Germans. Older individuals report worse health satisfaction and more hospital visits but also better mental health. Note, however, that individuals above the age of 58 are excluded from the sample. Private health insurance is associated with better health, the same holds for children in the household (the latter not for mental health). Although no coefficient has a causal interpretation, they have, in general, the expected signs.

Table 4 reports the results when fixed effects are taken into account. Here, the time-invariant variables (male, foreigner, west) cannot be included. Note here the difference between the conditional logit and the fixed-effects ordered logit. Because only individuals who change their health outcome at least once in the observed time period can be used in the analysis, there is a high loss of information in the hospital equation. That is, many individuals have either no hospital visit at all in the entire period or regularly enter a hospital. The loss is much smaller in the health satisfaction equation in which only individuals are dropped who never change their health satisfaction on an 11-point scale, which is rarely the case.

The size of almost all coefficients markedly decreases after controlling for fixed effects. This is also true for the coefficients of the unemployment dummies. That means, individual unobserved effects determine the likelihood of becoming (and staying) unemployed and, at the same time, being in bad health to a great deal. However, there are decisive differences in effects for unemployed due to plant closure and those due to all other reasons. In the first group there are no negative effects at all. The estimated coefficients even turn positive (but insignificant). In contrast, the coefficients of health satisfaction and mental health are still significantly negative in the case of unemployment due to all other reasons. We argue, however, that this last result cannot be interpreted as a causal negative effect because only in the first group we can safely rule out potential reversed causality. Thus, we cannot rule out that there are individuals in this group that endogenously became unemployed (i.e., they quit their job or lost it) due to health problems. Since we cannot quantify the effect of potential reversed causality in this latter group, any interpretation from these coefficients should be done very cautiously. Therefore, we draw the major conclusions on the results of the unemployed due to plant closure.

Note that the insignificant effects of unemployment due to plant closure do not arise from the decreased number of identifying

Table 3
Pooled models.

	Health satisfaction (Ordered logit)		No hospital visit (Logit)		Mental health score (OLS)	
Unemployed plant closure	−0.343*	(0.079)	−0.170	(0.128)	−1.533	(0.849)
Unemployed other reasons	−0.410*	(0.026)	−0.228*	(0.039)	−2.142*	(0.233)
28 ≤ Age ≤ 32	−0.377*	(0.023)	−0.081	(0.048)	−1.011*	(0.214)
33 ≤ Age ≤ 37	−0.634*	(0.027)	−0.018	(0.052)	−1.158*	(0.234)
38 ≤ Age ≤ 42	−0.869*	(0.029)	0.004	(0.053)	−1.112*	(0.235)
43 ≤ Age ≤ 47	−1.033*	(0.030)	−0.125*	(0.053)	−0.705*	(0.232)
48 ≤ Age ≤ 52	−1.181*	(0.031)	−0.261*	(0.055)	−0.384	(0.246)
53 ≤ Age ≤ 58	−1.342*	(0.033)	−0.387*	(0.055)	0.129	(0.250)
Male	0.077*	(0.023)	0.385*	(0.036)	1.584*	(0.155)
Foreign	0.145*	(0.032)	0.066	(0.049)	0.388	(0.249)
West	0.196*	(0.022)	−0.033	(0.034)	0.801*	(0.150)
Years of education	0.030*	(0.004)	0.028*	(0.007)	0.052	(0.030)
Married	0.013	(0.021)	−0.050	(0.035)	1.278*	(0.152)
Children in household	0.102*	(0.019)	0.094*	(0.031)	−0.249	(0.138)
Private insurance	0.164*	(0.031)	0.106	(0.054)	0.908*	(0.213)
Education/ Vocational training	0.006	(0.028)	−0.078	(0.048)	−0.678*	(0.249)
Blue collar	−0.162*	(0.025)	−0.044	(0.042)	−0.625*	(0.189)
Self-employed	−0.022	(0.034)	0.140*	(0.059)	−0.368	(0.236)
Civil servant	−0.114*	(0.053)	−0.219*	(0.086)	−0.953*	(0.370)
Other position	0.028	(0.038)	−0.036	(0.066)	0.460	(0.325)
Quarter of interview = 2	0.064*	(0.014)	−0.004	(0.024)	−0.234*	(0.117)
Quarter of interview = 3	0.101*	(0.023)	0.077	(0.041)	−0.219	(0.208)
Quarter of interview = 4	0.130*	(0.062)	0.091	(0.098)	−1.730	(1.083)
Constant			0.558*	(0.125)	47.757*	(0.522)
Year dummies	yes		yes		yes	
Industry dummies	yes		yes		yes	
Observations	180,117		90,562		45,664	

Standard errors in parentheses; $^{*}p<0.05$.
Cut-off points for the ordered logit model not presented here.
White collar workers are the reference group for job position.

Table 4
Fixed-effects models.

	Health satisfaction (FE ordered logit)		No hospital visit (FE logit)		Mental health score (Linear FE)	
Unemployed plant closure	0.084	(0.081)	0.199	(0.167)	0.492	(0.696)
Unemployed other reasons	−0.125*	(0.024)	0.148*	(0.050)	−1.100*	(0.210)
28 ≤ Age ≤ 32	0.046	(0.030)	0.112	(0.072)	−0.612*	(0.272)
33 ≤ Age ≤ 37	0.058	(0.043)	0.359*	(0.101)	−0.765*	(0.387)
38 ≤ Age ≤ 42	0.073	(0.057)	0.458*	(0.130)	−1.034*	(0.480)
43 ≤ Age ≤ 47	0.070	(0.070)	0.341*	(0.160)	−0.852	(0.571)
48 ≤ Age ≤ 52	0.078	(0.085)	0.206	(0.191)	−0.715	(0.665)
53 ≤ Age ≤ 58	−0.033	(0.101)	0.064	(0.224)	−0.883	(0.769)
Years of education	0.017*	(0.008)	−0.008	(0.019)	0.160	(0.081)
Married	−0.068*	(0.024)	−0.215*	(0.057)	0.951*	(0.212)
Children in household	0.016	(0.019)	0.180*	(0.044)	−0.036	(0.162)
Private insurance	0.070	(0.036)	−0.292*	(0.090)	0.163	(0.306)
Education/Vocational training	0.040	(0.029)	0.073	(0.069)	−0.149	(0.247)
Blue collar	−0.061*	(0.026)	0.046	(0.059)	−0.221	(0.215)
Self-employed	−0.010	(0.038)	0.198*	(0.094)	−0.710*	(0.320)
Civil servant	−0.021	(0.075)	−0.389*	(0.181)	−0.589	(0.659)
Other position	−0.087*	(0.040)	−0.135	(0.099)	0.246	(0.343)
Quarter of interview = 2	0.020	(0.014)	0.010	(0.034)	−0.263*	(0.114)
Quarter of interview = 3	0.039	(0.024)	0.045	(0.063)	−0.363	(0.211)
Quarter of interview = 4	−0.037	(0.068)	0.418*	(0.150)	−1.637	(1.205)
Constant					48.529*	(1.280)
Year dummies	yes		yes		yes	
Industry dummies	yes		yes		yes	
Observations	173,311		39,185		45,664	

Standard errors in parentheses; $^{*}p<0.05$.

observations when we consider this group. Although the standard errors here are about three times as high as for the other group, the differences are mainly due to the strong differences in the point estimates. When testing for the difference in both coefficients we can reject the hypothesis that both are equal at a 5% level for health satisfaction and mental health.

The results for hospital visits are somewhat puzzling for the group of unemployed due to all reasons. While we find no significant effect for the unemployed due to plant closure, there is a positive effect for the former group which is rather intuitive. Also, both coefficients are not significantly different from each other.

Although the small number of unemployed due to plant closure in the sample does not prevent us from making interpretations in a statistical sense, one should be cautious in generalising the results. Strictly speaking, the finding of no negative health effects of unemployment is very local and, first, does only hold for this group. Second, it only holds for this particular reason of unemployment. The first point seems to be a minor problem since unemployment due to plant closure is an exogenous event and the group of unemployed due to this reason should not differ systematically from others — conditional on several observables and the fixed effect. However, we cannot analyse if unemployment due to other reasons, for instance because a person gets fired due to low productivity has, say, negative mental health effects. The significant positive coefficient of unemployment due to other reasons might either reflect a true negative health effect or reversed causality. However, this is a general problem of studies using unemployment due to plant closure as exogenous entry reasons and not special for this one.

5. Robustness checks

We find no significant effect of unemployment on health for the entire sample. However, it may well be that some groups suffer differently from unemployment than others. To check the robustness of the results we split up the sample into subgroups and again carry out the fixed-effects estimations. Table 5 reports the results of the different regressions. Here, only the two most interesting coefficients on unemployment are presented. The results indicate that there is no negative effect unemployment due to plant closure for males, females, for West Germans and East Germans and for individuals above the age of 50 according to all measures. Especially the number of observations in the subsample of those aged 50 to 58 is strongly reduced. This might be the reason for the implausibly high (but insignificant positive) coefficient of the mental health score.

As another robustness check we use a set of different dependent variables. As regards the hospital visit, we first use the original variable in the SOEP, a hospital visit within the previous twelve months. This variable has the drawback that hospital visits might possibly be counted before the unemployment spell started. Therefore, this variable is not the preferred one and is only used for a robustness check. Second, we use the total number of hospital stays within the next four years instead of the binary variable to exploit all the available information. Third, we use the number of doctor visits in the previous three months as a health measure. On the one hand, the latter might be better than the hospital visits as a health measure because it does not only capture severe health problems (as the hospital visit mainly does) but also smaller ones. On the other hand, while, in general, a hospital visit can be assumed to be involuntary for the unemployed, this is not necessarily the case for a doctor visit. As the opportunity costs decrease with unemployment, more doctor visits than before need not necessarily reflect a worse health status but maybe just more available time. As another objective health measure, we use the body-mass index and a dummy for overweight (BMI>25) as an outcome variable.

Finally, we change the measure of the mental health. While before, we used the information of several questions regarding mental health (collapsed into one measure), we now focus on one of these questions and define a dummy variable indicating phases of feeling run-down or melancholy at least sometimes within the previous four weeks (almost never or never being the reference). On the one hand, while being highly correlated with MCS, this variable contains less information on the health status than the Mental Component Summary Scale. On the other hand, it is more easily interpreted in quantitative terms than the overall score. The last three variables (BMI, overweight, melancholy) are available for the years 2002, 2004, 2006, and 2008 in the data set.

Table 5
Fixed-effects models — subsamples.

	Health satisfaction (FE ordered logit)		No hospital visit (FE Logit)		Mental health score (Linear FE)	
Males						
Unemployed plant closure	0.021	(0.110)	0.271	(0.233)	0.211	(0.853)
Unemployed other reasons	−0.164*	(0.033)	0.242*	(0.072)	−0.708*	(0.286)
Observations	93,921		20,722		24,234	
Females						
Unemployed plant closure	0.177	(0.122)	0.253	(0.246)	0.964	(1.185)
Unemployed other reasons	−0.082*	(0.033)	0.092	(0.072)	−1.455*	(0.314)
Observations	79,390		18,463		21,430	
West						
Unemployed plant closure	0.097	(0.110)	0.587*	(0.240)	0.668	(0.846)
Unemployed other reasons	−0.155*	(0.031)	0.287*	(0.070)	−1.219*	(0.270)
Observations	127,730		26,925		34,527	
East						
Unemployed plant closure	0.051	(0.122)	−0.215	(0.244)	0.316	(1.227)
Unemployed other reasons	−0.092*	(0.038)	0.019	(0.076)	−0.725*	(0.348)
Observations	44,917		11,978		11,137	
Over 50 years						
Unemployed plant closure	−0.140	(0.153)	−0.222	(0.328)	1.629	(1.453)
Unemployed other reasons	−0.137*	(0.059)	0.139	(0.117)	−2.071*	(0.530)
Observations	32,004		7072		10,573	

* $p<0.05$. Standard errors in parentheses. Same controls as in Table 4 included but not presented.

Since the number of hospital visits and the number of doctor visits are count variables, we use a fixed-effects negative binomial model as presented in, e.g., Cameron and Trivedi (2005) for this estimation.[9] Conditional logit models are used for the binary variables and linear fixed effects for the BMI. Table 6 reports the results when these health measures are used. In contrast to before, higher values of these variables indicate a worse health status. That is, a positive coefficient implies a negative impact on health. The coefficients of unemployment due to plant closure are small and insignificant. Moreover, they are not of the expected sign in the case of hospital visits, body-mass index and overweight. The coefficient of melancholy is positive but insignificant. Again, it is important to take into account the reason for unemployment. In four out of six cases, we find a positive coefficient for the group of unemployed due to other reasons. Of course, the limited interpretability of this last result also applies here. Altogether, the results do not seem to be sensitive to the choice of the health measures.

Since the assumption of a time-invariant fixed effect might be too strong for a period of 17 years, we re-estimate the models only including the years 2002–2008. The results (available upon request) do not change.

In a final robustness check we change the explanatory variable from *unemployed* to *job loss*. This variable takes on the value one if an individual lost her job (at the time after the job loss). There are

[9] The stata command *xtnbreg* was used for the estimation.

Table 6
Fixed-effect models with plant closure — other health measures.

	Hospital visit previous year (FE logit)	# Hospital visits next 4 years (FE Negbin)	# Doctor visits (FE Negbin)	Body-mass index (Linear FE)	Overweight (FE logit)	Melancholy (FE logit)
Unemployed plant closure	−0.244 (0.158)	−0.002 (0.087)	0.048 (0.043)	−0.196 (0.138)	−0.524 (0.365)	0.178 (0.238)
Unemployed other reasons	0.384* (0.041)	−0.069* (0.026)	0.102* (0.012)	0.153* (0.041)	−0.094 (0.124)	0.408* (0.074)
Observations	78,575	46,082	162,266	46,659	8823	22,010

* $p<0.05$. Standard errors in parentheses. Same controls as in Table 4 included but not presented.

advantages and disadvantages of this as an explanatory variable as compared to the original one. One advantage for the econometric analysis is that more individuals suffer from a job loss between two waves of the survey than change their status from work to unemployment. Specifically, there is a number of individuals losing their job between two waves and directly finding a new one. When *job loss* is the explanatory variable, the number of individuals suffering from a plant closure increases from 899 to 1432 for all those with information on health satisfaction (and likewise for the other measures). The difference is those who are unemployed for a very short duration only.

The second advantage is that the very short-time unemployed who are not included in the analysis when unemployment is the explanatory variable, also contribute to the results. It is often argued that the results could be biased if healthier individuals are more likely to find a job after unemployment (as indeed shown by Stewart, 2001). The fixed-effects estimation method reduces this problem to a great deal — still we have to assume that changes in health due to unemployment are similar likely for sick and unhealthy individuals.

The major drawback of this approach is that a great deal of individuals has found a job quickly after unemployment and before the health question is asked again in the next wave — thus, it is not fully clear what the variable job loss measures. The estimated effect of job loss on health is a mixture of those who are working again and those who stay unemployed.[10] Therefore, it is more difficult to derive a policy conclusion from such an analysis.

Table 7 reports the results of the same regressions as Table 4 but with the above defined variable *job loss*. The results are similar to the ones from Table 4. We do not find a significantly negative effect for those who lost their job due to plant closure. For those who lost their job due to any other reason, signs and significance for health satisfaction and hospital visits are the same as in the original specification. The mental health score, however, does not have a significant coefficient anymore.

6. Conclusion

We estimate the causal effect of unemployment on health using data from the German Socio-Economic Panel for 1991–2008. With fixed-effect methods and exogenous entries into unemployment we do not find an effect of unemployment on health. These results hold for various health measures and across several subgroups. In contrast, taking all other reasons for unemployment together, the estimation results imply a negative effect of unemployment on health for this group. However, this last result is likely to be biased as reversed causality might contribute to it.

The results are not in line with an earlier study by Romeu Gordo (2006) who finds negative effects of unemployment using the same data set. Our results indicate that the major reason for the difference is that we consider truly exogenously unemployed individuals in the preferred specification while the former study does not make this distinction. We argue that it is crucial to take the possible endogeneity of unemployment (and, thus, reversed causality) into account to get consistent estimates.

This is the first study that analyses the effect of unemployment on mental health for Germany. This is especially interesting since it can be assumed that unemployment first reduces mental health before it deteriorates the overall health status. However, we do not find evidence for a negative effect of unemployment on mental health.

One potential shortcoming of our study might be the health measures. Although satisfaction with health is likely to be the most interesting outcome variable in terms of a utility measure it might be prone to measurement error. Especially in the health-and-retirement literature it is often argued that self-stated health indicators might suffer from a justification bias. Transferred to our study this means that unemployed feel uncomfortable with telling the interviewer about not yet having found a job and state a poor health status as an excuse. It is debatable if this is the case in Germany where unemployment is more widely perceived as bad luck than as one's own fault. Even if this were the case and the health satisfaction variable suffered from a justification bias, the negative effects of unemployment on health would be overestimated — yet, we do not find negative effects. Moreover, the results also hold when more objective health measures are used.

A second shortcoming might be the limited scope to generalise the results. Strictly speaking, we can only establish a non-negative effect of unemployment due to plant closure. While this reason is clearly exogenous and the group that suffers from unemployment due to this reason should not differ from others (conditional on observables and the fixed effect), we cannot rule out that unemployment because, say, someone gets fired, or due to other endogenous reasons may indeed have a deteriorating effect on health.

Our results indicate that the selection of ill workers into unemployment and healthy workers out of unemployment mainly contributes to the observation that the stock of unemployed has on average a worse health status than the stock of employed but that there is no causal effect of unemployment on health. These results are also in line with those found in the recent international health-economic literature (Browning et al., 2006; Salm, 2009; Böckerman and Ilmakunnas, 2009). One reason for the absence of negative effects on health in Germany (as well as in the Scandinavian countries cited above) might be the following. First, before the most recent labour market reform, Germany had an unemployment insurance system that was characterised by generous insurance benefits and especially by long entitlement durations of unemployment benefits. Therefore, the income loss in the case of unemployment was (and still is) usually moderate. Moreover, Frijters et al. (2005) find only a very small causal effect of income on health in Germany. Second, job loss never causes the loss of health insurance in Germany. Health care utilisation should, therefore, not be affected by financial constraints due to unemployment. This could explain why unemployment does not lead to

Table 7
Effects of job loss on health.

	(1) Health satisfaction		(2) No hospital visit		(3) Mental health score	
Job loss plant closure	0.053	(0.046)	−0.049	(0.102)	0.010	(0.479)
Job loss other reason	−0.051*	(0.023)	0.121*	(0.050)	−0.048	(0.246)
Observations	170,715		39,094		45,591	

* $p<0.05$. Standard errors in parentheses. Same controls as in Table 4 included but not presented.

[10] Interacting the effect with a dummy for still being unemployed does not solve the problem if worries about selection out of unemployment are the reason for using job loss instead of unemployment.

adverse health outcomes in Germany compared to, e.g., the US, where some authors do find negative health effects of unemployment or job loss (e.g., Sullivan and von Wachter, 2009).

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Appendix A

Table A1
SF-12v2 questionnaire in the SOEP.
Source: SOEP Individual question form. Available at http://panel.gsoep.de/soepinfo2008/.

	Very Good	Good	Satisfactory	Poor	Bad
How would you describe your current health?					
	Greatly	Slightly	Not at all	–	–
When you ascend stairs, i.e. go up several floors on foot: Does your state of health affect you greatly, slightly or not at all?					
And what about having to cope with other tiring everyday tasks, i.e. where one has to lift something heavy or where one requires agility: Does your state of health affect you greatly, slightly or not at all?					
Please think about the last four weeks.	Always	Often	Sometimes	Almost never	Never
How often did it occur within this period of time, …					
◊ that you felt rushed or pressed for time?					
◊ that you felt run-down and melancholy?					
◊ that you felt relaxed and well-balanced?					
◊ that you used up a lot of energy?					
◊ that you had strong physical pains?					
◊ that due to physical health problems					
... you achieved less than you wanted to					
... at work or in everyday tasks?					
... you were limited in some form					
... at work or in everyday tasks?					
◊ that due to mental health or emotional problems					
... you achieved less than you wanted to					
... at work or in everyday tasks?					
... you carried out your work or everyday tasks					
... less thoroughly than usual?					
◊ that due to physical or mental health problems you were limited socially, i.e. in contact with friends, acquaintances or relatives?					

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