# THE CAUSAL IMPACT OF FEAR OF UNEMPLOYMENT ON PSYCHOLOGICAL HEALTH*

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**Abstract**

We analyze the effect of job insecurity on psychological health. We extend the group of people being affected to employees who have insecure jobs to account for a broader measure of the mental health consequences of potential unemployment. Using panel data with staff reductions in the company as an exogenous source of job insecurity, we find that an increase in fear of unemployment substantially decreases the mental health status of employees. Quantile regression results yield particularly strong effects for individuals of already poor mental health.

***JEL codes:*** *I10, I18, J28, J65*

***Keywords:*** *fear of unemployment, mental health, job insecurity, staff reduction, labor market dynamics*

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# 1 Introduction

The interdependence of labor market dynamics and health has been well established in the economic literature. Empirical research based on aggregated data dates back to the nineteen-seventies, most notably to the research conducted by Brenner (see, e.g., Brenner, 1971, 1979, 1987). He reports a positive correlation of fluctuations in the unemployment rate with different health indicators, such as the prevalence of schizophrenia, heart disease mortality, and aggregate mortality. Since then, many studies have reported results that contradict his finding of a general adverse health effect of labor market recessions (e.g., Ruhm, 2000; Laporte, 2004). However, the negative association between unemployment and psychological health has survived further scrutiny. By analyzing cause-specific mortality rates, Ruhm (2000) observes that, as an exception, suicide mortality significantly increases when unemployment rises. In line with this, Tefft (2011) shows a positive association between weekly unemployment insurance claims and Google web searches for 'depression' and 'anxiety'.

The present analysis assesses the causal effect of job insecurity on psychological health based on individual-level data. Although the inverse relationship between the two measures is widely documented in the psychological literature (for a comprehensive review, see Ferrie, 2001), attempts at analyzing the direction of causation are scarce despite its relevance for policy.[1] Even the most recent economic literature in this field, though based on panel-data methods controlling for unobserved heterogeneity, inadequately addresses the potential for reverse causality biasing the confirming results (Green, 2011; Knabe and Rätzel, 2010, 2011). For instance, the observed effect may reflect the fact that bad mental health status results in job insecurity, whereas there is no reverse effect of job insecurity on mental health. Thus, economic policy measures to increase job security may not be an effective means of, for instance, reducing the number of suicides. We account for the possible endogeneity by instrumenting job insecurity with staff reductions in the company.

This paper adds to the literature on the effects of unemployment on health. This is important because the question of under which circumstances, to what extent, and within what time frame unemployment influences individual health is still unsettled due to the ambiguous empirical evidence. On the one hand, Sullivan and von Wachter (2009) report strong effects of involuntary job loss on subsequent mortality of high-seniority male workers and Green (2011) observes an

[1] We only found one study (Ferrie et al., 1995) that addresses the effect of job insecurity on psychological morbidity by exploiting the exogenous variation (plant closure) of job insecurity over time. Results indicate significant effects on general health but not on mental health. However, a serious limitation of the study is that the estimates may be biased due to structural sample attrition which results from the non-responders in the group of employees with increasing exogenous job insecurity over time being relatively younger and healthier at baseline. Luechinger et al. (2010) show the negative effects of high unemployment rates on individual well-being.

inverse association between unemployment and mental health as well as well-being. Huber et al. (2011) find positive effects of transitions from welfare to employment on mental health and a negative effect on the number of symptoms pointing to health problems. In contrast, Böckerman and Ilmakunnas (2009) find no impact of unemployment on self-assessed health. Schmitz (2011) reports qualitatively similar results exploiting plant closures as exogenous variation. Moreover, he does not observe any effect of unemployment on the number of hospital visits and the mental health status.

In this analysis, we extend the group of people potentially being affected by unemployment to employees whose jobs are at risk but who eventually retain them. If they indeed experience a worsening in mental health, then the overall effect of unemployment on health has not been fully taken into account in the micro econometric literature. Moreover, empirical applications which rely on a comparison group consisting of employees with uncertain jobs that eventually have not become unemployed will necessarily underestimate the effect of unemployment on mental health.[2] In other words, the stable unit treatment value assumption is violated. In addition to that, if the employees who become unemployed really anticipate the loss of their jobs, a problem similar to the one described by Ashenfelter (1978) aggravates the underestimation of the effect.

Using individual level data from the German Socioeconomic Panel (SOEP) for the years 2002–2008, we find that employees who are concerned about losing their jobs are less psychologically healthy than if they had secure jobs. Different estimation methods all yield the same qualitative result. Quantile regressions reveal that this effect applies to the whole mental health distribution. Alarmingly, the effects are stronger for individuals that already suffer from a bad mental health status.

The remainder of this paper is organized as follows. The subsequent section introduces the data, section 3 discusses the empirical approach, and section 4 presents the estimation results. Section 5 summarizes our main findings and concludes.

## 2 Data

The analysis is based on data from the German Socioeconomic Panel (SOEP), a large longitudinal household survey that started in 1984 (Haisken-DeNew and Frick, 2005). The SOEP includes a wide range of information at the individual and the household level such as working and living conditions, as well as variables describing the individual (mental) health status. The data we use

[2] Because the empirical literature also points at adverse physical health effects of job insecurity, this applies to the effects of unemployment on physical health, too. For instance, Mattiasson et al. (1990) and Jensen (2001) provide evidence for an increased likelihood of chest pains, cardiovascular disease or heart attack, alcohol consumption and smoking.

cover more than 37,000 person–time observations over the 2002–2008 time period.

Our outcome measure is the mental component summary scale (*MCS*) provided by the SOEP group. The *MCS* has been shown to be both a valid measure of mental health in epidemiological research and a useful screening tool for people with severe mental illnesses (Salyers et al., 2000), such as depression (Gill et al., 2007). It is calculated using explorative factor analysis (for a detailed description, see Andersen et al., 2007) and is based on twelve questions related to psychological well-being, emotionality, social functioning, and vitality. The exact questions, which all refer to the period within four weeks before the interview, are presented in Table A1 in the Appendix. The calculation algorithm is as close as possible to the procedure of the original SF12v2 Health Survey Scoring (see Ware et al., 2002). The *MCS* lies between 0 and 100, with higher values indicating a better mental health status. The mean value of the SOEP 2004 population is set to 50 with a standard deviation of 10. For the years 2003, 2005 and 2007, there is no information on the *MCS* available.

On a yearly basis, the interviewees were asked about whether they were very, somewhat or not concerned at all about their job security. Based on this variable, we construct the binary variable 'fear of unemployment' (taking the value 1 if the individual is very concerned about their job security and 0 otherwise), which is used as a proxy for self-perceived job insecurity.[3] As the data for this variable are available for 2002, 2004, 2006 and 2008, we have a panel structure that allows us to exploit variation over individuals and time.

The data also contains a variable that indicates whether the company, an individual is employed with, reduced its workforce during the last twelve months. It is used to construct the dummy variable 'staff reduction' that serves as the instrument in the instrumental-variable (IV) estimation (see Section 3). This variable is available for the same years as the *MCS* except for 2006. Thus, in the present analysis, when estimating IV regressions, we focus on the waves 2002, 2004, and 2008.

As control variables, we use socioeconomic characteristics, such as sex, age, years of education, a dummy indicating being born abroad, household size, and an indicator for living together with a partner. We also include the number of children younger than 18 and the marital status (married, non-married). This is done because dismissal protection is especially strict for married people and those with dependent children. Hence, both are potential determinants of individual fear of job loss.

We also control for the working environment in order to account for individual differences in

[3] All results presented in this paper, are robust to fear of unemployment taking the value 1 if the individuals are very or somewhat concerned about their job security and 0 if they are not at all concerned about their job security.

dismissal protection. First, we use a set of dummy variables, capturing firm size, i.e., (i) up to five, (ii) more than five, and (iii) more than 2,000 employees. Here, small firms serve as the reference category. Other working environment variables closely related to individual job insecurity are firm tenure and a dummy indicating a temporary contract. Besides these, we control for holding a secondary employment as well as for marginal employment ('mini-job' or 'midi-job'), which is often less stable than ordinary employment. We also include a set of dummies capturing occupation, i.e., (i) unskilled blue-collar, (ii) skilled blue-collar, (iii) low-skilled white-collar, and (iv) high-skilled white-collar, where the first serves as reference.

Personal gross labor income, measured in €1,000 per month, also enters the empirical model as a control. In order to avoid potential bias resulting from reverse causality, income enters the analysis once-lagged. For individuals that were unemployed during the previous period, the income variable takes on the value zero. Along with income, we also include a dummy variable indicating being unemployed in the previous year. Further covariates, which also enter the model in terms of one year lags are employability,[4] job satisfaction and an indicator for working overtime. In addition, year and state dummy variables are included.

In the analysis, we focus on employed individuals who are potentially affected by unemployment. While this applies to private sector employees, in particular, other groups of jobholders cannot be laid off as, for instance, conscripts, self-employed, and public servants. The latter have a special legal protection against dismissal in Germany because they are subject to public law and special obligations such as exercising their office on behalf of the common good and serving in a relationship of loyalty. They are permanently employed but prohibited from going on strike (FMI, 2007). This holds true in a similar way to public sector employees which almost acquire public servant status.[5] In fact, they are by far less concerned about their job security than private sector employees, as the data shows.

In order to concentrate on employees for which job insecurity really matters, we restrict the sample to individuals who were at least once employed in the private sector during the considered periods, while allowing for individuals who were temporary unemployed, temporary employed as public servant, etc. For a description of the sample composition, see Table 1. We do not confine the analysis to individuals permanently employed in the private sector as this might result in severe self-selection bias. Yet, this raises the question of how to deal with individuals

[4]The relevant question is: 'If you were currently looking for a new job, is it or would it be easy, difficult or almost impossible to find an appropriate position?' We use two dummy variables to indicate individuals who report to find an appropriate position with some difficulties and easily, respectively.

[5]Although they are employed on the basis of a contract under private law which applies to all employees in Germany, their specific working conditions, that are set out in collective agreements negotiated between the public employers and labor unions, include an enhanced dismissal protection (FMI, 2007).

Table 1: **Distribution of Labor Market Status (estimation sample)**

| | 2002 | 2004 | 2006 | 2008 | Total |
|---|---|---|---|---|---|
| *private sector employees* | 7,296 | 7,295 | 6,635 | 6,827 | 28,053 |
| *unemployed* | 1,151 | 1,303 | 1,185 | 693 | 4,332 |
| *self employed* | 152 | 228 | 323 | 292 | 995 |
| *government employee* | 438 | 518 | 441 | 451 | 1,848 |
| *public servant* | 15 | 25 | 29 | 36 | 105 |
| *pensioner* | 90 | 267 | 464 | 615 | 1,436 |
| *other* | 41 | 259 | 260 | 197 | 757 |
| | 9,183 | 9,895 | 9,337 | 9,111 | 37,526 |

*Notes:* Statistics for the sample used for estimating the basic OLS-model.
Own calculations.

whose labor market status changed over time. This matters particularly for explanatory variables that are only meaningfully defined conditional on the labor market status. Firm size, for instance, can neither be observed for jobless individuals nor be regarded as a determinant of their mental health. Our approach is to assign the value of zero to all variables that are unobserved or undefined conditional on the labor market status while controlling for the latter by a set of indicators. This guarantees that identification of the effect of – say – firm size on mental health exclusively rests on observations, for which firm size is observed.[6] Morris (2006) takes a similar approach.

This leads to an estimation sample which consists of 4,928 individual-level observations for 2002. For the year 2004, 2006 and 2008, the corresponding numbers are 5,890, 4,966, and 5,374 observations, respectively. In 2002, the average *MCS* amounted to 49.6 with a standard deviation of 9.4. The sample average *MCS* over the years 2004, 2006 and 2008, was 50.3. For the distribution of the *M*CS by sex, averaged over all four years; see Figure A1 in the Appendix.

The average sample age is 41 years. Almost 50 percent of the individuals are female. White-collar workers comprise almost 60 percent. The average sample individual has 12 years of education and earns a monthly gross wage of € 1,960. Most (64 percent) observations are satisfied with their job. The majority does not work overtime. Only 18 percent of the individuals report that it would be easy for them to find an adequate new job. For comprehensive descriptive statistics, see Table 2.

Regarding the key explanatory variable in 2002, we observe that 39.6 percent of the individuals were somewhat and 14.6 percent were very concerned about their job security. In 2004, these shares amounted to 38.9 and 18.9 percent, in 2006 to 37.2 and 16.8, and in 2008 to 36.1 and 13.1 percent. The mean *MCS* among employees who were not concerned about their job security amounted to 50.3. In contrast, the corresponding figure for employees who were very concerned about their job security was 47.2. This difference indicates that job worries worsen mental health

[6]We take a similar approach for dealing with item non-response in the data. Rather excluding all observations with missing information for only a few variables, we 'technically' assign the value of zero to missing values and include a set of dummies, indicating for which items no information is available, as ancillary regressors. For variables that exhibit only a small number of missing values, we stick to the conventional approach of excluding the relevant observations.

Table 2: **Descriptive Statistics**

| | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|
| **dependent variable** | | | | |
| *MCS* | 49.929 | 9.511 | 5.324 | 77.774 |
| **endogenous regressor**: *fear of unemployment* | | | | |
| *concerned about job-security: not at all or somewhat concerned* | 0.820 | 0.483 | 0 | 1 |
| *very concerned* | 0.149 | 0.357 | 0 | 1 |
| *missing* | 0.031 | 0.172 | 0 | 1 |
| **instrument** | | | | |
| *staff reduction*# | 0.243 | 0.429 | 0 | 1 |
| *staff reduction missing* | 0.031 | 0.174 | 0 | 1 |
| **controls** | | | | |
| *employability (lag): difficult*° | 0.587 | 0.492 | 0 | 1 |
| *good* | 0.183 | 0.386 | 0 | 1 |
| *job satisfaction (lag): low*° | 0.222 | 0.416 | 0 | 1 |
| *medium* | 0.208 | 0.406 | 0 | 1 |
| *overtime (lag)*° | 0.369 | 0.483 | 0 | 1 |
| *age* (*years*) | 40.728 | 12.660 | 18 | 87 |
| *male* | 0.522 | 0.500 | 0 | 1 |
| *migration background: direct* | 0.128 | 0.334 | 0 | 1 |
| *indirect* | 0.053 | 0.223 | 0 | 1 |
| *years of education*° | 11.527 | 3.449 | 0 | 18 |
| *married* | 0.607 | 0.489 | 0 | 1 |
| *living with partner* | 0.700 | 0.458 | 0 | 1 |
| *household size* | 2.938 | 1.281 | 1 | 13 |
| *number of kids under 18* | 0.655 | 0.943 | 0 | 9 |
| *occupation: blue-collar skilled* | 0.151 | 0.358 | 0 | 1 |
| *white-collar low skilled* | 0.305 | 0.460 | 0 | 1 |
| *white-collar high skilled* | 0.138 | 0.345 | 0 | 1 |
| *tenure* (*years*) | 7.407 | 8.965 | 0 | 56.4 |
| *type of job: mini*° | 0.077 | 0.267 | 0 | 1 |
| *midi job* | 0.031 | 0.174 | 0 | 1 |
| *temporary work contract*° | 0.108 | 0.310 | 0 | 1 |
| *side job* | 0.069 | 0.253 | 0 | 1 |
| *firm size: medium*° (*6-2,000 employees*) | 0.393 | 0.488 | 0 | 1 |
| *large* (*more than 2,000 employees*) | 0.320 | 0.467 | 0 | 1 |
| *personal gross income*° (*1,000 € per month, lag*) | 1.963 | 2.251 | 0 | 36 |
| *unemployed (lag)* | 0.143 | 0.350 | 0 | 1 |
| *year 2002* | 0.245 | 0.430 | 0 | 1 |
| *year 2004* | 0.264 | 0.441 | 0 | 1 |
| *year 2006* | 0.249 | 0.432 | 0 | 1 |

*Notes:* Statistics for the sample used for estimating the basic OLS-model (37,526 obs.); cf. Section 4. # Statistics for the sample used for estimating the IV-FE-model (24,340 obs.). °Missing values assigned to the reference category. For the controls, no statistics for the reference categories reported.
Own calculations.

– estimating just how much of that difference is causal is the aim of the paper.

# 3 Estimation Strategy

In this section, we present the estimation strategies employed in this paper. In order to identify the causal effect of fear of unemployment on mental health, we estimate different regression models aimed at providing a more complete picture of the hypothesized relationship.

## 3.1 Ordinary least-squares (OLS) estimation

Consider the employee $i$ at year $t$ in state $s$. Let $MCS_{it}$ be the dependent variable. Because $MCS_{it}$ is a continuous interval scale variable, we employ a linear regression model. Let $A_{it}$ be the key

explanatory variable 'fear of unemployment'. The equation we estimate via OLS appears as follows:

$$MCS_{it} = X1_{it}\beta_1 + X2_i\beta_2 + J_{it}\delta + A_{it}\gamma + \mu_s + \nu_t + \epsilon_{it}. \quad (1)$$

$X1_{it}$ is the vector of time-varying personal characteristics including, e.g., the variable 'living with a partner'. $X2_i$ is the vector of time-invariant personal characteristics including, e.g., gender. $J_{it}$ is the vector of job characteristics. The state ($\mu_s$) and year ($\nu_t$) effects are included to control for regional differences and time trends. The random error term is represented by $\epsilon_{it}$ while $\gamma$, $\beta$, and $\delta$ are coefficients subject to estimation.

### 3.2 Fixed effects (FE) estimation

The variable 'fear of unemployment' may suffer from endogeneity due to unobserved heterogeneity, rendering OLS regression results biased. For instance, generally optimistic individuals may generally have less worries and, at the same time, a better mental health. In this case, besides the particular concern about their job security, the OLS estimator for $\gamma$ captures the effect of being optimistic. In order to tackle this problem, we re-estimate Equation 1 by regressing the time-demeaned dependent variable ( $\overline{MCS}_{it} = MCS_{it} - \frac{1}{T}\sum_{t=1}^{T_i} MCS_{it}$) on the time-demeaned regressors. For the FE estimation, we exclude the time-constant vectors.

### 3.3 IV-FE estimation

The FE estimate of $\gamma_A$ may still capture confounding factors if these are time-varying, unobserved, and correlated with both job insecurity and mental health. As an example for such a confounder, consider a new head of the department putting more trust in the employees' working ability and at the same time exerting less pressure on them. A second and important source of bias in the FE estimation may still arise from reverse causality, i.e., changes in the mental health status affect employment perspectives.

To overcome both sources of bias, we employ a two-stage least-squares (2SLS) FE estimation, using staff reduction $D_{it}$ to instrument $A_{it}$:

$$\overline{A}_{it} = \overline{X1}_{it}\kappa + \overline{J}_{it}\lambda + \overline{D}_{it}\rho + \overline{\nu}_t + \eta_{it}, \quad (2)$$

$$\overline{MCS}_{it} = \overline{X1}_{it}\beta_1 + \overline{J}_{it}\delta + \widehat{A}_{it}\gamma + \overline{\nu}_t + \tilde{\epsilon}_{it}. \quad (3)$$

Equation 2 is the instrumental equation, where job insecurity is regressed on the time-varying

covariates and the instrument. Equation 3 is the structural equation which apart from the FE formulation differs from Equation 1 in that it includes the fitted values of job insecurity $\widehat{A}_{it}$ instead of $\overline{A}_{it}$.[7] 2SLS estimation isolates $\gamma$ from confounding factors if the instrument is valid. Instrument validity presumes that the instrumental variable is uncorrelated with $\tilde{\epsilon}_{it}$ conditional on the included covariates (see, e.g., Angrist and Pischke, 2008). This means that the instrument is required to operate on the dependent variable only through the endogenous explanatory variable.

The intuition behind the suggested instrumental variable is that employees may estimate their individual risk of job loss on basis of the recent employment trend in the company. We assume that if a company reduced its workforce during the last 12 months, their employees, on average, perceive their jobs to be less secure. We argue that employees cannot influence the company's decision to reduce the workforce, i.e., it is exogenous to the individuals.

Nevertheless, our instrumental variable might indirectly suffer from endogeneity due to the place of work representing a choice variable. For instance, if jobs become less secure, better qualified and motivated individuals may be more likely to change their employer than inactive ones, rendering the instrument to be potentially correlated with individual characteristics. This problem is strongly reduced by the use of fixed effects which remove any unobserved time-invariant personal characteristics that are potentially correlated with the instrumental variable. Moreover, we control for changes in the employees' employability, job satisfaction and overtime by including these variables in terms of one period lags. They capture the potential selection effect of individuals with reduced alternatives working for a company with reductions in the workforce.

The instrument validity assumption is not directly testable. Fortunately, we can indirectly assess whether staff reduction operates through other channels than job insecurity. Since public servants are strictly protected against dismissal and, in turn, will by no means be concerned about becoming unemployment, staff reduction is uncorrelated with the mental health status for this group of individuals if the instrument is valid.

In order to test this, we estimate the reduced form FE model of Equation 2 and Equation 3 for public servants. The point estimate yields no significant association between the instrument and the dependent variable (right part of Table A2 in the Appendix). In contrast, using the actual estimation sample, primarily consisting of private sector employees, yields a significant and negative coefficient of staff reduction (left part of the table). This is a strong indication for staff reduction in a respondent's firm exerting effects on *MCS* only through the respondent's concerns about individual job insecurity, i.e., the results are indicative for instrument validity.

[7] We correct the variance–covariance matrix by applying the correct mean squared errors. We use the *xtivreg2* Stata ado-file (Schaffer, 2005).

# 4 Results

In this section, we present the estimation results obtained from the different regression models discussed above. Moreover, we check for the robustness of the results and analyze the heterogeneity of the estimated mean effects.

## 4.1 Estimated Mean Effects

Though our focus is on the effect of the fear of unemployment on mental health, we first take a brief look at the results for the controls. We find that males are of significantly better psychological health than females. Conclusive results are also found with respect to age and immigration status, that is, especially natives and the young suffer from mental health problems. Satisfaction with the job and stress at work also matter for psychological health. Here, dissatisfied individuals exhibit a significantly worse *MCS*. Working overtime also goes along with smaller values of the *MCS*, with points at work-related stress exerting adverse mental health effects. The negative coefficient attached to holding a side or secondary job points in the same direction. Having previously been unemployed is found to be associated with better mental health. This most likely reflects the positive effect of recently becoming reemployed. The finding of a positive effect of cohabiting with a parter in the FE specifications may be interpreted in a similar way. That is, it is not cohabiting per se that matters for mental well-being but rather splitting up and coupling. While occupation matters for mental health – with low-skilled blue collar workers being particularly worse off – this does not hold for firm size which seems to be immaterial for the *MCS*.

We find a highly significant adverse effect of fear of unemployment on mental health in the OLS regression. In quantitative terms, the estimated value of $-2.819$ indicates a strong effect of becoming very concerned about the individual job security as it corresponds to a shift from the median to the 40th percentile of the distribution of the *MCS*. However, OLS is likely to fail to disentangle the genuine causal effect from the impact of confounding factors. In line with this argument, the coefficient obtained from the FE estimation is less than half as large as the one obtained from OLS. That is, OLS is likely to overestimate the causal effect of fear of unemployment due to individual characteristics causing individuals to be more concerned about their jobs and to be, at the same time, less healthy. Nevertheless, even with fixed effects included, a highly significant and adverse effect is found.

Since FE fails to address a possible bias that originates from reverse causality and confounding factors that vary over time, we turn to the IV-FE estimation results. Concerning the instrumental equation (left part of Table A3), staff reduction exhibits the expected positive sign. The test on

Table 3: **Estimated Effects on MCS**

| | OLS[#] | | FE | | IV-FE | |
|---|---|---|---|---|---|---|
| | Coefficient | S.E. | Coefficient | S.E. | Coefficient | S.E. |
| *fear of unemployment*° | −2.819* | (0.145) | −1.228* | (0.163) | −5.310* | (1.904) |
| *employability (lag): difficult*° | 0.236+ | (0.143) | −0.018 | (0.163) | 0.020 | (0.226) |
| *good* | 0.613* | (0.182) | 0.063 | (0.217) | −0.049 | (0.303) |
| *job satisfaction (lag): low*° | −3.931* | (0.202) | −0.506* | (0.206) | −0.638* | (0.285) |
| *medium* | −3.266* | (0.125) | −0.225 | (0.137) | −0.314+ | (0.178) |
| *overtime (lag)*° | −1.280* | (0.118) | −0.326* | (0.135) | −0.579* | (0.176) |
| *unemployed (lag)* | 2.142* | (0.250) | 0.345 | (0.254) | 0.226 | (0.346) |
| *self employed (lag)* | 0.093 | (0.429) | −0.465 | (0.438) | 0.185 | (0.584) |
| *labor market status: unemployed* | 0.787 | (1.345) | −0.665+ | (0.358) | −1.031 | (0.740) |
| *self employed* | 0.232 | (0.406) | 0.482 | (0.422) | −0.014 | (0.557) |
| *government employee* | −0.177 | (0.280) | 0.320 | (0.287) | 0.011 | (0.338) |
| *public servant* | 0.643 | (1.147) | −0.546 | (1.117) | −2.592+ | (1.544) |
| *pensioner* | 1.408 | (1.384) | −0.252 | (0.478) | −0.775 | (0.829) |
| *other* | 1.194 | (1.392) | −0.487 | (0.490) | −1.452+ | (0.848) |
| *married* | 0.162 | (0.163) | −0.150 | (0.281) | −0.578 | (0.355) |
| *living with partner* | 0.336* | (0.166) | 1.209* | (0.263) | 1.215* | (0.327) |
| *household size* | 0.533* | (0.056) | 0.077 | (0.097) | 0.114 | (0.119) |
| *# of kids under 18* | −0.819* | (0.075) | −0.082 | (0.134) | −0.192 | (0.161) |
| *personal income (lag)* | −0.003 | (0.033) | −0.089+ | (0.046) | −0.068 | (0.053) |
| *occupation: blue-collar skilled* | 0.157 | (0.170) | 0.371 | (0.239) | 0.288 | (0.304) |
| *white-collar low skilled* | 0.418* | (0.153) | 0.253 | (0.211) | 0.184 | (0.272) |
| *white-collar high skilled* | 0.349 | (0.217) | 0.260 | (0.302) | −0.257 | (0.396) |
| *mini job*° | −0.213 | (0.210) | 0.170 | (0.257) | 0.139 | (0.338) |
| *midi job* | −0.082 | (0.288) | −0.404 | (0.301) | −0.524 | (0.350) |
| *temporary work contract*° | 0.433* | (0.182) | 0.090 | (0.204) | 0.546+ | (0.311) |
| *side job* | −1.132* | (0.199) | −0.467+ | (0.239) | −0.489 | (0.313) |
| *firm size: medium*° | 0.220 | (0.185) | 0.252 | (0.244) | 0.262 | (0.299) |
| *large* | 0.187 | (0.194) | 0.335 | (0.273) | 0.441 | (0.336) |
| *year 2002* | −0.665* | (0.151) | −0.188 | (0.149) | −0.187 | (0.168) |
| *year 2004* | −0.130 | (0.131) | −0.071 | (0.116) | 0.148 | (0.180) |
| *year 2006* | −0.062 | (0.136) | −0.071 | (0.111) | | |
| *tenure* | 0.009 | (0.007) | | | | |
| *age* | 0.054* | (0.006) | | | | |
| *male* | 2.099* | (0.113) | | | | |
| *migration background: direct*° | 0.776* | (0.153) | | | | |
| *indirect* | 0.327 | (0.230) | | | | |
| *education in years*° | −0.022 | (0.025) | | | | |
| constant | 48.208* | (0.555) | | | | |
| number of observations | 37526 | | 35164 | | 24340 | |
| F-statistic | 45.882* | | 4.110* | | 2.667* | |

*Notes:* * significant at 5%; + significant at 10%; robust standard errors in parentheses. Dummy variables indicating the occupational position during the previous year included. °Missing values set to zero and regressor augmented by 'missing' indicator.[#] State indicators included.
Own calculations.

instrument relevance yields an *F*-statistic as high as 135.1, dispelling any concern about the instrument being weak. With respect to the controls in the instrumental equation, as expected, we find a significant negative effect for high-skilled white-collar worker and for employees with a good employability. Moreover, the marginally employed are less worried about being laid off. A low job satisfaction and having a temporary contract are positively linked to job insecurity. In the year 2002 and 2004, job worries were significantly higher than in 2008. Note that most interviews were held before the start of the financial crisis in fall 2008, at a time when the economy was still good. In contrast, between 2002 and 2004 the German labor market performed weakly. We do not observe a significant effect either of the marital status and the number of under-age dependents. This result might be explained by increased family responsibilities genuinely yielding concerns about unemployment but also increasing dismissal protection by the relevant regulations.

Turning to the structural equation, in accordance with OLS and FE results, the estimate for

the effect of fear of unemployment is negative and highly significant. The coefficient amounts to $-5.310$. This corresponds to a shift from the median to 30th percentile of the distribution of the *MCS* suggesting a substantial deterioration in the mental health status. The estimated effect size exceeds the corresponding FE and OLS values. This conflicts with our earlier reasoning of ignored reverse causality most likely resulting in an – in absolute terms – upward biased estimate, wherefore the IV-FE estimation should yield more moderate estimated effects.

One likely explanation for this pattern is that the IV-FE results have to be interpreted in terms of local average treatment effects (LATE, cf. Imbens and Angrist, 1994). This means that we estimate the average effect of fear of unemployment on those respondents for whom the firm's staff reduction is a key determinant of self-perceived job insecurity. These individuals may not be representative for the population of interest. For instance, individuals who assess their job security primarily on basis of their individual competence may not care much about other – eventually differently qualified and trained – employees losing their jobs. They may also be more self-confident and less vulnerable to job worries. However, precisely these individuals are effectively ignored by the IV-FE approach. In turn, the result may primarily rest on individuals of vulnerable mental health.

Another explanation is that, in contrast to OLS and FE, the IV-FE estimation identifies the effect under scrutiny focusing on one specific source of job insecurity. Yet, it may well be that the adverse mental health effects differ across the sources of fear of unemployment. Imagine two situations. In situation one, there is uncertainty about the economic performance of the company. In situation two, the company already starts to reduce the workforce because of economic difficulties. Although both situations may cause employees to be concerned about their jobs, the latter is likely to be more depressing to them and, hence, is more likely to result in a deterioration in mental health. A similar explanation bases on the idea that from the perspective of employees, a staff reduction by the firm represents an uncontrollable source of job insecurity. Compared to endogenous causes of job insecurity that may effectively be moderated, uncontrollable sources exert more deleterious psychological effects (Maier and Jackson, 1979).

## 4.2 Heterogeneity in Effects

The pattern of different estimates of the mean effect of fear of unemployment on mental health depending on the choice of the regression model points at pronounced effect heterogeneity at the individual level. In this section, we aim at identifying its determinants. First, we consider selected explanatory variables by source of heterogeneity. That is, we (i) interact the variable

'fear of unemployment' with the two regressors capturing the degree of employability, and (ii) estimate separate models for males and females. Second, we address effect heterogeneity across the mental health status by estimating quantile regressions.

In order to investigate whether employability matters for the effect that fear of job loss exerts on mental health, we re-estimate the regression models including interaction terms of 'fear of unemployment' with the two categories of 'employability' (difficult/good). Green (2011) finds strong evidence for good employability attenuating detrimental effects of unemployment and job insecurity on life satisfaction as well as self-perceived mental health. Based on our OLS and FE results, we cannot confirm this. The estimated effects do not vary significantly across the categories of 'employability'. However, IV-FE estimation yields a quite different pattern, see Table 4. While a small chance of finding an appropriate position compared to almost no chance does not make much difference for the mental health status, a good employability certainly does. here, the negative effect of job insecurity disappears. That is, employees that easily find an appropriate job are not negatively affected in their mental health. In quantitative terms, the employability differential in the effect on mental health amounts to 6.5 points on the MCS scale.

Estimating the model separately for males and females yields a moderate gender differential. The estimated OLS-coefficients are $-2.595$ for males compared to $-3.066$ for females; see Table A4. In the FE-model the gender differential diminishes substantially. Turning to the IV-FE estimates, we find an insignificant coefficient for females. For males, the effect is a little higher and significant. The LATE seems to reflect the traditional males' gender role, i.e., the family's breadwinner, which suggests that job-security is more important for the psychological stability of men. Yet, if there is any gender differential, it is not the key driving source for the effect heterogeneity.

Finally, we turn to the left-hand side variable as a potential source of heterogeneity by employing quantile regression techniques. Quantile regression, first introduced by Koenker and Bassett (1978), allows for addressing distributional effects of changes in the explanatory variables. Following Cameron and Trivedi (2005), the concept of quantile regression can be briefly characterized as follows: For any quantile $\theta$ of the distribution of the *MCS*, a regression function is fitted such that the *MCS* conditional on the explanatory variables is less than or equal to the value of the regression function with probability $\theta$. Hence, quantile regression allows for identifying the effect of job insecurity at any quantile of the distribution of the *MCS*. Here, we use the simplest approach, i.e., ordinary quantile regression.[8] Figure 1 displays estimated quantile-coefficient functions for the fear of unemployment. Dotted lines indicate the 95-percent confidence interval. As a refer-

[8]Generalizing the results of the IV model by employing IV quantile regression (Abadie et al., 2002; Froelich and Melly, 2010) yields a similar pattern of heterogeneity like the ordinary quantile regression.

Table 4: **Estimated Effects on MCS: Interaction Effects**

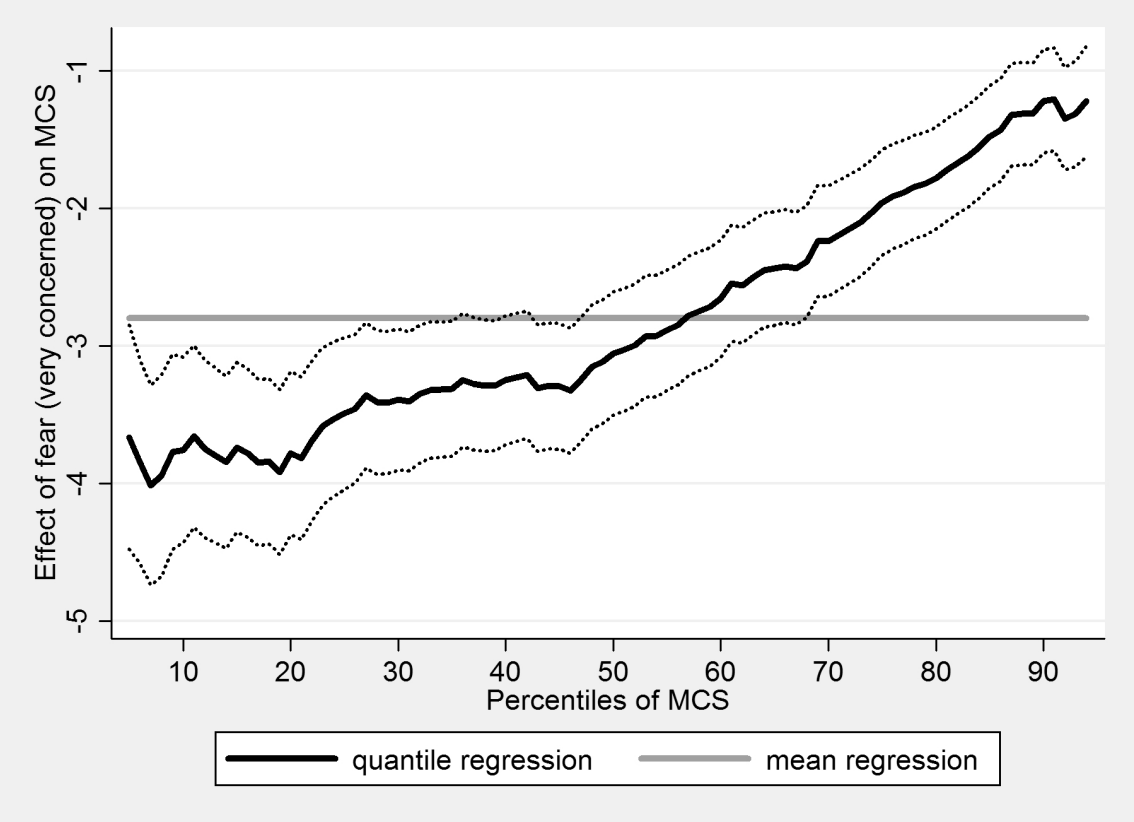
| | OLS[#] | | FE | | IV-FE | |
|---|---|---|---|---|---|---|
| | Coefficient | S.E. | Coefficient | S.E. | Coefficient | S.E. |
| *fear of unemployment° (by categories of 'employability'):* | | | | | | |
| *almost non-employable (lag)°* | −3.038* | (0.295) | −1.257* | (0.302) | −6.569* | (2.318) |
| *moderate employability (lag)* | −2.478* | (0.216) | −1.205* | (0.240) | −6.108* | (1.952) |
| *good employability (lag)* | −2.871* | (0.448) | −1.452* | (0.498) | 0.570 | (6.060) |
| *job satisfaction (lag): low°* | −3.932* | (0.202) | −0.506* | (0.206) | −0.651* | (0.287) |
| *medium* | −3.266* | (0.125) | −0.225 | (0.137) | −0.304+ | (0.179) |
| *overtime (lag)°* | −1.281* | (0.118) | −0.326* | (0.135) | −0.594* | (0.180) |
| *unemployed (lag)* | 2.141* | (0.250) | 0.344 | (0.254) | 0.243 | (0.349) |
| *labor market status: unemployed* | 0.800 | (1.344) | −0.666+ | (0.358) | −1.110 | (0.739) |
| *self employed* | 0.232 | (0.405) | 0.483 | (0.422) | −0.016 | (0.561) |
| *government employee* | −0.171 | (0.280) | 0.323 | (0.287) | −0.079 | (0.348) |
| *public servant* | 0.618 | (1.146) | −0.556 | (1.116) | −2.627+ | (1.551) |
| *pensioner* | 1.402 | (1.383) | −0.256 | (0.479) | −0.845 | (0.831) |
| *other* | 1.195 | (1.391) | −0.489 | (0.490) | −1.536+ | (0.850) |
| *married* | 0.165 | (0.163) | −0.147 | (0.281) | −0.647+ | (0.363) |
| *living with partner* | 0.337* | (0.166) | 1.208* | (0.263) | 1.186* | (0.328) |
| *household size* | 0.533* | (0.056) | 0.078 | (0.097) | 0.115 | (0.120) |
| *# of kids under 18* | −0.820* | (0.075) | −0.083 | (0.134) | −0.176 | (0.163) |
| *income (lag) °* | −0.002 | (0.033) | −0.089+ | (0.046) | −0.077 | (0.054) |
| *occupation: blue-collar skilled* | 0.158 | (0.170) | 0.371 | (0.239) | 0.270 | (0.307) |
| *white-collar low skilled* | 0.418* | (0.153) | 0.253 | (0.211) | 0.186 | (0.274) |
| *white-collar high skilled* | 0.347 | (0.217) | 0.261 | (0.302) | −0.251 | (0.402) |
| *mini job°* | −0.215 | (0.210) | 0.171 | (0.257) | 0.095 | (0.340) |
| *midi job* | −0.081 | (0.288) | −0.404 | (0.301) | −0.500 | (0.353) |
| *temporary contract°* | 0.428* | (0.182) | 0.089 | (0.204) | 0.536+ | (0.317) |
| *side job* | −1.129* | (0.199) | −0.466+ | (0.239) | −0.501 | (0.314) |
| *firm size: medium°* | 0.221 | (0.185) | 0.253 | (0.244) | 0.176 | (0.313) |
| *large* | 0.186 | (0.194) | 0.335 | (0.273) | 0.381 | (0.344) |
| *year 2002* | −0.670* | (0.151) | −0.190 | (0.149) | −0.137 | (0.172) |
| *year 2004* | −0.132 | (0.131) | −0.071 | (0.116) | 0.154 | (0.180) |
| *year 2006* | −0.064 | (0.136) | −0.071 | (0.111) | | |
| *tenure* | 0.009 | (0.007) | | | | |
| *age* | 0.054* | (0.006) | | | | |
| *male* | 2.099* | (0.113) | | | | |
| *migration background: direct°* | 0.773* | (0.153) | | | | |
| *indirect* | 0.326 | (0.230) | | | | |
| *education in years°* | −0.022 | (0.025) | | | | |
| *constant* | 48.268* | (0.558) | | | | |
| number of observations | 37526 | | 35164 | | 24340 | |
| F-statistic | 44.598* | | 3.928* | | 2.637 * | |

*Notes:* * significant at 5%; + significant at 10%; robust standard errors in parentheses. Dummy variables indicating the occupational position during the previous year included. °Missing values set to zero and regressor augmented by 'missing' indicator.[#] State indicators included.
Own calculations.

ence, the result from the OLS estimation are represented by the horizontal line. The estimated quantile-coefficients function exhibits a distinct positive slope. This indicates that the detrimental effect diminishes for individuals with higher values of the *MCS* and that those already of poor mental health are particularly harmed by job worries. This picture is statistically robust as the estimated confidence band does not overlap with the estimated mean effect for a substantial range of percentiles of the *MCS*. In quantitative terms, the effect is roughly 1.3 times stronger for the tenth percentile of the *M*CS than for the median, while for the 90th percentile, the ratio even amounts to 2.9. Comparing quantile regression with OLS, for the 10th percentile, the former yields effects that are 26 percent lager, while for the 90th percentile the estimated effect is 110 percent smaller compared to OLS.

In essence, results from quantile regression suggest that the mental health status itself represents a major source of heterogeneity in the effects. This is bad news because the fear of un-

Figure 1: **Quantile Regression: estimated Effects of Fear on MCS**



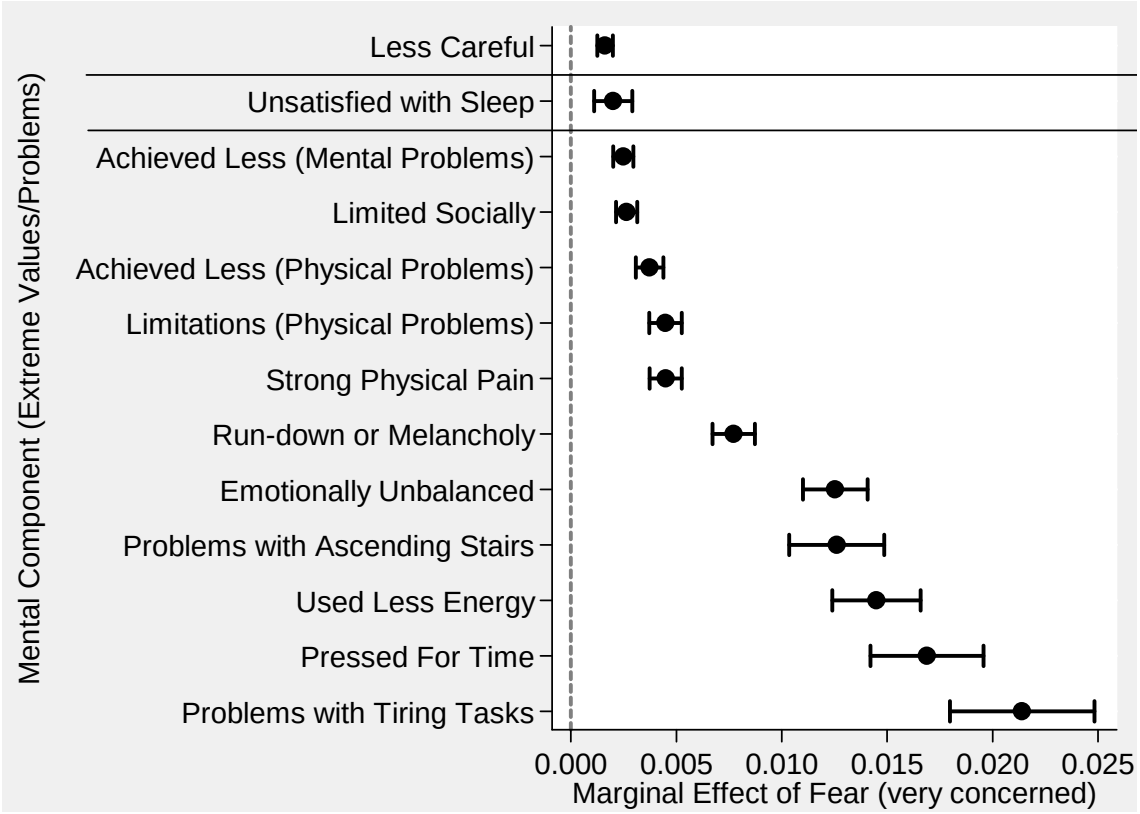

Own calculations.

employment does not simply shift or compress the distribution of the *MCS* but increases heterogeneity in mental health. Even a moderate average effect does not rule out drastic effects on those who already suffer from poor psychological health. Hence, for instance, the fear of unemployment may seriously threaten the ability to work for this group of individuals.

## 4.3 Robustness Checks

Although well established in the literature, the *MCS* might still be regarded as a somewhat problematic measure of mental health as it condenses information on various questions into a scalar index. In particular, one might argue that the estimated effects on *MCS* do not represent genuine effects on mental health but on certain variables that enter the *MCS*. In order to show that this is not the case here, we run the regression model separately for each component of the *MCS*. As these components are all ordinal variables, we estimate an ordered probit model using the same specification and the estimation sample as in the first OLS model. For each component of the *MCS*, Figure 2 displays the estimated marginal effect of fear of unemployment on the probability to realize the least favorable category. The corresponding 95-percent confidence intervals are also indicated.

Figure 2: **Estimated Effects of Fear on Each Component of the MCS**




Note that 'sleep' is not part of the *MCS*.

Own calculations.

The figure yields a consistent picture. Fear of unemployment exerts a detrimental and statistically significant effect on any single variable that enters the *MCS*. This means that the identified overall effect does not represent an artifact of the *MCS* calculation algorithm.[9] We are, thus, confident that the above results do allow for being interpreted as effects on individuals' mental health.

To further validate our results, we run an ordered probit regression with an ordinal variable indicating the respondents' satisfaction with their sleep as the dependent variable and job insecurity along with the other covariates as regressors. Note that this variable does not form part of the questions related to the *M*CS. The estimated marginal effect of fear of unemployment on the probability to be least satisfied with the own sleep is positive and significant, too (see the framed line in Figure 2). This gives further reason to interpret the observed effect as fear of unemployment causing genuine mental health problems.

[9] Aggregating the variables in a different way will most likely yield qualitatively equivalent results.

# 5 Conclusion

Based on German panel data, the present analysis yields convincing evidence for the idea that the fear of unemployment exerts a significant and detrimental effect on mental health. Applying different regression techniques based on different strategies for identification, such as fixed effects and instrumental variables fixed effects, our results prove to be robust in qualitative terms. Yet, in quantitative terms, the estimated mean effects vary. This is most likely explained by pronounced effect heterogeneity at the individual level and different estimation strategies effectively estimating mean effects for different sub populations.

We find that employees with a good employability are not affected by job insecurity, confirming the result of Green (2011). The notion of heterogeneity in the effect of the fear of unemployment on mental health is supported further by quantile regression results, which yield particularly strong effects for individuals of already poor mental health. This finding, however, raises doubts about the population average effect representing an appropriate measure for answering the question of whether the fear of unemployment represents a relevant threat to the employees' psychological health. Even if the average effect were moderate or small, certain groups of individuals may still develop severe mental health problems due to job worries. These might result in the inability to work and suicide at the extreme.

The policy implications of the above results point in the direction of ensuring job security. For instance, flexicurity policies aimed at limiting job separations may reduce the negative mental health impact of potential unemployment. While the size of the average effect of reducing job insecurity on mental health is rather vague, we provide evidence here that indicates that such policies benefit the most vulnerable group, i.e., those that are already in poor mental health.

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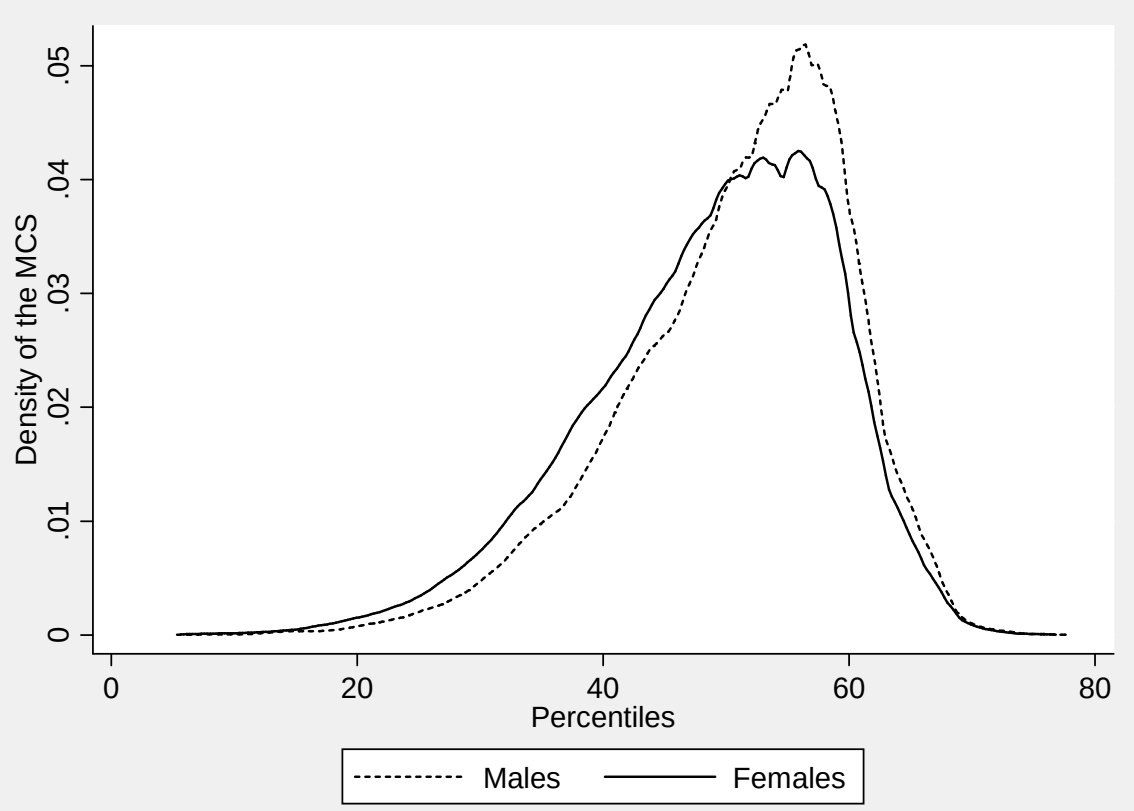
# Appendix

Table A1: **SF-12v2 questionnaire in the SOEP**

| | | | | | |
|---|---|---|---|---|---|
| | 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?<br>• And what about having to cope with other tiring everyday tasks, i.e. when one has to lift something heavy or when 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 | Some-times | Almost never | Never |
| How often did it occur within this period of time, ...<br><br>• that you felt rushed or pressed for time?<br>• that you felt run-down and melancholy?<br>• that you felt relaxed and well-balanced?<br>• that you used up a lot of energy?<br>• that you had strong physical pains?<br>• that due to physical health problems:<br>–you achieved less than you wanted to at work or in everyday tasks?<br>–you were limited in some form at work or in everyday tasks?<br>• that due to mental health or emotional problems:<br>–you achieved less than you wanted to at work or in everyday tasks?<br>–you carried out your work or everyday tasks less thoroughly than usual?<br>• that due to physical or mental problems you were limited socially, i.e. in contact with friends, acquaintances or relatives? | | | | | |

Figure A1: **Distribution of the *M*CS by Sex**




Own calculations.

Table A2: **Reduced From FE Results**

| | **Private Sector Employees** | | **Civil Servants** | |
|---|---|---|---|---|
| | Coefficient | S.E. | Coefficient | S.E. |
| *staff reduction* | −0.483∗ | (0.171) | 0.353 | (0.484) |
| *employability (lag): difficult°* | 0.164 | (0.215) | 0.291 | (0.520) |
| *good* | 0.236 | (0.278) | 0.605 | (0.657) |
| *job satisfaction (lag): low°* | −0.801∗ | (0.273) | −0.956 | (0.982) |
| *medium* | −0.380∗ | (0.174) | −1.291∗ | (0.589) |
| *overtime (lag)* | −0.638∗ | (0.172) | 0.207 | (0.472) |
| *married* | −0.566 | (0.351) | −0.780 | (1.058) |
| *living with partner* | 1.179∗ | (0.324) | 1.075 | (0.911) |
| *household size* | 0.116 | (0.118) | −0.231 | (0.359) |
| *# of kids under 18* | −0.143 | (0.158) | 0.482 | (0.476) |
| *personal income (lag)°* | −0.061 | (0.052) | 0.217 | (0.167) |
| *occupation: blue-collar skilled* | 0.233 | (0.299) | 3.015 | (4.194) |
| *white-collar low skilled* | 0.278 | (0.267) | −0.578 | (2.057) |
| *white-collar high skilled* | −0.007 | (0.385) | −1.935 | (2.342) |
| *mini job* | 0.279 | (0.327) | −6.655∗ | (2.711) |
| *midi job* | −0.436 | (0.348) | −0.224 | (1.065) |
| *temporary work contract* | 0.068 | (0.259) | −1.304 | (0.919) |
| *side job* | −0.589+ | (0.307) | −0.881 | (0.855) |
| *firm size: medium* | 0.230 | (0.298) | 3.630 | (3.071) |
| *large* | 0.402 | (0.333) | 3.813 | (3.013) |
| *unemployed (lag)* | 0.306 | (0.338) | 1.834 | (1.973) |
| *labor market status: unemployed* | −0.046 | (0.616) | −1.474 | (2.567) |
| *self employed* | −0.042 | (0.551) | −2.168 | (3.605) |
| *government employee* | 0.129 | (0.334) | −3.358+ | (2.037) |
| *public servant* | −2.364 | (1.524) | −4.091+ | (2.227) |
| *pensioner* | 0.039 | (0.745) | −2.545 | (2.576) |
| *other* | −0.749 | (0.778) | 0.684 | (2.843) |
| *year 2002* | −0.839∗∗∗ | 0.197 | −1.468∗ | 0.752 |
| *year 2004* | −0.312∗ | 0.166 | −0.023 | 0.481 |
| *year 2006* | | | | |
| number of observations | 24340 | | 2496 | |
| F-statistic | 2.811∗ | | 1.931∗ | |

*Notes:* * significant at 5%; + significant at 10%; robust standard errors in parentheses. Dummy variables indicating the occupational position during the previous year included. °Missing values set to zero and regressor augmented by 'missing' indicator.
Own calculations.

Table A3: **Instrumental Equation: FE Estimation Explaining Fear of Unemployment**

| | **Without Interaction** | | **With Interaction** | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Fear of Unemployment × High Employability | | Fear of Unemployment × Low Employability | |
| *staff reduction*° | 0.091* | (0.008) | 0.129* | (0.017) | −0.004+ | (0.002) | −0.028* | (0.010) |
| *staff reduction×employability difficult (lag)* | | | −0.035+ | (0.019) | 0.006+ | (0.003) | 0.132* | (0.013) |
| *staff reduction×employability good (lag)* | | | −0.097* | (0.022) | 0.063* | (0.012) | 0.015 | (0.013) |
| *employability (lag): difficult*° | −0.027* | (0.009) | −0.019+ | (0.010) | −0.004+ | (0.002) | 0.154* | (0.008) |
| *good* | −0.054* | (0.011) | −0.035* | (0.011) | 0.077* | (0.005) | 0.052* | (0.008) |
| *job satisfaction (lag): low*° | 0.031* | (0.012) | 0.030* | (0.012) | 0.005 | (0.004) | 0.022* | (0.010) |
| *medium* | 0.012 | (0.008) | 0.011 | (0.008) | 0.001 | (0.003) | 0.007 | (0.006) |
| *overtime (lag)*° | 0.011 | (0.007) | 0.012 | (0.007) | 0.002 | (0.003) | 0.014* | (0.006) |
| *unemployed (lag)* | −0.015 | (0.014) | −0.014 | (0.014) | −0.006 | (0.005) | 0.005 | (0.012) |
| *labor market status: unemployed* | −0.184* | (0.028) | −0.183* | (0.028) | −0.011 | (0.008) | −0.126* | (0.023) |
| *self employed* | 0.005 | (0.023) | 0.004 | (0.023) | 0.002 | (0.009) | −0.004 | (0.019) |
| *government employee* | −0.022 | (0.014) | −0.022 | (0.014) | 0.009+ | (0.005) | −0.025* | (0.012) |
| *public servant* | −0.043 | (0.051) | −0.044 | (0.050) | 0.003 | (0.016) | −0.048 | (0.031) |
| *pensioner* | −0.151* | (0.028) | −0.145* | (0.028) | −0.012 | (0.008) | −0.079* | (0.022) |
| *other* | −0.131* | (0.031) | −0.127* | (0.031) | −0.007 | (0.009) | −0.065* | (0.026) |
| *married* | −0.002 | (0.013) | −0.002 | (0.013) | 0.009+ | (0.005) | −0.017 | (0.012) |
| *living with partner* | 0.007 | (0.012) | 0.007 | (0.012) | 0.004 | (0.006) | 0.007 | (0.010) |
| *household size* | −0.000 | (0.004) | −0.001 | (0.004) | 0.000 | (0.002) | −0.003 | (0.004) |
| *# of kids under 18* | −0.009 | (0.006) | −0.009 | (0.006) | −0.003 | (0.002) | −0.001 | (0.006) |
| *income (lag)* ° | −0.001 | (0.002) | −0.001 | (0.002) | 0.001 | (0.001) | −0.002 | (0.002) |
| *occupation: blue-collar skilled* | 0.010 | (0.014) | 0.010 | (0.014) | 0.004 | (0.006) | 0.004 | (0.012) |
| *white-collar low skilled* | −0.018 | (0.011) | −0.017 | (0.011) | −0.002 | (0.005) | −0.010 | (0.009) |
| *white-collar high skilled* | −0.047* | (0.015) | −0.047* | (0.015) | −0.005 | (0.006) | −0.042* | (0.012) |
| *mini job*° | −0.027* | (0.012) | −0.027* | (0.012) | 0.003 | (0.005) | −0.019+ | (0.010) |
| *midi job* | −0.017 | (0.013) | −0.017 | (0.013) | −0.005 | (0.005) | −0.008 | (0.011) |
| *temporary contract* | 0.090* | (0.012) | 0.091* | (0.012) | 0.010+ | (0.005) | 0.067* | (0.010) |
| *side job* | 0.019+ | (0.011) | 0.018+ | (0.011) | 0.004 | (0.005) | 0.011 | (0.009) |
| *firm size: medium*° | 0.006 | (0.012) | 0.005 | (0.012) | 0.012* | (0.005) | −0.001 | (0.010) |
| *large* | 0.008 | (0.014) | 0.007 | (0.014) | 0.008 | (0.005) | 0.010 | (0.011) |
| *year 2002* | 0.013+ | (0.006) | 0.013* | (0.006) | −0.005* | (0.002) | 0.011* | (0.005) |
| *year 2004* | 0.059* | (0.005) | 0.059* | (0.005) | 0.006* | (0.002) | 0.039* | (0.004) |
| number of observations | 24340 | | 24340 | | 24340 | | 24340 | |
| F-statistic | 24.526* | | 23.567* | | 7.448* | | 30.657* | |

*Notes:* * significant at 5%; + significant at 10%; robust standard errors in parentheses. °Missing values set to zero and regressor augmented by 'missing' indicator. Consistent estimation of the mental health effects of fear of unemployment and its interactions with the employability indicators requires three instrumental equations. If staff reduction is a valid instrument for fear of unemployment, the interaction between staff reduction and employability is a valid instrument for the interaction between fear of unemployment and employability (see, e.g., Wooldridge, 2002).
Own calculations.

Table A4: **Estimated Effects on MCS by Gender**

| | OLS[#] | | | | FE | | | | IV-FE | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Males | | Females | | Males | | Females | | Males | | Females | |
| | Coefficient | S.E. | Coefficient | S.E. | Coefficient | S.E. | Coefficient | S.E. | Coefficient | S.E. | Coefficient | S.E. |
| *fear of unemployment* ° | −2.595* | (0.187) | −3.066* | (0.228) | −1.215* | (0.211) | −1.265* | (0.253) | −5.501* | (2.091) | −5.398 | (3.836) |
| *employability (lag): difficult*° | 0.115 | (0.188) | 0.329 | (0.219) | 0.114 | (0.215) | −0.158 | (0.247) | 0.003 | (0.292) | 0.067 | (0.359) |
| *good* | 0.574* | (0.241) | 0.635* | (0.274) | 0.106 | (0.290) | −0.008 | (0.323) | −0.321 | (0.396) | 0.218 | (0.473) |
| *job satisfaction (lag): low*° | −4.436* | (0.278) | −3.327* | (0.292) | −0.493+ | (0.285) | −0.467 | (0.298) | −0.531 | (0.396) | −0.680 | (0.415) |
| *medium* | −3.371* | (0.167) | −3.134* | (0.189) | −0.372* | (0.181) | −0.069 | (0.208) | −0.367 | (0.232) | −0.273 | (0.279) |
| *overtime (lag)*° | −1.356* | (0.155) | −1.165* | (0.182) | −0.456* | (0.175) | −0.133 | (0.209) | −0.922* | (0.226) | −0.140 | (0.288) |
| *unemployed (lag)* | 2.476* | (0.360) | 1.751* | (0.356) | 0.308 | (0.367) | 0.267 | (0.365) | 0.044 | (0.503) | 0.328 | (0.493) |
| *labor market status: unemployed* | −0.274 | (1.450) | 1.555 | (1.797) | −0.153 | (0.542) | −1.045* | (0.480) | −0.088 | (1.083) | −1.596 | (1.075) |
| *self employed* | 0.566 | (0.546) | −0.150 | (0.614) | 0.965 | (0.587) | 0.051 | (0.609) | 0.560 | (0.739) | −0.485 | (0.832) |
| *government employee* | −0.048 | (0.442) | −0.274 | (0.363) | 0.162 | (0.425) | 0.413 | (0.384) | −0.383 | (0.501) | 0.286 | (0.450) |
| *public servant* | 2.785* | (1.260) | −3.369 | (2.189) | 1.375 | (1.182) | −4.279* | (2.017) | −1.706 | (1.894) | −4.742* | (2.407) |
| *pensioner* | 0.912 | (1.515) | 1.436 | (1.871) | 0.664 | (0.664) | −1.023 | (0.715) | 0.418 | (1.188) | −1.512 | (1.199) |
| *other* | 0.021 | (1.548) | 2.037 | (1.864) | 0.208 | (0.756) | −1.027 | (0.650) | −0.115 | (1.280) | −2.480* | (1.177) |
| *married* | 0.110 | (0.224) | 0.131 | (0.235) | −0.055 | (0.386) | −0.229 | (0.405) | −0.260 | (0.477) | −0.867+ | (0.524) |
| *living with partner* | −0.195 | (0.232) | 0.754* | (0.238) | 1.193* | (0.381) | 1.281* | (0.363) | 1.180* | (0.464) | 1.267* | (0.479) |
| *household size* | 0.433* | (0.075) | 0.623* | (0.085) | 0.084 | (0.136) | 0.072 | (0.138) | 0.143 | (0.169) | 0.105 | (0.168) |
| *# of kids under 18* | −0.499* | (0.101) | −1.121* | (0.114) | −0.193 | (0.184) | 0.046 | (0.200) | −0.255 | (0.223) | −0.144 | (0.238) |
| *income (lag)*° | 0.056 | (0.039) | −0.157* | (0.078) | −0.053 | (0.054) | −0.243* | (0.105) | −0.041 | (0.061) | −0.203 | (0.124) |
| *occupation: blue-collar skilled* | −0.027 | (0.202) | 0.270 | (0.381) | 0.375 | (0.282) | 0.349 | (0.503) | 0.326 | (0.356) | −0.047 | (0.655) |
| *white-collar low skilled* | −0.031 | (0.226) | 0.766* | (0.212) | 0.127 | (0.314) | 0.319 | (0.291) | −0.090 | (0.400) | 0.359 | (0.377) |
| *white-collar high skilled* | −0.025 | (0.275) | 1.160* | (0.377) | 0.079 | (0.382) | 0.641 | (0.514) | −0.715 | (0.485) | 0.523 | (0.709) |
| *mini job*° | 0.264 | (0.460) | −0.315 | (0.251) | 0.876+ | (0.491) | −0.123 | (0.309) | 0.932 | (0.671) | −0.054 | (0.408) |
| *midi job* | −0.839 | (0.816) | −0.048 | (0.320) | 0.199 | (0.852) | −0.491 | (0.332) | −0.005 | (0.944) | −0.457 | (0.389) |
| *temporary contract*° | 0.169 | (0.252) | 0.673* | (0.264) | 0.006 | (0.285) | 0.129 | (0.293) | 0.617 | (0.411) | 0.401 | (0.499) |
| *side job* | −0.625* | (0.267) | −1.622* | (0.295) | −0.457 | (0.331) | −0.449 | (0.342) | −0.220 | (0.420) | −0.660 | (0.476) |
| *firm size: medium*° | 0.517+ | (0.292) | 0.018 | (0.241) | 0.914* | (0.370) | −0.240 | (0.326) | 1.244* | (0.445) | −0.492 | (0.404) |
| *large* | 0.380 | (0.298) | 0.186 | (0.264) | 0.713+ | (0.399) | 0.160 | (0.379) | 0.925+ | (0.481) | 0.240 | (0.470) |
| *year 2002* | −0.557* | (0.198) | −0.756* | (0.233) | 0.001 | (0.201) | −0.332 | (0.224) | 0.106 | (0.229) | −0.489+ | (0.253) |
| *year 2004* | −0.009 | (0.173) | −0.255 | (0.199) | 0.088 | (0.153) | −0.249 | (0.174) | 0.341 | (0.226) | −0.088 | (0.295) |
| *year 2006* | 0.061 | (0.181) | −0.195 | (0.204) | 0.047 | (0.150) | −0.204 | (0.166) | | | | |
| *tenure* | 0.001 | (0.009) | 0.025* | (0.011) | | | | | | | | |
| *age* | 0.060* | (0.008) | 0.053* | (0.008) | | | | | | | | |
| *migration background: direct*° | 0.850* | (0.204) | 0.694* | (0.231) | | | | | | | | |
| *indirect* | 0.903* | (0.295) | −0.334 | (0.356) | | | | | | | | |
| *education in years*° | −0.043 | (0.033) | 0.005 | (0.037) | | | | | | | | |
| *constant* | 50.616* | (0.749) | 47.575* | (0.831) | | | | | | | | |
| number of observations | 19601 | | 17925 | | 18287 | | 16877 | | 12733 | | 11607 | |
| F-statistic | 22.200* | | 18.750* | | 2.747* | | 2.413* | | 2.180* | | 1.655* | |

*Notes:* * significant at 5%; + significant at 10%; robust standard errors in parentheses. Dummy variables indicating the occupational position during the previous year included. °Missing values set to zero and regressor augmented by 'missing' indicator.[#] State indicators included.
Own calculations.